COMPARING THE ACCURACY OF MACHINE CLASSIFIED LANDSAT IMAGERY TO MANUALLY DELINEATED AERIAL PHOTOGRAPHS FOR COUNTY APPRAISAL DISTRICT USE

A Thesis

by

MATTHEW PALMER FALTER

Submitted to the Office of Graduate Studies of
Texas A&M University
in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

May 1995

Major Subject: Forestry

COMPARING THE ACCURACY OF MACHINE CLASSIFIED LANDSAT IMAGERY TO MANUALLY DELINEATED AERIAL PHOTOGRAPHS FOR COUNTY APPRAISAL DISTRICT USE

A Thesis

by

MATTHEW PALMER FALTER

Submitted to Texas A&M University
in partial fulfillment of the requirements
for the degree of

MASTER OF SCIENCE

Approved as to style and content by:

Robert D. Baker
(Chair of Committee)

William J. Lowe
(Member)

Kenneth L. White
(Member)

Richard F. Fisher
(Head of Department)

May 1995

Major Subject: Forestry

ABSTRACT

Comparing the Accuracy of Machine Classified Landsat Imagery to Manually Delineated Aerial Photographs for County Appraisal District Use.

(May 1995)

Matthew Palmer Falter,

B.S., Texas A&M University

Chair of Advisory Committee: Dr. Robert D. Baker

The purpose of this study was to compare the results of a computer classified satellite image to human classified aerial photographs, and to determine the accuracy of the satellite image for land-use/land-cover mapping of forested areas.

One 1:24,000 quadrangle map (Chester) was used to test the supervised and unsupervised classification methods and a second (Boggy Lake) was used to verify the classification. The resulting maps were then tested for accuracy by comparing them to human classified aerial photographs of the same area.

Verification was accomplished using systematically located points with a random start. Each map was analyzed for errors of omission and errors of commission.

The results of this study showed accuracy levels of the satellite images as compared to the aerial photographs were below 50 percent for both quadrangle map areas and both classification methods. No significant difference was detected between the supervised and the unsupervised classification methods for either quadrangle map area. The verification process using the Boggy Lake Quadrangle map, did not show a significant difference from the developmental map, the Chester Quadrangle, for either classification method.

ACKNOWLEDGEMENTS

During the last two and half years, I have received assistance on this project from numerous people. First, I wish to thank my committee chair, Dr. Robert D. Baker. Dr. Baker helped in getting this project started and gave necessary criticism throughout. Also, his patience with me helped with the *learning* process of writing a thesis. Next, the members of my committee, Dr. Kenneth L. White and Dr. William J. Lowe, both whose expertise in their fields made parts of this project easier with their guidance, sense of humor, and honesty. Also, I would like to thank Dr. Lowe for being my mentor for the past four years and for his help in sparking my interest in conducting research.

My co-workers, Daniel Rodriguez, Dolph Scott, and Tony McKinney for their respect and help with the nuts and bolts of this project.

My parents, Florence and Kenneth Falter, whose support I could not have done without during this project. My brothers, David and Andrew, for the constant reminder to stay focused.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

The present property tax system for private commercial forest land in Texas uses a combination of forest types, soil productivity types, timber growth data, and prices and costs in a capitalization formula to determine its timber-use value. The forest types are presently derived from interpreted aerial photographs, which is a slow and expensive process. Automating the classification of the forest type data would improve county appraisal district procedures. With the increased power of computers, decreased cost of hardware and software, and the increase in resolution of satellite imagery, a new method of forest classification needs to be examined. This method can be accomplished with the use of Landsat Thematic Mapper (TM) satellite imagery.

The objective of this study was to classify forest types in Tyler County, Texas, using Landsat TM imagery, and to compare that classification to delineated aerial photographs.

This thesis follows the style of Photogrammetric Engineering and Remote Sensing.

LITERATURE REVIEW

The first Landsat satellite was launched in July, 1972. It carried a multispectral scanner (MSS) system for data collection. The system had four bands, two in the visible, and two in the near infrared portion of the electromagnetic spectrum. The spatial resolution of the MSS system was 79 meters. This first Landsat satellite was followed by two similar satellites in 1975 and 1978 (Lillesand and Kiefer, 1987).

In July, 1982, Landsat 4 was launched. It was followed by Landsat 5 in 1984. In addition to having an MSS system, Landsats 4 and 5 also carried a thematic mapper (TM) sensor. The TM has seven bands, three in the visible, one in the near infrared, two in the mid infrared, and one in the thermal infrared portion of the electromagnetic spectrum. The spatial resolution of the TM was 120 meters for the thermal infrared band, and 30 meters for the other six bands (Lillesand and Kiefer, 1987). Resolution is measured in pixels which are defined as picture elements, or the smallest measurable unit in an image (Avery and Berlin, 1992). Each scene is approximately 115 miles on a side, containing approximately 6500 pixels, which is equivalent to over eight million acres of coverage (Bowlin and Lachowski, 1987).

The two major differences between MSS data and TM data are spatial resolution and the number of spectral bands. In terms of spatial resolution, Bowlin and Lachowski (1987) believe that TM data with 30 meter resolution provides too much information for vegetation classification. However, Häme (1984) states that if a pixel straddles the border between two sites and the border is sharp, the pixel may get its value from both sites and therefore may be classified as its own type. With finer resolution, a decrease in the number of mixed pixels should increase the accuracy (Williams et al., 1984).

With MSS the number of spectral bands available is limited. However, with TM data, one band each from the visible, near infrared, and mid infrared should be used for forest classification (Hopkins et al., 1988; Benson and DeGloria, 1985; Moore and Bauer, 1990; Bolstad and Lillesand, 1992). However, the high spatial resolution does not have as vital an impact on computer classification as the increased spectral information (Hopkins et al., 1988; Williams et al., 1984; Latty and Hoffer, 1981; Moore and Bauer, 1990). This fact leads to the decision that TM data is better suited for classifying forests for inventory purposes.

Classifying forest types digitally can be accomplished using either an unsupervised classification or a supervised classification system with a predetermined variance. An unsupervised classification allows the computer to group similar pixels into categories. A supervised classification allows the user to choose sample pixels from which the computer will compare and group similar pixels with the sample. Unsupervised classifications have been used for forest inventory and assessment in western states (Bowlin and Lachowski, 1987), forest inventory in Canada (Beaubien, 1979), and for classifying conifers by species, size, and density in northern California (Mayer and Fox, 1981).

Supervised classifications have been used for improving forest classification in northern Wisconsin using a combination of soils, terrain, and TM data (Bolstad and Lillesand, 1992), classifying forests in the Great Lake States area (Hopkins et al., 1988), and classifying forest types in northern Minnesota (Moore and Bauer, 1990). The accuracies for both classification methods vary, usually depending upon the topography of the area being classified and the amount of reflectance of the forested areas (Beaubien, 1979; Bolstad and Lillesand, 1992).

An example of a supervised classification showed an overall accuracy of 85 percent and an average class accuracy of 78 percent (Hopkins et al., 1988). Another example of a supervised classification showed results ranging between 35 and 68 percent for different level II and level III classes

(Moore and Bauer, 1990). The terms level II and level III are part of a hierarchical classification system developed by Anderson et al. (1976). An example of the use of this classification system demonstrates how loblolly pine would be classified at levels I through III. At level III, the most specific of the three levels, loblolly pine would be classified as 421. The first digit representing forest land, the second digit representing evergreen forest land, and the third digit representing the species. At level II, the classification would be a 42, and at level I the classification would be a 4.

Results of an unsupervised classification of conifer species which included a mixed category showed accuracies ranging from 68 to 96 percent (Mayer and Fox, 1981). These tests were conducted in forest ecosystems other than the South.

Another example of a supervised classification was a study completed by the USDA Forest Service on the Kisatchie National Forest, in Louisiana. This study incorporated forest stand boundaries into the classification to assist in training sample selection to avoid including areas of mixed vegetation types. The results from this study yielded accuracies of 83.8 percent for pine stands, 65.0 percent for hardwood stands, and 32.9 percent for mixed areas (Evans, 1994). One point about this study that should be noted is that in the 1950s the hardwoods growing in the pine stands were deadened, thus producing, in the literal sense, pure pine stands (Baker, personal communication, 1994).

MATERIALS AND METHODS

Study Site

Two areas were chosen to test forestland classification systems from a Landsat image. The areas were the Chester and Boggy Lake USGS 7.5 minute quadrangle maps of Tyler County in southeast Texas (Figure 1). The Chester quadrangle map area was used to develop and test the classification methods and the Boggy Lake quadrangle map area was used to verify the accuracy found using the classification employed for the Chester quadrangle. Both study sites were within the Tyler County Appraisal District.

The forest types within the study sites consisted of large areas of mixed forested land, pine and hardwood. These areas of mixed forest consisted of some small patches of pine and hardwood, and some literally mixed areas. Some young pine plantations were also in the study area. A portion of the young pine plantations contained a hardwood component. In addition, the young pine plantations had exposed soil.

Imagery

The Landsat TM scene was taken on September 8, 1988. The test areas were located and extracted from this scene. This was accomplished by rectifying the image using ground

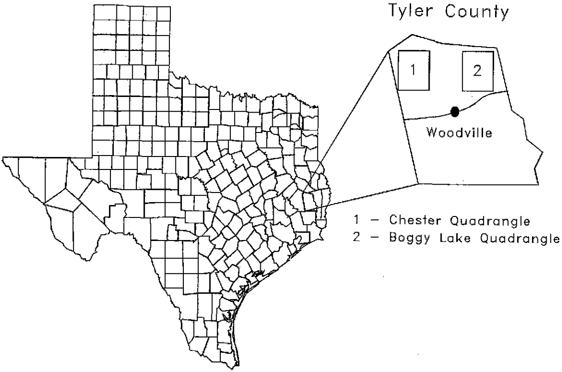

Figure 1: Texas counties showing Tyler County and the two selected quadrangle maps.

control points. Ground control points selected from the TM image were pipeline - road intersections and road - road intersections. These intersections were then located on a 1:100,000 or 1:24,000 map. A total of 25 ground control points were co-located on the image and the maps.

The next step was locating each point in the field. A Trimble Pathfinder GPS (1992) was used to obtain the ground coordinates for each control point. Of the original 25 ground control points, only 18 were used due to limited access to some intersections and adverse road conditions. Eighteen ground control points were sufficient according to the ERDAS Field Guide (1991), which states that for a first order linear transformation, a minimum of 3 ground control points are required. However using the minimum number of control points can lead to a high root mean square (RMS) error. The RMS error is the distance between the verified control point and the location of the control point on the image after the image has been rectified (ERDAS, 1991). With the 18 control points used in this study, the RMS error was 0.811 pixels (about 20 meters). The image was then georectified using the ERDAS image processing system.

The color infrared (CIR) aerial photographs of the test sites were taken for the National Aerial Photography Project (NAPP) on February 22, 1989, at a scale of 1:40,000. The interpretation was done on contact prints from this mission.

Classification of the Imagery

The classification of the Landsat image and the CIR photographs was based on the system developed by Anderson et al. (1976). For this system, code 41 represented deciduous, code 42 represented evergreen, code 43 represented mixed forest, and code 76 represented transitional areas and was used for other nonforested areas as well. Areas defined as deciduous had less than one-third evergreen component, and areas defined as evergreen had less than one-third deciduous component. Areas defined as mixed had a greater than one-third intermixture of evergreen and deciduous species (Anderson et al., 1976). In a winter CIR photograph, deciduous trees appear blue or green and evergreen trees appear red (Avery and Berlin, 1992).

The aerial photographs had been classified by an experienced photograph interpreter and field verified for accuracy. They were accepted as accurate by the taxation specialist for the Tyler County Appraisal District (CAD), therefore they were considered as "correct" and formed the basis for the comparison.

After the aerial photographs were verified, the scale of the classified overlays was transferred to match the scale of the 1:24,000 quadrangle maps. This was done using a Kail reflecting projector.

The Landsat image was classified using the ERDAS (1991) image processing system. Based on current methodology used in the Upper Midwest, bands 5, 4, and 3 have been the norm for forest type classification. The order of the numbers represent the three color guns, red, green, and blue, on the computer monitor. For this study, however, different band combinations were visually inspected to determine which combination provided the best image for classification purposes. For this visual inspection, bands 4, 3, and 2 (false color infrared) were determined to be the best band combination for this study. This combination provided the user with better tonal contrast between the land cover types as compared to the other combinations.

Classification of the Chester Quadrangle Map Area

The first classification done on the Chester map area was unsupervised. Initially a statistically clustered, STATCL, unsupervised algorithm was used; however it only yielded four classes, two pine, one nonforested and one hardwood/mixed. Since the hardwood and the mixed areas were not separated, this particular algorithm was unsuitable for this study. A second unsupervised algorithm was then used. This was the ISODATA algorithm (Iterative Self-Organizing Data Analysis Technique (Tou and Gonzalez, 1974)). Using the ISODATA algorithm, the user determines the number of clusters to be used for classification. For this level of classification, it was decided that eight clusters would be sufficient to depict the four classes. The classes were determined by comparing areas on the aerial photographs with the same areas on the classified image. This led to the breakdown of the eight clusters into the four classes mentioned earlier (Figure 2).

The supervised classification was performed next. This was accomplished by selecting and digitizing training sets from the image. These training sets were selected by the user, based on the homogeneity of the pixels in an area. Several training sets for the four classes were selected. Using the training sets, a maximum likelihood classifier was then used to classify the whole quadrangle map coverage (Figure 3).

After both classification methods were completed, the map area was plotted and checked against the aerial photographs for accuracy.

Classification of the Boggy Lake Quadrangle Map Area

The methodology used in classifying the Boggy Lake map area was similar to that used for the Chester map area. The principal difference between the methods was that the image covering the Boggy Lake map area had clouds and their shadows present. In the unsupervised classification, using

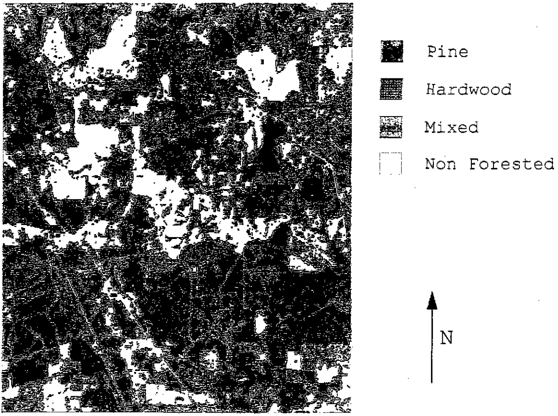

Figure 2: The unsupervised classification of the Chester Quadrangle area - RF 1:125,000.

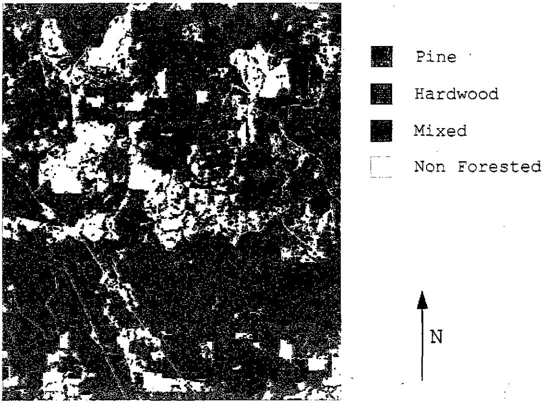

Figure 3: The supervised classification of the Chester Quadrangle area - RF 1:125,000.

eight clusters, clouds and nonforested areas could not be separated, therefore ten clusters were used (Figure 4). Also, for the supervised classification, training sets for the clouds and shadows were included with the other training sets (Figure 5). Clouds and shadows were excluded from the verification process.

Sample Selection

The accuracy of the classified Landsat image was based on a comparison to the classified aerial photographs. Anderson et al. (1976) state that: "The minimum level of interpretation accuracy in the identification of land-use and land-cover categories from remote sensor data should be at least 85 percent." This statement led to a null hypothesis for each category of: H_o: $P >= 0.85$, and the alternative hypothesis of: H_a: $P < 0.85$, where P was the percent of correctly classified points. These sample points were systematically located using a randomly selected starting point for each quadrangle map area. The minimum number of sample points per category at the 95 percent confidence level with 85 percent accuracy was 19 (Rosenfield et al., 1982). Sample points were only used if they were located completely within a polygon on the Landsat classifications and on the aerial photograph. Also, on the

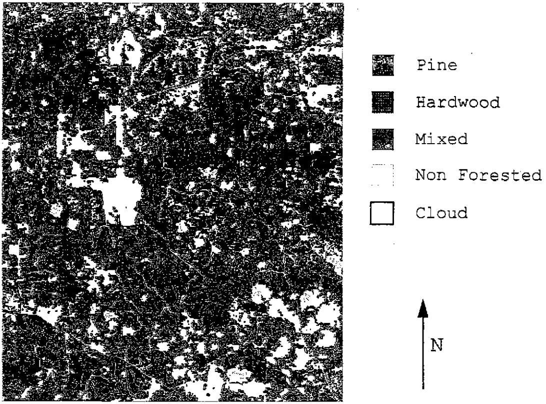

Figure 4: The unsupervised classification of the Boggy Lake Quadrangle area - RF 1:125,000.

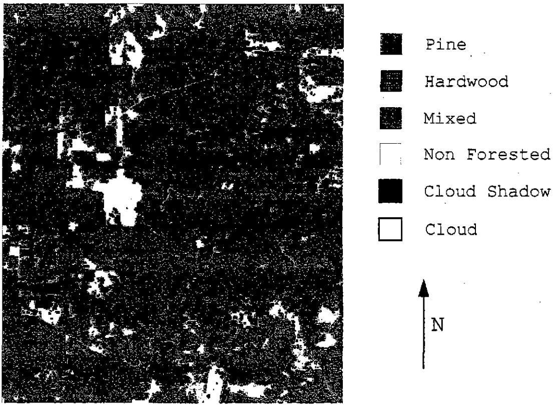

Figure 5: The supervised classification of the Boggy Lake Quadrangle area - RF 1:125,000.

Boggy Lake map area, when a sample point fell within a cloud or its shadow, it was not used.

A binomial probability was calculated based on the number of sample points in each category from the aerial photographs. The use of a binomial probability to calculate the number of sample points was based on experience of other studies, such as Hord and Brooner (1976), and Rosenfield et al. (1982). Using the 85 percent accuracy level, a "critical value" was calculated (Table 1). This value is one less than the minimum number of sample points which must be correctly classified from any one category to achieve a certain percent of accuracy, in this case 85 percent (Rosenfield et al., 1982). If the number of correctly classified points for a single category was greater than the critical value, the null hypothesis failed to be rejected. That is, the accuracy for that category was at least the predetermined 85 percent, based on the acceptable error and a 95 percent confidence interval.

Table 1: The critical value calculated for each sample size, N

N	Critical Value
15	9
16	10
19	12
44	32
65	49
87	67
123	97
131	103

Sample Size and Distribution

The sample size for both of the classifications produced for the Chester map area were 255 points, randomly selected as has been stated. On the Boggy Lake map area there were 245 points. The distribution of the points between classes on each map area is listed (Tables 2 and 3).

Data Verification

The verification process involved placing an overlay displaying the sample points over both the classified map areas produced from the aerial photographs and the classified map areas produced from the computer classification. Each point was then assigned to one of the four classes. The results were tabulated and compared to the aerial photographs.

A paired comparison T-test was performed on the means from both classification methods and quadrangle map areas. This determined whether or not there was a significant difference between the classifications and quadrangle map areas.

Table 2: Distribution of sample points for the Chester Quadrangle Map area based on photograph interpretation

Class	Points	Percent of Total points
41 (Hardwood)	15	5.88
42 (Evergreen)	131	51.37
43 (Mixed)	65	25.49
76 (Nonforested)	44	17.25

Table 3: Distribution of sample points for the Boggy Lake Quadrangle Map area based on photograph interpretation

Class	Points	Percent of Total points
41 (Hardwood)	16	6.53
42 (Evergreen)	123	50.20
43 (Mixed)	87	35.51
76 (Nonforested)	19	7.76

RESULTS

Chester Quadrangle Map Area

The accuracy of the classifications done on the Chester Quadrangle area are summarized in the two error matrices (Tables 4 and 5). The overall accuracy for the supervised classification was 34.9 percent, and for the unsupervised classification was 40.0 percent. No significant difference was detected between the supervised and unsupervised classification methods for the Chester Quadrangle map area.

Table 4: Error matrix and summary of agreement for the supervised classification of the Chester Quadrangle

Aerial Photographs	Classified Image 41	42	43	76	Total	Percent Correct[1]
41	7	0	6	2	15	46.7
42	24	36	52	19	131	27.5
43	7	14	27	17	65	41.5
76	8	5	12	19	44	43.2
Total	46	55	97	57	255	
Percent Correct[2]	15.2	65.4	27.8	33.3		**34.9**[3]

[1]considering only omission errors

[2]considering only commission errors

[3]overall classification accuracy; ratio of the sum of diagonal values to the total number of points

Table 5: Error matrix and summary of agreement for the unsupervised classification of the Chester Quadrangle

Aerial Photographs	Classified Image 41	42	43	76	Total	Percent Correct[1]
41	1	9	3	2	15	6.7
42	18	56	36	21	131	42.7
43	2	25	23	15	65	35.4
76	4	10	8	22	44	50.0
Total	25	100	70	60	255	
Percent Correct[2]	4.0	56.0	32.9	36.7		**40.0**[3]

[1]considering only omission errors

[2]considering only commission errors

[3]overall classification accuracy; ratio of the sum of diagonal values to the total number of points

When looking at the error matrices for the different classification methods, one can examine them for errors of omission and commission. Errors of omission are defined as the number of sample points incorrectly classified on the image for each class on the aerial photographs. For example, the supervised classification of the Chester Quadrangle map area showed seven correctly classified points for class 41 (hardwood). Six points were incorrectly classified as mixed and two points were incorrectly classified as nonforested. The eight points, incorrectly classified, represent the errors of omission.

Errors of commission are defined as the number of sample points misclassified in one particular class from the image (Fitzpatrick-Lins, 1980). For example the supervised classification of the Chester Quadrangle map area showed seven correctly classified points for class 41. Twenty-four points classified on the image as 41 were actually evergreen on the photographs, seven points were actually mixed, and eight points were actually nonforested.

When examining the data on the supervised classification in terms of errors of omission the null hypothesis was rejected for all four classes (Table 4). The accuracy in terms of errors of omission from the supervised classification was not significantly different from that of the unsupervised classification (Tables 4 and 5).

When assessing the accuracy of both classification methods in terms of errors of commission, the number of sample points incorrectly classified in one particular class from the image, similar results were found (Tables 4 and 5). For example, in class 43 (mixed) on the unsupervised image, 33 percent of the points classified from the image were correctly classified as 43, or 67 percent of the points from the image were misclassified (Table 5).

Boggy Lake Quadrangle Map Area

The results from the classifications completed on the Boggy Lake Quadrangle map area were similar to the results found in the Chester Quadrangle classifications. The overall accuracy for the supervised classification was 42.0 percent and for the unsupervised classification was 29.4 percent. There were no significant differences between the classification methods for this map area. The accuracies for the Boggy Lake map area are summarized in error matrices (Tables 6 and 7).

Table 6: Error matrix and summary of agreement for the supervised classification of the Boggy Lake Quadrangle

Aerial Photographs	Classified Image					
	41	42	43	76	Total	Percent Correct[1]
41	6	6	4	0	16	37.5
42	22	29	53	19	123	23.6
43	19	6	58	4	87	66.7
76	1	1	7	10	19	52.6
Total	48	42	122	33	245	
Percent Correct[2]	12.5	69.1	47.5	30.3		**41.9**[3]

[1]considering only omission errors

[2]considering only commission errors

[3]overall classification accuracy; ratio of the sum of diagonal values to the total number of points

Table 7: Error matrix and summary of agreement for the unsupervised classification of the Boggy Lake Quadrangle

Aerial Photographs	Classified Image 41	42	43	76	Total	Percent Correct[1]
41	2	6	7	1	16	12.5
42	29	39	28	27	123	31.7
43	31	22	21	13	87	24.1
76	0	5	4	10	19	52.6
Total	62	72	60	51	245	
Percent Correct[2]	3.2	54.1	35.0	19.6		29.4[3]

[1]considering only omission errors

[2]considering only commission errors

[3]overall classification accuracy; ratio of the sum of diagonal values to the total number of points

When examining the data of the supervised classification in terms of errors of omission, the null hypothesis was rejected in all four classes (Table 6). The low accuracy obtained, in terms of errors of omission, for the supervised classification was not significantly different from the unsupervised classification, as shown by the results of the unsupervised classification (Table 7). In terms of errors of commission, the results were similar to the errors found for the Chester Quadrangle (Tables 6 and 7).

DISCUSSION AND RECOMMENDATIONS

Overall, the accuracy of machine classification was not acceptable for use in County Appraisal Districts. A possible reason could be the mixture of forest types in East Texas which consist of large areas of mixed forested land. These areas of mixed forest consist of some small patches of pine and hardwood, and some literally mixed areas. Whether or not a stand is pine or mixed can lead to some errors of omission. Of the portion of points classified as pine (42) from the aerial photographs, the majority of the points not classified as such from the satellite image were categorized as mixed forest.

The seasonal differences between the forest types on the aerial photographs, taken in February, were leaf-off condition and those on the satellite image, taken in September, were leaf-on condition. This may have underestimated the hardwood component. As was stated earlier, in leaf-off CIR photography, hardwoods appear green, however, with leaf-on imagery on CIR photographs hardwoods appear red (Avery and Berlin, 1992). In September some hardwoods may have dropped their leaves, which would have caused the imagery to have more than one spectral signature for hardwoods. If this is not considered in the classification scheme, lower accuracy for the hardwood category may result. Also, when the computer classification clusters similar pixels by their spectral values, the spectral differences between hardwoods and pines in leaf-on imagery may be to minimal to separate by class.

Another possible reason for the inaccuracy may have been large age differences between pine stands. Young pine plantations or new plantations with a large hardwood component would be classified on the aerial photographs as pine because the interpreter knows that that plantation is meant to be pine. It would appear on the satellite image as a mixed stand, due to the spectral signatures produced from the training sets. Also, freshly planted pine with a large amount of ground showing will normally be classified as pine by the photograph interpreter because the interpreter can make the distinction that it is a pine plantation. As compared to the satellite image, the area would be classified as nonforested. The satellite image would show this as having a different spectral value as compared to a mostly pure pine stand.

Another cause for the poor accuracy could have been caused by the fact that many pine stands do not have a closed canopy. For a mature tree with a crown diameter of 45 feet, the area represented by this crown would be 1590 sq.ft. The area of a pixel on this image is 8742 sq.ft. At these measurements, it would take 5.5 tree crowns to fill a pixel. Because crown density varies within a stand and between stands, different spectral values in terms of how much ground and/or hardwood understory is showing between crowns can be obtained. Because of this, certain stands of timber maybe classified from the satellite image as mixed due to the hardwood undergrowth in a mature pine stand.

The errors of commission can be explained in a similar manner. For example, small hardwood stringers in a nonforested area would be classified by the photograph interpreter as a part of the nonforested area, whereas the computer would separate them into hardwood and nonforested areas (Figure 6).

Errors of commission also occurred within the mixed category as classified by the computer. A large portion of the errors of commission were found when the computer classified a stand as mixed when it was actually pine (Figure 7). This was found to be evident in both classification methods for both quadrangle map areas. This supports the point made earlier, where the photograph interpreter can distinguish between stands of pine with some visible hardwoods present and stands that are truly mixed.

Evidence of this is also found when examining the points the computer classified as nonforested land. In all cases, a minimum number of points (0, 1, 2, and 2) were

Figure 6: An example showing hardwood stringers in a nonforested area. The top image is the photograph, the lower image is the classification, 'A' shows the area concerned. Stringers show as green in the lower image.

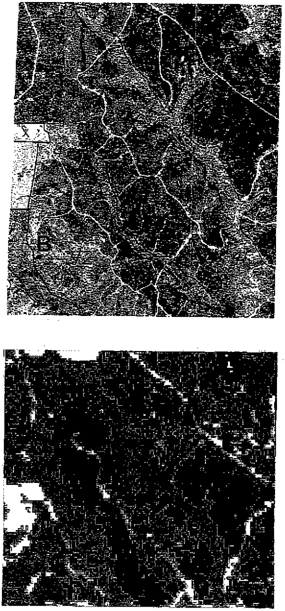

Figure 7: An example showing where the computer classified a stand as mixed when it was actually pine. The top image is the photograph, the lower image is the classification, 'B' shows the area concerned. The mixed stand shows as blue in the lower image. Pine is red.

classified as nonforested, when they should have been classified as hardwood. This was most likely due to the fact that areas classified as hardwood on the aerial photographs either followed stream courses and were densely crowded or there were no young hardwood plantations where the ground could be clearly seen as compared to the pine class.

When comparing the computer classified nonforested points to what the photograph interpreter classified as pine, one finds a large number of misclassified points, 19 out of 57 in Table 4, 21 out of 60 in Table 5, 19 out of 33 in Table 6, and 27 out of 51 in Table 7. This was partially due to the substantial amount of highly reflective ground visible in areas of newly planted pine. The spectral value of these areas were closer to that of actual nonforested areas as opposed to pine forested areas.

Another method to compare the results of the study is to estimate the timber-use value based on the satellite image for each forest type and compare that to the actual timber-use value calculated for the appraisal district. Using the supervised classification for the two quadrangle map areas, the acreage for each forest type were averaged and the timber-use values were calculated. In comparing the percentages each forest type represented, the hardwood was overassessed, the pine was underassessed, and the mixed timber type was within three percent of the actual timber-use value (Table 8). The county appraisal district would not want the hardwood to be overassessed since it is worth less per acre than pine. Similarly, with pine being underassessed, the landowners would have to pay less per acre in taxes for pine.

Table 8: Percentage of timber-use values by timber type from the Tyler County Appraisal District and the averaged supervised classifications of both quadrangle map areas

	Hardwood 41	Evergreen 42	Mixed 43
Tyler County Appraisal District	4.23	42.35	53.42
Average from both quadrangle areas	9.62	34.14	56.24

Another difference between photograph interpretation and computer classification are recognition elements. The experienced photograph interpreter uses recognition elements to assist in classification. These elements include tone, texture, location and association and pattern, as compared to the computer which uses only differences in spectral values or tone. By comparison, the photograph interpreter uses four recognition elements to assist in classification, while the computer uses only one element. This may have contributed to the low accuracy of the computer classification of the forest types.

One aspect not included in this study was topography. As was stated earlier, photograph interpreters use location and association as one tool in classification. When viewing photographs in stereo, the interpreter can separate areas of varying elevation. In three studies using satellite imagery for classification of forest vegetation, classification and inventory, and classification of timberland productivity, digital terrain models and topographic data was used to assist in the classification (Bolstad and Lillesand, 1992; Strahler et al., 1979; Fox et al., 1985). One of the studies directly compared classification with soil texture and terrain data with supervised classification. The enhanced classification resulted in improved overall accuracies in forest types found in Wisconsin (Bolstad and Lillesand, 1992). Use of terrain data may need to be incorporated with the classification methods to increase accuracy in east Texas.

SUMMARY

Even though the results of this study showed that the computer classification scheme failed to meet the minimum accuracy standards, some other aspects need to be addressed and possibly studied further. First, thematic mapper data with 28.5 meter pixel size using a maximum likelihood classifier cannot readily distinguish between the patchy forest types and stand types common in East Texas. This is due primarily to the large age differences and composition of the timber stands. Second, as mentioned in the previous section, possibly including terrain or topographic data with the classification may improve accuracy. Third, with the accuracy of the computer classification not reaching the minimum accuracy required, photograph interpretation is still the best option for forest type classification for use in county appraisal district. However, this may change with future developments in satellite imagery.

REFERENCES

Anderson, J. R., E. E. Hardy, J. T. Roach, and R. E. Witmer, 1976. A Land Use and Land Cover Classification System for Use with Remote Sensor Data. USGS Professional Paper 964. Washington D.C. 28 p.

Avery, T. E., and G. L. Berlin, 1992. Fundamentals of Remote Sensing and Airphoto Interpretation. Fifth Edition. MacMillan Publishing Co., New York, 472 p.

Beaubien, J., 1979. Forest Type Mapping From Landsat Digital Data. Photogrammetric Engineering and Remote Sensing, 45(8):1135-1144.

Benson, A. S. and S. D. DeGloria, 1985. Interpretation of Landsat-4 Thematic Mapper and Multispectral Scanner Data for Forest Surveys. Photogrammetric Engineering and Remote Sensing, 51(9):1281-1289.

Bolstad, P. V., and T. M. Lillesand, 1992. Improved Classification of Forest Vegetation in Northern Wisconsin Through a Rule Based Combination of Soils, Terrain, and Landsat Thematic Mapper Data. Forest Science, 38(1):5-20.

Bowlin, H. L., and H. M. Lachowski, 1987. Forest Inventory and Assessment with Satellite Imagery in the Western States. Proceedings, SAF National Convention, Economics and Social Development, Minneapolis, Minnesota, pp. 54-57.

ERDAS, 1991. ERDAS Field Guide, version 7.5, ERDAS, Inc., Atlanta, Georgia, 394 p.

ERDAS, 1991. ERDAS Image Processing Software, version 7.5, Erdas, Inc., Atlanta, Georgia.

Evans, D. L., 1994. Forest Cover from Landsat Thematic Mapper Data for Use in the Catahoula Ranger District Geographic Information System, U.S.D.A. Forest Service General Technical Report SO-99. New Orleans, Louisiana. 14 p.

Fitzpatrick-Lins, K., 1980. The Accuracy of Selected Land Use and Land Cover Maps of Scales of 1:250,000 and 1:100,000, U.S. Geological Survey Circular 829. Alexandria, Virginia. 24 p.

Fox, L., III, J. A. Brockhaus, and N. D. Tosta, 1985. Classification of Timberland Productivity in Northwestern California Using Landsat, Topographic and Ecological Data. Photogrammetric Engineering and Remote Sensing, 51(11):1745-1752.

Häme, T., 1984. Landsat-Aided Forest Site Type Mapping. Photogrammetric Engineering and Remote Sensing, 50(6):1175-1183.

Hopkins, P. F., A. L. Maclean, T. M. Lillesand, 1988. Assessment of Thematic Mapper Imagery for Forestry Applications Under Lake States Conditions. Photogrammetric Engineering and Remote Sensing, 54(1):61-68.

Hord, R. M., and W. Brooner, 1976. Land-Use Map Accuracy Criteria. Photogrammetric Engineering and Remote Sensing, 42(5):671-677.

Latty, R. S., and R. M. Hoffer, 1981. Computer-based Classification Accuracy Due to the Spatial Resolution using Per-Point versus Per-Field Classification Techniques. Proceedings, Symposium on Machine Processing of Remotely Sensed Data, Purdue University, West Lafayette, Indiana, pp. 384-393.

Lillesand, T. M. and R. W. Kiefer, 1987. Remote Sensing and Image Interpretation. Second Edition. John Wiley and Sons, Inc., New York, 721 p.

Mayer, K. and L. Fox III, 1981. Identification of Conifer Species Groupings from Landsat Digital Classifications. Photogrammetric Engineering and Remote Sensing, 48(11):1607-1614.

Moore, M. and M. E. Bauer, 1990. Classification of Forest Vegetation in North Central Minnesota Using Landsat Multispectral Scanner and Thematic Mapper Data. Forest Science, 36(2):330-342.

Rosenfield, G. H., K. Fitzpatrick-Lins, and H. S. Ling, 1982. Sampling for Thematic Map Accuracy Testing. Photogrammetric Engineering and Remote Sensing, 48(1):131-137.

Strahler, A. H., T. L. Logan, and C. E. Woodcock, 1979. Forest Classification and Inventory System Using Landsat, Digital Terrain, and Ground Sample Data. Proceedings, 13th International Symposium on Remote Sensing of Environment, Environmental Research Institute of Michigan, Ann Arbor, Michigan, pp. 1541-1557.

Tou, J. T. and R. C. Gonzalez, 1974. Pattern Recognition Principles. Addison-Wesley Publishing Co., Reading, Massachusetts, 377 p.

Trimble Navigation Ltd., 1992. Trimble Pathfinder GPS Software, version 2.31, Sunnyvale, California.

Williams, D. L., J. R. Irons, B. L. Markham, R. F. Nelson, D. L. Toll, R. S. Latty, and M. L. Stauffer, 1984. A Statistical Evaluation of the Advantages of LANDSAT Thematic Mapper Data in Comparison to Multispectral Scanner Data. IEEE Transactions on Geoscience and Remote Sensing, 22(3):294-301.

VITA

Name:	Matthew Palmer Falter
Date of Birth:	February 4, 1969
Place of Birth:	Las Vegas, NV
Permanent Address:	Texas A&M University Forest Science Department Hort./Forest Science Bldg. College Station, TX 77843-2135
Education:	Buffalo Grove High School, Buffalo Grove, IL Diploma, 1987
	Texas A&M University College Station, TX Bachelor of Science, Forestry, 1992
	Texas A&M University Master of Science, Forestry, 1995
Honors:	Xi Sigma Pi, National Forestry Honor Society Outstanding Graduate Student, 1993 and 1994

The author is presently working on a project comparing changes in 1982 and 1992 vegetation data from the Lower Mississippi River.