ACT Publication No. 94-05

Discrimination Between Advanced Secondary Succession and Mature Moist Forest Near Altamira, Brazil Using Landsat TM Data

Y. Li, E. F. Moran, E. S. Brondizio, P. Mausel, and Y. Wu

Reprinted from: **Proceedings of the American Society for Photogrammetry and Remote Sensing. 1994 annual meeting of ASPRS in Reno, NV.**

Anthropological Center for Training and Research on Global Environmental Change
Indiana University, Student Building 331, 701 E. Kirkwood Ave., 47405-7100, U.S.A.
Phone: (812) 855-6181, Fax: (812) 855-3000, Email: act@indiana.edu, internet: www.Indiana.edu/~act

1994 ASPRS/ACSM

Annual Convention

& Exposition

ASPRS Technical Papers

Reno, Nevada

ASPRS 60th Annual Convention
ACSM 54th Annual Convention

Volume One: ASPRS

DISCRIMINATION BETWEEN ADVANCED SECONDARY SUCCESSION AND MATURE MOIST FOREST NEAR ALTAMIRA, BRAZIL, USING LANDSAT TM DATA

Yinghong Li, Paul Mausel, and You Wu
Department of Geography and Geology
Indiana State University
Terre Haute, IN 47809

Emilio Moran and Eduardo Brondizio
Department of Anthropology/ACT
Indiana University
Bloomington, IN 47405

ABSTRACT

Advanced secondary succession (SS) forests have developed many features similar to those of undisturbed mature moist forest in the Transamazon Highway area west of Altamira, Brazil. Their successful differentiation has become critical for assessment of land use and land cover changes after initial deforestation. Landsat TM data (July 1991), combined with 1992 and 1993 field survey information, were used to identify these two forest classes. A 12-band data set comprised of original data, two principal component bands, one additive band, and several varieties of NDVI ratio bands were developed to improve discrimination between these two features when classified. Training and test samples were developed from analysis of the field survey data in conjunction with spectral patterns. Supervised classifications using three different classifiers--ECHO, maximum-likelihood, and minimum Euclidean distance--were implemented on the training and test samples. These classification results suggest that the ECHO--a texture maximum-likelihood classifier--provides the best classification of advanced SS and mature moist forest in the study area with an accuracy of 93 to 97 percent. Three subareas representative of a highly developed area adjacent to Altamira, a moderately developed area along the Transamazon Highway, and a slightly developed frontier area were classified using ECHO. The amount and patterns of mature moist forest and advanced SS in each of these subareas were realistic based on field knowledge of these areas.

INTRODUCTION

Deforestation of the Amazon Basin has been a focus of research interest in the global change community (Booth 1989; Shukla et al. 1990). Brazil has the most deforestation in Latin America and ranks fourth among world nations as an atmospheric carbon contributor (Goldemberg 1989). By 1992, more than 11 percent of Brazilian Amazon forests had been cut or in other ways impacted by deforestation (Skole and Tucker 1993).

Numerous studies of deforestation have been conducted using Landsat, SPOT, and AVHRR data (Tucker 1985, 1989; Nelson and Holben 1986; Woodwell 1989; Malingreau et al. 1989; Berta et al. 1990; Sader et al. 1990; Campbell and Browder 1992). A majority of these studies focus on deforestation per se with little attention given to analysis of detailed land use and land cover change in order to assess processes involved with such changes. Mausel et al. (in press) and Moran et al. (in press) posed the following questions to assist understanding of processes associated with land use changes following deforestation: What are the reasons for and the nature of patterns of land use following initial cutting? What are the characteristics of the soil and terrain in deforested areas and how do variations in physical parameters impact regrowth? What socioeconomic factors affect initial deforestation and patterns of land use change following cutting? Answers to these questions will address the critical issue of how and why cut mature moist forest areas take different rates of secondary succession.

These concerns, which require detailed multitemporal information, are beginning to be addressed in part through analyses of SPOT data (Campbell and Browder 1992) and analyses of Landsat TM data (Mausel et al. in press; Moran et al. in press). Critical to addressing these questions is the ability to assess changing land use and land cover patterns after initial deforestation. Land use and land cover change data, when integrated with other physical and socioeconomic parameters, theoretically can lead to understanding environmental processes to a point where models can be developed and applied to guide an assess intelligent development of tropical forest areas.

A major research interest of the project is differentiation of mature moist forest (basically undisturbed) from areas that are designated in this paper as advanced secondary succession. Advanced secondary succession are those forest areas that are nearing a return to their original state in several of their characteristics. They are nearly comparable to an original forest in terms of biomass and height, but they still may differ to some degree in species composition and canopy structure. It is important to know how much deforested area has returned back to its original state. It is also important to know the varying rates at which deforested areas move toward their original state. Answers to these questions are prerequisite for developing an ecological model that integrates physical and cultural parameters.

SCOPE OF RESEARCH/OBJECTIVES

This paper focuses specifically on evaluating the capability of supervised classification of Landsat TM data to discriminate between undisturbed mature moist forest and advanced secondary forest growth in a study area west of Altamira, Brazil. These are the only two feature classes considered in this research report, although a preliminary nine category classification has been conducted which included other less advanced secondary succession classes, agricultural classes, water, wetlands, and bare/soil (Mausel et al. in press; Moran et al. in press). This preliminary research provided insights into spectral signatures of the features of interest. Ground-based information acquired from the study area in

1992 resulted in developing an accurate supervised classification for all classes except advanced secondary succession. The 1992 ground-based information provided a sufficient number of training samples to develop a reasonable spectral signature for advanced succession, but an insufficient number of test samples to assess the accuracy of this class. Many additional samples of advanced secondary succession were acquired during 1993 field work, thereby permitting improved classification and accuracy assessment of this class reported in this paper.

STUDY AREA CHARACTERISTICS AND DATA

A 60 km by 50 km area bounded on the east by the city of Altamira, Brazil, and the Xingú River delineates the study area (Fig. 1). Figure 2 is a Landsat TM Band 4 image of the study area which clearly shows development along the Transamazon Highway and regularly spaced feeder roads which are perpendicular to it. The land off the floodplain is rolling, with local relief up to 60 meters. In general, soils are of above average quality for the Amazon Basin; Alfisols provide better substrates whereas Oxisols and Ultisols are lower in quality for plant growth. Annual precipitation averages 1700 mm/year concentrated from late October through early June. The dominant native vegetations are mature moist forest and liana forest (Pires 1983). This area has been subjected to major deforestation since initial construction of the Transamazon Highway in 1972 (Moran 1976, 1981).

Deforested areas are devoted to commercial agricultural crops (rice, sugar, cocoa, and pepper), food crops (manioc, beans, corn, and other vegetables), tree crops, and pasture primarily for cattle. A typical sequence of land use following deforestation is cropland followed by pasture. After a few years, pasture becomes degraded with shrubs and trees and, if left undisturbed, eventually may return to a forest state similar to its original condition. The sequence of vegetation from a clean pasture to dense forest regrowth is referred to as secondary succession (SS).

Currently four July or August Landsat TM scenes (1985, 1987, 1988, 1991) are being used for a comprehensive research project whose focus is ecological modeling suitable to aid in environmental planning of tropical forest regions. The July 1991 Landsat TM scene is used to explore the effectiveness of supervised classification of the mature moist forest and those advanced SS forest that have developed many characteristics similar to those found in the undisturbed mature forests. Supportive of this classification was 1992 field work in which more than 300 on-site observations were made and 25 field histories dating back 10 years or more were acquired. In 1993, additional ground-based data similar in magnitude to that acquired in 1992 were obtained. Topographic maps (1:100,000 scale) and soil data from selected areas were also acquired.

Mature moist forest and advanced secondary succession both have multicanopies with selected trees exceeding 20 m heights. Forest density and biomass conditions are similar. It is likely that there is more species diversity and other measures of forest complexity in the mature moist forest than in the advanced SS forest; however, the degree to which this is true is not known. Field work is in progress to determine the degree of this correspondence. Spectrally, mature moist forest is very similar to advanced SS forests.

METHODS

The following methods were implemented to classify mature moist forest and advanced SS and to assess the accuracy of classification results.

1. A 12-band data set derived from July 20, 1991, Landsat TM data (Path 226, Row 67) was developed (Table 1). This data set included five original TM bands (TM 1 and TM [illegible] were excluded.), two principal component bands, an additive band, and several varieties of NDVI ratio bands.

2. Training samples (Samples of areas from which spectral statistics of known features were acquired for classification implementation.) and test samples (Samples of areas of known character classified using training statistics to assess accuracy of feature discrimination.) of mature moist forest and advanced SS were developed using the field data acquired in 1992 and 1993.

3. Training samples were subjected to isodata clustering to identify possible significant anomalies in each sample. Major anomalies identified (i.e., a small logged area within a forest area) were edited out of the training samples. Transformed divergence was applied to clusters within each training sample to verify training use suitability.

4. The individual training field statistics for each feature were merged into the two classes mature moist forest and advanced SS.

5. Training fields were classified using 1) minimum Euclidean distance; 2) maximum likelihood; and 3) ECHO (a texture classifier that uses maximum likelihood). Training samples that failed to perform well in at least one classification were reassessed and either modified or cut.

6. Test fields were classified once the final training fields were developed. The same three classification algorithms were applied to the test fields as the training fields.

7. Test fields with low accuracy in all three classification approaches were reviewed to ascertain reasons for poor results. Adjustments to classifier options (particularly ECHO), such as weighing and cell size, driven by knowledge of the area were implemented to improve classification results.

8. Initially, all 12 bands of data were used in classification; however, transformed divergence was applied to the training field statistics to

evaluate the number and relative quality of various band subsets for classification.

9. Classification of three subareas (Figures 3-5) was conducted using training statistics from the band combinations that test field classification indicated was most accurate. The three subareas are:

   A. An area immediately west and south of Altamira which has experienced the longest and most intense cultural impacts. This area has only vestiges of mature moist forest remaining, thus secondary succession forest areas dominate.

   B. An area 45 km southwest of Altamira which contains the small agricultural town of Brazil Novo and is transected by the Transamazon Highway and one of its feeder roads. This area represents moderate cultural impact associated with agriculture. Both mature moist forest and SS types, including a significant amount of advanced SS, are present.

   C. An area 60 km west of Altamira is in an isolated frontier area at the end of a feeder road. This area represents one of the least developed sections of the study area and as such is dominated by mature moist forest and has very little advanced SS.

10. The subarea classification results using the three different supervised classification algorithms were evaluated.

11. All training field, test field, and subarea classification results were evaluated and conclusions are presented.

All processing was done on a MacIntosh Quadra 900 using MULTISPEC software (Landgrebe and Biehl 1993). MULTISPEC is a microcomputer version of many of the mainframe LARSYS/LARSFRIS programs developed at LARS/Purdue University with the addition of many new algorithms. The software is ERDAS data format compatible and is designed for hyperspectral analysis as well as more standard multispectral analysis. The algorithms used most in the methods discussed below are 1) transformed divergence and divergence used for separability analysis; 2) statistics for developing training samples; and 4) maximum likelihood, Euclidean minimum distance, and ECHO classifiers for classification.

RESULTS AND DISCUSSION

Divergence Analysis

The advanced SS and mature moist forest training fields developed from the 12 band 1991 TM data set comprised of original and transformed bands was subjected to transformed divergence. Divergence results provided insights into the spectral distinction between the training fields of the two classes of interest, which can be broadly predictive of classification accuracy. In addition, the results suggest the best bands from the 12-band data set which are needed for good classification. Table 1 identifies the 12 bands available for analysis and Table 2 shows the transformed divergence for the best single band and multiple band combinations.

It is evident from interpretation of Table 2 that it takes at least nine bands of data to achieve a transformed divergence value that at best achieves marginal spectral separation between the two features of interest. The 12 band divergence value of 1254 between advanced SS and mature moist forest training field statistics is not suggestive of accurate separation of these two classes. This result was not unexpected since the two classes are very similar. However, transformed divergence is not a definitive predictor of classification accuracy, particularly when transformed data are considered. Thus, a divergence of 1254 does not prohibit the possibility of differentiation between the two classes. Nevertheless, the divergence analysis does suggest that a majority of the 12 bands need to be used to achieve even a modest level of spectral distinctiveness between the two very similar features.

Classification of Training Fields

Nine mature moist forest training fields (3,092 pixels) and six advanced secondary succession training fields (501 pixels) were collected randomly from known areas of these classes. The classification of these training fields using the ECHO classifier was excellent, but it was poor or marginal using the maximum likelihood and Euclidean minimum distance classifiers. The overall training field classification accuracy for advanced SS for the three classifiers was 97.0, 78.8, and 64.5 percent respectively, while for mature moist forest training fields the classification accuracies were 95.6, 68.9, and 67.6 percent respectively. ECHO, which is a maximum likelihood classifier that has texture classification characteristics of combining and analyzing groups of pixels, was distinctly better than the other two, more commonly used, classification approaches.

Classification of Test Fields

Thirteen mature moist forest test fields (3259 pixels) and eight advanced secondary succession test fields (440 pixels) were classified using the same three algorithms used in training field accuracy assessment. Table 3 provides test field accuracy results for the ECHO classification whose 92.8 percent overall accuracy was superior to the other two classification algorithms. The maximum likelihood classification had an overall test field accuracy of 71.5 percent (73.6 percent for advanced succession and 71.2 percent for forest) with individual field accuracy ranging from 48.3 to 94.6 percent. The Euclidean minimum distance classification had an overall test field accuracy of 68.0 percent (65.9 percent for advanced succession and 68.3 percent for forest) with individual field accuracy ranging from 27.8 to 98.2 percent. The ECHO classifier proved to be so superior (reasons why will be discussed later) in classifying the two designated classes that it was used exclusively in developing large subarea classifications of diverse environments in the greater Altamira study site shown in Figure 2.

Classification of Altamira Subareas

Three subareas, representative of three intensities of cultural impact, were classified using the ECHO classifier. A subarea, designated Altamira, found immediately to the west and south of the city represents the longest and most intensely developed part of the study area (the eastern most polygon shown on Figure 2). Ground observations and historical data indicate that a great majority of the area has been deforested and is in secondary succession. A large share of the secondary succession is advanced due to early deforestation in many parts of the subarea. A few mature moist forests exist principally in rough terrain or near water courses.

Figure 3 shows the ECHO classification of the subarea which delineates the three classes of advanced SS, mature moist forest, and other. More than 30 percent of the area was advanced SS while less than three percent was mature moist forest. This result is consist with known land cover patterns in the area and helps validate the test field accuracy results.

A second subarea, centered on an agricultural village 46 km southwest of Altamira (the central polygon shown on Figure 2), was classified using ECHO. This subarea, designated Brazil Novo, represents a relatively old (20 years) settlement, but with less intense cultural modification than that found in the highly populated Altamira subregion. The Transamazon highway and feeder roads are in this subsite as are relatively undeveloped forest areas found between the feeder roads. Ground-based knowledge of the area indicates that areas near the Transamazon Highway and its feeder roads are almost totally dominated by pasture, crop, and various stages of secondary succession, including large areas of advanced SS. The land between the feeder roads may be subject to minor forest product extraction, but mature moist forest dominates.

Figure 4 shows the ECHO classification of this area for the two classes of interest and "Other." More than 27 percent of the area was classified as advanced SS and most of it was in fields near roads as field observation suggested. Approximately 29 percent of the area was mature moist forest and nearly all of that total was associated with remote areas between feeder roads. The proportion of advanced secondary SS, mature moist forest, and other land cover types is what was expected based on one of the author's 20 years of field experience in the area (EM).

The third subarea, approximately 60 km west of Altamira (the western most polygon shown on Figure 2), is representative of an area with minor cultural impacts. This subarea, designated as the frontier, lies at the end of a recently developed feeder road of the Transamazon Highway. The area has some agricultural development, but mature moist forests that are not impacted greatly by cultural activities dominate. Field observations indicate that the areas cut out

of the forest near the feeder road are in secondary succession or some agricultural activity, but most of the land is in forest. These forests are only slightly impacted by forest product extraction activities. Figure 5 shows the ECHO classification of this subarea. The area has 69 percent mature moist forest and ten percent advanced SS, which is consistent with known ground conditions.

Table 4 summarizes the classification results of the classes mature moist forest, advanced SS, and "Other" for the three subregions which provide a cross-section of land use intensity. It is evident that in the most developed areas of the greater Altamira study area mature moist forest is a minor class and secondary succession classes are most abundant. The amount of mature moist forest decreases as the intensity or length of time an area has been under development increases. Thus, in the most remote areas, mature moist forest is overwhelmingly dominant, but secondary succession domination (along with agricultural land uses) begins in areas with long and moderately intensive development near major transportation routes. The accuracy results for the test fields suggest that these three areas are classified well. The classification results of the subareas are consistent with regional field observations which helps verify the test field classification accuracy results.

ECHO CLASSIFICATION

Classifiers that are sensitive to texture or that are influenced by the patterning of pixel groupings rather than those which treat each pixel as an independent "individual" prior to final classification are not new in remote sensing. However, they are not commonly used. Texture-type classifiers have more parameters and, thus, may be more difficult to use. However, for some classification purposes, a classifier like ECHO potentially can do a better job of information extraction than non-texture classifiers. In this research, use of maximum likelihood and Euclidean distance approaches provided test field accuracies near 70 percent for the two features of interest. This level of accuracy was about all that was anticipated considering the spectral similarity between classes as indicated by transformed divergence. Intensive experimentation and use of ECHO raised the level of test field accuracy from 72 percent with a maximum likelihood classifier to more than 92 percent with the ECHO classifier. This magnitude of improvement was rechecked several times and was consistently found to be valid. Previous personal experience with ECHO in the U.S. Midwest agricultural applications often resulted in an accuracy improvement of five percent, but never 20 percent. The question "Is ECHO or another texture-type classifier more appropriate for delineation of tropical forests and their successional forms than maximum likelihood classifiers?" is posed by these research results. A brief description of ECHO and some preliminary thoughts about why this classifier worked so well on a very difficult problem in feature discrimination is appropriate.

The ECHO classifier is described by Landgrebe and Biehl (1993) in the following way: ECHO or Extraction and Classification of Homogeneous Objects is a spatial-spectral classifier. It uses a two-stage process, first segmenting the scene into statistically homogeneous regions, and then classifying the data using a maximum likelihood approach. It uses the same training fields and statistics as a conventional maximum likelihood classifier; however, there are three selective parameters which are used to vary the degree and character of spatial relationships used in classification.

The segmentation stage is conducted in two stages. In the first stage cells consisting of contiguous n x n regions (user set) are checked with a test for statistical homogeneity (also user set). Cells failing this test are considered singular and the pixels within the n x n cell are classified in a per pixel manner. This allows for the proper classification of isolated cells within otherwise homogeneous objects. After the cell selection test, next neighboring cells are compared with a statistical homogeneity test that is user specified. Those cells passing this test are annexed, thus growing regions comprised of multiple cells. These regions are then classified using a maximum likelihood scheme.

The extraordinary success of the ECHO approach in delineating the two classes of interest are probably related to the structure of the two forest types in which spectrally advanced SS can statistically appear to be mature moist forest in any given pixel while in some pixels forest can appear to be advanced SS spectrally. The very subtle variations in canopy geometry, species composition, and biomass between the two often lead to classification confusion when viewed pixel by pixel. However, in mature forest areas or in advanced SS areas, there appear to be a subtle similarity within each class and a subtle dissimilarity between each class. These similarities and dissimilarities become more evident when the data are viewed and analyzed as pixel groupings or cells. In this research a 2 x 2 or 3 x 3 cell, comprised of four or nine pixels respectively, gave the appropriate identification of cells in most instances. For example, a nine pixel cell (3 x 3) in a mature moist forest area might have the following results if classified on a per pixel basis: six pixels are mature moist forest and three pixels are advanced SS. The spectral statistics of the combined nine pixels would lead to a cell classification of mature moist forest (all nine pixels would be classified as this forest). The per pixel classification would be 67 percent accurate, but the cell classifier would give 100 percent accurate results for that cell. In many ways ECHO acts like a low pass filter; however, it is much more versatile and has sophisticated classification capabilities.

CONCLUSIONS

The discrimination between mature moist forest and advanced secondary succession is difficult using satellite remotely sensed data. In this research the incorporation of enhanced Landsat TM with original Landsat TM bands made it possible to distinguish between these two classes using supervised classification approaches. Twelve band original/enhanced Landsat TM data classified using maximum likelihood and Euclidean minimum distance approaches provided a marginal test field accuracy of approximately 70 percent for each of these two classes. The implementation of the texture-based classifier ECHO in

classification of test fields greatly improved accuracy to better than 90 percent for each class. This research suggests that it is possible to discriminate between mature moist forest and advanced secondary succession forest if the classifier implemented considers texture and uses enhanced data integrated with original TM data. The degree to which these methods can be applied successfully throughout all tropical moist and rain forest areas remains to be determined, but we have demonstrated that the methods implemented are well-suited to most forest/secondary succession areas near Altamira along the Transamazon Highway in Brazil.

ACKNOWLEDGEMENTS

This study was made possible by a grant from the National Science Foundation (grant 9100526) Program in Geography and Regional Science and the Program in Geography and Regional Science and the Program on the Human Dimensions of Global Environment Change. Supplementary funds were provided by grants from the Midwestern Center of the National Institutes of Global Environment Change. Responsibility for the views expressed in this paper are the sole responsibility of the authors and do not reflect the views of the funding sources or collaborators.

REFERENCES

Berta, M. S., P. W. Mausel, and J. A. Harrington. 1990, Multidate Image Analysis of Forest Degradation in Equatorial Africa: Geocarto International, Vol. 5, No. 4, pp. 57-61.

Booth, W. 1989, Monitoring the Fate of the Forest from Space: Science, Vol. 243, pp. 1428-1429.

Campbell, J.B., and J.O. Browder. 1992, SPOT Survey of Agricultural Land Uses in the Brazilian Amazon: ISPRS Commission VII, XXIX (Part B-7), pp. 159-165.

Goldemberg, J. 1989, Introduction: Amazonia: Facts, Problems and Solutions: Fundação da Univ. de São Paulo and INPE, São Paulo.

Landgrebe, D., and L. Biehl. 1993, An Introduction to MULTISPEC, Purdue University, West Lafayette, IN.

Malingreau, J.P., C.J. Tucker, and N. LaPorte. 1989, AVHRR for Monitoring Global Tropical Deforestation: Int. Jour. of Remote Sensing, Vol. 10, pp. 855-867.

Mausel, P., Y. Wu, Y. Li, E. Moran, and E. Brondizio. In press, Spectral Identification of Successional Stages Following Deforestation in the Amazon: Geocarto International, Vol. 8, No. 4, 10 pp.

Moran, E.F., E. Brondizio, P. Mausel, and Y. Wu. In press, Deforestation in Amazonia: Land Use Change from Ground- and Satellite-level Perspectives: Bioscience. 10 pp.

Moran, E.F. 1981, Developing the Amazon, Indiana University Press, Bloomington, Indiana.

Moran, E.F. 1976, Agricultural Development along the Transamazon Highway: Center for Latin American Studies Monograph Series, Indiana Unversity, Bloomington, Indiana.

Nelson, R., and B. Holben. 1989, Identifying Deforestation in Brazil Using Multiresolution Satellite Data: Int. Jour. of Remote Sensing, Vol. 7, pp. 429-448.

Pires, J. M. 1983, Tipos de vegetacao da Amazonia. Belem: Museu Paarense Emilio Goeldi, Vol. 20, pp. 179-202.

Sader, S.A., T.T. Stone, and A.T. Joyce. 1990, Remote Sensing of Tropical Forests: An Overview of Research and Application Using Non-photographic Sensors: Photogram. Eng. and Remote Sensing, Vol. 56, pp. 1343-1351.

Shukla, J., C.Nobre, and P.Sellers. 1990, Amazon Deforestation and Climate Change: Science, Vol. 247, pp. 1322-1325.

Skole, D., and C. Tucker. 1993, Tropical Deforestation and Habitat Fragmentation in the Amazon: Satellite Data from 1978 to 1988: Science, Vol. 270, pp. 377-407.

Tucker, C. J. 1989, Comparing SMMR and AVHRR Data for Drought Monitoring. Internat J. of Remote Sensing, 10:1663-1672.

---. 1985, African Land-Cover Classification Using SatelliteData: Science, 227: 369-375.

Woodwell, G. M., R. A. H. Houghton, T. A. Stone, R. F. Nelson, and V. Kovalick. 1987, Deforestation in the Tropics: New Measurements in the Amazon Basin using Landsat and NOAA AVHRR Imagery: Journal of Geophysical Research, 92: 2157-2163,

TABLES AND FIGURES

Table 1. Twelve Bands Landsat TM Data Set (July 20, 1991) Used for Classification of Mature Moist Forest and Advanced SS in the Altamira Area of Brazil

Band Number	Formula or Source
1	TM2
2	TM3
3	TM4
4	TM5
5	TM7
6	0.0638TM2+0.1183TM3+0.42061TM4+0.84736TM5+0.29496TM7 (PC1)
7	-0.117349TM2-0.34164TM3+0.82469TM4-0.22732TM5-0.34841TM7 (PC2)
8	70+((TM4-TM3)/(TM4+TM3))*250
9	130+((TM5-TM3)/(TM5+TM3))*190
10	200+((TM7-TM3)/(TM7+TM3))*190
11	200+((TM3-TM2)/(TM3+TM2))*30
12	((TM4+TM5+TM7)/36)*30

Table 2. Identification of Band(s) with Highest Transformed Divergence Considering Mature Moist Forest and Adv. SS Training Fields for all Possible Combinations Derived from the Twelve Bands (July 20, 1991) Landsat TM Data Set

# of Band	Best Bands Combination	Divergence
1	12	237
2	4,9	307
3	2,5,10	785
4	2,5,7,10	911
5	2,4,5,9,10	1016
6	1,2,4,5,9,10	1051
7	2,3,4,5,8,9,10	1139
8	2,3,4,5,7,8,9,10	1172
9	1,2,3,4,5,8,9,10,11	1214
10	1,2,3,4,5,7,8,9,10,11	1228
11	1,2,3,4,5,6,8,9,10,11,12	1240
12	1,2,3,4,5,6,7,8,9,10,11,12	1254

Table 3. Accuracy in Identification of Mature Moist Forest and Adv. SS as Derived from ECHO Classification of Test Fields

Test Class Performance

Class Name	Class Number	Percent Correct	Number Pixels	SS3	Forest	Other
SS3	1	95.0	440	418	9	13
Forest	2	92.5	3259	129	3013	117

Table 3 continued . . .
Test Field Performance

Field Name	Class Number	Percent Correct	Number Pixels	SS3	Forest	Other
SS3-TEST1	1	99.2	120	119	0	1
SS3-TEST2	1	98.2	56	55	0	1
SS3-TEST3	1	88.3	60	53	0	2
SS3-TEST4	1	100.0	36	36	0	0
SS3-TEST5	1	92.5	40	37	1	2
SS3-TEST6	1	100.0	36	36	0	0
SS3-TEST7	1	90.0	60	54	0	6
SS3-TEST8	1	87.5	32	28	3	1
FOR-TEST1	2	94.4	357	16	337	4
FOR-TEST2	2	88.1	405	27	357	21
FOR-TEST3	2	94.9	99	3	94	2
FOR-TEST4	2	96.7	391	9	378	4
FOR-TEST5	2	90.3	361	21	326	14
FOR-TEST6	2	87.3	63	3	55	5
FOR-TEST7	2	90.1	81	8	73	0
FOR-TEST8	2	83.8	99	2	83	14
FOR-TEST9	2	91.8	255	12	234	9
FOR-TEST10	2	92.7	247	8	229	10
FOR-TEST11	2	94.6	315	2	298	15
FOR-TEST12	2	93.3	225	2	210	13
FOR-TEST13	2	93.9	361	16	339	6

Overall Performance (3431/3699) = 92.8%

Table 4. ECHO Classification Results of Three Subareas in the Altamira Study Area

Subarea	Pixels #	SS3(%)	Forest(%)	Other (%)
Altamira	162825	50609(31.08)	4589 (2.82)	107627(66.1)
Brazil Novo	120701	33609(27.84)	35072(29.06)	52020(43.1)
Frontier	60200	6050(10.05)	41660(69.20)	12490(20.75)

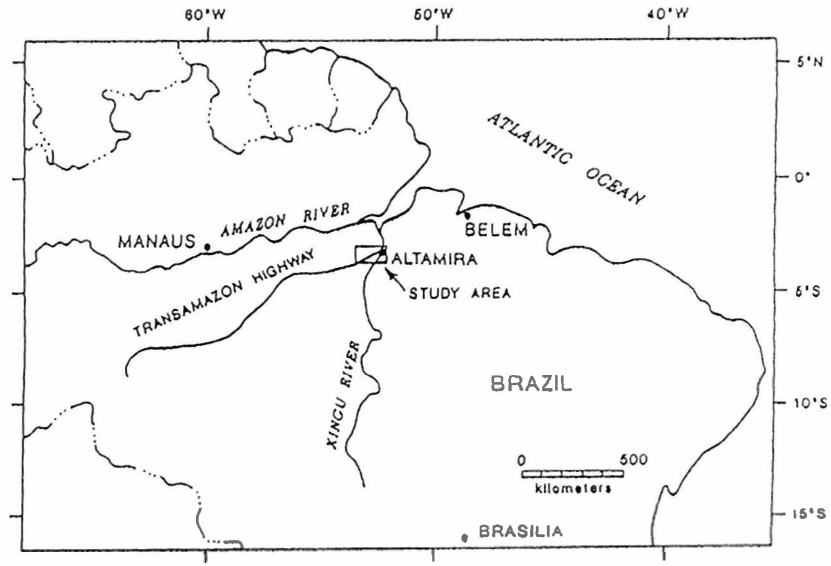

Figure 1. Study area

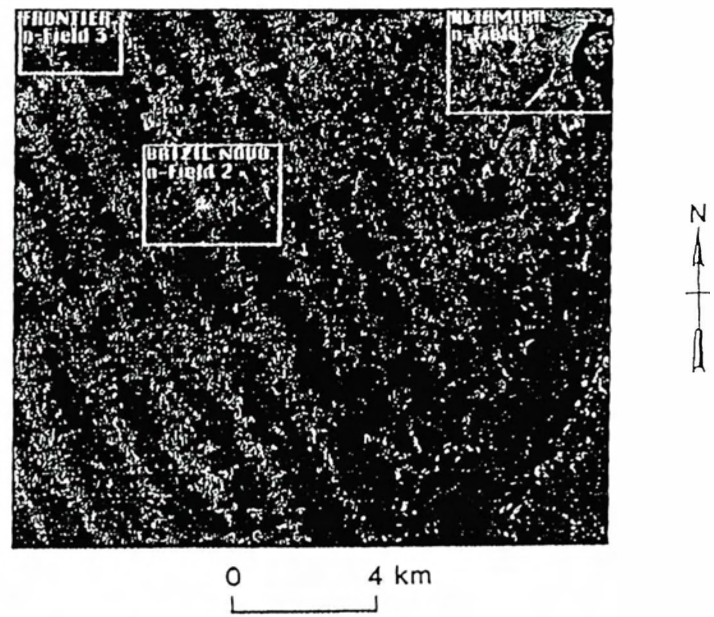

Figure 2. Altamira study area as shown using Landsat TM band 4, July 20, 1991 data (subsites used for classification are indicated)

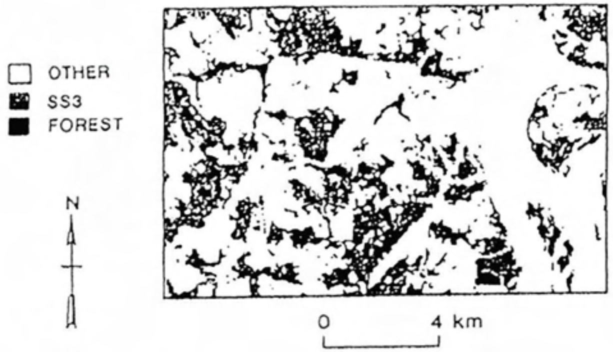

Figure 3. Forest and advanced SS (1991) near the city of Altamira

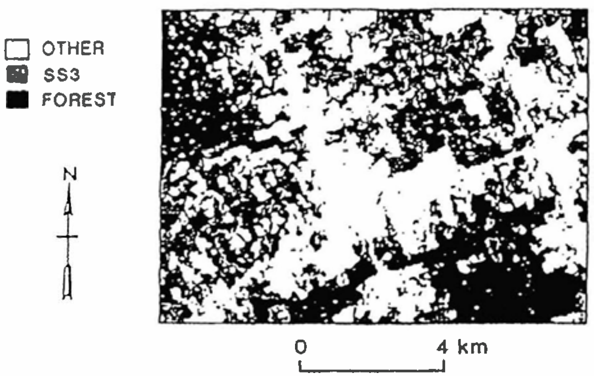

Figure 4. Forest and advanced SS (1991) near Brazil Novo

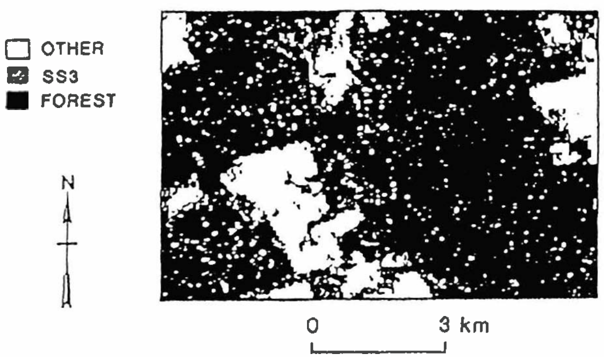

Figure 5. Forest and advanced SS (1991) in a frontier area NW of Brazil Novo

OKEFENOKEE SWAMP VEGETATION MAPPING WITH LANDSAT THEMATIC MAPPER DATA: AN EVALUATION

C. P. Lo
Department of Geography
University of Georgia
Athens, GA 30602-2502

Lee J. Watson
Department of Geography and Regional Planning
Salisbury State University
Salisbury, Maryland 21801-6837

ABSTRACT

The capability of Landsat TM data in mapping the vegetation communities of the Okefenokee Swamp was evaluated using a GIS approach. Because of the nature of the Okefenokee Swamp as a mosaic of dynamically related vegetation patches representing different stages of temporal succession, the spatial resolution of the TM data was found to be inadequate to produce a 21-class vegetation map compatible in accuracy to that of the reference map produced from large-scale color infra-red aerial photographs and field work. By aggregating the 21 classes of wetland vegetation into 6 classes of gross vegetation types, the accuracy of the map was greatly improved. The evaluation indicated the usefulness of principal components analysis and Normalized Difference Vegetation Index (NDVI) in digital image classification of wetland vegetation. Further improvement in wetland vegetation mapping using digital satellite image data should focus on the development of a vegetation classification scheme based on spectrally distinctive classes.

INTRODUCTION

Mapping vegetation communities in a wetland environment presents unique complexities, caused by the dynamic nature of wetlands and the complicated interrelations between hydrology, soils, and vegetation (Carter, 1982). Some specific factors contributing to the difficulty includes: fluctuations in water levels; transitional areas between different vegetation communities; changes in water turbidity; accumulation and migration of free floating aquatic vegetation; the effects of ditching and beaver activities; and the inability to detect submerged aquatic vegetation (Carter, 1979).

Today, the mapping of wetland vegetation communities is carried out most commonly by remote sensing supplemented by field checks. Color infra-red aerial photography is the preferred form of image data for this purpose (Gammon and Carter, 1979, Carter et al., 1979). With the availability of high resolution Landsat Thematic Mapper (TM) data since 1982, interest has been drawn to its use in wetland vegetation mapping by means of a computer-assisted approach (Dottavio and Dottavio, 1984, Jensen et al., 1987). All these works

ACT Publications 1993

No. 93-01
Mausel, P., Y. Wu, Y. Li, E.F. Moran, and E.S. Brondizio. "Spectral Identification of Successional Stages following Deforestation in the Amazon." *Geocarto International* 8(4):61-81.

No. 93-02
Moran, E. F. "Managing Amazonian Variability with Indigenous Knowledge" In *Tropical Forests, People and Food: Biocultural Interactions and Applications to Development*. C.M. Hadlik et al. (eds.). Pp. 753-765. Paris: UNESCO/Parthenon Publ. Vol. 15 in Man and the Biosphere Series.

No. 93-03
Moran, E.F. "Deforestation and Land Use in the Brazilian Amazon." *Human Ecology* 21:1-21.

No. 93-04
Moran, E.F., E.S. Brondizio, P. Mausel, and Y. Li. "Assinaturas Espectrais Diferenciando Etapas de Sucessao Secundaria no Leste Amazonico" *Anais do VII Simposio Brasileiro de Sensoriamento Remoto*. 2: 202-209.

No. 93-05
Brondizio, E.S., E.F. Moran, P. Mausel, and Y. Wu. "Padroes de Assentamento Caboclo no Baixo Amazonas: Analise Temporal de Imagens de Satelite para estudos de Ecologia Humana de Populacoes da Amazonia". *Anais do VII Simposio Brasileiro de Sensoriamento Remoto* 1: 16-26.

No. 93-06
Brondizio, E.S., E.F. Moran, P. Mausel, and Y. Wu. "Dinamica na Vegetacao do Baixo Amazonas: Analise temporal do Uso da Terra integrando imagens Landsat TM, levantamentos florísticos, e etnograficos" . *Anais do VII Simposio Brasileiro de Sensoriamento Remoto* 2: 38-46.

No. 93-07
Moran, E.F. "Minimum Data for Comparative Human Ecological Studies: Examples From Studies in Amazonia." *Advances in Human Ecology* 2:187-209.

No. 93-08
A. Siqueira, E. Brondizio, R. Murrieta, H. da Silva, W. Neves, R. Viertler. " Estratégias de Subsistência da Populaçâo Ribeirinha Do Igarapé Paricatuba, Ilha de Marajó, Brasil." Bol. Mus. Para. Emilio Goeldt. Sér Antropol. 9(2): 153-170. 1993.

No. 92-01
R. Murrieta, E. Brondizio, A. Siqueira, E.F. Moran. " Estratégias de Subsistência da Comunidade de Praia Grande, Ilha de Marajó, Pará, Brasil." Bol. Mus. Para. Emilio Goeldt. Sér Antropol. 8(2): 185-201. 1992.