COMPARISON OF LAND-COVER CLASSIFICATION METHODS IN THE BRAZILIAN AMAZON BASIN

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ABSTRACT

Numerous classifiers have been developed and different classifiers have their own characteristics. Controversial results often occurred depending on the landscape complexity of the study area and the data used. Therefore, this paper aims to find a suitable classifier for the tropical land cover classification. Five classifiers – minimum distance classifier (MDC), maximum likelihood classifier (MLC), fisher linear discriminant (FLD), extraction and classification of homogeneous objects (ECHO), and linear spectral mixture analysis (LSMA) – were tested using Landsat Thematic Mapper (TM) data in the Amazon basin using the same training sample data sets. Seven land cover classes – mature forest, advanced succession forest, initial secondary succession forest, pasture, agricultural lands, bare lands, and water – were classified. Overall classification accuracy and kappa analysis were calculated. The results indicate that LSMA and ECHO classifiers provided better classification accuracies than the MDC, MLC, and FLD in the moist tropical region. The overall accuracy of LSMA approach reaches 86% associated with 0.82 kappa coefficient.

INTRODUCTION

Classification methods can be roughly grouped into two categories: supervised and unsupervised classification. The supervised classification methods are closely controlled by the analyst. Samples of spectral data from each feature of interest are provided for "training" the classifier to identify pixels that are spectrally similar to feature classes. Training sample data must be spectrally representative of the features of interest to effectively implement a supervised classification. Unsupervised classification is more computer-automated. Its implementation depends on the image spectral data itself to group pixels with similar spectral characteristics into the same spectral category or cluster. After classification, an analyst has the responsibility to ascertain the physical nature of each cluster and then often merges spectrally similar clusters into meaningful land-cover classes.

Land-cover classification accuracy is a major concern in remote sensing applications. In order to improve classification accuracy, scientists have made great efforts to develop advanced classification algorithms such as Extraction and Classification of Homogeneous Objects (ECHO) classifier (Kettig and Landgrebe, 1976; Landgrebe

1980), neural network (Chen *et al.*, 1995; Foody *et al.*, 1995; Foody, 1996a; Bruzzone *et al.*, 1997; Foschi and Smith, 1997; Paola and Schowengerdt, 1997; Augusteijn and Warrender, 1998; Tso and Mather, 2001), fuzzy set classification (Foody, 1996b; Maselli *et al.*, 1996; Mannan *et al.*, 1998; Metternicht, 1999), spectral mixture analysis (Adams *et al.*, 1995; Roberts *et al.*, 1998; Mustard and Sunshine, 1999; Lu *et al.*, in press), expert classifier (ERDAS Inc., 1999), subpixel classifier (Huguenin *et al.*, 1997; Applied Analysis Inc., 2000), and per-field classification (Pedley and Curran, 1991; Aplin *et al.*, 1999). However, classification results are often greatly influenced by a variety of factors, including (1) ground truth data and ancillary data available; (2) the complexity of landscape and analyst's knowledge about the study area; (3) image band selection and processing; and (4) the classification algorithm and analysts experience with the classifiers used.

In practice, it is difficult to identify a suitable approach for a given study area, but using a suitable classifier is of considerable importance in improving land-cover classification accuracy. Different results and conclusions can be reached depending on the classifiers used, the characteristics of the study area, the image data used, and training sample data available. In this paper, five classifiers – minimum distance classifier (MDC), maximum likelihood classifier (MLC), fisher linear discriminant (FLD), extraction and classification of homogeneous objects (ECHO), and linear spectral mixture analysis (LSMA) – were applied in classification using Landsat Thematic Mapper (TM) data in an Amazon basin study area, using identical training samples and test data sets. Seven land-cover classes – mature forest, advanced secondary succession forest (SS2), initial secondary succession forest (SS1), pasture, agricultural lands, bare lands, and water – were classified. Overall accuracy and kappa analysis were determined for each classification approach tested and results were compared among the classifiers. The purpose of this paper is to identify the classifier or classifiers most suitable for land-cover classification in the moist tropical study area.

METHOD

Description of the Study Area

Rondônia had high deforestation rates in the Brazilian Amazon during the last twenty years (INPE, 2002). Following the national strategy of regional occupation and development, colonization projects initiated by the Brazilian government in the 1970s played a major role in this settlement process (Schmink and Wood, 1992). Most colonization projects in the state were designed to settle landless migrants. Settlement began in this area in the mid-1980s, and the immigrants transformed the landscape into a mosaic of forest remnants, cultivated crops, pastures,

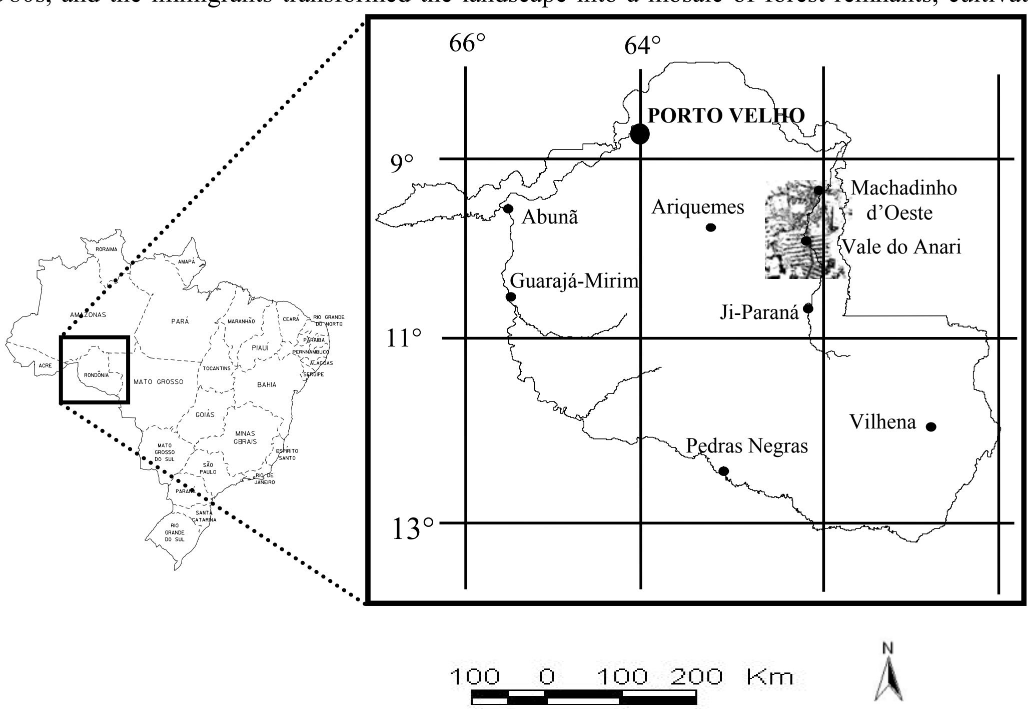

Figure 1. Location of Machadinho d'Oeste in the State of Rondônia, Brazil

and fallow land. The dominant pristine vegetation is tropical moist forest, associated with some bamboo and palms. The terrain is undulated, ranging from 100 to 450 m above sea level. The data used in this study were collected in Machadinho d'Oeste in northeastern Rondônia (Figure 1).

Data Collection and Image Preprocessing

Field data were collected during the dry season of 1999 and 2000. Preliminary image classification and band composite printouts were used to identify candidate areas to be surveyed, and a flight over the areas provided visual insights about the size, condition, and accessibility of each site. After driving extensively throughout the settlements, field observations gave a sense about the structure of regrowth stages, mainly regarding total height and ground cover of dominant species. Indicator species, such as *Cecropia sp*., *Vismia sp*., palms, grassy vegetation, and lianas also helped to assign the successional stages. During the fieldwork every plot was registered with a Global Positioning System (GPS) device to allow integration with spatial data in Geographic Information Systems (GIS) and image processing systems. The field data were randomly separated into two groups. One group was used for training data for supervised classification, and another group was used for test data for accuracy assessment.

TM data (18 June 1998) were atmospherically corrected into apparent reflectance using an image-based dark object subtraction model (Lu *et al.*, 2002). The path radiance was identified based on clear water for each band. The atmospheric transmittance was ignored because of lack of atmospheric data to estimate the value for each band. The image was geometrically rectified based on control points taken from topographic maps at 1:100,000 scale (UTM south 20 zone). A nearest-neighbor resampling technique was used and a root-mean squared error (RMSE) of less than 0.5 was obtained.

Classification Methods

MDC and MLC are the two most common methods used in remote sensing classification applications. MDC is a non-parametric classifier that has no assumption of data normality for features of interest. It is also fast and simple in computation. MLC is a parametric classifier that assumes normal or near normal spectral distribution for each feature of interest. Equal prior probability among the classes are also assumed. MLC requires sufficient representative spectral training sample data for each class to accurately estimate the mean vector and covariance matrix needed by the classification algorithm. When the training samples are limited or non-representative then inaccurate estimation of the elements often results in poor classification. Thus, MDC is possibly more suitable to use when training samples are few because the estimation of covariance matrix is not required (Jensen, 1996). Detailed descriptions of both classifiers can be found in many textbooks (Jensen, 1996; Richards and Jia, 1999). Almost all commercial image processing software and GIS software provided these functions. The FLD, ECHO, and LSMA classifiers are relatively new or less commonly used, consequently they are not found in many remote sensing textbooks or software packages. These three classifiers are described below and the characteristics of all five classifiers are described in Table 1.

FLD. Fisher linear discriminant analysis was first proposed for classification by Fisher (1936) in which a linear combination maximized differences among classes while minimizing variation within classes. The key assumption is that variance/covariance matrices of variables are homogeneous across groups (Klecka, 1980; McGarigal *et al.*, 2000). There are as many classification functions as there are classes. Each function allows computing classification scores for each pixel for each class using the formula:

$$S_i = c_i + \sum_{j=1}^{m} (w_{i,j} x_i)$$

Where the subscript i denotes the respective class; the subscripts j, j=1, 2, …, m denote the m bands; c_i is a constant for i'th class, w_{ij} is the weight for the j'th band in the computation of the classification score for the i'th class; x_i is the observed value for the respective case for the i'th class. S_i is the score for class i. In this model, the independent variables are the spectral image bands, while the dependent variable is the measure of support. The candidate pixels are assigned the class with the highest score. Detailed description about the FLD for classification can be found in Klecka (1980) and McGarigal *et al.* (2000).

ECHO. ECHO classifier was developed by Kettig and Landgrebe at the Laboratory for Applications of Remote Sensing (LARS) at Purdue University (Kettig and Landgrebe, 1976; Landgrebe, 1980; Biehl and Landgrebe, 2002). ECHO was initially part of LARS' experimental classification algorithms found in their LARSFRIS software. Currently ECHO is supported in both Windows and Mac formats in the Purdue/NASA MultiSpec software package that is available at no cost from the MultiSpec website (http://dynamo.ecn.purdue.edu/~biehl/MultiSpec/).

Table 1. Characteristics of Selected Classifiers

Classifier	Code	Characteristics
Minimum distance classifier	MDC	MDC is a non-parametric classifier. It is computationally simple and fast that it only requires the mean vectors for each band from the training data. Candidate pixels are assigned to the class that is spectrally closer to the sample mean. This method does not consider class variability, thus big differences in the variance of the classes often lead to misclassification.
Maximum likelihood classifier	MLC	MLC is a parametric classifier that assumes normal distribution for the training data statistics for each class in each band. It is based on the probability that a pixel belongs to a particular class. It takes variability of classes into account by using the covariance matrix, thus it requires more computation per pixel than MDC. Insufficient numbers of training samples or multimode distributions often result in poor classification.
Fisher linear discriminant	FLD	FLD is also a parametric classifier in which homogeneous variance/covariance matrices of variables are assumed. A linear discriminant analysis of the training data is implemented to form a set of linear functions that express the degree of support for each class. The independent variables are the image bands and dependent variable is the measure of support. This method maximizes the variance between classes and minimizes the variance within classes. The assigned class for each pixel is the class that receives the highest support after evaluation of all functions.
Extraction and classification of homogeneous objects	ECHO	ECHO is a multistage spatial-spectral classifier that has elements of a parametric per-pixel classifier and elements related to texture classification, hence it is hybrid in character. Four stages are involved in this classification: (1) an analyst partitions the feature space into cells (2x2, 3x3, 4x4, etc.); (2) homogeneity of pixels within each cell is determined by user set thresholds and each cell is either considered a single entity or individual pixels within the cell remain as single pixels; (3) cells and individual pixels are aggregated based on spectral statistical associations between them; and (4) the aggregate of cells of pixels and single pixels are processed by a MLC to provide final results.
Linear spectral mixture analysis	LSMA	LSMA assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel. Selection of suitable endmembers and image bands are two most important aspects to develop high quality fraction images. Constrained or unconstrained solutions can be used to unmix the image into different fractions. The fractions represent the areal proportions of the endmembers within a pixel. Thus, different land-cover types have different proportion compositions. The classification is based on the fraction images through using a decision tree classifier. Training sample data are important to define the thresholds for each class.

Research has indicated that incorporation of textural or spatial or object-oriented data enhances the information content of per pixel spectral data in many applications (Woodcock and Strahler, 1987; Alonso and Soria, 1991; Arai, 1993; Kartikeyan *et al.*, 1994; Foody *et al.*, 1996). ECHO was one of the algorithms to incorporate spatial/contextual data into remote sensing classifications and has proven to be successful in several humid moist forest applications in Brazil. ECHO was used successfully to accurately delineate three classes of secondary succession using Landsat TM data supported by very detailed field measured data near Altamira, Brazil (Mausel *et al.*, 1993; Moran *et al.*, 1994). An application of ECHO in Marajo Island in the Amazon Estuary area had similar successful results in differentiating three secondary succession forest types as well as other flood-plain forest features not present in Altamira using TM data (Brondízio *et al.*, 1996). Similar classification success was achieved in another distinctly different part of the Amazon in Tome Acu using TM data (Batistella, 2000). Thus, several different research project directors in very different parts of the Amazon have had classification success using ECHO. In every instance excellent ground truth support was available to support ECHO classification.

In unpublished research, one of the authors of this article (P. Mausel) used ECHO extensively in classifying typical crops of the Midwestern U.S. (corn, soybeans, and wheat). Classification accuracy using ECHO in this context was no better than using more standard classifiers such as MLC. It is hypothesized that ECHO does best where classes of interest are very mixed with high variance that typically causes per pixel classifiers to have great difficulty in feature discrimination. ECHO simplifies complex mixtures of pixels and often can extract the essence of a mass of seemingly complex spectral responses and often accurately extract the dominant class. In the Amazon study areas, spectral-spatial relationships were very complex and ECHO did a good job of penetrating this complexity better than other classifiers initially used. However in the Midwest croplands, the spectral-spatial framework was relatively simple and ECHO just became one of many classifiers that could be used to do an adequate job of feature discrimination. Thus, like many classifiers, but perhaps more so for ECHO, there are optimal uses for a given classifier and an analyst must understand the relationships between the structure of a classifier's algorithm and the spectral nature of features to be classified.

LSMA. LSMA is regarded as a physically based image processing tool. It assumes that the spectrum measured by a sensor is a linear combination of the spectra of all components within the pixel (Adams *et al.*, 1995; Roberts *et al.*, 1998; Ustin *et al.*, 1998; Petrou 1999). It supports repeatable and accurate extraction of quantitative sub-pixel information (Smith *et al.*, 1990; Roberts *et al.*, 1998). The fractions of the endmembers represent the areal proportions within the pixel. The LSMA approach involves four steps: (1) image processing, (2) endmember selection, (3) unmixing solution, and (4) analysis of fraction image.

Image preprocessing, including geometric rectification and atmospheric correction, was conducted as previously described. Before implementing the LSMA approach, it is necessary to reduce the correlation between TM bands because high correlations exist between visible TM bands. Standardized principal component analysis (SPCA) was used to transform the atmospherically calibrated TM images into principal components (PC). The last two PCs were discarded due to their very limited information contents. The first four PCs were used in the LSMA approach to convert the image signatures into physically based fraction images.

Different endmember selection methods have been used (Adams *et al.*, 1993; Settle and Drake 1993; Boardman *et al.*, 1995; Bateson and Curtiss 1996; Tompkins *et al.*, 1997; Mustard and Sunshine 1999). For many remote sensing applications of LSMA, the image-based endmember selection method is often used because they are obtained easily and represent spectra measured at the same scale as the image data (Roberts *et al.*, 1998). The endmembers are regarded as the extremes of the triangles of an image scattergram. Thus, the image endmembers are derived from the extremes of the image feature space, assuming they represent the purest pixels in the images (Mustard and Sunshine 1999). In this paper, three endmembers (shade, soil, and green vegetation or GV) were identified from the scattergram of the first two PCs derived from SPCA. An average of 30 to 50 pixels of these vertices was calculated for each endmember. When selecting the endmembers, caution needs to be taken to identify outliers. Appropriate selection of image endmembers is often an iterative process. Checking fraction images and RMSE images are a feasible way to assess whether the selected endmembers are appropriate or not.

After selection of endmembers, an unconstrained least RMSE solution was used to unmix the first four PCs into three endmember fraction images. Because the fractions represent the biophysical characteristics, different vegetation stand structure and land-cover types will have different proportion compositions. A detailed description of LSMA approach can be found in Adams *et al.* (1995), Roberts *et al.* (1998), and Mustard and Sunshine (1999). In this paper the fraction images were used to classify the seven land-cover types in the Brazilian Amazon basin previously identified and used in the decision tree classifier. The threshold of each class was identified based on the integration of sample data and fraction images. A detailed description of the definition of thresholds was described in Lu *et al.*, (in press).

Accuracy Assessment

A common method for classification accuracy assessment is through the use of an error matrix. Previous literature has provided the meanings and calculation methods for overall accuracy (OA), producer's accuracy (PA), user's accuracy (UA), and Kappa coefficient (Congalton *et al.*, 1983; Congalton 1991; Janssen and van der Wel 1994; Kalkhan *et al.*, 1997; Khorram 1999; Smits *et al.*, 1999). The Kappa coefficient is a measure of overall agreement of a matrix. It takes non-diagonal elements into account. Kappa analysis was recognized as a powerful technique used for analyzing a single error matrix and comparing the difference between different error matrices (Congalton 1991; Smits *et al.*, 1999). A detailed description about the Kappa analysis can be found in Congalton *et al.* (1983), Hudson and Ramm (1987), Congalton (1991), Kalkhan *et al.* (1997), and Smits *et al.* (1999). In this paper, an error matrix for each classification method was produced. UA, PA, OA were calculated for each classification method. The KHAT statistic, Kappa variance, and Z statistic were used to compare the performance among different classification methods. A total of 320 sample sites, covering different land-cover types, were randomly allocated and examined using field data and IKONOS data.

RESULTS AND DISCUSSION

The seven land-cover classes: mature forest, SS2, SS1, pasture, agricultural lands, bare lands, and water, were classified using five different classifiers and classification accuracy assessments were conducted. Table 2 provides the UA and PA for each land-cover types and OA for each classifier. The classification accuracies of forest, pasture, agricultural land, and water were satisfactory, but the accuracy of forest successional stages, especially the SS2, was poor. In this study area, SS2 was often confused with some SS1 sites and some coffee plantations in the agricultural land class. SS1 was confused with selected degraded pastures and some agricultural lands. Sparse pasture sites were sometimes confused with bare lands. The LSMA approach to classification generally provided the highest accuracies of successional forests, pasture, and agricultural lands. Considering the overall accuracy, LSMA provided the best classification results with 85.9% and MDC provided the poorest results with overall accuracy of 77.2%.

Table 2. Comparison of Classification Percent Accuracy among Different Classifiers

Land-cover types	MDC		MLC		FLD		ECHO		LSMA	
	UA	PA	UA	PA	UA	PA	UA	PA	UA	PA
Forest	94.33	98.71	93.65	98.71	94.28	98.65	94.71	99.47	95.73	98.77
SS2	29.30	59.35	31.37	58.39	32.08	52.73	28.26	48.79	35.02	62.58
SS1	74.04	67.74	84.98	69.31	88.91	68.23	92.87	58.16	91.43	70.95
Pasture	85.25	58.98	86.95	65.83	85.00	74.68	83.97	87.96	84.96	89.02
Agriculture	80.53	80.66	72.17	83.14	82.70	79.01	75.33	82.03	87.71	84.96
Bare land	60.98	93.77	65.96	97.66	56.62	100.00	85.75	100.00	98.22	86.68
Water	100.00	87.17	100.00	88.18	100.00	90.91	100.00	91.82	100.00	92.73
OA	77.17		79.75		81.26		83.11		85.90	

Figure 2 illustrates three land-cover classification images using MDC, FLD, and LSMA, respectively. A road layer was overlaid to illustrate the land-cover distribution. It is evident that agricultural lands, pasture, and successional forests were mainly distributed near the roads and mature forest was primarily located away from the roads.

Table 3 provides a comparison of kappa analysis results among the different classifiers. It indicates that LSMA has a significantly better KHAT than MDC and MLC at a 90% confidence level and better than FLD at 80% confidence level. ECHO has a significant better KHAT than MDC at a 90% confidence level. FLD, MLC, and MDC do not have a significant difference in the KHAT coefficients.

Table 3. Comparison of Kappa Analysis Results among Different Error Matrices

Classifier	No.	KHAT	Variance	Combination	Z_stat	Sig.	Combination	Z_stat	Sig.
MDC	1	0.7162	0.000871	(5) vs. (1)	2.6912	S (95%)	(4) vs. (2)	0.9196	NS
MLC	2	0.7560	0.000788	(5) vs. (2)	1.6693	S (90%)	(4) vs. (3)	0.6482	NS
FLD	3	0.7668	0.000765	(5) vs. (3)	1.3806	S (80%)	(3) vs. (1)	1.2505	NS
ECHO	4	0.7920	0.000745	(5) vs. (4)	0.6787	NS	(3) vs. (2)	0.2744	NS
LSMA	5	0.8160	0.000503	(4) vs. (1)	1.8850	S (90%)	(2) vs. (1)	0.9762	NS

Note: Z_stat = Z statistic; S = significant; NS = not significant.

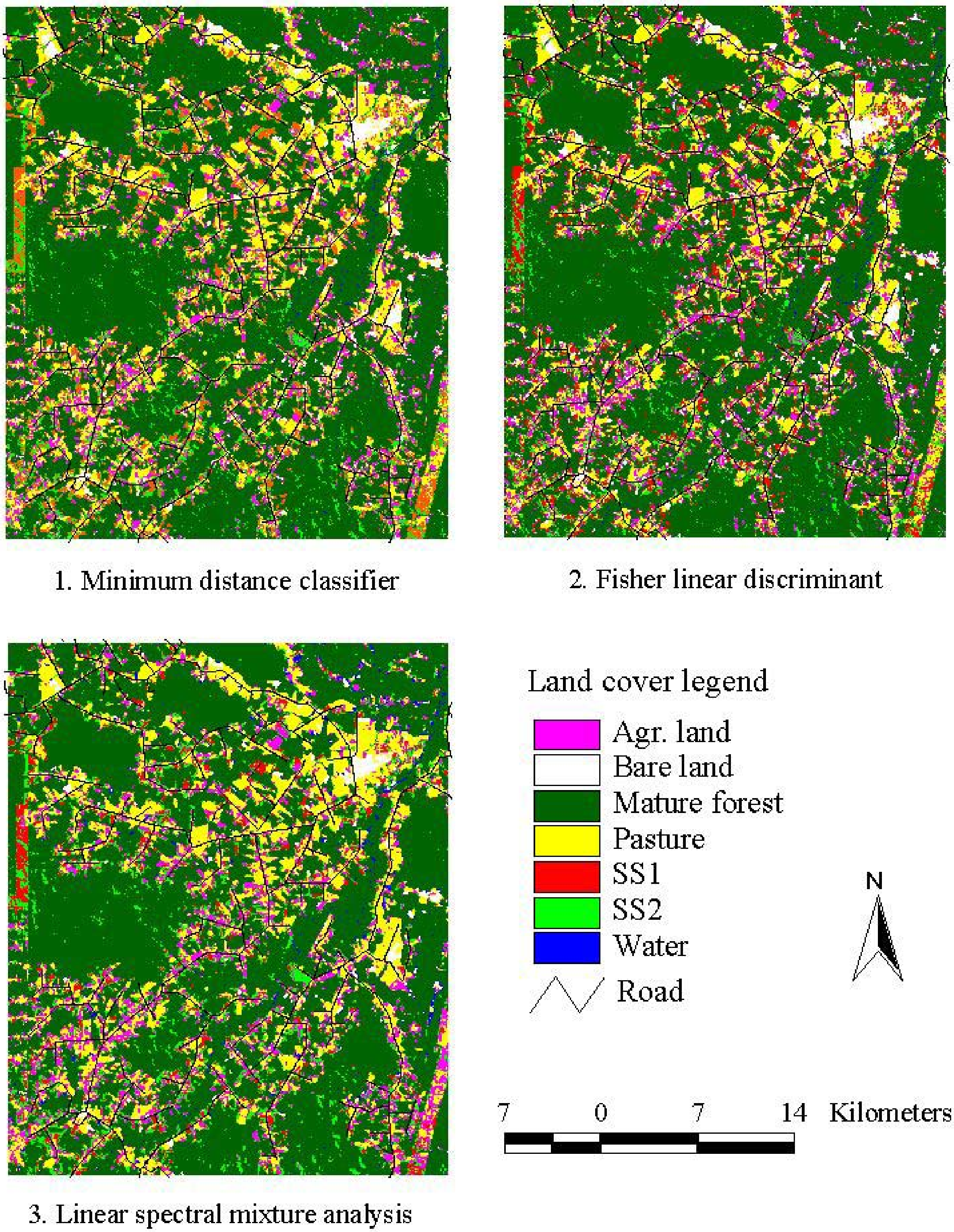

Figure 2. Comparison of Land-Cover Distributions Derived from Different Classifiers

The classification results indicate that confusion existed among SS2, SS1, degraded pasture, and coffee plantations classes. Also the variance within the classes varies depending on the land-cover types. For example, mature forest has relative smaller variance than successional forests, pasture, and agricultural lands. This characteristic makes mature forest easier to classification using any of the different classifiers. For those land covers, such as pasture, with relatively larger variance, MDC produced lower classification accuracy due to the fact that MDC only use the mean vector and ignored the covariance between the classes. So the MLC and FLD produced relatively higher accuracy than MDC because they take the covariance into consideration in their classifiers. However, MLC and FLD assume that the histograms of the classes are normally distributed and such assumptions are not always true. Also the MDC, MLC, and FLD only consider per-pixel information and ignored texture or contextual information. Study areas with complex landscape benefit from incorporation of texture information in improving the classification results, thus ECHO provided better classification results, for selected classes, in this study area.

The landscape and environmental conditions are very complex in the moist tropical region of Amazon. Mixed pixels are common in TM data due to the heterogeneity of landscape and limitation of 30 m spatial resolution of the image data. Traditional per-pixel classifiers such as MLC and MDC are difficult to use to accurately classify the land covers based purely on remote sensing spectral signatures. Three major methods can be implemented to improve classification accuracy: (1) assuming abundant and high quality of ground truth data are available, the FLD method can slightly improve the classification accuracy through linear transform of the image data, by maximizing the variance between the classes, based on the sample data; (2) using advanced classifiers, such as ECHO, that incorporate spectral and textural information in the classification; and (3) unmixing the image data into fractions using LSMA through selection of endmembers. Another possible method is to combine different classifiers. For example, using LSMA to convert image data into fractions, then using ECHO classifier to classify the fraction images into different land-cover types using training sample data.

CONCLUSIONS

Different classifiers have their own advantages and disadvantages. For a given study area and project, deciding which classifier is best suitable depends on a variety of factors. If good training sample data and different classifiers are available, selecting a suitable classifier has considerable significance. This research indicates that LSMA and ECHO classifiers are the two recommended approaches suitable for moist tropical land-cover classification. Even though some classifiers provide more accurate results than others, all five used in this research are useful in extracting information in the study area.

It is interesting to note that the overall accuracies of the five classifiers used in this study are basically in the order of the least complex or most automated algorithms having the lowest accuracy and the most complex or multistage classifiers having the highest accuracy. The LSMA approach is conceptually the most complex algorithm and ECHO has four decision stages requiring analyst input. Analysts with extensive experience working with the more complex classification approaches often will get good results, but analysts with limited experience with certain complex classifiers may get poor results initially. Thus consideration of an analysts' experience and understanding of a given classifier also should be an important factor in selecting which algorithm to use in addition to which algorithms might theoretically be most powerful.

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