Comparison of Segment and Pixel-based Non-parametric Land Cover Classification in the Brazilian Amazon Using Multitemporal Landsat TM/ETM+ Imagery

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Abstract

This study evaluated segment-based classification paired with non-parametric methods (CART® and kNN) and inter-annual, multi-temporal data in the classification of an 11-year chronosequence of Landsat TM/ETM+ imagery in the Brazilian Amazon. The kNN and CART® classification methods, with the integration of multi-temporal data, performed equally well in the separation of cleared, re-vegetated, and primary forest classes with overall accuracies ranging from 77 percent to 91 percent, with pixel-based CART® classifications resulting in significantly lower variance than all other methods (3.2 percent versus an average of 13.2 percent). Segmentation did not improve classification success over pixel-based methods with the used datasets. Through appropriate band selection methods, multi-temporal bands were chosen in 38 of 44 total classifications, strongly suggesting the utility of inter-annual, multi-temporal data for the given classes and region. The land-cover maps from this study allow for an accurate annualized analysis of land-cover and landscape change in the region.

Introduction

The rainforests of Rondônia, Brazil have been subject to rapid landscape change over the past 30 years due to various rural development programs and the construction of BR-364, an interstate highway providing access into the region and the state of Rondônia in particular (Browder and Godfrey, 1997; Perz, 2002). The intent of these regional programs (POLONOROESTE, and PLANALFORO) was to open areas to settlement for landless sharecroppers and to promote sustainable farming systems such as perennial agriculture. As a result, the population in Rondônia grew from approximately 111,000 in 1970 to 1,588,600 in 1990, near the start date of this study (Browder and Godfrey, 1997; Perz, 2002). The immigration of farmers into the region has led to forest clearing intended for agriculture, resulting in extensive deforestation (INPE, 2001). Implications of such considerable ecological alteration include decreases in global carbon sequestration and increases in greenhouse gas emissions (Grace *et al.*, 1996; Fearnside, 1997), potential loss of biodiversity (Lugo, 1988; Fearnside, 1999), and degradation of soil (De Souza *et al.*, 1996). Understanding the factors that influence land-cover conversion over time in the Amazonian frontier is necessary to address these ecological issues while promoting sustainable development in the region.

One common pattern of settlement in Rondônia begins with clearing for perennial and annual agriculture followed by conversion to pasture and cattle production (Browder, 1996; McCracken *et al.*, 2002). This kind of trajectory, or land-use pathway through time, can be associated with socioeconomic conditions, household labor capacity, market prices of agricultural and forest resources, regulatory prices, and landowner perceptions to further the understanding of the smallholder decision process on farm practices and land-use management (Browder, 1996). Likewise, it is valuable to understand the impacts of these land-use changes on the landscape both at a farm level and a more regional scale.

The prominent categories of land-use in the Amazon include primary forest, pasture, perennial agriculture (cocoa, coffee), secondary growth, and annual agriculture. The amount of remaining primary forest in the region has been a focus of many studies because of its global ecological importance in terms of carbon sequestration and biodiversity (Tardin *et al.*, 1979; Skole and Tucker, 1993; Alves *et al.*, 1998; Alves, 1999). While the intent of the development programs was to promote sustainable agricultural systems such as perennial production, pasture has become the dominant land-use in the region (Browder and Godfrey, 1997; Porro, 2002). Pasture areas tend to be large in size, in some instances encompassing an entire 100 hectare property.

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On satellite imagery they usually appear as cleared, barren land during the dry season, and occasionally as re-vegetated land when few cattle are being managed. Perennial agriculture includes coffee, cocoa, and agroforestry plantations; it appears as cleared in the first year or two of establishment and will gradually transition to a re-vegetated shrub stage. Secondary growth is re-vegetated land that has been abandoned following agricultural practices or clearing (Perz and Walker, 2002). Once permitted to re-grow, these abandoned areas can return to forest and can serve many of the same functions as primary forest, both ecologically and culturally (Hölscher *et al.*, 1997; Walker, 1999; Perz and Walker, 2002). Secondary growth can range in land-cover from grass with low-lying shrubs to late successional secondary forest. Spectrally differentiating between cleared areas and initial succession and between advanced succession (greater than 10 years, greater than 20 meter canopy) and primary forest has been a challenge in previous studies (Mausel *et al.*, 1993; Brondizio *et al.*, 1996; Lu *et al.*, 2003). Annual agriculture consists of crops such as maize, beans, and rice managed primarily for subsistence agriculture and for sale in small local markets (McCracken *et al.*, 2002). Areas in annuals tend to be very small in size and represent the lowest proportion of land in production of the aforementioned land-uses. During the dry season, areas in annual agriculture are fallow and therefore appear cleared in satellite imagery.

The significant anthropogenic land-uses in the Brazilian Amazon do not directly correspond to distinct land-cover classes that are identifiable in satellite imagery. For this reason it is imperative that ground level information be utilized in conjunction with remote sensing techniques to understand both the factors influencing land-use change and the impacts of land-use changes of smallholder farmers on the landscape.

Remote sensing techniques have become prominent in landscape classification in the Amazon Basin largely due to the expanse of the region and its inaccessibility (Skole and Tucker, 1993; Roberts *et al.*, 2003). Several studies have proven the efficiency of remote sensing in image classification for estimating forest area versus non-forest area with high overall accuracies (>90 percent or kappa >0.9) and dominated the remote sensing research activity in the Amazon through the 1980s and 1990s (Tardin *et al.*, 1979; Skole and Tucker, 1993; Alves *et al.*, 1998; Alves, 1999). A more recent focus of remote sensing applications in the Amazon has been on land-cover classification beyond forest and non-forest classes (Donnely-Morrison, 1994; Brondizio *et al.*, 1996; Moraes *et al.*, 1998; Roberts *et al.*, 2002; Roberts *et al.*, 2003; Guild *et al.*, 2004). Generally clearing, re-vegetation, and forest can be successfully mapped using Landsat imagery in this region. Guild *et al.* (2004) were able to perform a pathway analysis using three different image years (1984, 1986, and 1992) in Rondônia, Brazil. The Landsat TM imagery was combined using both the tasseled cap and principal components transformations. Unsupervised techniques were used to train a maximum likelihood classification that produced 17 total land-cover classes of varying combinations of forest, cleared, flooded, dry, and re-growth. The tasseled cap land-cover change classification produced an overall accuracy of 79.3 percent (kappa = 0.78) with individual class accuracies ranging from 54 percent to 100 percent. Using Landsat MSS/TM imagery, Roberts *et al.* (2002) were able to classify primary forest, pasture and green pasture, second growth, soil/urban, water, and cloud using spectral mixture analysis and a decision tree classifier and were able to obtain an overall accuracy of 85 percent (kappa = 0.76).

The introduction of multi-temporal imagery is valuable in land-use/land-cover classification with Landsat TM data (Lo *et al.*, 1986; Wynne *et al.*, 2000; Ippoliti-Ramilo *et al.*, 2003; Guild *et al.*, 2004). Among the most accurate land-use classification techniques are those using multi-temporal imagery throughout a single year to exploit seasonal transitions in land-cover (Ippoliti-Ramilo, 2003). Although intraannual, multi-temporal classification is a successful technique, it is not practical for use in the tropical region of Brazil. Within the Amazon Basin acquisition of multiple cloud-free images within the same year is rarely feasible. Multi-temporal classification is thus limited to the use of inter-annual imagery for the majority of the Amazon region. Several studies have used inter-annual, multi-temporal imagery to strengthen land-cover identification in tropical regions (Helmer *et al.*, 2000) including the Brazilian Amazon (Lucas *et al.*, 1993; Adams *et al.*, 1995; Alves and Skole, 1996; Alves *et al.*, 2003; Guild *et al.*, 2004). However, most of these studies have commented on the post-classification utility of inter-annual imagery in distinguishing between land-cover classes and have not attempted to use multi-temporal imagery in the classification phase. For example, Lucas *et al.* (1993) used post-classification techniques to determine patterns of forest re-growth and ultimately a secondary forest classification was developed.

Most traditional classifiers are parametric, based upon statistical assumptions, including the multivariate normal distribution within spectral classes. This assumption does not fit all applications, and is difficult to implement in complex landscapes with classes of high variance (Hansen *et al.*, 1996). Alternatively, non-parametric methods are not limited by such assumptions and are not based upon class statistics such as mean vectors and covariance matrices. Traditionally, land-use/land-cover classification in the Amazon has been done using parametric algorithms including minimum distance (Alves *et al.*, 2003) and maximum likelihood (Alves and Skole, 1996; Guild *et al.*, 2004; Pan *et al.*, 2004). The heterogeneity of land-cover within the Amazon region of Brazil has caused classification difficulty in the past (Alves and Skole, 1996; Brondizio *et al.*, 1996). As a result, some have turned to the use of non-parametric algorithms (Roberts *et al.*, 2002). Non-parametric techniques, including artificial neural networks (ANN) and classification and regression trees (CART®) have become prominent in recent literature to eliminate the restriction of parametric statistical assumptions (Hansen *et al.*, 1996; Friedl and Brodley, 1997; Lawrence and Wright, 2001; Pal and Mather, 2003; Rogan *et al.*, 2003; Krishnaswamy *et al.*, 2004). Although ANN classification has been shown to greatly improve accuracy over traditional parametric methods with reduced training sets, the process to implement classification is not straightforward and can be time consuming (Pal and Mather, 2003). Pal and Mather (2003) found that CART® classification provided higher accuracy than ANN classification for Landsat ETM+ imagery in Eastern England for seven land-cover types (wheat, potato, sugar beet, onion, peas, lettuce, and beans). In addition to its non-parametric nature, CART® is gaining increasing attention due to its ease of use and computational efficiency (Lawrence and Wright, 2001; Pal and Mather, 2003; Lawrence *et al.*, 2004). During the CART® classification process, a binary tree is created where decision boundaries are estimated empirically from the training data. A test in the form of $x_i > c$ is performed at each node where x_i is the feature or spectral band and c is the threshold estimated from the distribution of x_i (Breiman *et al.*, 1984). Several studies have found CART® to be an acceptable classification method (Hansen *et al.*, 1996; Lawrence and Wright, 2001; Rogan *et al.*, 2003; Krishnaswamy *et al.*, 2004) and have shown improvements in accuracy over traditional parametric classifiers (Friedl and Brodley, 1997; Pal and Mather, 2003).

Another non-parametric classification technique that has been recently explored and improved upon in many forest cover classifications is *k*-nearest neighbor (*k*NN). *k*NN uses a fuzzy non-parametric supervised classification (minimum distance) to assign pixels to informational classes. Rather than assigning a pixel to the mean of the closest spectral class, the classifier assigns a pixel to the majority of the *k* closest training pixels in spectral space. Serpico *et al.* (1996) compared traditional *k*NN methods with three neural network techniques and found *k*NN to have the highest overall accuracy, however, the difference was not significant. While *k*NN was the most accurate classifier and the simplest during the training phase, the authors claimed it to be more difficult during the classification stage than the neural network classifiers, likely due to the multiple classifications needed to determine the optimal *k* value. The *k*NN algorithm has been successfully implemented in several national forest inventory programs, including in Finland, where it was popularized (Katila and Tomppo, 2001; Tomppo and Halme, 2004) and in the United States (Franco-Lopez *et al.*, 2001; McRoberts *et al.*, 2002; Haapanen *et al.*, 2004). In several of these studies forest inventory information is coupled with satellite imagery to predict forest and land-use attributes of a continuous digital surface (McRoberts *et al.*, 2002; Tomppo and Halme, 2004).

The majority of remote sensing classifications in the Amazon have used point or pixel-specific methods in which each pixel is classified individually without regard to the spatial relationship of neighboring pixels (Lo *et al.*, 1986; Donnelly-Morrison, 1994; Alves and Skole, 1996; Ippoliti-Ramilo *et al.*, 2003; Guild *et al.*, 2004) although segment based approaches have gained recent attention (Palubinkas *et al.*, 1995; Brondizio *et al.*, 1996; Lu *et al.*, 2004b). Pixel-based classification often results in high heterogeneity giving low classification accuracy for complex landscapes and a "salt and pepper" appearance to the classified image. Contextual or segment-based classification incorporates spatial relationships among pixels in an attempt to extract homogeneous objects on the landscape and thus decrease the heterogeneity that is an artifact of pixel-based methods (Richards and Jia, 1999; Campbell, 2002). Many studies have shown an improvement over pixel-based land-use classification accuracy through the incorporation of segment-based methods (Palubinkas *et al.*, 1995; Lobo *et al.*, 1996; Shandley *et al.*, 1996). One of the primary benefits of segment-based classification, as noted by De Wit and Clevers (2004), is the ability to capture the spectral variability within land-use types such as shadowing, moisture conditions, and species variability.

Segment-based classification has been used in several studies within the Amazon region of Brazil (Palubinkas *et al.*, 1995; Brondizio *et al.*, 1996; Lu *et al.*, 2004b). Palubinkas *et al.*, (1995) compared the results from eight different texture based methods (based on a Markov random fields model) with traditional minimum distance and maximum likelihood classifiers to segment Landsat TM imagery for classification of regenerating forest. Six of the varying segment extraction approaches used maximum likelihood classification, while two used minimum distance classification. Those classifiers that implemented a maximum likelihood algorithm following segmentation consistently out-performed the pixel-based classification methods in terms of overall accuracy.

This study evaluated the ability of segment-based classification paired with non-parametric methods (CART®) and *k*NN) to classify a chronosequence of Landsat TM/ETM+ imagery spanning from 1992 to 2002 within the state of Rondônia, Brazil. Pixel-based classification was also implemented for comparison. Inter-annual, multi-temporal composites were used in each classification in an attempt to increase the separation of primary forest, cleared, and re-vegetated classes within a given year.

Objectives
The principal aim of this study was to produce accurate annual maps of Amazonian land-cover (cleared, re-vegetated, and primary forest) using non-parametric techniques applied to inter-annual, multi-temporal Landsat TM/ETM+ imagery. The specific objectives were (a) to determine the preferred non-parametric classification technique between the *k*-nearest neighbor (*k*NN) and classification and regression trees (CART®) methods, (b) to determine whether land-cover classification using segment-based methods is more accurate than comparable efforts using per-pixel methods, and (c) to assess the utility of interannual multitemporal data in the classification of a single year.

Methods
A flowchart outlining the basic processing steps of this study is shown in Figure 1.

Study Area
The analysis of land-cover pathways was performed in two study sites located in western Brazil in the state of Rondônia. The first site is located in the municipio of Nova União (UL 62°41′W × 10°48′S, LR 62°29′W × 10°56′S) and the second in the municipio of Rolim de Moura (UL 62°57′W × 10°29′S, LR 62°49′W × 10°48′S) (Figure 2). While the colonization of Rondônia has been occurring since the seventeenth century, a series of regional development programs in the 1970s, along with the construction of a highway providing access to the region, spurred extensive migration into the region (Mahar, 1979; Fearnside, 1986; Goodman, 1990; Browder, and Godfrey, 1997). The development plan included grid-like settlement areas with individual plots totaling approximately 100 hectares each. As farmers have colonized the region the conversion from forest to various agricultural systems has generally originated near the road and extended toward the rear of the property. Prominent agricultural systems include coffee, cocoa, annuals, and pasture.

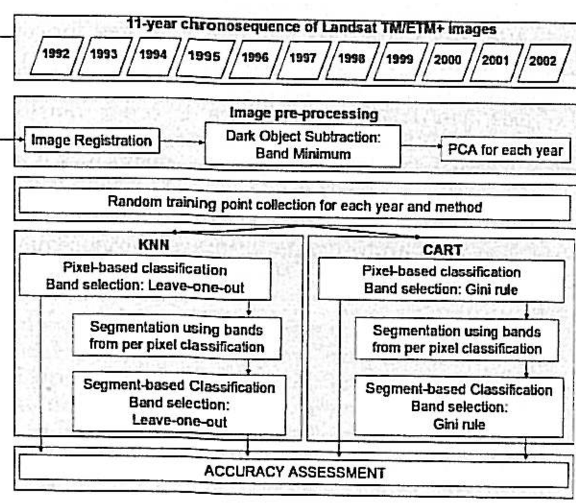

Figure 1. Flowchart of processing steps.

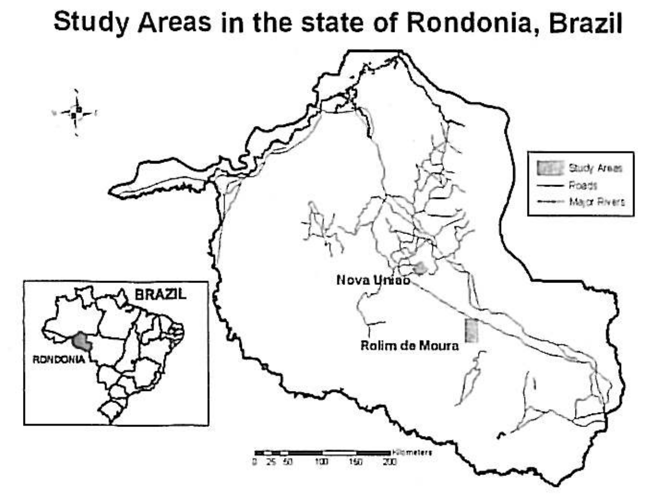

Figure 2. Study areas in Rondônia, Brazil.

The major natural vegetation cover within the study region is transitional tropical seasonal moist forest (TTSMF). The dry season extends from June to September, with an average annual rainfall in Nova União and Rolim de Moura ranging from 1,600 to 1,700 mm and 2,000 to 2,250 mm, respectively. Elevation ranges from 100 to 225 meters in Nova União and is 250 meters in Rolim de Moura (IBGE elevation maps, 1974). The main soil type in Nova União is a eutrophic yellow-red podsol with patches of eutrophic litolic soil. In Rolim de Moura the prominent soil type is a eutrophic yellow-red podsol and non-hydromorphic cambisol (Projeto Radambrasil Mapa Exploratório de Solos, 1:1 000 000, 1979).

Data and Preprocessing

The digital data consist of a multitemporal series of Landsat Thematic Mapper (TM) and Enhanced Mapper (TM/ETM+) images (path 231/row 68) from 1992 through 2002 (Table 1). Figure 3 provides an example of a Landsat TM image (1992) for path 231, row 68. All images were registered to the 2002 image, which was rectified by EROS Data Center prior to purchase. Registration was performed in ERDAS Imagine® 8.7 software. At least 75 control points were created for each image pair, one-third of which were randomly selected as check points. A control point root mean squared error (RMSE) of less than one-fifth pixel for a 1st order transformation was met for all registrations with check point error not exceeding 0.21 pixels. Dai and Khorram (1998) found that an RMSE of less than one-fifth pixel was necessary to achieve a change error of less than 10 percent. Using these same criteria for use with multi-temporal image chronosequences is just as, if not more, needed. Nearest neighbor resampling was used.

Although conversion to reflectance is desirable when working with multi-temporal imagery, the variety of sources, preprocessing methods, and the lack of metadata associated with the imagery precluded it. Due to this limitation, band minimum dark object subtraction was implemented as a technique to radiometrically normalize the chronosequence from 1992 to 2002 (Chavez, 1989).

A principal component analysis (PCA) was performed on all images to reduce the amount of data and to highlight the greatest variability within the images.

Table 1. Landsat TM/ETM+ Image Dates Used in Study

Sensor	Date
TM	July 25, 1992
TM	May 25, 1993
TM	July 15, 1994
TM	August 3, 1995
TM	July 20, 1996
TM	June 21, 1997
TM	May 23, 1998
ETM+	August 6, 1999
ETM+	August 24, 2000
ETM+	August 11, 2001
ETM+	May 26, 2002

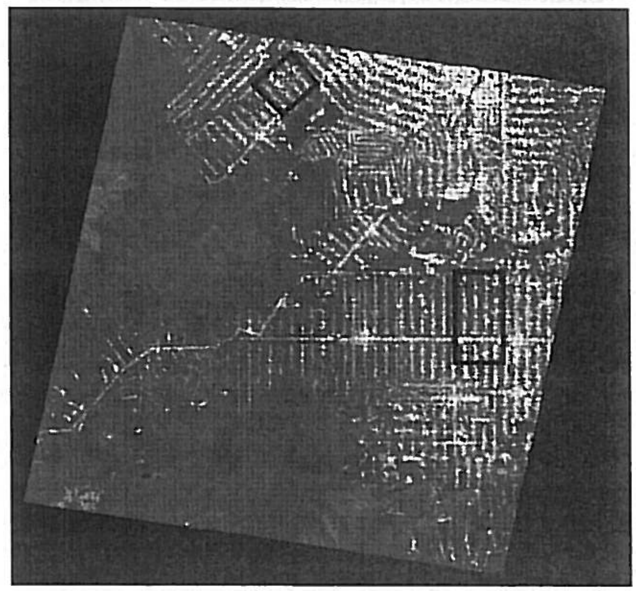

Figure 3. Full Landsat TM image for path 231, row 68 (25 July 1992) in grayscale (bands 4, 3, 2 in R, G, B). The Nova União study area is outlined in the upper left portion of the image and the Rolim de Moura study area is outlined in the lower right portion of the image.

Training Data and Classes

There are several different sources that can be used in collecting training pixels including *in situ* data, ancillary data such as topographic maps, aerial photographs, or satellite imagery (Richards and Jia, 1999). In remote regions, such as the Amazon, inaccessibility limits the ability to collect *in situ* field data. When collecting training data in a similar remote environment, Frizzelle *et al.*, (2003) incorporated several different sources to create a training data set including GPS data, field sketch maps, a longitudinal social survey, and satellite imagery. In conjunction with ancillary data the imagery to be classified has also been used to collect training and validation points (Cohen *et al.*, 1998; Sader *et al.*, 2003).

As a part of the larger study, research crews collected detailed information through field interviews with farmers within both study areas in 1992 and 2002. In addition, detailed interviews were conducted in conjunction with GPS point collection in 2003 to gain information on land conversion through years 1993 to 2001. In both 1992 and 2002, detailed maps were created of each farm included in the study (Figure 4). Using information from the 1992 and 2002 maps, detailed interviews in 2003, and Landsat imagery, a random sample of 838 training pixels was labeled for each year. Fifty points per class were randomly removed from each annual training set prior to classification for use as a validation sample. A random sample of training points ensures the inclusion of edge and mixed pixels, which are necessary in avoiding inflated accuracies, particularly in the validation sample (Powell *et al.*, 2004).

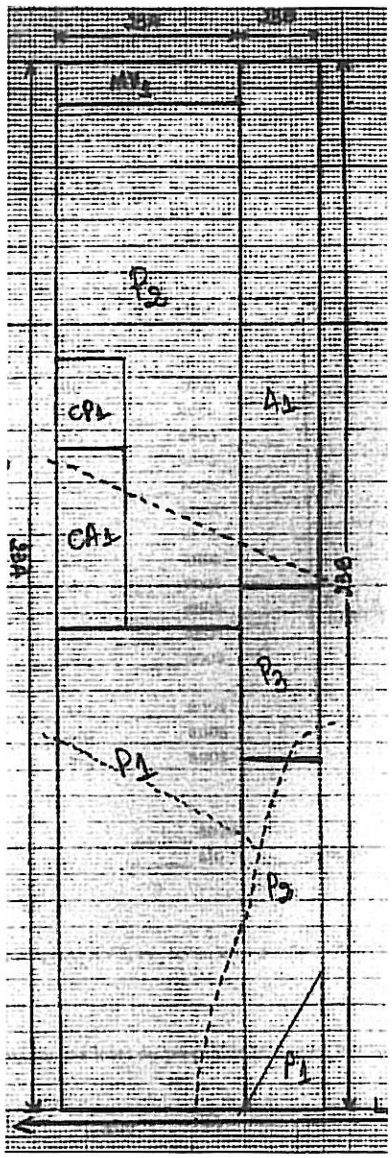

Figure 4. Example of a detailed map constructed during the interview processes in 1992 and 2002. *P* represents pasture, *CA* represents coffee, *CP* represents *copeira* or unmanaged land, *A* represents annuals, *MV* represents *mata virgem* or primary forest. The dashed lines represent streams running through the property. This particular farm-level representation is a full 100 hectare property that was sub-divided into two (23A and 23B) properties with separate ownership.

Based on the literature, the two non-parametric classification methods used in this study have differing requirements for training data for optimal classification. The same training data were used for both pixel-based and segment-based classifications to enable an accurate comparison of each technique. Hardin (1994) performed several nearest neighbor classifications, including *k*NN, using a large training set where the proportions of samples within classes represented the proportions within the population. A reduced training set was also used with all classification methods. The results indicated that when large training data sets are used where class proportions are the same as the population to be classified, nearest neighbor techniques are statistically superior to the best parametric classifiers. The results from the reduced training set were not as consistent and were often inferior to parametric methods. CART® alternatively, performs best when the training data set has approximately the same number of samples in each class to prevent over-representation in class assignment for classes with more samples (Rogan *et al.*, 2003; Lawrence *et al.*, 2004).

To optimize results for each classification method, the original dataset was reduced to obtain both a random sample of proportional classes to the population (for use in *k*NN classification) and a random sample of equal classes (for use in CART® classification) (Figure 5). Each dataset contained the same number of training pixels and was limited by the number of points in the class with the minimum samples by year (Table 2).

Three different land-use classes were included in the study; primary forest, cleared, and re-vegetated, following the classification scheme of Guild *et al.* (2004). Forest areas consist of primary forest. Re-vegetated areas include perennial agriculture following clearing (e.g., cocoa and coffee plantations), secondary growth, and occasionally "dirty" poorly managed pasture. The cleared class contains areas that are primarily rotated for cattle production. Cleared areas can also represent annual agriculture (which are not vegetated during dry season months), recently abandoned areas, and first year perennial agriculture plots.

Classification

Two non-parametric classification methods, *k*-nearest neighbor (*k*NN) and classification and regression trees (CART®) were applied to both image pixels and image segments.

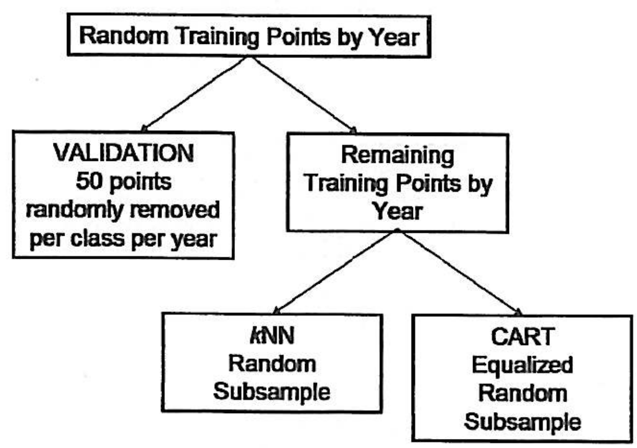

Figure 5. Breakdown of training data subsets for the validation sample, *k*NN subsample, and CART® subsample.

TABLE 2. TRAINING POINTS BY YEAR FOR THE VALIDATION SAMPLE, THE kNN Random Subsample, and the CART® Equalized Random Subsample. Class 1 is Cleared, Class 2 is Re-vegetated, and Class 3 is Primary Forest

	Validation			kNN			CART		
Year	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
1992	50	50	50	131	77	179	129	129	129
1993	50	50	50	173	140	218	177	177	177
1994	50	50	50	199	150	203	184	184	184
1995	50	50	50	226	92	138	152	152	152
1996	50	50	50	216	103	140	153	153	153
1997	50	50	50	226	85	121	144	144	144
1998	50	50	50	260	134	125	173	173	173
1999	50	50	50	217	75	77	123	123	123
2000	50	50	50	245	64	78	129	129	129
2001	50	50	50	197	63	40	100	100	100
2002	50	50	50	162	74	37	91	91	91

Multi-temporal Band Selection

An inter-annual, multi-temporal image from the available Landsat TM/ETM+ imagery was created to perform land-use classification of each single date, using the target year, the three previous (backward) years, and three forward years where applicable. Previous literature emphasizes the utility of incorporating multi-temporal imagery in land-use/land-cover classification (Lo *et al.*, 1986; Alves and Skole, 1996; Wynne *et al.*, 2000; Guild *et al.*, 2004); however, it was unknown what combination of years and bands would be most beneficial to the analysis. For this reason all principal components (PCs) for the target year were evaluated along with the first PC from each of the three backward years and three forward years from the target date (Figure 6). The extensive processing time of the kNN algorithm limited the number of total bands that could be evaluated, therefore only the first PC of the non-target years was evaluated, which explained greater than 70 percent and up to 91 percent of the variability within all Landsat TM/ETM+ images.

The band selection technique used in the kNN algorithm is a leave-one-out approach that tests each possible band (and k) combination using the input training data. The best band combination is the one that has the highest overall accuracy. During this band selection process, all PCs that increase accuracy are selected, even if the increase is only incremental. CART® 5.0 inherently chooses the best possible bands to classify the data in a binary tree, and has been used as a method of band selection (Brieman *et al.*, 1984; Bittencourt and Clarke, 2004). The Gini splitting rule was applied to all CART® classifications, which attempts to separate classes by focusing on one class at a time, and is given by:

$$Gini(c) = 1 - \sum_j p_j^2 \quad (1)$$

where p_j is the probability of class j in c. The Gini rule sequentially looks for the largest class in the training data and strives to isolate it from all other classes. CART® 5.0 grows trees until it is not possible to grow them any further. Once each full tree is generated, smaller trees are obtained by pruning away branches. The CART® 5.0 algorithm uses a 10-fold cross validation approach to prune the full tree. Pruning is performed so bands that add only small incremental increases in accuracy are eliminated, resulting in the "optimal" tree.

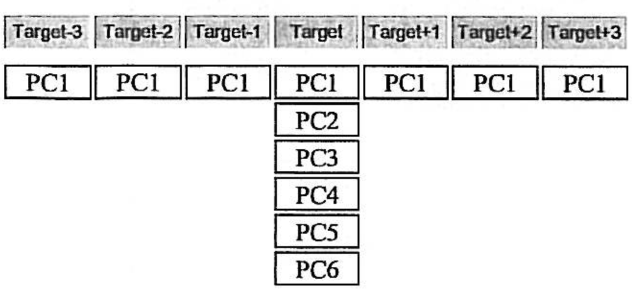

Figure 6. Principal component bands evaluated for each target year and the three forward and backward years.

CART®

CART® classification was performed using CART® 5.0 (Salford Systems, 2002; Lawrence *et al.*, 2004). There are numerous attribute selection methods that can be used in the creation of decision boundaries. Pal and Mather (2003) tested the effects of five different attribute selection methods on CART® classification accuracy and found differences to be minimal and not important to overall accuracy. Lawrence *et al.* (2004) used CART® 5.0 (Salford Systems, 2002) to perform CART® classification and tested each of the available attribute selection methods for each application. The authors used the optimal method, based on overall accuracy, in final classification. The available selection methods in CART® 5.0 include Gini, Symmetric Gini, Entropy, Class Probability, Twoing, and Ordered Twoing. The Gini splitting rule and the pruned optimal tree were used in all CART® classifications to standardize the procedure.

kNN

Non-parametric kNN classification was performed using a program developed specifically for this project in Fortran 95. A Euclidean distance metric was implemented to locate the k nearest neighbors (Serpico *et al.*, 1996; Franco-Lopez *et al.*, 2001; McRoberts *et al.*, 2002; Haapanen *et al.*, 2004) and constant weighting of the nearest neighbors was used giving all neighbors equal influence over class assignment, which has been shown to outperform other weighting schemes (Franco-Lopez *et al.*, 2001; McRoberts *et al.*, 2002; Haapanen *et al.*, 2004).

McRoberts *et al.* (2002) provide a careful discussion on the selection criterion for k. The authors state that an objective criterion should be chosen, implemented, and reported. In addition, the resulting k value should not be extended to other studies with differing data sets. They found in their own study predicting forest land proportion that an optimum k-value, using the same objective criterion was $7 \leq k \leq 13$ for one study area and data set while it was $21 \leq k \leq 33$ for another. Our objective criteria for k selection was the k-value that minimizes overall classification error using a leave-one-out evaluation (integrated into the band selection process) of the training data with a maximum possible k of 20. This process iterated through all possible band and k combinations for the given training data to select both the optimal k and band combination. The maximum threshold (k of 20) was determined through preliminary testing and no classifications exceeded a k of 17. This objective criterion was applied separately for each dataset, therefore the k values varied by year.

The kNN program was implemented on a SGI Altix 3300 supercluster to reduce processing time.

Image Segmentation

An object-oriented, multi-resolution segmentation algorithm (eCognition 3.0) was used to segment each multitemporal image into image segments for further classification. The eCognition algorithm is a hierarchical classifier that uses spectral and shape information to perform segmentation of imagery at a constant scale throughout the image (Baatz and Schäpe, 2000). The developers of this method claim that it is robust for a wide variety of data types, results are repeatable, and the segmentation approach has been successful in many natural resource applications (Schiewe *et al.*, 2001; Antunes *et al.*, 2003; Laliberte *et al.*, 2004; Van Aardt *et al.*, 2006). The segmentation process used in eCognition serves to reduce the heterogeneity of objects at a specified scale. The heterogeneity of image objects is defined by the color and shape of the input image (eCognition User's Manual, 2003). The default color/shape ratio in eCognition is 0.8/0.2. This color/shape ratio has been found to be acceptable (Laliberte *et al.*, 2004), and in some cases optimum, for segmentation results in natural resource applications (Van Aardt, 2004), and was found to be acceptable for this study through visual inspection.

The optimum segmentation for a given application is also highly dependent on the defined scale parameter. The scale parameter is a measure of the allowed change in heterogeneity between two merging objects and serves as a threshold to terminate segmentation (eCognition User's Manual, 2003). The process of determining the optimal scale parameter is not straightforward. The methods in recent literature are still highly subjective and have included a simple visual inspection (Schiewe *et al.*, 2001). The optimal scale parameter for this study was chosen through an evaluation of confused training samples. Confused training samples were training samples of differing classes that fell within the same image segment. The optimal scale parameter was determined to be 5 because it was the smallest scale parameter that could be computed on all images given the large image size, and also the scale parameter that minimized the number of confused training samples. The confused training points that were of differing classes and fell within the same image object or segment were removed prior to each classification (Table 3).

The bands included in the segmentation process were determined by the bands selected during the pixel-based kNN and CART® classification (Tables 8 through 11) to optimize the segmentation for the given data and classes. Multitemporal bands were therefore used in all segmentations. This process resulted in 22 total segmentations for further classification.

TABLE 3. CONFUSED TRAINING POINTS REMOVED FOR EACH METHOD AND YEAR FOR SEGMENT-BASED CLASSIFICATION. CLASS 1 IS CLEARED, CLASS 2 IS RE-VEGETATED, AND CLASS 3 IS PRIMARY FOREST

	kNN			CART		
Year	Class 1	Class 2	Class 3	Class 1	Class 2	Class 3
1992	4	3	0	4	4	2
1993	5	8	1	7	6	2
1994	15	14	2	9	5	0
1995	5	5	1	5	9	3
1996	7	8	2	1	2	1
1997	4	4	0	5	7	4
1998	12	7	3	5	6	2
1999	4	7	5	2	3	1
2000	1	1	0	1	3	2
2001	2	2	1	2	5	5
2002	2	3	1	1	2	2

Accuracy Assessment

The validation data set was used to assess the accuracy of each classification. There were 50 validation points for each class per year. Multivariate techniques were used to perform the accuracy assessment, including both an error matrix and a kappa coefficient of agreement (Congalton, 1991) by class and overall classification. As noted by Foody (2004), the kappa coefficient (formally estimated by $\hat{K}$) is based on the comparison of predicted and actual class labels for each case in the validation data set, and is calculated as

$$\hat{K} = \frac{p_o - p_c}{1 - p_c} \tag{2}$$

where p_o is the proportion of cases in agreement and p_c is the proportion of agreement expected by chance. Kappa variances and Z-scores were calculated to determine the significance (= 0.05) of each classification (Congalton and Green, 1999) given the following hypotheses:

$$H_0 : \hat{K} = 0$$
$$H_1 : \hat{K} \neq 0 \tag{3}$$

The error matrix was also used to calculate producer's accuracy, user's accuracy, and overall accuracy. The producer's accuracy relates to the probability that a reference sample was correctly mapped and measures the omission error (1 – producer's accuracy). In contrast, the user's accuracy indicates the probability that a sample from the land-cover map actually matches what it was in the reference data and measures the commission error (1 – user's accuracy).

Eleven classifications were performed for each method (one per year from 1992 through 2002). A series of F-tests (H_0: $\sigma_1^2 - \sigma_2^2 = 0$, H_1: $\sigma_1^2 - \sigma_2^2 \neq 0$) determined that the variances were not equal among methods. Since this result precluded an analysis of variance, four t-tests were performed (H_0: $\mu_1^2 - \mu_2^2 = 0$, H_1: $\mu_1^2 - \mu_2^2 \neq 0$) to assess whether or not the means differed among techniques ($n = 11$ in all cases). A Kruskal-Wallis test (H_0: population medians are not equal) was included due to the small sample size and low associated power of the t-tests.

Results

Classification results for the CART® (pixel-based) classification are shown in Figure 7 for 1992 and 2002. Evaluation of summary statistics including overall accuracy (Table 4; Figure 8), kappa coefficient of agreement (Table 4), the Kruskal-Wallis test for equal medians (data not shown), and a series of four t-tests (Table 5) reveal that the classifi-

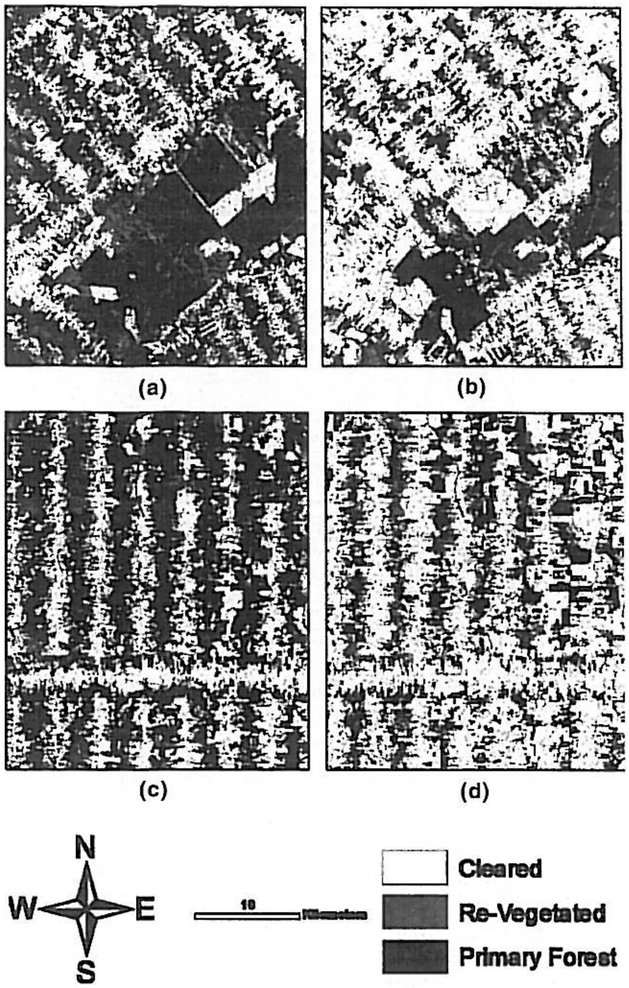

Figure 7. Classification results for the CART® pixel-based classification for years 1992 and 2002 and for each study area: (a) 1992 Nova União, (b) 2002 Nova União, (c) 1992 Rolim de Moura, and (d) 2002 Rolim de Moura.

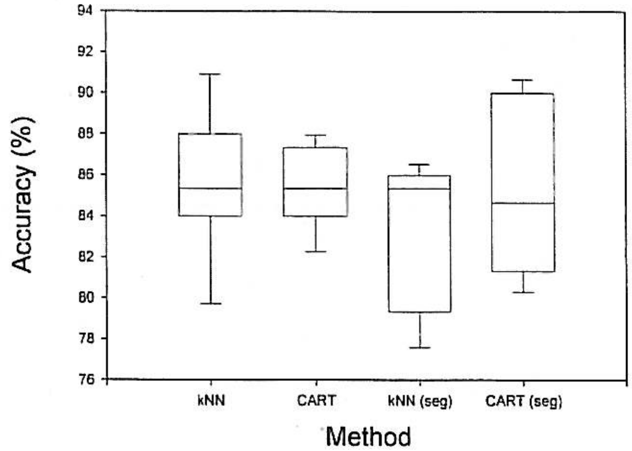

Figure 8. Box and whisker plot of mean overall classification accuracy by method.

Table 4. Percent Overall Accuracy and Kappa Coefficient of Agreement by Classification Method and Year

	*k*NN		CART		*k*NN (seg)		CART (seg)	
Year	OA (%)	Kappa (%)	OA (%)	Kappa (%)	OA (%)	Kappa (%)	OA (%)	Kappa (%)
1992	81.3	72.0	87.3	81.0	79.3	69.0	81.3	72.0
1993	86.6	80.0	87.7	80.0	80.7	71.0	82.0	73.0
1994	88.0	82.0	86.0	79.0	86.0	79.0	84.7	77.0
1995	84.7	77.0	84.0	76.0	78.7	68.0	80.0	70.0
1996	86.0	79.0	85.3	78.0	82.0	73.0	83.3	75.0
1997	89.3	84.0	84.0	76.0	86.0	79.0	90.7	86.0
1998	84.0	76.0	82.0	73.0	86.0	79.0	81.3	72.0
1999	85.3	78.0	85.3	78.0	86.0	79.0	90.7	86.0
2000	84.7	77.0	84.7	77.0	85.3	78.0	90.0	85.0
2001	91.3	87.0	88.0	82.0	86.7	80.0	86.0	79.0
2002	79.3	69.0	83.3	75.0	77.3	66.0	86.0	79.0
Mean	85.5	78.3	85.2	77.7	83.1	74.6	85.1	77.6
σ^2	10.5	23.7	3.3	6.6	11.4	25.7	14.1	31.7

Table 5. T-tests and Associated *p*-values for the Classification of Cleared, Re-vegetated, and Primary Forest Using Four Methods in the Amazon Region of Brazil

t-test	*p*-value (t-test)
*k*NN (pixel) versus CART (pixel)	0.7831
CART (pixel) versus CART (seg)	0.9454
*k*NN (seg) versus CART (seg)	0.2250
*k*NN (pixel) versus *k*NN (seg)	0.1181

cation methods performed equally well and were not significantly different. The Kruskal-Wallis test results indicate that the classification medians are not different ($p = 0.605$) and the t-tests indicate that the classification means are not different (Table 5, $n = 11$ for all methods). All classifications were significant at an alpha level of 0.05 and the overall accuracies (ranging from 77 percent to 91 percent) are comparable to other studies (Roberts *et al.*, 2002). Although the overall accuracies were not significantly different between the four classification methods, an F-test revealed that the variances between the CART® (pixel-based) technique were significantly lower ($\sigma^2 = 3.60$) than all of the three other classification methods (*k*NN pixel-based $\sigma^2 = 11.5$, $p = 0.04$; *k*NN segment-based $\sigma^2 = 12.6$, $p = 0.03$; and CART® segment-based $\sigma^2 = 15.5$, $p = 0.02$) indicating that this technique produced more consistent results in this case. The CART® (segment-based) classification, however had variances similar to the *k*NN (pixel and segment-based) classifications.

Tables 6 and 7 summarize the mean producer's and user's accuracies by class for each classification method. All classifications successfully separated primary forest with both producer's and user's accuracies greater than 90 percent. The classes that were the most difficult to separate were the re-vegetated and cleared classes. All methods tended to over-represent the cleared class by labeling many of the re-vegetated areas as cleared. This was particularly prevalent with both the pixel and segment-based *k*NN classifications, as can be inferred from the large discrepancies in producer's and user's accuracies between the cleared and re-vegetated classes (Tables 6 and 7).

Table 6. Mean Producer's Accuracies for All Classifications (Bounds are Given at a 95 Percent Confidence Level)

	Producer's Accuracy			
	*k*NN (Pixel-Based)	CART (Pixel-Based)	*k*NN (Segment-Based)	CART (Segment-Based)
Cleared	95.5% ± 2.0%	88.2% ± 5.1%	92.7% ± 3.0%	84.4% ± 5.4%
Re-Vegetated	67.3% ± 5.2%	73.5% ± 5.7%	65.7% ± 7.6%	80.0% ± 4.5%
Primary Forest	93.1% ± 3.1%	93.8% ± 2.1%	91.3% ± 3.6%	90.9% ± 4.0%

Table 7. Mean User's Accuracies for All Classifications (Bounds are Given at a 95 Percent Confidence Level)

	User's Accuracy			
	*k*NN (Pixel-Based)	CART (Pixel-Based)	*k*NN (Segment-Based)	CART (Segment-Based)
Cleared	78.3% ± 3.5%	82.1% ± 3.1%	75.9% ± 3.5%	85.3% ± 3.3%
Re-Vegetated	87.5% ± 4.2%	82.2% ± 4.3%	83.3% ± 4.7%	72.2% ± 5.8%
Primary Forest	92.7% ± 2.3%	92.5% ± 2.5%	92.9% ± 2.9%	85.2% ± 1.6%

As suggested by McRoberts *et al.* (2002), the optimal *k* varied drastically by dataset (Tables 8 and 10) ranging from a *k* of 1 to 17. This result reiterates that no one *k* can be applied to all classifications within the same study region or with varying datasets. Similarly, the number of nodes selected through the Gini rule and 10-fold cross validation (CART®) varied drastically across datasets from 3 to 21.

Tables 8 through 11 summarize the PCs for the target year and the backward and forward years selected for *k*NN and CART® classifications using the leave-one-out approach and the Gini splitting rule with pruning, respectively. For target years 1992, 1993, and 1994, all backward years could not be evaluated in the band selection processes, and for target years 2000, 2001, and 2002, all forward years could not be evaluated in the band selection processes, as indicated by the shaded boxes in Tables 8 through 11. Multitemporal bands (either forward or backward years) were selected for 38 out of the 44 total classifications, with bands selected for all of the 22 pixel-based classifications and 16 out of the 22 segment-based classifications. Due to the years of imagery included in the study (1992 through 2002), not all of the desired years (three forward and three backward from the target year) were able to be included for all classifications leaving 20 total classifications where all desired forward and backward years were used as inputs. The band that was selected most for both *k*NN and CART® methods was the first PC of the target year (8 of 10, and 10 of 10 classifications, respectively) followed by the second PC of the target year (7 of 10, and 8 of 10 classifications, respectively). This is to be expected, as the first two principal components explain the

Table 8. Bands and *k* Selected by Year Using a Leave-One-Out Approach for Pixel-based *k*NN Classifications by Year

	Selected Bands and *k*: *k*NN Pixel Based Classification							
Target Year	Target Year − 3 (1st PC)	Target Year − 2 (1st PC)	Target Year − 1 (1st PC)	Target Year (all 6 PC's)	Target Year + 1 (1st PC)	Target Year + 2 (1st PC)	Target Year + 3 (1st PC)	*k*
1992	N/A	N/A	N/A	1,6	1	1	0	11
1993	N/A	N/A	0	1,2,3,5	1	1	0	7
1994	N/A	0	0	1,3	0	0	1	3
1995	0	1	1	1,2,5,6	0	1	1	3
1996	0	1	1	1,5,6	0	0	1	17
1997	0	1	0	1,2,3,6	1	0	0	16
1998	0	0	1	2,3	0	1	0	4
1999	0	1	0	1,2,4,5,6	1	0	1	4
2000	0	0	1	1,2,6	1	1	N/A	6
2001	0	0	1	1,3,5,6	0	N/A	N/A	3
2002	0	1	1	2,5,6	N/A	N/A	N/A	9

Table 9. Bands Selected and Number of Nodes in Optimal Tree Using the Gini Selection Method and 10-fold Cross Validation for Pixel-based CART® Classification by Year

	Selected Bands: CART Pixel-Based Classification							
Target Year	Target Year − 3 (1st PC)	Target Year − 2 (1st PC)	Target Year − 1 (1st PC)	Target Year (all 6 PC's)	Target Year + 1 (1st PC)	Target Year + 2 (1st PC)	Target Year + 3 (1st PC)	Nodes
1992	N/A	N/A	N/A	1,2,3,5,6	1	1	1	21
1993	N/A	N/A	1	1,2,3,4,6	0	1	1	20
1994	N/A	1	1	1,3,4	1	0	0	12
1995	0	0	0	1,2	0	1	0	5
1996	0	0	1	1,2,3,5	1	0	1	17
1997	0	0	1	1	0	0	0	3
1998	0	0	1	1,2,3,4	1	0	0	12
1999	1	1	1	1,2,3	1	1	0	16
2000	1	1	0	1,2	1	0	N/A	14
2001	1	0	0	1	0	N/A	N/A	3
2002	1	0	1	1,2,3	N/A	N/A	N/A	7

Table 10. Bands and k Selected by Year Using a Leave-One-Out Approach for Segment-based kNN Classifications by Year

Target Year	Target Year − 3 (1st PC)	Target Year − 2 (1st PC)	Target Year − 1 (1st PC)	Target Year (all 6 PC's)	Target Year + 1 (1st PC)	Target Year + 2 (1st PC)	Target Year + 3 (1st PC)	k
	Selected Bands and k: kNN Segment Based Classification							
1992	N/A	N/A	N/A	1,3,5	0	0	0	14
1993	N/A	N/A	1	1,3,4	1	1	1	1
1994	N/A	0	0	1,3	0	0	0	8
1995	0	0	1	1,2	1	0	0	4
1996	0	0	0	1,3,6	0	1	1	13
1997	0	1	1	2,3,4	0	1	0	9
1998	0	0	0	1,3,4	0	0	0	5
1999	0	0	1	1,2,4,6	0	0	0	15
2000	0	0	0	1,2,3,6	0	1	N/A	6
2001	1	0	0	1,2,3,5,6	0	N/A	N/A	5
2002	0	0	0	1,3	N/A	N/A	N/A	7

Table 11. Bands Selected and Number of Nodes in Optimal Tree Using the Gini Selection Method and 10-fold Cross Validation for Segment-based CART® Classifications by Year

Target Year	Target Year − 3 (1st PC)	Target Year − 2 (1st PC)	Target Year − 1 (1st PC)	Target Year (all 6 PC's)	Target Year + 1 (1st PC)	Target Year + 2 (1st PC)	Target Year + 3 (1st PC)	Nodes
	Selected Bands: CART Segment-Based Classification							
1992	N/A	N/A	N/A	1	0	0	0	3
1993	N/A	N/A	1	1,2,3	1	1	1	14
1994	N/A	1	0	1,2	0	0	1	6
1995	1	1	0	1,2,3	1	1	0	13
1996	1	0	0	1,2,3	0	0	1	8
1997	0	0	0	1,2	0	0	0	6
1998	0	0	1	1,2,3,4	1	0	0	8
1999	1	0	0	1	0	0	0	4
2000	1	0	0	1	1	0	N/A	7
2001	1	0	0	1,3	0	N/A	N/A	5
2002	0	1	1	1,2,3,6	N/A	N/A	N/A	12

majority of the variance within most multispectral images (Richards and Jia, 1999) and explained over 90 percent of the variance within all images included in this study. The first principal component of the first forward and first backward years was also commonly selected (11 and 8 times out of 20 classifications, respectively). The fourth, fifth, and sixth PCs were commonly selected using the kNN *unpruned* leave-one-out method (13 of 20 classifications), while the CART® Gini index with pruning did not commonly select those PCs (3 of 20 classifications).

Discussion

This study indicates that multitemporal classification using non-parametric k-nearest neighbor and classification and regression trees can accurately separate cleared, re-vegetated, and primary forest classes in the Brazilian Amazon with accuracies comparable to past studies (Roberts *et al.*, 2002). The tested non-parametric techniques were relatively simple to implement, particularly since there was no need to meet the statistical assumptions inherent to common parametric decision rules (e.g., that spectral classes have multivariate normal distributions). The CART® method is computationally simpler than the kNN method, and therefore took less time to process.

The kNN and CART® band selection techniques differed in that the selected CART® bands were pruned using 10-fold cross validation while no pruning was involved in the leave-one-out band selection process of kNN. Pruning eliminates bands from the classification process that add only small, incremental increases in classification accuracy. Because no *pruning* was incorporated into the kNN classification, the bands that increased classification accuracy, even if only slightly, were included in the classification. This may reveal the reason for the common selection of PCs explaining very little variance within the original image (PC bands 4, 5, and 6, explaining less than four percent of the variance of the original image when combined) for kNN classifications, while the CART® method rarely used these bands in the optimal classification tree. For example, the 1995 pixel-based kNN classification included PCs 5 and 6 of the target year, while the 1995 pixel-based CART® classification did not. However, these two PCs were included in the un-pruned 1995 pixel-based CART® tree. These bands were eliminated from the optimal tree because of the low contribution these PCs made to the classification. Table 12 gives the variable importance for each of the 18 PCs used in the band-selection process for the 1995 pixel-based CART® classification with the score reflecting the contribution of each PC to the classification of the data.

Both kNN and CART® performed equally well in terms of overall accuracy. However, the pixel-based CART® classification had significantly lower variance among the 11 annual classifications. This indicates that the CART® classification was thus accurate and consistent, which is desirable when evaluating land-cover change over several subsequent years. If the terminal years are eliminated (where no multitemporal dates were available either backward in time or forward in time), however, the results from the kNN

Table 12. Variable Importance of the 1995 Pixel-based CART® Classification

Year	Band	Score
Target	PC 1	100
Target + 1	PC 1	87
Target + 2	PC 1	68
Target + 3	PC 1	64
Target − 1	PC 1	62
Target − 2	PC 1	46
Target − 3	PC 1	20
Target	PC 2	17
Target	PC 3	8
Target	PC 6	5
Target	PC 5	5
Target	PC 4	3

classifications are more consistent (also reflected in Figure 8) indicating that the difference in variance between the *k*NN and CART® methods lies primarily within these two years (1992 and 2002).

Although the CART® method produced more consistent results in the pixel-based case, indicated by low variability among the 11 annual classifications, this result did not carry through to the segment-based case. Furthermore, segment-based classification was not significantly better than pixel-based classification for either the *k*NN or CART® non-parametric methods.

Segment-based classification, however, has been successful and has been an improvement over pixel-based classification in many previous studies (Lobo *et al.*, 1996; Shandley *et al.*, 1996) including in the Amazon region (Palubinkas *et al.*, 1995; Lu *et al.*, 2004b). This current research differs from these previous studies in that multi-temporal imagery was used in segment creation and classification. The use of inter-annual, multi-temporal imagery in the segmentation process may not be appropriate due to changes occurring in the landscape over time and the inability for segments to act as continuous units through several consecutive years. Plate 1 shows a small portion of the segmentation used in the 1995 CART® classification overlaid on the 1992 Landsat TM image and the 1995 Landsat TM image. The bands used in segmentation did not include the 1992 PC; however, the 1992 PC was used in the segment-based CART® classification (Tables 9 and 11). From inspection of the Landsat TM images, it is apparent that the highlighted segment was not one continuous land-cover in both years.

All classifications accurately separated primary forest from cleared and re-vegetated classes. Differentiating primary forest from secondary growth has been difficult in past studies due to the spectral similarities in late successional secondary growth or re-vegetation to primary forest (Brondizio *et al.*, 1996). Several studies have improved the classification of secondary forest growth through the incorporation of multitemporal Landsat TM/ETM+ data (Lucas *et al.*, 1993; Nelson *et al.*, 2000; Castro *et al.*, 2003; Lu *et al.*, 2004a). These studies, however, have focused on the use of multi-temporal imagery to monitor forest growth and land-cover change over time and have not used the multi-temporal data in the classification of a single year (Lucas *et al.*, 1993; Nelson *et al.*, 2000; Lu *et al.*, 2004a). The ability to accurately separate these two classes in the current study may be a result of the incorporation of multi-temporal data in the classification of a single year or one point in time. Many of the CART® classifications selected a backward multi-temporal year to specifically separate re-vegetated areas from primary forest. Plate 2 illustrates the 2001 CART® pixel-based classification and corresponding Landsat TM (1998) and Landsat ETM+ (2001) images. The areas highlighted in white were classified as re-vegetated in 2001. From inspection of the 2001 Landsat image alone, these areas are indistinguishable from surrounding primary forest. Through evaluation of the 1998 image, it is more evident that these areas had been cleared in the past. The 1998 PC was used in the 2001 CART® pixel-based classification specifically to separate primary forest and re-vegetated classes (Table 9), and may explain why these areas were classified as re-vegetated rather than primary forest in this case. It is possible that the addition of more inter-annual, multi-temporal data may further increase the separability of re-vegetated and primary forest classes. The incorporation of inter-annual, multi-temporal data in this manner, in conjunction with the appropriate ground level data, may contribute to current efforts in the classification of secondary forest growth for use in biomass or forest stand age estimation and to subsequently improve carbon estimates.

The incorporation of inter-annual, multi-temporal imagery may have also played a role in the separation between cleared and re-vegetated areas. Guild *et al.* (2004) found that areas that were cleared for successive years were predominantly used for pasture and areas that were infrequently cleared with periods of re-vegetation were predominantly used for perennial agriculture. The use of forward PCs were often used in CART® to separate cleared from re-vegetated classes, such as the 1996 pixel-based CART® classification that used both the 1997 and 1999 PCs to specifically target these two classes.

Overall, inter-annual, multi-temporal data was useful in the separation of cleared, re-vegetated, and primary forest classes as indicated by Tables 8 through 12. Table 12 reveals how important inter-annual, multi-temporal data were for the 1995 pixel-based CART® classification. With exception of the first PC of the target year, all forward and backward PCs were more important than all of the other target year PCs.

With the dataset used in this study, CART® (pixel-based) was the preferred classifier due to its consistency and computational efficiency. Additionally, this classifier did not over-represent the cleared class (through labeling re-vegetated areas as cleared) to the extent of the *k*NN classifier. Although the differences were not significant, the increase in accuracy between these classes is valuable.

Conclusions

The Amazon basin remains a major hotspot of tropical deforestation (Lepers *et al.*, 2005), presenting a clear need for timely, accurate, consistent data on land-cover change. Annual classifications produced using inter-annual, multi-temporal imagery were quite accurate using both *k*NN and CART®. The results are comparable to previous studies, and are of a quality that enables the use of these maps in subsequent analysis of landscape change and deforestation processes. While the non-parametric classifiers performed equally well in terms of overall accuracy, the consistency among pixel-based CART® classifications, coupled with the computational efficiency of the technique, suggest that it is preferred. Additionally, slight improvements over *k*NN methods were observed (although not significant) in the separation of cleared and re-vegetated land-covers.

Although segment-based classifiers have resulted in improved classifications over traditional pixel-based methods in past research in the Amazon (e.g., Palubinkas *et al.*, 1995), this finding was not observed with the data used in this study. The ability for individual segments to act as a continuous unit through time is not always feasible at the smallest scale parameter that could be used, indicating that the use of segments in classification when also incorporating

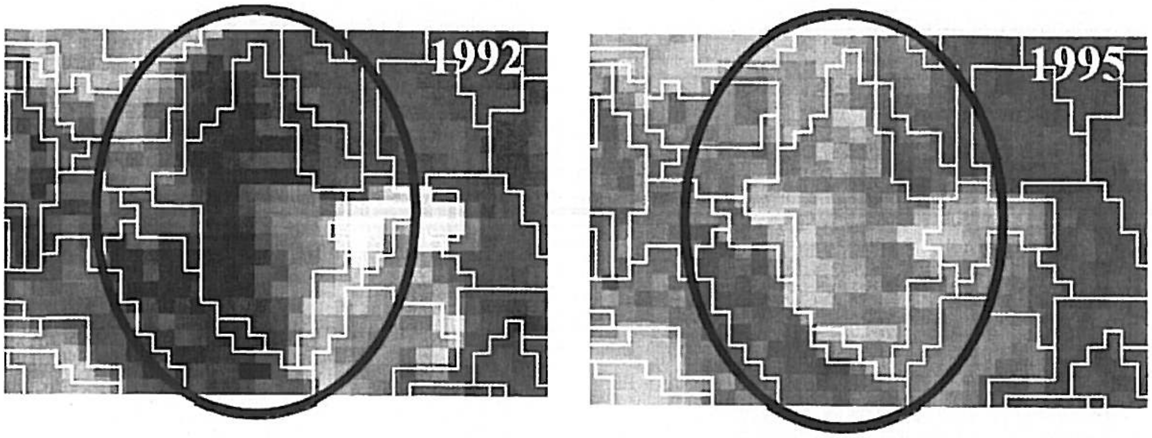

Plate 1. 1995 CART® segmentation overlaid on the 1992 and 1995 Landsat TM images.

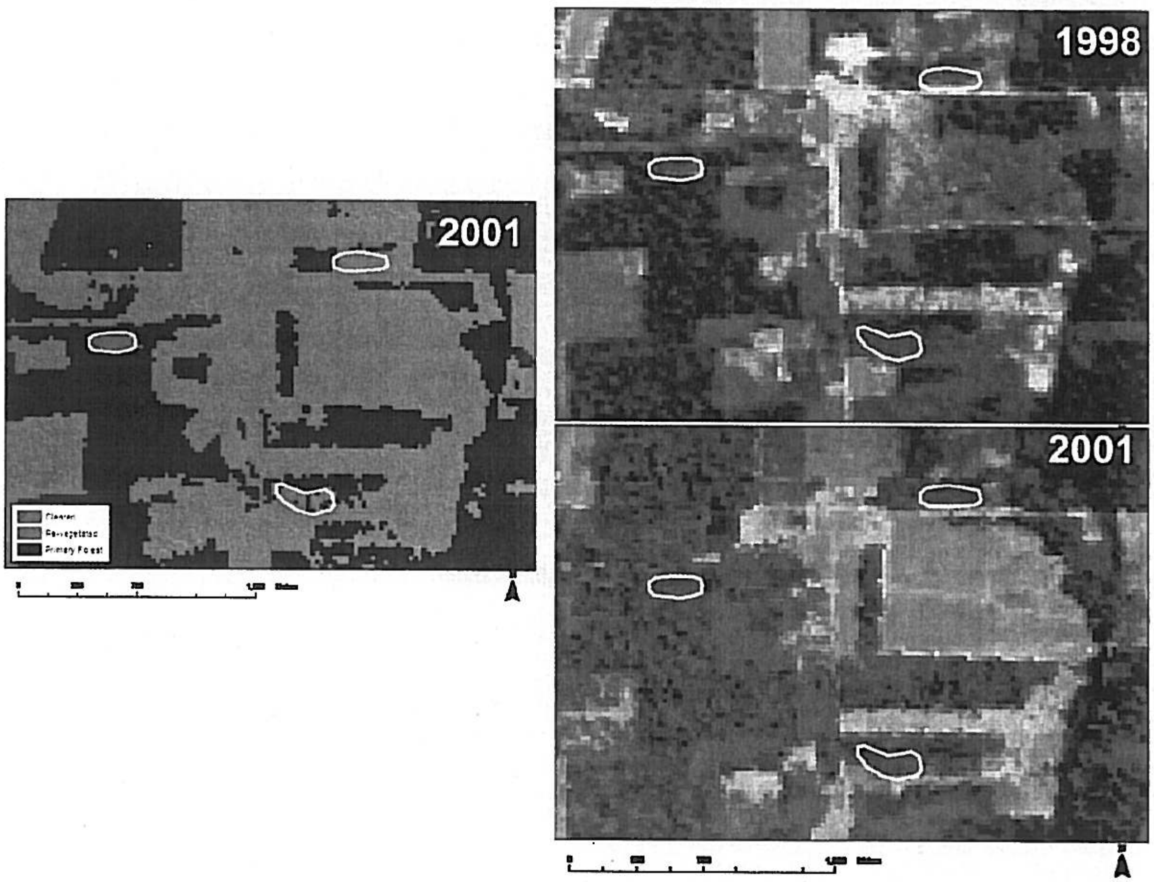

Plate 2. 2001 CART® pixel-based classification and corresponding Landsat TM (1998) and Landsat ETM (2001) images. From inspection of the 2001 Landsat image alone, the areas encompassed by the white polygons are indistinguishable from surrounding primary forest; the 1998 image reveals that these areas had been cleared in the past.

multi-temporal data may be inappropriate. The creation and use of segments rather than individual pixels in classification did not significantly change overall accuracy, and was therefore an unnecessary step in the classification process.

The band-selection methods embedded in both the CART® and *k*NN classifications found that PCs of additional years (supplementary to the PCs of the target year), increased accuracy for all pixel-based classifiers and for 16 of the 22 segment-based classifiers, strongly implying the utility of inter-annual, multi-temporal data in separating cleared, re-vegetated, and primary forest in the Brazilian Amazon.

There is a potential to extend these methods to other areas of Rondônia as well as other tropical regions to understand differences of land-cover change at varying scales. Additionally, the utility of multi-temporal bands should be evaluated further through the inclusion of more forward and backward years and also the inclusion of additional principal component bands or raw image bands. The inclusion of added data, however, stretches the computational efficiency of kNN when using a leave-one-out band and k selection approach. As such, using 10-fold cross validation is recommended for larger datasets.

The accurate, annual land-cover maps produced in this study are essential to a fuller understanding of the patterns and processes of deforestation in the Amazon basin. Similar datasets have been successfully used in the Amazon to understand and predict population-environment dynamics at the household level through the incorporation of small farm holder surveys and landscape metrics (Pan *et al.*, 2002), and in other tropical regions to analyze socioeconomic drivers of land-use and land-cover change at multiple scales using a geographic approach (e.g., Overmars and Verburg, 2005).

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