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Detection of deforestation and land conversion in Rondônia, Brazil using change detection techniques

L. S. GUILD*

NASA Ames Research Center, Moffett Field, CA 94035, USA;
e-mail: lguild@gaia.arc.nasa.gov

W. B. COHEN

Department of Forest Science, Oregon State University, Corvallis, OR 97331, USA

and J. B. KAUFFMAN

Department of Fisheries and Wildlife, Oregon State University, Corvallis, OR 97331, USA

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Abstract. Fires associated with tropical deforestation, land conversion and land use greatly contribute to emissions as well as the depletion of carbon and nutrient pools. The objective of this research was to compare change detection techniques for identifying deforestation and cattle pasture formation during a period of early colonization and agricultural expansion in the vicinity of Jamari, Rondônia. Multi-date Landsat Thematic Mapper (TM) data between 1984 and 1992 were examined in a 94 370 ha area of active deforestation to map land cover change. The tasselled cap (TC) transformation was used to enhance the contrast between forest, cleared areas and regrowth. TC images were stacked into a composite multi-date TC and used in a principal components (PC) transformation to identify change components. In addition, consecutive TC image pairs were differenced and stacked into a composite multi-date differenced image. A maximum likelihood classification of each image composite was compared for identification of land cover change. The multi-date TC composite classification had the best accuracy of 0.78 (kappa). By 1984, only 5% of the study area had been cleared, but by 1992, 11% of the area had been deforested, primarily for pasture, and 7% lost due to hydroelectric dam flooding. Finally, discrimination of pasture versus cultivation was improved due to the ability to detect land under sustained clearing opposed to land exhibiting regrowth with infrequent clearing.

1. Introduction

Before 1975, deforestation in the Brazilian Amazon was less than 1%; however, the deforestation rate increased exponentially between 1975 and 1987 (Moran 1993). According to Fearnside (1997), approximately 11% (421 600 km^2) of the forested area of Amazonia had been cleared as of 1991. Deforestation rates

*Corresponding author.

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increased in the 1980s due to colonization projects that created fiscal incentives for agricultural expansion in remote areas of the Amazon (Molion 1991, Hecht 1993, Moran 1993, Browder and Godfrey 1997). Rondônia, a western state in Brazil, has had a recent history of high rates of deforestation. Beginning in 1960, with the tin rush and the opening of the unpaved BR-364 highway providing an overland route between Rondônia and the Atlantic Coast, prospectors and settlers have been migrating to Rondônia (Browder and Godfrey 1997). Paving of the BR-364 highway was completed in 1984 with the intent to increase immigration and stimulate markets for agriculture and forest products (Tucker *et al.* 1984, Stone *et al.* 1991, Browder and Godfrey 1997). Rondônia comprises an area of 243 000 km^2 of the Brazilian Legal Amazon's 5 000 000 km^2. By 1997, nearly 24% (50 529 km^2) of the original 215 000 km^2 Rondônian forest area had been deforested (Instituto National de Pesquisas Espaciais (INPE) 1998). Annual deforestation rates (excluding forest loss from hydroelectric dams) in Rondônia were 2100 km^2 (1978–1988), 1400 km^2 (1988–1989), 1700 km^2 (1989–1990) and 1100 km^2 (1990–1991); at annual rates of 1% or less (Fearnside 1997). Recent estimates by INPE (1998) suggest that average annual deforestation estimates were 2767 km^2 or an annual rate of 1.3% (1994–1997). Deforestation rates in Rondônia have remained high relative to other Amazonian states (Fearnside 1997).

In spite of numerous estimates of deforestation using satellite imagery and other sources, several uncertainties exist, including estimates of the rates and extent of deforestation and land uses mapped with satellite imagery. In most studies, a single date of satellite imagery is used to map deforestation and land clearing (Tardin *et al.* 1980, Tucker *et al.* 1984, Woodwell *et al.* 1986, Skole and Tucker 1993, Fearnside 1997). In general, forest clearing, vegetation regrowth and water can be distinguished visually in Landsat data. It is difficult, however, to differentiate land cover types exhibiting vegetation regrowth such as regenerating forest, cultivation and young pastures and to identify logging and surface fires, particularly in a single date of imagery (Tucker *et al.* 1984, Woodwell *et al.* 1986, 1987, Nepstad *et al.* 1999). Hence, there are conflicting and limited data on rates and the areal extent of deforestation and land conversion. The extent of deforestation in Rondônia in 1978 was estimated in the range of 4200 km^2 (Tardin *et al.* 1980) to 6300 km^2 (Fearnside 1997). By 1982, the range was 9200 km^2 (Tucker *et al.* 1984) to 11 400 km^2 (Woodwell *et al.* 1987) and as of 1988, 24 000 km^2 (Skole and Tucker 1993), 29 600 km^2 (Fearnside 1997) and 37 200–37 900 km^2 (Stone *et al.* 1991) was reported.

In other tropical and temperate regions, change detection techniques in a time series of imagery have been used to monitor changes in land use, shifting cultivation, vegetation phenology, pasture development and to assess deforestation, crop stress and damage (Singh 1989, Collins and Woodcock 1996, Coppin and Bauer 1996, Cohen *et al.* 1998). Digital change detection allows quantification of temporal phenomena in multi-date satellite imagery (Coppin and Bauer 1996). Change detection techniques using multi-date tasselled cap, principal components analysis and image differencing integrate spectral transformations to enhance change in land cover features (Richards 1984, Fung 1990, Cohen *et al.* 1998).

The tasselled cap (TC) linear transformation, or data plane rotation, is used to reduce the spectral redundancy of the Landsat Thematic Mapper (TM) visible and infrared bands to create the vegetation indices of brightness, greenness and wetness (Crist and Cicone 1984, Schowengerdt 1997). The weights of the TC transformation are fixed, sensor specific, and are not scene dependent.

Cohen *et al.* (1995) reported that, as canopies develop in old-growth forests of the Pacific Northwest, USA, although leaf area index is relatively high, shadowing increases. Therefore, we infer that brightness and greenness will generally be lower for mature or primary forests than for regrowing vegetation due to shadowing from variation in canopy heights in later stages of succession. Old-growth forests generally are lower in brightness and higher in greenness and wetness than in clear-cut areas (Cohen *et al.* 1998). In contrast, a deciduous forest stand would have higher brightness and greenness, but lower wetness than evergreen forest (Cohen *et al.* 1995). Therefore, in the Amazon, primary forest and areas of well-established vegetation regrowth would likely have high values of wetness. In cleared areas undergoing vegetation regrowth, greenness will generally increase to the point of canopy closure. Depending on soil colour and moisture content, brightness will either increase or decrease during regrowth. If the regrowing vegetation is brighter than the soils and the soils have moderately high reflectance, TC brightness would likely increase during regrowth. Darker soil types and moist soils will decrease in brightness. Brightness, however, may decrease initially during vegetation regrowth due to shadowing, but increases as vegetation cover density increases, eliminating the shadowing effect.

The principal components (PC) transformation is also a data compression technique but, unlike TC, is not physically based. PC images have new coordinate axes that are orthogonal to each other and explain decreasing levels of variance with each successive component (similar to TC) (Richards 1984, Singh 1989, Collins and Woodcock 1996, Coppin and Bauer 1996, Schowengerdt 1997). Unlike TC, the weights in PC transformation matrix are not fixed and are scene dependent (Schowengerdt 1997). By combining multi-date TM data in a PC analysis, a spectral–temporal transformation results, creating some components indicative of change over time. Richards (1984) combined two Multispectral Scanner (MSS) scenes in a PC analysis to examine change from fire damage to vegetation regrowth. Richards found that, in addition to lower order components, higher order components can highlight land cover change. For example, change from vegetation in the first date to burn scar in the second date or change from burn scar on the first date to vegetation regrowth on the second date was detected in higher order components. In addition to change components, stable components (commonly the first component) may be used in land cover change classification. Stable components can provide a frame of reference and improve classification results (Cohen and Fiorella 1998). However, Collins and Woodcock (1996) selected change components for classification and further analysis, leaving out stable components, which usually account for spatial scene variation and not variation between dates.

Image differencing is a third common change detection approach for forested and agricultural areas (Woodwell *et al.* 1986, Singh 1989, Fung 1990, Coppin and Bauer 1996, Cohen *et al.* 1998). Image differencing is a simple approach whereby coincident bands of spatially registered date pairs are subtracted. The output image of positive and negative values represents change and the values close to zero represent no change. Interpreting the differenced image can be difficult because different input values can have the same result after subtraction and the original pixel value information is not retained (Singh 1989, Cohen and Fiorella 1998). Further confusion could be associated with change caused by atmospheric conditions or Sun angle differences between dates rather than land cover change. Also, it is difficult to determine where to select threshold boundaries of change and no change (Singh 1989). In Rondônia, Woodwell *et al.* (1986, 1987) used change detection techniques of red and near-infrared band differencing between image date pairs using the Landsat MSS data. Woodwell found that deforested areas would show an increase in reflectance in the red band and a decrease in reflectance in the near-infrared band. Therefore, for a deforested area, the difference between the red bands between dates would be on a positive scale and the difference between the near-infrared bands would be on a negative scale, provided the earlier date was subtracted from the later date. Fung (1990) used image differencing between two dates of TM data. The differenced image for the near-infrared band gave high accuracy (100%) in detecting change from bare soil to pasture, among other crop, pasture and bare soil cover types. However, there was difficulty in detecting change for cover types with low near-infrared reflectances, possibly due to date of acquisition and phenology. Cohen *et al.* (1998) found that both merged image differencing and simultaneous image differencing yielded high accuracy ($>90\%$) for clear-cut harvest activity. Both merged and simultaneous image differencing techniques were based on TC indices which further enhanced the spectral contrast of clear-cut logging in forested land.

The objective of this research was to use multi-date TM data for the period 1984–1992 to compare change detection techniques for creating a land cover and change map. The purpose of this project is to map reliably forest clearing and to differentiate pasture (sustained clearing) and shifting cultivation (clearing interrupted with periods of regrowth) in an area of Amazon forest in Rondônia, Brazil. This area was undergoing active deforestation and land cover change associated with early colonization.

2. Methods

To develop a method to map land cover and change, we compared three change detection techniques to detect change in land cover types (primary forest, regenerating forest and cleared/pasture) using: (1) multi-date TC images, (2) PC analysis of TC images, and (3) image differencing of TC images.

2.1. *Study area*

We examined land use/land cover change from 1984–1992 over a 94 370 ha area of primary forest in Rondônia, Brazil. The study area is located along the BR-364 highway in an area of recent colonization, coinciding with the completion of the highway in 1984, and resulting in active deforestation during the period of our study. Areas along the BR-364 highway have been subject to intense deforestation for cultivation, cattle pastures, timber exploitation and mining. The study area is centred at approximately 9° 11′ S and 63° 10′ W and about 100 km south-east of the State's capital, Pôrto Velho (figure 1). The small town of Jamari is located along the Jamari River, a backwater tributary of the Madeira River. The study area consists of both small landholdings of subsistence farms and large ranches. It is adjacent to the Jamari National Forest, which contains the Santa Bárbara tin mine.

We chose to conduct our study in this region because it is thought to represent typical patterns of relatively recent colonization and deforestation activity at the onset of our analysis (since the early 1980s). In addition, the availability of relevant long-term ground-based data and knowledge of land use in the area assisted the interpretation of land use types and practices (Kauffman *et al.* 1995, 1998, Guild *et al.* 1998, Hughes *et al.* 2000). Other related research in the region has occurred south of Jamari from Ariquemes to Vilhena along the BR-364 highway, where more

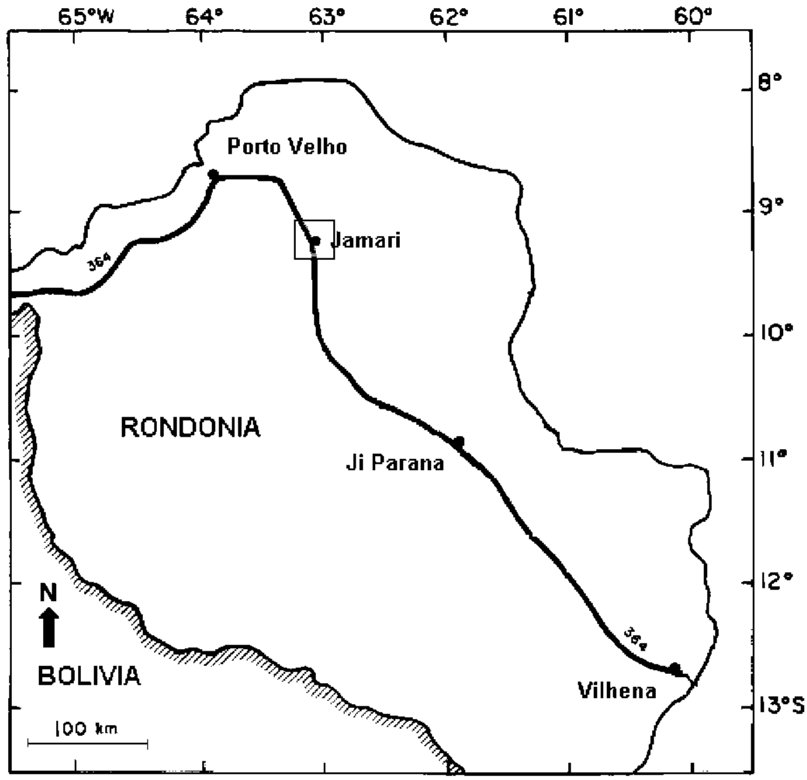

Figure 1. The Brazilian state of Rondônia comprises an area of 243 000 km^2. The location of the study area is 100 km south-east of Pôrto Velho in the vicinity of Jamari along the BR-364 highway. The study area is 94 372 ha and is centred at 9° 11′ S and 63° 10′ W with the approximate extent outlined on the map.

long-term deforestation, agriculture and mining have occurred (Tucker *et al.* 1984, Neill *et al.* 1997, Fujisaka *et al.* 1998, Moraes *et al.* 1998).

The primary forest type of Rondônia and the study region is submontane open forest consisting of over-storey broadleaved canopy and subcanopy with an abundance of palms and vines (Departmento Nacional de Produção Mineral 1978, Instituto Brasileiro de Desenvolvimento Florestal (IBDF) and Instituto Brasileiro de Geographia e Estatística (IBGE) 1993, Cummings 1998). Soil types include red–yellow podzolic latosols and red–yellow latosols (Neill *et al.* 1997).

Climatological data come from Pôrto Velho, Rondônia, about 100 km north of the region. Mean annual precipitation is 2354 mm (Departmento Nacional de Meteorologia 1992). During the dry season, between June and September, mean precipitation is typically <100 mm per month. Dry season mean temperature is $\sim$25°C, ranging from a minimum of $\sim$21°C to a maximum of 31°C, with a mean relative humidity of 85%.

2.2. *Data*

Available Landsat TM data for path 232, row 66 were selected from the National Aeronautics and Space Administration (NASA) Landsat Data Collection at the Earth Resource Observation System (EROS) Data Center, Distributed

Active Archive Center (DAAC). This scene extends from Pôrto Velho in the north and south to just north of Ariquemes, Rondônia, following the Jamari River and the BR-364 highway. The study area corresponds to a 1024×1024 pixel subscene of approximately 94 370 ha, with a centre point at roughly $9^\circ 11' S$ and $63^\circ 10' W$. From the archive, dry season dates were selected for minimizing spectral variability associated with phenological differences. Therefore, scenes were selected on anniversary dates. The following cloud-free images were selected: 24 June 1984, 16 July 1986 and 24 July 1992. Scenes were co-registered using an automated tie point and area correlation technique (Kennedy and Cohen 2003). The procedure locates tie points by maximizing an index of normalized cross-correlation for small subsets of the two images to be matched. Required user input is limited: pixel size, relative rotation of the two images, an initialization point in the two images, and the desired density of the output grid of tie points. Images were co-registered to the 1992 image using a second-order transformation. Radiometric correction was considered but not performed because preliminary analysis indicated that the spectral change associated with deforestation and land clearing is far greater than changes associated with Sun angle and atmospheric variation (Cohen *et al.* 1998). Moreover, because we analysed the digital numbers in a set of statistical analyses for land cover classification, calibration was not important.

2.3. *Change detection*

We tested three methods of change detection to map deforestation and land cover change between 1984 and 1992. We chose to use the TC transformation as the basis of the three methods because the TC images show sharp contrasts between forest, regrowth and cleared land (figure 2(*a*), (*b*) and (*c*)).

2.3.1. *Composited tasselled cap*

Brightness, greenness and wetness indices were generated for the 1984, 1986 and 1992 TM images using Landsat 4 and Landsat 5 TM TC coefficients, respectively. The three TC images were stacked to create a nine-band, multi-date composite. To improve classification performance on the multi-date composite, a classification of the 1992 TC image using unsupervised techniques in a maximum likelihood classification was used to delineate primary forest and non-forest. This classification was used to create a mask of primary forest and non-forest and the forest mask was used to eliminate this area of no change from further analysis in the multi-date composite. Using the masked multi-date composite, unsupervised techniques were used to train a second-level maximum likelihood classification, producing a 60-class image. Although ground data were not available, familiarity with the site from field visits assisted visual interpretation of the original TC data for comparison with the classification. Groupings of similar classes were determined and an 18-class land cover change map for the 1984–1992 time period was generated. Change class labels include combinations of forest, cleared areas, vegetation regrowth, vegetation dieback, flooded areas, dry/barren areas and water.

2.3.2. *Tasselled cap with principal components analysis*

In a second method, we combined all TC brightness, greenness and wetness bands for each of the three dates in one unstandardized PC transformation. We found that several of the components were dominated by a change in the expanse of

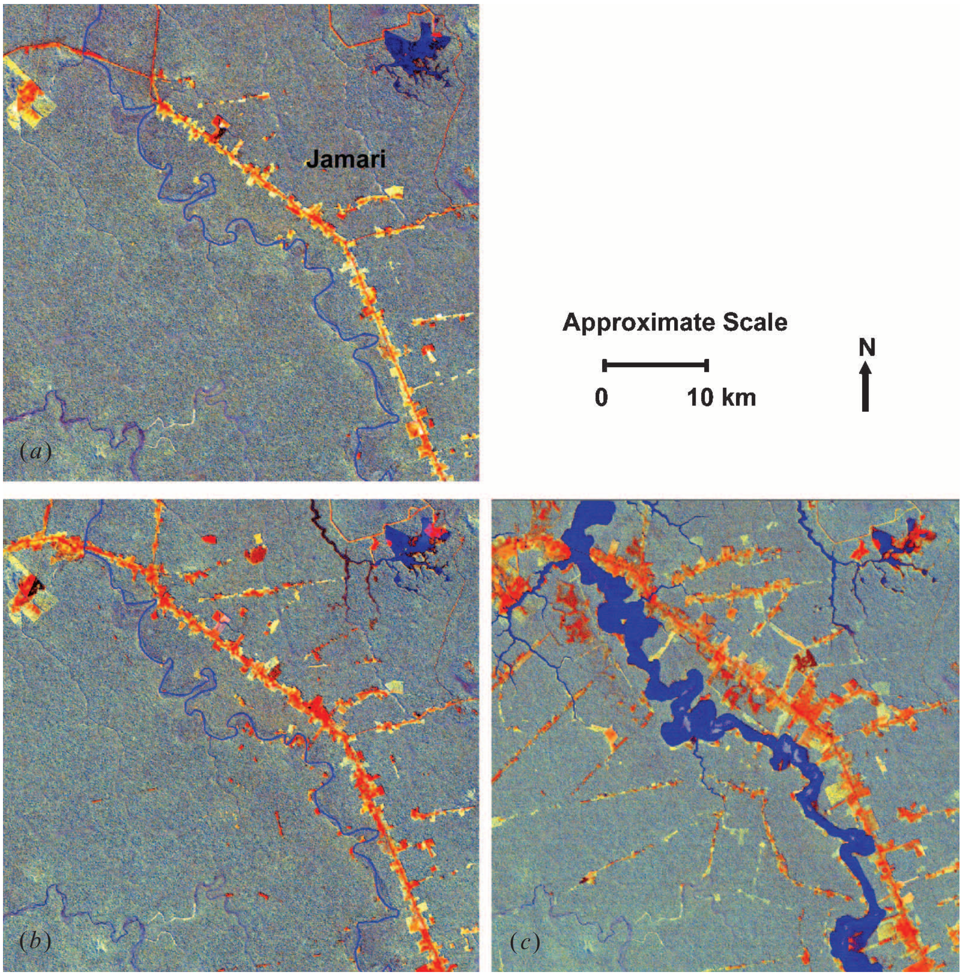

Figure 2. Tasselled cap images from Landsat TM data for the Jamari, Rondônia study area. (*a*) 24 June 1984. Forest conversion for pasture and cultivation is present along the highway. Red indicates cleared areas with little or no vegetation, yellow represents areas of vegetation regrowth, green/blue designates primary forest, and blue areas are water. (*b*) 16 July 1986. Forest conversion for pasture and cultivation has expanded along the BR-364 highway and radiates out from the highway. (*c*) 24 July 1992. The Jamari River extent increased due to completion of the Samuel Hydroelectric Dam in 1989. Some forest, pasture and cultivation areas were lost due to flooding of the Jamari River.

the Jamari River that made other land cover change features more subtle and not as easily delineated. The construction of the Samuel Hydroelectric Dam in 1989 caused a substantial increase in the expanse of the Jamari River between the 1984/1986 images and the 1992 image. Therefore to eliminate this expanse change from the PC analysis, a mask of the river's extent in 1992 was used on all three dates prior to performing the PC transformation. Nine components, one for each input band, were generated in the PC transformation based on the covariance matrix. Each component was evaluated along with the PC eigenvectors, which are linear combinations for the PC axes rotations. The PC factor loadings, describing the correlation between the original bands and the PC bands, were plotted for each component against the corresponding TC indices. The graphs indicated contrasts occurring between dates as well as within and among indices. This analysis assisted inspection of single PC band images for change, but did not indicate the type of change. Band by band, the PC images were analysed with the original TC images, the eigenvectors and the factor loadings to identify component bands exhibiting change through time due to deforestation, clearing and regrowth. Three resultant principal components indicating change during the 1984–1992 study period, together with the first component, were used in a maximum likelihood classification using unsupervised techniques. The first component was a stable component that was used as a reference for change to improve the classification (Collins and Woodcock 1996, Cohen and Fiorella 1998). Without the inclusion of the first component or stable component in the classification, there appeared to be no frame of reference and the spatial integrity of the image was lost. The original TC images for each of the three dates were used to interpret 60 classes in the classification. Subsequent grouping of similar classes generated a 13-class land cover change map using the same land cover labels used in the TC classification previously described.

2.3.3. *Tasselled cap image differencing*

TC image date pairs were subtracted one from the other to create TC differenced images. Subtracted image date pairs included: (1) 1984 and 1986, and (2) 1986 and 1992. The two TC differenced images along with the 1992 TC image, which served as a reference image for change, were combined into one image creating a nine-band composite image. A maximum likelihood classification using unsupervised techniques was performed on this nine-band image creating 60 classes. Following inspection of the classes with the original TC images, 18 unique change classes were identified with the land cover labels previously discussed in the TC classification.

2.4. *Accuracy assessment*

An equalized stratified random sampling approach was used to assess the accuracy of each of the three land cover change classifications. Approximately 15 random pixels were selected for each class and visually compared with the original TC images. Based on the number of classes, between 195 and 270 points per classification were verified for classification accuracy. The class label was unknown when the pixels were compared with the TC images. In addition, validation of the land cover change classes came from knowledge of the history of the land use in the area based upon experiences of ground-based research in this region. An error matrix was used to calculate producer's accuracy (indication of omission errors), user's accuracy (indication of commission errors) and the overall accuracy of the classifications. In addition, the more conservative kappa statistic was calculated. Kappa is a maximum likelihood estimate from a multinominal distribution that measures the actual agreement of the classification output with what is observed in the information or data used for 'truthing' minus the chance agreement. Essentially, kappa is the difference between the observed accuracy and the chance agreement divided by one minus the chance agreement (Lillesand and Kiefer 1994). Finally, kappa was calculated using only the 12 classes that were common to all three change detection classifications.

3. Results

3.1. *Comparison of methods*

Clearing of primary forest was evident and easily detected in the land cover change classification approaches. All three classification techniques yielded acceptable accuracy given the number of unique classes generated for each land cover change map and for a multi-date analysis (tables 1, 2 and 3). The PC classification had fewer classes (13 classes) than the TC (18 classes) and TC difference (18 classes) classifications because areas associated with flooding and the Jamari River were masked out prior to classification. Masking out these areas eliminated classification of these features. The PC classification missed classifying an area that was in regrowth between 1984 and 1986 and was cleared by 1992 (Class 16). The TC difference classification missed two classes identified in the TC classification. Both of these classes involved regrowth or cleared areas that were flooded by 1992 (Classes 2 and 6). The TC classification, however, missed a class delineated in both the TC difference and PC classification that indicated areas in a cleared state between 1984 and 1986, but had regrowing vegetation by 1992 (Class 18). The TC difference classification gave a high accuracy for Class 18, but the PC classification had only moderate accuracy. Discrepancies with class 18 are likely to be due to confusion with areas in a cleared state for the entire study period. A second class that was missed by the TC classification, but was captured by the TC difference classification, was water in 1984, cleared (bare soil) in 1986 and water in 1992 (Class 19). This class is associated with the variation in water levels in the tin mine reservoir and is not a change of interest for this study. The TC classification performed better than the other classifications in capturing clearing of both primary forest and areas in a stage of regrowth.

The TC classification gave the highest accuracy of all three approaches, with an overall accuracy of 79.3% and kappa of 0.78 (table 1 and figure 3). Additionally, kappa for the 12 classes common to all three change detection approaches was 0.725. The TC classification gave high producer's accuracies (87–100%) and user's accuracies (67–100%) for classes of primary forests converted to clearing (Classes 5, 7, 9, 10, 12). For classes of primary forest that were cleared and followed by regrowth (Classes 11 and 14), the producer's accuracies were 69% and 100% and user's accuracies were 56% and 100%. For the class that was interpreted as being in a state of sustained clearing (Class 8), the producer's accuracy was 41% and the user's accuracy was 54%. The low accuracy is associated with spectral confusion of regrowth areas. We suspect that some of the uncertainty in the classification is associated with sprouting of surviving vegetation and the establishment and rapid growth of secondary broadleaved plants in pastures. This situation could be exhibiting relatively high brightness and greenness similar to vegetation regrowth in shifting cultivation sites. Therefore, some of the error may be overestimated. Similarly, a class interpreted as cleared followed by regrowing vegetation (Class 17) had a producer's accuracy of 78% and a user's accuracy of 47%. In other words, although 78% of all areas cleared and allowed to regrow were correctly identified as this class, only 47% of the areas identified as 'clearing followed by regrowth' within the classification were actually that class. The spectral confusion associated with this class was with assignment of regrowth areas to clearing. Because it is impossible to ground-truth historic satellite data, there could be some error in our visual interpretation of this class in the TC images over time. Perhaps some of the error is overestimated. Additionally, this class represented less than 1% (351 ha)

Table 1. Error matrix for the tasselled cap land cover change classification. User's accuracy and producer's accuracy are reported for each class. Overall accuracy was 79.3% and kappa statistic was 0.78.

	Reference data																		
Class	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	User's accuracy (%)
0 Forest 84–92	15																		100
1 Water 84–92		11		1	3														73
2 Cleared 84–86, Flooded 92			13																100
3 Flooded 84–86, Dry 92		1		14															93
4 Forest 84–86, Flooded 92		1			14														93
5 Forest 84, Cleared 86, Flooded 92			1			14													93
6 Regrowth 84–86, Flooded 92		1	1				12									1			80
7 Forest 84–86, Cleared 92								10						4	1				67
8 Cleared 84–92									7					2		2		2	54
9 Forest 84, Cleared 86–92										13						1			93
10 Forest 84, Regrowth 86, Cleared 92									2		10				2	1			67
11 Forest 84, Cleared 86, Regrowth 92												15							100
12 Forest 84–86, Regrowth 92													14						100
13 Regrowth 84–92														12	1	2			80
14 Forest 84, Regrowth 86–92														7	9				56
15 Regrowth 84, Cleared 86–92									1	2						13			81
16 Regrowth 84–86, Cleared 92									1							6	8		53
17 Cleared 84, Regrowth 86–92								1	6							1		7	47
Producer's accuracy (%)	100	79	87	93	82	100	100	91	41	87	100	100	100	46	69	50	100	78	
Overall accuracy (%)																			79.3
Kappa statistic																			0.78
Kappa statistic (classes 0, 3, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17)																			0.725

Table 2. Error matrix for the tasselled cap with principal components land cover change classification. User's accuracy and producer's accuracy are reported for each class. Overall accuracy was 68.4% and kappa statistic was 0.66.

	Reference data																			
Class	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	User's accuracy (%)
0 Forest 84–92	14												1		1					88
1 Water 84–92																				
2 Cleared 84–86, Flooded 92																				
3 Flooded 84–86, Dry 92				14																100
4 Forest 84–86, Flooded 92																				
5 Forest 84, Cleared 86, Flooded 92																				
6 Regrowth 84–86, Flooded 92																				
7 Forest 84–86, Cleared 92								14					1							93
8 Cleared 84–92									7					1		2		2	1	54
9 Forest 84, Cleared 86–92									1	5		7	2		1					31
10 Forest 84, Regrowth 86, Cleared 92									3		4				6			2		27
11 Forest 84, Cleared 86, Regrowth 92										1		13				1				87
12 Forest 84–86, Regrowth 92													15							100
13 Regrowth 84–92									2		1			8		2		1		57
14 Forest 84, Regrowth 86–92	3										1		4		8					50
15 Regrowth 84, Cleared 86–92														2		13				87
16 Regrowth 84–86, Cleared 92																				
17 Cleared 84, Regrowth 86–92									3					1				11		73
18 Cleared 84–86, Regrowth 92									4			1				1		2	6	43
Producer's accuracy (%)	82			100				100	35	83	67	62	65	67	50	68		61	86	
Overall accuracy (%)																				68.4
Kappa statistic																				0.66
Kappa statistic (classes 0, 3, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17)																				0.65

Table 3. Error matrix for the tasselled cap image differencing. User's accuracy and producer's accuracy are reported for each class. Overall accuracy was 71.4% and kappa statistic was 0.67.

	Reference data																				
Class	0	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	User's accuracy (%)
0 Forest 84–92	13												1								93
1 Water 84–92		13		1																	93
2 Cleared 84–86, Flooded 92																					
3 Water 84–86, Dry 92				15																	100
4 Forest 84–86, Flooded 92	1				14	1															88
5 Forest 84, Cleared 86, Flooded 92		1			5	9															60
6 Regrowth 84–86, Flooded 92																					
7 Forest 84–86, Cleared 92								15	1												94
8 Cleared 84–92									14	1											93
9 Forest 84, Cleared 86–92									5	7						3					45
10 Forest 84, Regrowth 86, Cleared 92					1	2			1		6			2		1	1	1			40
11 Forest 84, Cleared 86, Regrowth 92										3		8				2					62
12 Forest 84–86, Regrowth 92												2	14								88
13 Regrowth 84–92														15							100
14 Forest 84, Regrowth 86–92									1		1			4	5			3	1		33
15 Regrowth 84, Cleared 86–92									5							8			2		53
16 Regrowth 84–86, Cleared 92														6		2	7				45
17 Cleared 84, Regrowth 86–92									1									9	6		56
18 Cleared 84–86, Regrowth 92												1							5		83
19 Water 84, Cleared 86, Water 92									1	4										8	62
Producer's accuracy (%)	93	93		94	70	75		100	48	45	86	73	93	56	100	50	88	69	36	100	
Overall accuracy (%)																					71.4
Kappa statistic																					0.67
Kappa statistic (classes 0, 3, 7, 8, 9, 10, 11, 12, 13, 14, 15, 17)																					0.68

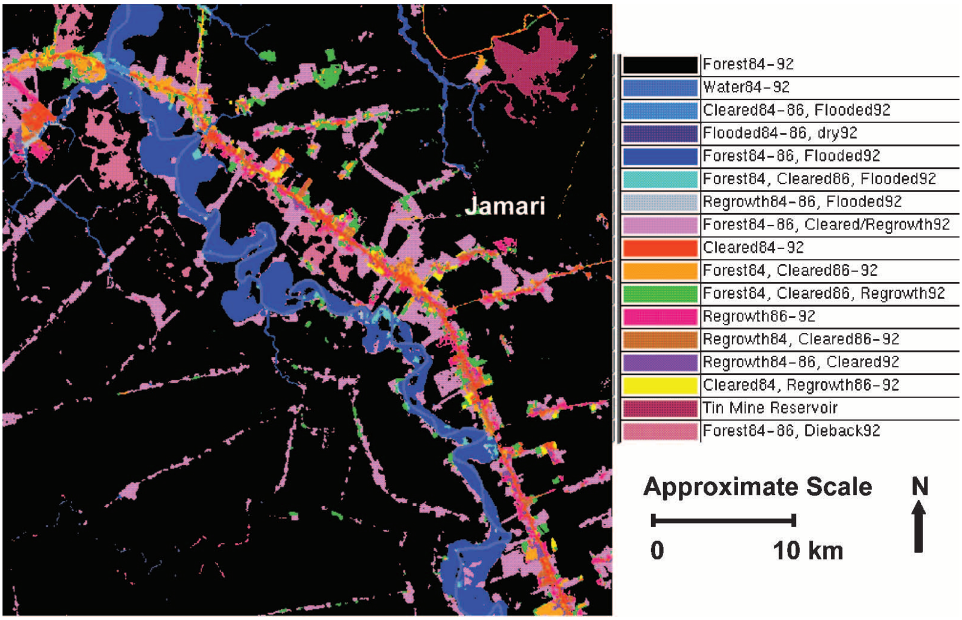

Figure 3. Classification of the tasselled cap composite image (1984, 1986 and 1992 TC indices) for the Jamari, Rondônia study area. Land cover change classes include primary forest, regrowth (regenerating forest/cultivation), cleared areas (pasture/cultivation), flooded (Samuel Dam), dieback (prior inundation), water (Jamari River and other tributaries) and reservoir (tin mine).

of the study area and hence does not lessen the high overall accuracy of this classification.

The TC difference classification had an overall accuracy of 71.4% and kappa of 0.67 (table 3). Kappa for the 12 classes common to the three approaches was 0.68. The TC principal components classification was the most computationally intensive and time-consuming technique, both in terms of time for computation of components for multiple dates and for interpretation of components, eigenvectors and factor loadings, but was the least reliable for capturing and identifying the type of change. The TC principal components classification yielded a 68.4% overall accuracy and a kappa of 0.66 (table 2). Kappa for the 12 classes present in the three classifications was 0.65.

3.2. *Change analysis*

The TC land cover change map was selected for land cover change analysis due to the classification's higher accuracy and number of classes (table 1 and figure 3). Four of the 16 classes represented no change in primary forest, regrowth, sustained clearing or water (including the Jamari River and the tin mine reservoir). The classification was successful in delineating the original extent of the Jamari River as well as the extent following the completion of the Samuel Dam in 1989. The classification shows that there were approximately 5440 ha of primary forest lost from the flooding and rise in the river level and associated tributaries (table 4). This area remained under water in 1992. In addition, an area of 1270 ha was lost due to inundation, but the water had receded leaving an area mostly devoid of green vegetation with relatively dry, bare soil resembling clearing in the 1992 data.

Table 4. Land cover change classes interpreted from the tasselled cap composite classification, which included TC indices for years 1984, 1986 and 1992. Land cover classes include primary forest, regrowth (regenerating forest/shifting cultivation), cleared areas (pasture/shifting cultivation), flooded (Samuel Dam), dieback (prior inundation), water (Jamari River and other tributaries) and reservoir (tin mine). The Jamari, Rondônia study area encompasses 94 372 ha.

Land cover change class	Area (ha)	Percentage of study area
Forest 1984		
No change	71 881	76.2
Flooded in 1992	5443	5.8
Flooded dieback 1992	1270	1.3
Cleared/regrowth by 1992	7352	7.8
Cleared/regrowth by 1986		
Flooded in 1992	192	0.2
Regrowth in 1992	1503	1.6
Cleared in 1992	898	0.9
Regrowth 1984		
No change	1305	1.4
Flooded in 1992	130	0.1
Cleared by 1992	213	0.2
Cleared by 1986		
Cleared in 1992	615	0.7
Cleared 1984		
Regrowth 1986–1992	352	0.4
Cleared 1986, Flooded in 1992	51	0.1
No change	1180	1.2
Reservoir 1984–1992 (tin mine)	892	0.9
Water 1984–1992	1095	1.2
Total	94 372	100.0

As of 1984, approximately 4740 ha, or nearly 5% of the 94 370 ha study area, had been cleared (including areas in regrowth) for agriculture or for the tin mine (table 4). Between 1984 and 1992, about 16 660 ha of additional primary forest were lost due to conversion to agriculture, pasture or inundation. This loss of primary forest represents nearly 18% of the study area. This contributed substantially to the study area's primary forest conversion (i.e. cleared, regrowth, inundation and tin mine) total of 23% (about 21 400 ha) as of 1992. In 1984, approximately 1230 ha, or 1% of the study area, was in a state of clearing and remained cleared by 1986. This area remaining in a cleared state is probably pasture, as shifting cultivation sites would have evidence of regrowth due to infrequent clearing. By 1986, the area in clearing/pasture increased to about 2690 ha, or 3% of the study area, and remained cleared as pasture until 1992. In addition, we found that between 1984 and 1992, only 615 ha of regenerating forest had been cleared and even less (213 ha) between 1986 and 1992. For each of these time periods, clearing of regenerating forest accounted for less than 1% of the study area.

In 1984, both areas in regrowth and in clearing each represented 2% of the study area (table 4). New areas in regrowth increased at a lower rate than new areas in clearing increased between 1984 and 1986, but the total area of each was essentially equal and each represented about 4% of the study area. Areas in regrowth for the duration of the study period represented a little over 1% of the study area. Both areas deforested between 1984 and 1986 and previously cleared areas that indicated sustained vegetation regrowth between 1986 and 1992 represented approximately 2% of the study area. Between 1986 and 1992, 8% of the study area was cleared and 3% remained in a state of clearing since 1984. During this period, the total area in a state of clearing increased whereas the area in regrowth decreased.

The resultant land cover change map identified deforestation (an indication of forest slash burning events), regrowth (an indication of regenerating forest/shifting cultivation and carbon sequestration) and areas in a state of clearing (an indication of areas maintained as pasture and continued carbon sources to the atmosphere). Our knowledge of land use in Rondônia from fieldwork and interviews with landowners is that sites that remained cleared during the study period were indicative of pastures, whereas clearings interrupted by regrowth through time indicated shifting cultivation. Classes indicating pasture and shifting cultivation land use sequences emerged from the TC classification. If a site remained cleared between two dates analysed during the study period, the site was presumed burned by each date to maintain pasture. For example, the class interpreted as forest in 1984, cleared/regrowth in 1986, and cleared in 1992 indicated that primary forest had been cleared and burned between 1984 and 1986, and that there was subsequent burning between 1986 and 1992 to maintain a state of clearing (table 4). Since this class had been cleared by 1986 and remained in a state of clearing by 1992, we assumed that this is an example of pasture maintenance. Cultivation is possible during the 1986–1992 period, however, because clearing was evident in the 1992 image and the timing of the 1992 image was early in the dry season and likely before clearing for the season occurred, the clearing identified corresponded to 1991. Therefore, only a five-year shifting cultivation cycle would have occurred. We assumed that it was more likely to have remained cleared for pasture. Under the typical pasture burning practices of this region, there were likely to have been two to three pasture burning events for this class between 1986 and 1992. Another class likely following characteristics of pasture maintenance is the class that was in a state of regrowth in 1984 and then was in clearing by 1986 and remained clear by 1992. This class was likely a fallow shifting cultivation site in 1984, with regenerating forest. By 1986, this class was cleared and presumably converted to pasture in 1986 and maintained as pasture through 1992. This class represents less than 1% of the study area. This class experienced a regenerating forest slash burn followed by a minimum of two pasture burns. A clearer example of a pasture site scenario is for the class that was in a state of clearing for all dates (i.e. 1984, 1986 and 1992); here we assumed a minimum of three burning events under a two- to three-year pasture burning scenario.

If regrowth was prevalent during the study period, shifting cultivation practices or regenerating forest was assumed and site burning only occurred when clearing was evident. The class depicted as regrowth between 1984 and 1986 and as cleared in 1992, indicates a regenerating forest slash burn between 1986 and 1992. Due to the infrequency of clearing, we assume this class likely represents a shifting cultivation scenario. Another possible example of shifting cultivation was found in the class that was forest in 1984, was in a state of clearing or regrowth in 1986, and continued to be in a state of vegetation regeneration by 1992. This particular shifting cultivation class had an initial primary forest burn, but was likely not followed by subsequent burning but to cultivation or second-growth forest establishment.

Deforestation of primary and regenerating forest was easily detected in the 30 m resolution classification of the multi-date TC composite. Most of the inaccuracy of the classification was associated with spectral confusion of some regrowth areas that were classified as being in a cleared state. If these regrowth areas were actually young pastures, with recently planted pasture grasses with fairly dense regenerating forest vegetation cover, these conditions could exhibit both relatively high brightness and greenness and give an indication of vegetation regrowth.

During the study period, the area of primary forest that was cleared comprised 8250 ha and represented 9% of the study area (table 4). We assume this scenario corresponded to primary forest conversion to pasture. In contrast, the primary forest area cleared and allowed to regrow as second-growth forest or to become cultivated represented less than 2% (1503 ha) of the study area. Regenerating forest areas were about equally likely to be cleared again or continue forest establishment. Each scenario represented about 1% of the study area. Finally, cleared areas remaining cleared (pasture) during the study period included 1180 ha and represented over 1% of the study area whereas areas cleared then allowed to regrow represented less than 1% (352 ha) of the study area. Additional areas that were forest or in a state of clearing prior to 1992, but were flooded by 1992 due to the completion of the Samuel Dam in 1989, were not interpreted as one of the above land use scenarios due to their flooded condition. These areas lost to flooding comprised an area of 7086 ha and represented 8% of the study area. This time series of imagery supports our and others' (C. Neill, personal communication 1995) observations that primary forest was more commonly converted to pasture than allowed to establish as second-growth forest in this area of subsistence agriculture in Rondônia.

4. Discussion

Previous studies in the Amazon have used single-date and multi-date satellite data to quantify deforestation, but most have neglected to identify shifting cultivation and pasture clearing (Woodwell *et al.* 1986, Stone *et al.* 1991, Skole and Tucker 1993, Alves and Skole 1996, Frohn *et al.* 1996, Rignot *et al.* 1997, Moraes *et al.* 1998). To quantify regional and global emissions, elemental pools and losses more accurately, land clearing and burning estimates are needed other than from conversion of primary forest. Many of the methods of previous research could be useful in identifying land clearing and burning. Frohn *et al.* (1996) classified forested and cleared areas in Rondônia in multi-date Landsat MSS and TM data. These classifications were compared with modelled simulations of clearing to describe the pattern of clearing in the study area, but did not classify type of clearing (i.e. pasture or cultivation). Stone *et al.* (1991) used single dates of MSS, TM and Advanced Very High Resolution Radiometer (AVHRR) data to map the area and rate of deforestation in Rondônia to look at spatial trends of clearing and for comparison with information in federal statistical atlases. The multi-date analysis of Stone *et al.* (1991) could have indicated additional types of land cover conversion (i.e. areas remaining cleared versus areas allowed to regenerate). Moraes *et al.* (1998) used a single date of TM data to map forests and pastures in a study area south of Ariquemes in Rondônia. Moraes *et al.* (1998) were able to map different ages of pastures with only 0.595 accuracy (kappa). The objective was to assign vegetation and soil carbon stocks to land cover types for estimating carbon pools and fluxes. A multi-date TM analysis may improve the accuracy of identifying pasture age for this study.

Alves and Skole (1996) used a time-series of Système pour l'Observation de la Terre (SPOT) data to map deforestation near Ariquemes, Rondônia, and to separate secondary vegetation regrowth within the deforested areas. Although the accuracy of these classifications was not reported, it was stated that a limitation was that cacao plantations could not be separated from secondary vegetation. The methods of Alves and Skole (1996) go beyond estimating deforestation to estimate secondary vegetation regrowth. It is likely that areas that remained cleared following deforestation, indicative of pasture, could have been identified using these methods. Rignot *et al.* (1997) analysed multi-resolution data of Spaceborne Imaging Radar C (SIR-C) for 1994, TM data for 1993, SPOT data for 1986, 1988, 1989, 1991, 1992 and 1994, and Japan Earth Resources Satellite (JERS-1) radar data for 1994 and 1995 to map deforestation and secondary growth in Rondônia. The combination of the radar data classifications with the TM classification allowed discrimination of forest, non-forest with no woody biomass, recent clearings with slash of high woody biomass, initial regrowth, intermediate regrowth, flooded dead forest, and open water. The researchers add that there was substantial variability of woody biomass within classes and they suggested that the classification was not appropriate for estimating biomass inputs for carbon models. These methods, however, likely identify land conversion rates and land cover change through time.

Woodwell *et al.* (1986) used multi-date MSS data to map forest to non-forest change in Rondônia. The methods could not determine change from bare ground to agriculture or pasture. In addition, forest clearing identified on MSS was compared to an AVHRR scene to develop methods to scale deforestation to the lower resolution AVHRR data. Finally, Skole and Tucker (1993) visually interpreted deforestation in black and white photos of TM mid-infrared data for 1988 Amazon deforestation. Deforestation for 1978 was digitized from deforestation maps derived from single-channel MSS data. Deforestation, forest fragments, and edge effects by Amazon state were reported for both dates; however, the nature of this comprehensive project and the state of computational capabilities would not have allowed a feasible means for analysis of land cover beyond forest and non-forest.

We found that analysis of a third date, during an eight-year period, provided the information on clearing needed to delineate a pasture from a shifting cultivation scenario. Additional TM data around the year 1989 could have improved the analysis since the six-year gap in our selected data from 1986 to 1992 may have confused interpretation of land cover change classes. The ability to identify clearing events/trends and the type of land cover cleared using our methods is valuable as clearing gives an indication of timing of burning. The value of predicting the extent and frequency of burning events and the type of land cover burned is that these data can be used to improve estimates of emissions from biomass burning and site elemental pool losses (Guild 2000, Guild *et al.* in press).

The utility of our methods in expanding the analysis to the state of Rondônia could be tested in other areas of the state experiencing the range of deforestation from early colonization to extensive agricultural expansion. The analysis of the full TM scene for each of the dates in our study period would be a logical next step for analysis and testing whether the methods are appropriate at the regional scale. Since the TC transformation reduces the dimensionality of the data, a TC composite of dates covering a full TM scene is appropriate. The computational limit in a TC composite classification would likely be due to the number of dates in the analysis. In addition, the date interval for the time series might be appropriate at two- to three-year intervals; whereas intervals of four to six years in areas of less rapid change may be appropriate. Both date interval selection of data and length of the time series are considerations for computational limitations.

Based on the utility of our methods, we suggest that mapping forest clearing and areas in pasture/agriculture could improve estimates of deforestation, regrowth (regenerating forest/cultivation) and pasture at a regional scale. Additionally, as TM data became more frequent with the launch of the Landsat 7 satellite in 1999 (having a repeat cycle offset from Landsat 5 by eight days), TM data are available every eight days for as long as Landsat 5 is operational. The use of high-resolution TM data has recently become more feasible and less expensive for regional analysis of multi-date imagery and will likely improve a variety of regional estimates associated with land cover/land use and change.

5. Conclusion

The importance of this multi-date TC classification was the reliable detection of clearing and the ability to predict the type of land cover that was cleared given the clearing rate. Since clearing is an indication of burning in this region of the Amazon, this land cover change map has already been used to estimate area burned associated with deforestation (Guild 2000, Guild *et al.* in press). Additionally, areas delineated as pasture on this map were used to model the cumulative area of pasture burned, accounting for the frequent burning cycle of pastures. It is important to distinguish primary forest burns from fires used to maintain pasture and to burn fallow fields for cultivation since the nature of the emissions and the biomass, carbon and nutrient contents are very different. Together, knowledge of land use pattern and multi-date TM imagery, instead of single TM date analysis, led to better interpretation of land cover types, contributed to resolving problems of interpreting the land use following clearing, and assisted quantification of burning frequency. Hence, estimates of resultant emissions and terrestrial carbon and nutrient pools and losses associated with deforestation and land conversion are likely to be improved.

Although not reported here, land cover change detected from this multi-date TC analysis can be useful in studies to quantify sources of atmospheric emissions associated with various land use burning practices and assessing their overall contribution of emissions to the region. This could be accomplished by a combination of ground-based data of biomass, carbon and nutrient dynamics with remote sensing data to better quantify local and regional elemental sinks, sources and atmospheric emissions (Guild *et al.* in press).

Finally, our study area and study period results come from a landscape in the early stages of disturbance and may provide some interesting deforestation and land use comparisons with landscape studies of areas following many years of intense disturbance.

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