Forest Cover Change in the Toledo District, Belize from 1975 to 1999: A Remote Sensing Approach*

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Measuring land-cover change is an essential part of sustainable conservation planning. This project uses Landsat MSS and ETM+ data to document forest cover change in the Toledo District, Belize, from 1975 to 1999 and provides an initial assessment of why these changes took place. Supervised and subpixel classification methods were employed. The results showed an aggregate forest loss of almost 10 percent, which is approximately 36,000 ha. Deforestation expanded significantly in the most populous Mayan areas of central Toledo District and along the Guatemalan border. Subpixel classification results showed that in 1999 the most densely forested areas were in northern Toledo District in the Maya Mountains. **Key Words: Belize, land-use, land-cover change, satellite remote sensing**

Introduction

Understanding land-use, land-cover (LULC) change in areas with tropical forests can contribute to sustainable conservation planning and management as well as global environmental change research. This project documents LULC change in the Toledo District, Belize, from 1975 to 1999 and provides an initial assessment of why these changes took place. The project has two primary objectives: one, to map the 1999 forest cover distribution and density of southern Belize, and, two, to measure changes in forest cover that occurred between 1975 and 1999. These questions are answered using a remote sensing approach because satellite imagery is the only longitudinal record of land cover in the area during the study period. Satellite imagery has been shown to be an accurate data source for measuring forest cover in tropical areas (King 1994; Skole et al. 1994; Palubinskas et al. 1995; Alves and Skole 1996; Entwisle et al. 1998). While the primary goal of this project is to report forest cover change, this article also explores several satellite image-processing methods for measuring deforestation in southern Belize. The results and accuracies of different classification methods are compared.

The study area is the Toledo District, the southernmost political division in Belize (Figure 1). The Toledo District is bounded to the west by Guatemala and to the east by the Caribbean Sea. The northern boundary runs along the main divide of the Maya Mountains. Toledo is 4,421 square km, roughly 95 km north to south and 40 km east to west. There are two distinct Mayan ethnic groups in the Toledo District, the Kekchi and Mopan. In the Toledo District, the *milpa* slash-and-burn agricultural system has evolved in response to local conditions and provides the Kekchi and Mopan Mayans of the region with most of their subsistence needs (Lambert and Arnason 1982; Osborn 1982; Wilk 1991; Emch 2003). The amount of land cultivated on a *milpa* each year is usually between 1.2 and 2.4 ha (Osborn 1982).

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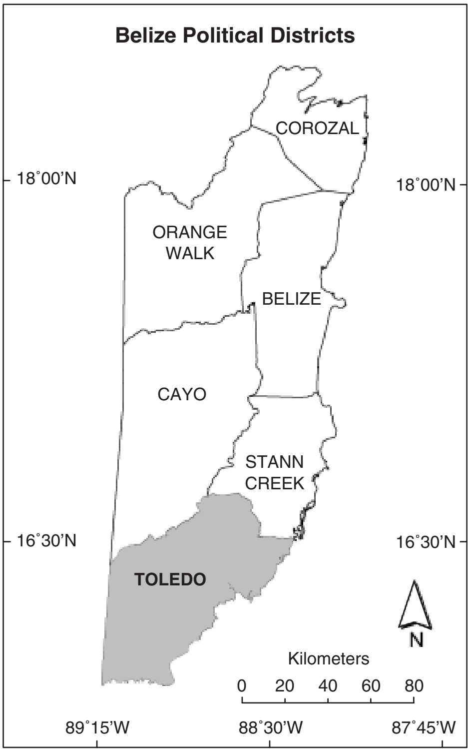

Figure 1 *Location Map.*

The *milpa* agricultural system, and therefore the LULC in the Toledo District, is changing because of increased population pressure (Emch 2003). From 1970 to 2000 the Toledo District population grew by 259 percent (Table 1).

The forests of southern Belize have been disturbed by a series of civilizations, including the ancient Mayan kingdoms, a British logging colony, and, presently, the multiethnic independent state of Belize (Furley et al. 1995; Furley 1998). Thus, the forests of Belize are by no means undisturbed; they are dynamic and range from freshly burned *milpas* to dense tropical forest. This article focuses on the changes in forest cover since 1975. While changes in LULC are very complex in this study area, some deforestation can be attributed to increased population in the Mayan areas, immigration of Mayans across the Guatemalan border, the improvement and construction of roads, and timber extraction practices (Levasseur and Oliver 2000). Since 1995, international logging companies have received licenses to log approximately 65,000 ha bordering several Mayan communities in the southern part of the district and approximately 10,000 ha of rainforest in the Columbia River and Maya Mountain Forest Reserves (these reserves straddle the Toledo-Cayo District boundary). During the study period, several new roads have been built and the main road into the district, the Southern Highway, has been improved. While these roads promote economic development, they have also been found to facilitate deforestation in southern Belize (Chomitz and Gray 1996). Population increases during the last several decades have put the Mayan *milpa* system of agriculture under pressure leading to reduced fallow periods in some areas (Masiolo and Musyoki 1978; Emch 2003).

Table 1 *Toledo District Population Change*

Year	1970	1980	1991	2000
Population	8,989	11,683	17,439	23,297

Sources: Osborn 1982; GOB 1991; GOB 2000.

Using a Remote Sensing Approach to Measure Forest Cover Change

This project uses Landsat Multispectral Scanner (MSS) and Enhanced Thematic Mapper Plus (ETM+) imagery to measure LULC change in the Toledo District. Traditional and subpixel classification algorithms are used to measure forest cover change from 1975 to 1999. The choice of remotely sensed data sources involves trade-offs between accuracy, specificity, and timeliness (Harris and Stephen 1995). Ideally, a change detection investigation will hold the temporal, spatial, spectral, and radiometric resolutions constant (Turner et al. 1989; Jensen 1996). If possible, images should be from the same season for each year. This change detection exercise is not ideal for several reasons. Few satellite images are available for the study area because of frequent cloud cover. While we attempted to find two satellite scenes on an anniversary date, the only images with limited cloud cover were from March 1975 and November 1999. In addition, the 1975 image has a spatial resolution of 60 m while the 1999 image has a spatial resolution of 30 m. The two sensors also have spectral sensitivity differences in the green, red, and near infrared bands, as well as different radiometric resolutions.

Two supervised classification methods were used to classify both satellite images: the maximum likelihood (ML) method and hybrid parallelepiped/maximum likelihood (PP/ML)[1] method (Jensen 1996; McGwire, Estes, and Star 1996; Richards and Xiuping 1999). The choice of a change detection method is influenced by issues of data quality, availability, and scale (Green, Kempka, and Lackey 1994). While there are many sophisticated change-detection methods, this study uses postclassification change detection because of limitations of the available data (Jensen et al. 1987; Singh 1989; Nellis, Lulla, and Jensen 1990; Mas 1999). The result is a pixel-by-pixel description of forest cover change in the area. While postclassification change detection is not a mathematically complicated methodology, it sometimes proves to be the most accurate measure of change (Mas 1999; Civco 2002). Postclassification change detection, however, is subject to the errors in each contributing classification (Jensen 1996). While not ideal, change detection can be highly accurate when using different satellite sensors with different resolutions, such as the MSS and ETM+ imagery used in this study (Stow, Collins, and McKinsey 1990).

One of the objectives of this study is to accurately calculate the present state of forest cover in the Toledo District. The aforementioned supervised classification methods result in a nominal LULC class for each pixel. Traditional classification algorithms such as the maximum likelihood classifier can successfully detect a material of interest (MOI), for example, dense forest, when that material dominates an image pixel. When a pixel contains only a fraction of the MOI, however, it may not be detected. To confront this mixed pixel problem, Erdas Imagine Subpixel Classifier software was used to determine the contribution of dense forest within the pixels of the 1999 image. The Erdas Imagine Subpixel Classifier uses the Applied Analysis Spectral Analytical Process to detect a subpixel MOI from a variety of background materials present in a pixel (Boudreau, Huguenin, and Karaska 1996; Huguenin et al. 1997). This subpixel classification method assumes that each pixel contains a combination of the MOI and unknown background materials. The subpixel classification technique provides additional information about the present state of forest cover in the Toledo District, namely a measure of the relative forest density per pixel.

Satellite Image Data and Preprocessing

The study data include one Landsat 2 MSS scene and one Landsat 7 ETM+ scene. Each image was subset to the political boundary of the Toledo District. A manually digitized cloud mask was also applied to each image so those areas covered by clouds could be removed. Figure 2 is a map of the Toledo District showing the cloud-free image data common to both acquisition dates; it includes 83.5 percent of the Toledo District and defines the effective study area for this project. The MSS scene was acquired on 25 March 1975 (WRS-1 Path 020 Row 049). The Landsat-2 MSS sensor acquired reflected radiance in four, 56-m $\times$ 79-m bands. Two are visible (band 4- 0.5–0.6 μm, band 5- 0.6–0.7 μm) and two are infrared (band 6- 0.7–0.8 μm, band 7- 0.8–1.1 μm). We obtained the imagery from the EROS Data Center (Sioux Falls, South Dakota), which resampled the 1975 image to a pixel resolution of 60 $\times$ 60 m. While the radiometric resolution of MSS is 6-bits when it is collected, EROS rescales the scenes to 8-bits before distribution. The ETM+ scene was acquired on 29 November 1999 (WRS-2 Path 019 Row 049). The Landsat-7 system collects data for six bands in the visible (band 1- 0.45–0.52 μm, band 2- 0.52–0.60 μm, band 3- 0.63–0.69 μm), near-IR (band 4- 0.76–0.90 μm), and mid-IR (band

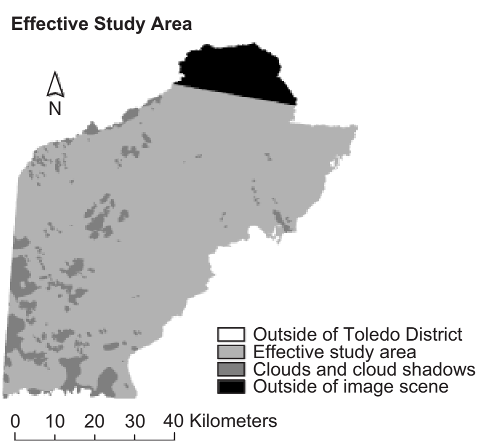

Figure 2 *Study Area.*

5- 1.55–1.75 μm, band 7- 2.09–2.35 μm) spectral regions. The ETM+ data have a spatial resolution of 30 × 30 m and the radiometric resolution of the product distributed by EROS is 8-bits. The ETM+ thermal and panchromatic bands were not used in this study.

Several preprocessing methods were implemented before the classification and change detection. The digital numbers for each image were converted to radiance values (Markham and Barker 1986) and then standardized for differences in sun illumination geometry and atmospheric effects using the COST model (Chavez 1996). An image-to-image rectification was performed resulting in a root mean square error of less than 0.5 pixel; the images were georeferenced to the UTM Zone 16, NAD27 datum. The 1975 MSS image contained stationary periodic noise in the form of striping (e.g., systematic lines with the same orientation). In order to assess and classify land cover, we carried out an additional processing step to remove the striping. The systematic noise was removed by enhancing a Fourier-transformed frequency image on a per band basis (Russ 1995). The enhancement used power spectrum averaging to adjust the Fourier transformation, resulting in removal of the systematic noise (Leica Geosystems GIS & Mapping, LLC 2003). Image transform methods were tested, including a noise-adjusted principle components analysis and several Fourier transform techniques. A Fourier transform was computed and the data cleaned by removing the extraneous noise from each of the four MSS spectral bands using ERDAS Imagine's Fourier Analysis Periodic Noise Removal module. The algorithm divides the data into overlapping 128 × 128 pixel blocks and then computes a Fourier transform of each block. Next, the log-magnitude of each Fast-Fourier-Transform (FFT) block is averaged, removing the periodic noise. The periodic striping affected the detail of the image, so the Minimum Affected Frequency (MAF) values were set relatively high. The Periodic Noise Removal module allows the user to interactively select the MAF on a scale of 1 to 100. MAF values of 92 (band 1), 88 (band 2), 96 (band 3), and 94 (band 4) were needed to remove the noise. Application of the Fourier transform resulted in a significant reduction of striping from the periodic noise for each band of MSS data. Band 3 did exhibit additional striping on the edges of the MSS scene; however these anomalies occurred outside the study area.

Classification Methods

The objective of postclassification change detection is to achieve the best possible independent classification for each data set and then assess any change as accurately as the data allow. The software packages we used for the image processing and subsequent spatial analysis include Erdas Imagine 8.7 and ArcInfo 9. The goal of traditional image classification is to classify all pixels, based on their brightness values, into one of a certain number of LULC types (Jensen 1996). The first step in the image classification process is to define the training areas used to extract pixel values or image statistics of each land class from the raw satellite data. Spectral patterns present in the image data are used in the classification process by training the computer to recognize such patterns in the image data. For each Landsat scene, we used corresponding land-cover maps of part of the study area that were derived from air photographs (King et al. 1986), ecosystem maps (Vreugdenhil et al. 2002), and field visits to the study area as reference data and as a means to collect classification training data. The training data provided a set of signatures specific to each land-cover type for the images being classified. These reference data sources were also used to find different representative pixels within each LULC type to assess the accuracy of each supervised classification.

A preliminary ISODATA unsupervised classification was carried out before the supervised classification to facilitate a qualitative analysis of the Landsat subsets (Jensen 1996). The unsupervised classification was used to evaluate the separability between classes represented in the Landsat imagery, thereby, providing guidance for the supervised classification. This procedure generated one hundred initial classes from the available multispectral bands, separating the data into distinct groups or clusters. These clusters were labeled through a visual examination of classes on the corresponding reference data. A qualitative analysis of vegetated lands allowed separation into the following classes: deforested/regrowth, forested, lowland

Table 2 Toledo District Land-Use Land-Cover Classification Scheme

Land Cover Type	General Description
Deforested/Regrowth	Secondary forest in some stage of regrowth.
Forested	Dense forest formed by trees at least 5 m tall with interlocking crowns and a canopy cover of 65 percent or greater.
Lowland Savanna	Grasslands, which may be flat or hilly, with a predominantly herbaceous community.
Open Water	Rivers, lakes, and flooded areas.
Wetlands	Swamps, mixed vegetation composed of rooted and/or floating plants that endure or need water covering the soil constantly or at most times of the year.
Farmland/Bare Soil/Towns	New *milpas*, roads, and/or towns with bare soil.

savanna, open water, wetlands, and farmland/bare soils/towns (Table 2). Farmland includes freshly tilled soil or newly burned *milpas*. The exact category and boundaries of mixed LULC classes were difficult to determine even by unsupervised grouping; therefore, mixed pixel areas were avoided. Once separated, spectral signatures of the six categories were extracted. The results of the unsupervised classification, in conjunction with the reference data, provided the initial basis for selecting spectral signatures for the supervised classifications.

Using these methods, we were able to locate representative locations for each of the six land-cover classes. These locations were located on the Landsat images, and then the Erdas Imagine region-growing and polygon-training tools were used to produce regions that corresponded to samples on the reference data. Polygon training areas were selected within large sites of homogeneous LULC class areas to minimize the chance of misclassification because of mixed pixels. From these regions/training areas, image statistics representing each of the six land categories were extracted from the spectral data. Once the image statistics were extracted, Erdas Imagine signature evaluation tools were used to determine which training set signatures were spectrally separable from one another. In the few cases when training set signatures were not spectrally separable, another training set was selected for that land cover type and evaluated. This procedure was repeated until all training set signatures were spectrally separable, thus providing the information needed for the ML and PP/ML supervised classification processes.

The forest training sets that were used for the supervised classifications were also used for the subpixel classification. The Erdas Imagine Subpixel Classifier software computes signatures for each MOI (i.e., dense forest) training set, then subtracts background spectra from each pixel, leaving a residual spectrum. When a pixel contains the MOI, the residual spectrum will only match the MOI signature, and the percentage of MOI contribution is determined (Boudreau, Huguenin, and Karaska 1996). An automated scene-derived normalization process was applied because changing illumination and atmospheric conditions can distort results. The process derives atmospheric and sun-angle correction factors directly from dark and bright surface features in an image without the use of predictive models (Huguenin et al. 1997).

Change Detection and Accuracy Assessment Methods

After the supervised classification was complete, the 1999 classified images were resampled to a 60×60-m pixel resolution to eliminate discrepancies in pixel sizes between the two dates. Change analysis by postclassification change detection (Jensen et al. 1987; Singh 1989; Nellis et al. 1990; Mas 1999) was used to detect LULC differences between 1975 and 1999.

The accuracies of the two 1975 Landsat MSS and two 1999 ETM+ classifications were assessed by comparing randomly selected pixels from the classified image data to the aforementioned reference data. A stratified random sampling scheme has been suggested by Van Genderen, Lock, and Vass (1978) and Congalton (1988) to be the most appropriate sampling method for collecting ground reference data for remote sensing projects because minor categories can be acceptably represented. We used a stratified random sampling scheme to locate a total of 246 sample points stratified by the six original classes and equalized by class area. Accuracy assessments were performed to deter-

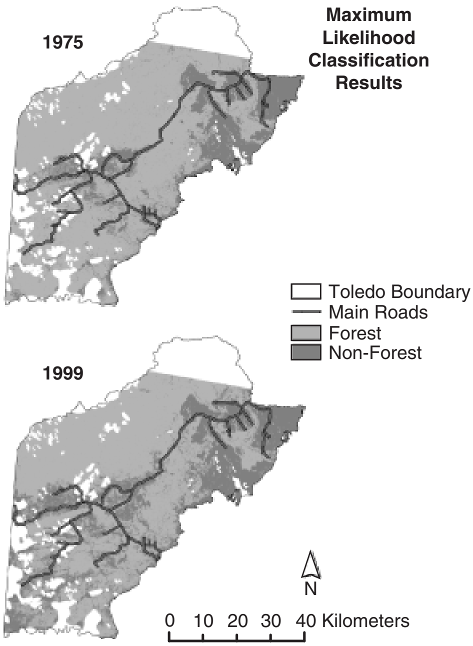

Figure 3 *Classification Maps.*

mine which method was the most accurate. Error matrices were created, and kappa coefficients, producer's, user's, and overall accuracies were calculated for each map (Congalton and Green 1993).

Results

Figure 3 shows the forest/nonforest maps derived from the ML classification; the PP/ML maps are not shown because they are very similar. The white areas within the Toledo District boundary were obscured by clouds for at least one of the image dates; the white area at the northern tip of the Toledo District was not part of the Landsat scene. A 3 × 3 pixel majority filter was used on each classified map to eliminate outlier pixels for presentation purposes. Table 3 summarizes the changes in the areas for each class during the study period. Approximately 14.4 percent of the forested area was lost during the study period, and 4.6 percent of the area gained forest, which is a net loss of almost 10 percent, that is, approximately 36,000 ha in the cloud-free area. Figure 4 shows the spatial distribution of forest-cover change from 1975 to 1999, based on the ML classifier. The black areas are those that were deforested from 1975 to 1999, and the dark gray tone represents areas that were reforested during the study period. Table 4 shows that the LULC class changed for approximately 26 percent of the study area between 1975 and 1999.

Table 5 summarizes the accuracy assessment results for each classification. The overall accuracies for the two 1975 classification methods are 95 percent, using the ML method, and 90 percent, using the PP/ML method; the kappa statistics are 89 percent and 78 percent, respectively. The overall accuracy for the two 1999 classification methods are 91 percent, using the ML method, and 84 percent, using the PP/ML method; the kappa statistics are 83 percent and 72 percent, respectively. Tables 6 and 7 show the confusion matrices as well as the producer's and user's accuracy statistics for each of the five classes, using the ML method. The accuracy statistics for the forest classifications are be-

Table 3 *Land-Use Land-Cover Change from 1975 to 1999 by Class*

Land Cover Type	Method	1975		1999		% Change		
		% Area	Hectares	% Area	Hectares	Gain	Loss	Net Gain- Loss
Deforested/Regrowth	ML	6.11	21,925	18.61	66,743	15.16	2.66	12.50
	PP/ML	6.12	21,948	18.71	67,108	15.22	2.63	12.59
Forested	ML	74.74	268,010	65.00	233,126	4.63	14.37	−9.74
	PP/ML	74.98	268,854	65.05	233,308	4.41	14.34	−9.93
Lowland savanna	ML	12.50	44,828	10.28	36,867	2.05	4.27	−2.22
	PP/ML	12.55	45,021	10.19	36,560	2.00	4.36	−2.36
Open water	ML	0.56	2,023	1.35	4,836	0.86	0.07	0.79
	PP/ML	0.60	2,136	1.33	4,756	0.81	0.08	0.73
Wetlands	ML	2.46	8,816	1.86	6,656	0.77	1.37	−0.60
	PP/ML	2.35	8,414	1.86	6,672	0.77	1.26	−0.49
Farmland/soil/towns	ML	3.62	12,977	2.90	10,419	2.42	3.13	−0.71
	PP/ML	3.40	12,206	2.85	10,232	2.37	2.93	−0.56

Note. ML = Maximum-likelihood; PP/ML = Parallelepiped/Maximum-likelihood.

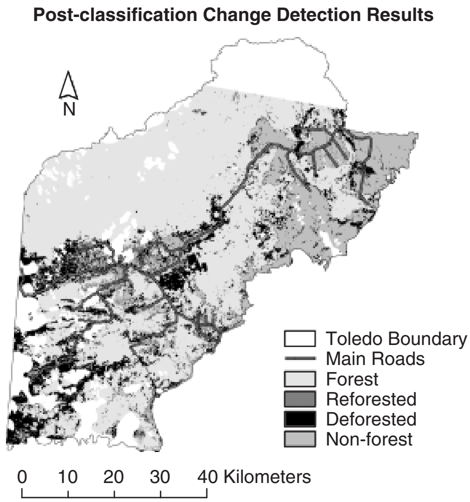

Figure 4 *Change Detection Map.*

tween 93 and 99 percent; however, many of the accuracy values for the nonforest classes are much lower. While the accuracy assessment revealed substantial confusion between several nonforest classes, especially with the farmland/bare soils/towns class, the main objective of this study is to distinguish between forest and nonforest. Table 8 shows the overall classification accuracy statistics between forest and nonforest for both years, using each classification method. The two methods resulted in very similar overall accuracies and kappa statistics. For the 1975 image, the ML classifier was more accurate than the PP/ML classifier, with an overall accuracy of 95.2 percent and a kappa statistic of 88.9 percent. For the 1999 image, the ML was slightly more accurate, with an overall accuracy of 90.8 percent and a kappa statistic of 83.1 percent. Table 9 lists the producer's and user's accuracy statistics for the forest and aggregate nonforest class. For the forest class, using the ML classifier on the 1975 image resulted in user's and producer's accuracies of 97.3 percent and 99.5 percent, respectively; using the ML classifier on the 1999 image resulted in user's and producer's accuracies of 95.7 percent and 98.1 percent, respectively. The nonforest accuracy assessment resulted in user's accuracies ranging from 96.6 to 98.4 percent and producer's accuracies ranging from 86.1 to 94.6 percent.

Table 4 *Overall Change from 1975 to 1999*

	Method	% Study Area	Hectares
No Change	ML	74.12%	265,796
	PP/ML	74.40%	266,800
Changed	ML	25.88%	92,783
	PP/ML	25.60%	91,779

Note. ML = Maximum-likelihood; PP/ML = Parallelepiped/Maximum-likelihood.

Table 5 *Overall Accuracy Statistics*

Method	Year	Overall Accuracy	Overall Kappa Statistics
ML	1975	95.20%	88.88%
	1999	90.80%	83.14%
PP/ML	1975	90.00%	77.67%
	1999	84.40%	71.84%

Note. ML = Maximum-likelihood; PP/ML = Parallelepiped/Maximum-likelihood.

Figure 5 shows the results of the 1999 subpixel classification. As one might expect, the most densely forested areas are in northern Toledo District, in the Maya Mountains. Table 10 shows the area represented by different density classes. About 45 percent of the pixels in the study area were identified as being at least 60 percent forest density, while nearly half were left unclassified with less than 20 percent forest density. Both traditional classifiers showed that the study area was composed of approximately 70 percent forest. Thus, the subpixel classifier offers somewhat different, although not contradictory, information illustrating more specific information about the nature of forest cover. The subpixel classification results reveal that much of the area identified, using the traditional supervised classifiers, as forest is not very dense.

The majority of areas that were deforested are along the Guatemalan border and in central Toledo District. Central Toledo District is the area with the highest Mayan population density; this area experienced substantial population growth during the study period. Much of this central region was already deforested prior to 1975 (King et al. 1986), while the areas adjacent to this Mayan population center experienced substantial deforestation. Thus, we surmise that the deforested area expanded at least partly because of population pressure. The area along the Guatemalan border that was deforested during the study period is consistent with deforestation caused by immigration from that country. Land is scarcer on the Guatemalan side of the border,

Table 6 *1975 Contingency Table for the Maximum Likelihood Classifier*

	Reference Data						
	Land Cover Class	**D/R**	**F/S/T**	**F**	**LS**	**W**	**Row Total**
Classified Data	Deforested/Regrowth	13	2	0	0	0	15
	Farmland/Soil/Towns	0	7	1	1	0	9
	Forest	4	1	182	0	0	187
	Lowland Savanna	0	2	0	28	1	31
	Wetlands	0	0	0	0	6	6
	Column Total	17	12	183	29	7	248

Note. D/R = deforested/regrowth, F/S/T = farmland/soil/towns, F = forest, LS = lowland savanna, W = wetland.

Land Cover Class	Producer's Accuracy	User's Accuracy	Kappa Statistics
Deforested/Regrowth	76.47%	86.67%	0.8569
Farmland/Soil/Towns	58.33%	77.78%	0.7666
Forest	99.45%	97.33%	0.9002
Lowland Savanna	96.55%	90.32%	0.8905
Wetlands	85.71%	100.00%	1.0000
Overall Accuracy: 95.20%		**Overall Kappa: 0.8888**	

and, therefore, farmers migrate to Belize to practice *milpa* agriculture. The two lighter-tone classes in Figure 4 are areas that did not change during the study period. The nonforest areas did not have forest cover in both study years, and the forest class represents areas in which there was forest cover in both years. Interestingly, the areas that experienced reforestation are mostly within the central Toledo District Mayan population center. This is consistent with reports suggesting that Mayans are increasingly growing cacao trees in an effort to gain usufruct ownership to land (Emch 2003). The area that was forested during both years is mostly in northern Toledo District, in the Maya Mountains. This region is mostly reserve forest, and very few people live there.

Discussion and Conclusions

This study traces the recent history of forest-cover change in southern Belize and provides an initial assessment of why it occurred. It also provides a baseline description of recent (i.e., 1999) cover in the Toledo District so the patterns can be followed into the future. Two recent events suggest that there may be an increase in the amount of deforestation in the future.

Table 7 *1999 Contingency Table for the Maximum Likelihood Classifier*

	Reference Data						
	Land Cover Class	**D/R**	**F/S/T**	**F**	**LS**	**W**	**Row Total**
Classified Data	Deforested/Regrowth	36	7	2	1	0	46
	Farmland/Soil/Towns	0	7	0	0	0	7
	Forest	4	1	155	2	0	162
	Lowland Savanna	1	0	0	24	1	26
	Wetlands	0	0	1	1	3	5
	Column Total	41	15	158	28	4	246

Note. D/R = deforested/regrowth, F/S/T = farmland/soil/towns, F = forest, LS = lowland savanna, W = wetland.

Land Cover Class	Producer's Accuracy	User's Accuracy	Kappa Statistics
Deforested/Regrowth	87.80%	76.60%	0.7200
Farmland/Soil/Towns	43.75%	100.00%	1.0000
Forest	98.10%	95.68%	0.8826
Lowland Savanna	85.71%	92.31%	0.9134
Wetlands	75.00%	60.00%	0.5935
Overall Accuracy: 90.80%			**Overall Kappa: 0.8314**

Table 8 *Overall Accuracy Statistics: Forest Versus Non-Forest*

Method	1975		1999	
	Overall	Kappa	Overall	Kappa
ML	95.20%	0.8888	90.80%	0.8314
PP/ML	90.00%	0.7767	84.40%	0.7184

Note. ML = Maximum-likelihood; PP/ML = Parallelepiped/Maximum likelihood.

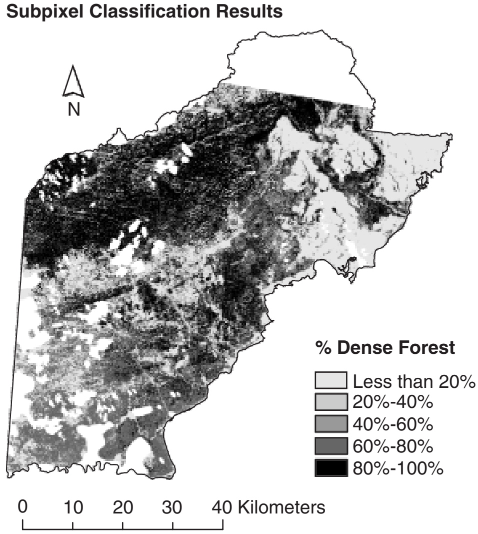

Figure 5 *1999 Forest Density.*

First, the Belizean government has recently sold licenses to both domestic and international logging companies to harvest about 75,000 ha in the Toledo District, including areas within the reserved forests. Second, the Southern Highway has been paved, and new roads are being built by the logging companies. These roads will likely facilitate both forest extraction and increased farming activity. Whitman, Brokaw, and Hagan (1997) found that canopy cover was significantly reduced by selective logging in northern Belize. These conditions threaten one of the largest forest areas in Central America, and, thus, remotely sensed imagery should be used to monitor future change.

The classification results showed an aggregate forest loss of almost 10 percent. The accuracies of the results were similar using both supervised classification methods; both methods resulted in reasonable accuracies. The subpixel classifier results showed more information concerning the forest density per pixel. The overall pattern of forest density agrees with that revealed by the supervised classification, but the subpixel classification results provide additional clarity concerning the present state of forest density. Deforestation expanded significantly in the populated areas of central Toledo District and along the Guatemalan border. This is consistent with population increases in central Toledo District (Emch 2003) and migration patterns along the Guatemalan border. The number of foreign-born people living in the Toledo District increased from 2,491 to 3,885 between the 1991 and 2000 censuses (GOB 1991, 2000). In 2000, 76.9 percent of these immigrants were from Guatemala. These figures only include those families who filled out census forms; therefore, there was probably a significant amount of underreporting, especially among people who do not have legal immigration status. Table 11 shows the age and sex distribution of all foreign-born people in the Toledo District. It shows that the migrants, who are mostly from Guatemala, are relatively evenly distributed by age and sex. Deforestation is likely more pronounced along the border than identified in this study because a substantial area along this border was obscured by clouds and was thus, effectively, not part of the study. This

Table 9 *Producer's and User's Accuracy Statistics: Forest Versus Non-Forest*

Class	1975		1999	
	Producer	User	Producer	User
Forest	ML 99.45% PP/ML 99.44%	ML 97.33% PP/ML 94.65%	ML 98.10% PP/ML 98.06%	ML 96.88% PP/ML 94.41%
Non-Forest	ML 92.54% PP/ML 86.11%	ML 98.41% PP/ML 98.41%	ML 94.57% PP/ML 90.53%	ML 96.67% PP/ML 96.63%

Note. ML = Maximum-likelihood; PP/ML = Parallelepiped/Maximum likelihood.

Table 10 *1999 Forest Density Determined Through Subpixel Classification*

% Dense Forest	Hectares	% total
Less than 20	220,224	47.59%
20–29	2,368	0.51%
30–39	4,961	1.07%
40–49	9,494	2.05%
50–59	16,322	3.53%
60–69	30,953	6.69%
70–79	53,861	11.64%
80–89	65,922	14.25%
90–100	58,623	12.67%

trend of deforestation along the Guatemalan border will probably increase in the future because of the planned construction of an all-weather road and international border crossing (*Belize Times* 2003).

This study only begins to explain LULC change in southern Belize. More image dates are necessary to understand the dynamics of the changes during the study period. Measuring forest-cover change in southern Belize is particularly difficult because it is one of the wettest places on earth (with approximately 4,000 mm per year) and most days have at least partial cloud cover (King et al. 1986). While we could have used radar imagery to measure changes in forest cover, the earliest radar senor, ERS-1, was launched in July 1991, and thus there is no longitudinal record prior to this time.

Furthermore, while many studies have successfully used radar satellite sensors to measure gross changes in forest cover (Dobson, Ulaby, and Pierce 1995; Luckman et al. 1997; Rignot, Salas, and Skole 1997), they have not been very effective at detecting subtle differences in LULC classes. While it is beyond the scope of this study, future research could determine how well single-channel radar data can differentiate between the Belizean LULC classes compared with the multispectral imagery used in this study. Even though more imagery would facilitate a more precise model of the spatiotemporal changes in LULC, a more comprehensive understanding of the reasons for the changes would require a multidisciplinary, ecological approach. In a study that began in late 2004, we will randomly identify pixels that have changed (i.e., deforested or reforested) and visit those locations to determine why they changed; a questionnaire will be administered to the land users to obtain this information. ■

Table 11 *2000 Age Distribution of Foreign-Born People in the Toledo District*

Age	Total	Percent	Male	Female
< 4	84	2.2	45	39
5 to 14	621	16	319	302
15 to 24	857	22.1	452	405
25 to 34	844	21.7	444	400
35 to 44	616	15.9	330	286
45 to 54	405	10.4	239	166
55 to 64	219	5.6	142	77
> 65	239	6.2	136	103
Total	3885	100	2107	1178

Note

[1] The ML decision rule was used for both overlapping PP classes and unclassified pixels.

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