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DETECTION AND MEASUREMENT OF AMAZON TROPICAL FOREST LOGGING USING REMOTE SENSING DATA

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ABSTRACT

DETECTION AND MEASUREMENT OF AMAZON TROPICAL FOREST LOGGING USING REMOTE SENSING DATA

By

Deborah Jean Janeczek

Because forests are complex, globally distributed ecosystems, remote sensing provides a valuable means for monitoring them. Satellite data have been used to determine the rate of deforestation in Brazil's Legal Amazon. The majority of deforestation measured thus far has been has been done by clear cutting, burning for pasture, and subsistence farming. An apparently new phenomenon occurring in Brazil's tropical forests is selective logging; generally, selective logging can be detected with Landsat TM data, although it is sometimes camouflaged by the crowns of the residual trees and can be misclassified as undisturbed forest in most classification techniques. A 1988 estimate for deforestation reported by Skole and Tucker (1993) and subsequent analyses by researchers at Michigan State University and Institudo national de Pesquisas Espaciais do not include selectively logged areas. The purpose of this study is to quantify the area of selective logging missed in previous deforestation estimates. It is the first basin-wide study, finding 5,309 km^2 of selective logging in the 1992 Landsat TM images.

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CHAPTER 1

THE PROBLEM

Selective logging in Brazil's Legal Amazon is a relatively new phenomenon not included in current deforestation estimates because it is not detected in unsupervised classifications. Recently, studies have been done on this phenomenon; however, they have not yet quantified selective logging in the entire Amazon basin nor has an automated method been developed that detects selective logging. The purpose of this study is to develop a method to detect selective logging and quantify the area affected in the Brazil's Legal Amazon.

BACKGROUND

As the largest contiguous tropical forest on the planet, Brazil's Legal Amazon, has received worldwide attention in natural resource and environmental studies. The Legal Amazon is an administrative area within the country of Brazil that includes $5x10^6$ km^2 of the nine states of Acre, Amapa, Amazonas, Para, Rondonia, Roraima, plus parts of Mato Grosso, Maranhao, and Tocantins (Figure 1.1). The most important concern for the Legal Amazon is its dramatic speed of deforestation. According to a group of NASA-funded scientists, 6% of the primary forest in Legal Amazon had been cut down by 1988; 90% of this was cut down after the 1970s (Skole and Tucker 1993).

The rapid and extensive clearing of Amazonia forest is highly correlated with the beginning of a government colonization program started in 1968, when the Brazilian federal government decided to "bring men without land to the land without men" to exploit this remote resource in the Amazon and to promote Brazil's economic growth. Road construction and improvement is an important component of the colonization program (Dale *et al.*, 1993), and are also considered proximate causes of deforestation in the Amazon (Pfaff 1997, Mertens 1997). With the extension of the road network, colonists moved into the frontier of the Amazon and cut the forests adjacent to the roads with the intent of establishing agricultural settlements.

For more than three centuries, logging was restricted to the floodplain forest bordering Amazonia's major rivers (Rankin, 1985). But the construction of strategic access roads into Amazonia coupled with the depletion of hardwood stocks in the south of Brazil have transformed Amazon logging from a minor activity to a major growth industry (Verissimo et al., 1992).

Selective logging has several environmental impacts, including increased fire susceptibility (Holdsworth and Uhl, 1997), damage to nearby trees and soils (Johns et al 1996), increased risk of local species extirpation (Martini et al 1994), and increased carbon emissions (Houghton 1995). Furthermore, uncontrolled exploration by loggers catalyzes deforestation by opening roads into unoccupied government lands and protected areas that are subsequently colonized by ranchers and farmers (Verissimo et al 1995).

Cryptic Deforestation

Selective logging is the process of removing four to twenty trees per hectare. Although this may seem to be a sustainable way of logging forests, it is not. Selective logging in the Amazon is not planned to minimize effects to surrounding forest. First, bulldozers are used to open a network of logging roads. Second, patches of forest are cleared at intervals along these logging roads to serve as log landings; log landings or patios are areas of forest that are cleared to stack logs waiting to be transported by trucks. Third, trees are felled and bucked. Fourth, logs are linked by choker cable to a bulldozer or skidder by maneuvering in the bole zone. Finally, the logs are skidded to patios in preparation for transport out of the logging area (Johns *et al.*, 1996). This process can devastate surrounding forest. In many instances, the logging roads that are created by bulldozers are not used to skid the logs to the patios; instead the bulldozer creates new roads to the patios, destroying even more forest. Also, vines in the forest canopy connect trees; thus when one tree is felled, it can potentially take down five to ten trees with it. Selective logging destroys surrounding forest and should be considered a form of deforestation. Although visible in Landsat TM imagery, selective logging is not easily detected using an unsupervised classification and is not, therefore, included in current deforestation estimates (Stone and Lefebvre, 1998). Because logging is not readily detected using most image classification techniques, some researchers have called it a "cryptic" form of deforestation (Nepstad *et al,* 1999). As such, the area affected by selective logging in the Amazon has not yet been quantified on a basin-wide level.

The process of deforestation by logging is complex, and results in a heavily degraded forest environment. Selective logging leaves behind primary and secondary roads, patios or truck loading areas, a mixture of intact forest with treefall gaps, and damaged trees. Loggers do not clear-cut the forest and then burn it. Logging does not usually kill all trees but it severely damages forests (Nepstad et al., 1999). Logging companies in Amazonia kill or damage 10-40% of the living biomass of the forest during the harvest process (Nepstad et al., 1999, Uhl et al., 1991, Verissimo et al., 1992, 1995). There is little quantitative information on this new trend despite its potentially large impact in terms of carbon release, forest biomass, hydrology, sustainable development, and biotic diversity (Stone and Lefebvre 1998).

Most selective logging can be visually identified in Landsat TM data by its pattern, or texture, in the forest canopy. Visual cues for selective logging in Landsat TM data include degradation in the forest canopy and increased shadow, extensive logging patios, and occurrence of primary and secondary roads (Figure 1.2). In some areas of logging, degradation in the forest canopy is not visible, but the secondary roads and extensive logging patios are, indicating logging activity. In this study, I'll refer to these areas as cryptic logging areas (Figure 1.3). Also, for the purpose of this study, the term "canopy degradation" refers to visible disturbance in the forest canopy around logging patios indicating an area of extensive logging and possibly has been burned.

Selective Logging and Fire

Uncontrolled fires are an underestimated and underreported disturbance in the Amazon basin (Cochrane, 1998). Undisturbed tropical forest is generally immune to fire, while selectively logged forests are susceptible to fire. Except for tree-fall gaps and areas of unusual fuel structure, in an undisturbed tropical forest, fire will spread as a thin, slowly creeping ribbon of flames a few tens of centimeters in height (Cochrane, 1998). Damage from logging, however, can increase the fuel availability by adding debris to the forest floor, and devastating fires can result. The effect of logging is to increase forest flammability by reducing forest leaf coverage by 14-50%, allowing sunlight to penetrate to the forest floor, where it dries out the organic debris created by the logging (Nepstad *et al.*, 1999). Although loggers often only extract four to eight trees per hectare, the resulting forest is fragmented into a mosaic of gaps and forest patches, where canopy cover is reduced by half (Uhl and Viera 1989). Post-logging fuel loads in logged forest are three times higher than in uncut primary forest, and large gaps from logging can burn after only five to six rainless days in the dry season (Uhl and Kauffman 1990). Most fires in Amazon are set intentionally in pastures and fields and then spread into nearby selectively logged areas.

Both logging and fire increase forest vulnerability to future burning and release forest carbon stocks into the atmosphere, potentially doubling net carbon emissions from regional land-use during severe El Nino episodes (Nepstad *et al.*, 1999). The average rate and intensity of forest burning and deforestation can be expected to increase as previously burned forest area expands (Cochrane et al., 1999).

Selective Logging and Carbon

Deforestation rates in Amazonia are used to determine human effects on the global carbon cycle. Most carbon studies include only outright deforestation but do not include logging but only accounts for clear-cut forests because forest conversion to agriculture is monitored from space easily using Landsat TM images allowing, large-scale deforestation maps to be developed. The forest openings created by logging and accidental surface fires are visible in Landsat TM images, but they are covered over by regrowing vegetation within one to five years, and are easily missed in the absence of accompanying field data (Nepstad *et al.*, 1999). This forest impoverishment can cause a significant release of carbon into the atmosphere, which is not included in existing estimates of the Amazonian carbon balance. Nepstad et al (1999), estimated that in 1996 logging released approximately 4-7% of the net annual carbon release estimated for deforestation in Brazilian Amazonia. Some of the studies of carbon release may be underestimating carbon loss to the atmosphere due to this new phenomenon.

Previous Studies

Skole and Tucker (1993) used Landsat satellite data for the Brazilian Amazon Basin, in 1978 and 1988 to measure deforestation and forest fragmentation. For 1988 they used black and white photographic images using channel five of the Landsat Thematic Mapper (TM) and then digitized the deforested areas using visual interpretation and standard vector GIS techniques. To determine the edge effects from fragmentation they extracted forest fragments which were <100 km^2 and computed edge effects for a buffer zone of 500 m and 1,000 m. They found that deforestation increased significantly between 1978 and 1988 (78,000 to 230,000 km^2) as did the total affected habitat (208,000 to 588,000 km^2). This study was the first widely published estimate of deforestation using satellite data analysis, but did not explicitly consider logging and forest degradation.

Stone and Lefebvre (1998) examined 1991, 1988, and 1986 Landsat satellite imagery to determine the extent of selective logging in areas west and northeast of the urban center of Paragominas, Para. They studied how fast selective logging was occurring and how long logging remains visible in Landsat TM data. All images were classified using either a supervised or unsupervised classification methods. They state "it is doubtful that an automatic classification procedure could be developed to define the location and extent of selective logging." They therefore relied on a visual interpretation to define the location and extent of forests affected by selective logging. These areas were digitized manually on a computer screen. The digitized polygons of selective logging were overlaid on TM images to define how much selective logging in areas classified as intact tropical moist forest. When comparing polygons of selective logging from 1986 and 1991 data in the western region they found no spatial overlap i.e., those areas, which were selectively logged in 1986 were not selectively logged in 1991. Also, there were no apparent visual cues in the 1991 imagery, which allowed location of the areas that were selectively logged in 1986. Of areas selectively logged in 1986, 91% were classified as forest in the 1991 imagery and only 9% were classified as fields, pasture, and regrowth.

Stone and Lefebvre also tested a texture analysis on TM band 4 (0.76-0.9 microns) to investigate whether forest canopy texture was significantly different in logged forest from that of undisturbed forest as well as a normalized difference vegetation index (NDVI) analysis was also computed on the images. They found that texture and NDVI images were not helpful in defining selectively logged forest. The tendency was for logged forest to resemble secondary growth.

Nepstad *et al* (1999) report that estimates of annual deforestation for Brazilian Amazonia, where one-third of the world's tropical forests are found, capture only 60% of the total forest area that is impoverished by humans each year. The remaining 40%, they claim, is due to logging. They state that "binary approaches such as monitoring deforestation by using imagery from Landsat TM neglects those forest alterations that reduce tree cover but do not eliminate it, such as selective logging and surface fires in standing forests." They did not use satellite data to estimate the amount of selective logging. Nepstad *et al* (1999) estimated the area of Brazilian Amazonia forest that is impoverished each year through logging by interviewing 1,393 wood mill operators, representing more that half of the mills located in 75 logging centers. They obtained each mill's harvest records of roundwood (tree trunks) for 1996 and 1997 and the roundwood harvest rate (m^3 of timber per ha of forest). Using this information, they calculating the forest area required to supply each center's timber production.

They also estimated the area subjected to surface fire each year by interviewing 202 landholders in five regions along a 2,200 km transect through the states of Para, Mato Grosso, Rondonia, and Acre. They had the landholders draw onto satellite images the forest areas on their property that had been deforested and the forest areas that had burned by surface fire (without prior forest felling) in 1994 and 1995.

Nepstad *et al* (1999) estimate that 10,000-15,000 km^2 of undisturbed forest are logged each year (1996 and 1997) by 2,300 sawmills operating in Brazilian Amazonia. According to Nepstad *et al* (1999), selective logging in 1996 affected an area of forest that was three-fourths as large as the satellite-based estimate of annual deforestation from 1992-1994 and equal to the estimate for 1991 and 1992. Nepstad *et al* (1999) suggests that cryptic forest impoverishment through selective logging causes a significant release of carbon into the atmosphere that is not included in existing estimates of the Amazonian carbon balance. As a result, the Brazilian contribution to the increase in atmospheric CO_2 has been underestimated and its success in curbing the rate of Amazonia forest impoverishment has been overestimated.

Nepstad *et al* (1999) found that within properties surveyed for the fire study, the area of standing forest that was affected by surface fire in 1994 and 1995 (310 km^2) was 1.5 times greater than the area that was deforested in those years (210 km^2). They state, "Although extrapolation of this data set to the entire Amazon is not warranted, these data indicate that the area of Amazon forest affected by surface fire each year may be similar in scale to the area affected by deforestation."

In a detailed study of logging in a 32,520 hectare area near Paragominas, Souza and Barreto (1999) present a method for estimating selective logging. They used Landsat TM images (bands 1-5, and 7) of their study area (path222/row62) for June 1984, July 1991, and July 1996. They used a linear mixture model to identify spectrally pure pixels and estimate the soil, vegetation, and shade fractions within each pixel of their TM images. Soil exposure enabled explicit detection of logging patios.

After identifying logging patios, they used a buffer routine to estimate the total area affected by selective logging. During field calibration trials, they determined the buffer size from data collected in 82.5 hectares of unplanned logged forest. The total area logged was divided by the number of log landings (n = 10) to estimate the average area of forest within reach of a logging patio (8.25 ha). An average extraction radius of 162 m was calculated using these data. However, it was necessary to use a multiple of the Landsat TM pixel size (30 m) for the buffer routine, so a radius of 180 m was used in the final analysis. They found 2,089 ha in 1984; 2,585 ha in 1991; and 662 ha in 1996 of selective logging.

To assess the accuracy of estimates of the area affected by logging Souza and Barreto (1999) applied the methodology to the 82.5 hectare area of typical logged forest. Using the estimated 180 m radius of extraction and the number of log landings in the logged area they calculated that logging affected an area of 80.5 hectares, 97% of the actual area. The area identified as potentially being logged included 294 of the 326 (90%) trees actually extracted from the site.

In a recent and important study of fire degradation, Cochrane *et al* (1999) studied forest fire dynamics in the Amazon to understand the effects of this disturbance force. They did field studies in the Tailandia region using ten 0.5-ha plots (eight fire-affected and two control) distributed over 100 km^2. These sites were established in 1996 to study fire impacts on forest structure, biomass, and species composition. After the dry season of 1997, fire recurrence, tree mortality, and biomass combustion levels within forests of different burn histories were quantified.

Cochrane et al also examined characteristics of fires while they were occurring in four forest types (previously unburned, once-burned, twice-burned, and more than two previous burns) in December 1997. For each fire observed, they measured flame heights and depths. The time the fireline took to move across a known distance was used to calculate the rate of spread. Cochrane et al found that the first fire to enter a forest usually moves slowly along the ground and consumes little besides the dry leaf litter. In these first fires, 95% of trees >1cm dbh are killed because of their characteristically thin bark. Second fires are faster moving and much more intense because of increased flame depth. They found that large trees have little survival advantage against the second fire during these more intense fires.

Cochrane et al used satellite images from Landsat TM to conduct multitemporal analyses of fire in the Tailandia and Paragominas regions. They used a linear mixture model to separate forest from nonforest and to classify burned forests in all images, they then cross-tabulated these images, which provided a history of deforestation and forest burning throughout the study regions. They found that areas that are minimally forested because of the recurrence of fire are likely to appear deforested in satellite imagery analyses.

They also conducted a detailed study of deforestation in burned forests, using imagery of Paragominas for the period from 1993 to 1995 to test whether the deforestation that had burned in 1992 was intentional or accidentally induced by fire. In the Paragominas region, they estimated that accidental fire-induced deforestation increased deforestation estimates by 129% between 1993 and 1995. Cochrane et al state, "This surprising result implies that the basin-wide jump in estimated deforestation rates may have occurred largely because of the widespread forest fires of 1992 and 1993."

The purpose of this analysis was to develop a method, which would be used to detect selectively logged areas. This study had two steps: (1) developing a model that can be run on satellite images to detect cryptic deforestation; and (2) making a visual inspection of Landsat TM 1992 images and identifying selectively logged areas. The visual inspection identifies areas of canopy degradation around logging patios and these areas are then digitized. The primary objective of this analysis was to quantify the area in Brazil's Legal Amazon that was selectively logged in 1992 and add this estimate to the 1992 deforestation data for a total area deforested.

Chapter 2

Experimental Efforts to Develop Automated Methods for Detection of Logging and Degradation

Introduction

The purpose of this analysis was to develop a procedure to define the location and extent of cryptic logging and degradation in the Brazilian Amazon forest, in order to enhance previous and current deforestation estimates. The area of selective logging targeted for detection was the portion of the forest canopy where trees have been removed but the area has not been clear-cut. The selective logging process removes 4-20 trees per hectare and leaves behind a mixture of intact forest with treefall gaps, primary and secondary roads, and logging patios.

The first step before developing a method was to test the unsupervised classification technique used on Landsat TM images to derive the 1992 deforestation data. I tested the unsupervised classification on a Landsat TM scene that contained selective logging with 45, 50, 55, and 60 classes; in all cases cryptic logging and canopy degradation was clumped with forest. I was unsuccessful at defining a separate spectral class for selectively logged forest.

Verifying the findings of Stone and Lefebvre (1998). This is because selectively logged sites are composed of a combination of intact forest canopy, damaged canopy, secondary growth forest, understorey vegetation, and bare soil, all of which are spectrally similar to other classes in an unsupervised classification. In most cases the logging patios and roads were also clumped in with forest.

Image classification procedures group pixels into classes or categories based upon distinctive, multispectral patterns of digital numbers (DN) and are normally categorized as either supervised or unsupervised. A supervised classifier uses training data input by an analyst that are based upon prior knowledge of land-cover at selective locations. The unsupervised classification determines the classes by spectral distinctions inherent in the data. The 1992 deforestation GIS layer was generated from an unsupervised classification. This GIS has seven classes: forest, nonforest, cerrado, secondary growth, water, cloud, and cloud shadow.

Unsupervised classifiers do not depend on the input of a training data set. They generate classes based upon clustering the multispectral values into groups based upon similarity (Lillesand and Kiefer, 1994). Once the spatial clusters are generated, an analyst attempts to determine the nature of the clusters and provide labels.

All of the attempts I made to detect cryptic deforestation using automated methods were unsuccessful; however, I was successful at detecting the logging patios and incorporated this material into my study with a buffer routine (discussed in Chapter 3). I've listed below the methods attempted and a description of how they worked.

<u>Standard Deviation Focal Analysis</u>

In the visible part of the electromagnetic spectrum, the spectral pattern of vegetation is dominated by absorption in the blue (450-520 nm) and red (630-690 nm) bands and reflectance in the green (520-600 nm) band. The dominant pigments in plants are chlorophyll A and B, and light absorption is required by plants to support photosynthesis. In this analysis, I used TM band 3, the red band, of the visible spectrum region because of the absorption by vegetation.

Cryptic deforestation leaves behind an intact forest canopy, treefall gaps, damaged trees, patios, and logging roads. Forest leaf coverage is reduced allowing the sun to penetrate to the forest floor to dry out debris and allow secondary vegetation to grow. I hypothesized that because of these changes, the digital numbers (DN) of the pixels in the red band would have high variation in areas of cryptic deforestation. Areas of intact forest canopy would have low DNs because of high absorption, while areas of treefall gaps would have higher DNs because of lower absorption and higher reflectance. Also, damaged and dying trees would have higher DNs than the intact forest canopy. Logging patios and roads would have the highest DNs in areas of cryptic deforestation due to little or no vegetation.

Using the above information, the first automated model I tried was a standard deviation focal analysis to detect variation in areas of cryptic deforestation. Using subset, an ERDAS IMAGINE command which breaks out a portion of a large file into one or more smaller files, I extracted TM band 3 from the full data set. A standard deviation focal analysis was conducted on the resulting image using a 3x3-moving window. The focal standard deviation module returns the standard deviation of the pixel DNs in the focal window around each pixel of the image. The resulting image was re-scaled and then inserted as TM band 3 into the spectral subsets 4, 3, 2 of the image. Then an unsupervised classification was run on the image using 45 classes and 12 iterations. I then analyzed and labeled the spectral clusters and found that the resulting classification captured logging patios and roads that were not identified in the 1992 deforestation estimates as deforestation, but classified the areas around the logging roads and patios as forest. Therefore, cryptic deforestation was not detected.

This attempt was unsuccessful in detecting cryptic deforestation because variation in the DNs of the disturbed forest canopy were not large enough for a standard deviation focal analysis to detect. The logging roads and patios did have enough variation to be detected. This, although when incorporated with an unsupervised classification this model was able to detect more detailed land-uses and could be utilized for future small area studies. However, it should not be utilized for large area studies because it resulted in greater mixing of classes, requiring more editing time.

Slope Analysis

The second automated model I evaluated was a SLOPE analysis using the DN values of the pixels in the forest canopy. I used SLOPE to identify the rate of change of the DN value from pixel to pixel. Since cryptic deforestation is classed as forest in the 1992 deforestation estimate. I wanted to detect this in the forest canopy, I masked out all land cover in the image except forest. I hypothesized that since areas of cryptic deforestation are highly disturbed with treefall gaps, logging roads, and patios, the canopy in areas of cryptic deforestation would have higher slope percentages than the surrounding undisturbed forest.

As per the standard deviation focal analysis, I used TM band 3 in this analysis. I converted band 3 of the image to a grid and in GRID used the SLOPE command to identify the rate of change from each cell to its neighbors, with the result being a percentile. The SLOPE function in GRID fits a plane to the values of a 3x3 cell neighborhood around the center cell. The actual algorithm that GRID uses to calculate slope is:

rise_run = SQRT (SQR (dz / dx) + SQR (dz / dy)) degree_slope = ATAN(rise_run) * 57.29578

The resulting output file was converted to an image file for analysis. To differentiate the sloped pixel values I color-coded them into intervals of twenty, using the Selection Criteria in the Raster Attribute Editor of ERDAS IMAGINE. When viewing the color-coded result, I could not determine any spatial pattern to map out selective logging areas. I then reclassed the color code, trying intervals of 30, 40, 50, and 60. None of these efforts indicated any spatial pattern; therefore, this method was also unsuccessful in detecting cryptic deforestation.

NDVI

The normalized difference vegetation index (NDVI) was also evaluated. Characteristically, green plants strongly absorb visible electromagnetic radiation and strongly scatter near-infrared radiation (Curran, 1980). The NDVI was developed to emphasize the difference between the absorption in the visible and the reflectance in the infrared through mathematical processing of multi-spectral bands, such as ratioing and differencing (Wulder, 1998). The NDVI is a commonly used vegetation index, calculated from the red (R) portion of the visible spectrum and the near-infrared (NIR) radiance in the form of:

$$\mathbf{NDVI = (NIR - R)/(NIR + R)}$$

NDVI has been demonstrated to assist in compensation for changing illumination conditions, surface slopes, and viewing aspects (Avery and Berlin, 1992).

After running an NDVI analysis on the image, I ran a texture analysis. This texture analysis is discussed below. I then analyzed the pixel values and removed all undisturbed forest, by the DN value of the pixels. After removing all undisturbed forest the image was analyzed and I determined that this method was unsuccessful. Like the standard deviation analysis, however, it also detected logging patios and roads.

Texture Analysis

The last model I tried was a texture analysis on TM bands 2, 3, 4, and 5 of an image to determine if cryptic deforestation could be detected. A texture analysis can be used to segment an image and classify its segments, giving the image sharper edges. It generally indicates the spatial variation in neighboring pixel values; further the addition of texture to an image may add structural information that will aid in the detection of cryptic deforestation.

The first step in this analysis was to mask out all land cover in the image except forest using the 1992 deforestation data. The second step was to, using subset in ERDAS IMAGINE, separate out the TM bands. The analysis was then run on each TM band using a variance algorithm with a 3x3, 5x5 and 7x7 window. The algorithm is:

$$\text{Variance} = \frac{\Sigma(xij - M)^2}{n-1}$$

where:

xij = DN value of pixel (i,j)

n = number of pixels in a window

M = Mean of the moving window, where:

$$\textbf{Mean} = \frac{\Sigma x_{ij}}{n}$$

The areas of undisturbed forest were then subtracted from the image. This method was also unsuccessful. Again however, the logging roads and patios were classified as deforestation in TM bands 3, 4, 5 of the images tested; these were particularly evident in TM band 5.

Conclusion

Although canopy degradation due to selective logging is visible in the Landsat TM images, it cannot be detected with the any of the above methods. This concurs with the findings of Stone and Lefebvre (1998) who were also unsuccessful at detecting selective logging using automated methods. Although the above methods were unsuccessful at detecting selective logging three of the methods were able to detect logging roads and patios that were previously classified as forest in the 1992 deforestation data. This was especially evident in the texture analysis run on TM band 5. Therefore, I incorporated this method into my research with a buffer routine and a visual interpretation. This method is discussed in more detail in chapter 3.

Chapter 3

Methods Employed for Mapping Logging and Degradation

Rationale

The various attempts to detect cryptic deforestation using automated methods, discussed in Chapter 2 were unsuccessful. Therefore, I incorporated techniques I developed along with methods in previous studies to quantify selective logging in the Legal Amazon basin.

Souza and Barreto (1999) developed a method to detect logging patios based on their spectral characteristics and then used a buffer routine to quantify the area of selective logging in a region in the state of Para. By taking ground measurements in an area of logging, they estimated the radius of logging around a patio to be 180 m. I incorporated the texture analysis on TM band five from Chapter 2 into my study to detect the logging patios and used the 180 m radius to buffer the patios that were detected. This method quantified areas of cryptic logging.

Watrin and Rocha (1990) and Stone and Lefebvre (1998) used a visual interpretation to quantify an area of selective logging. Stone and Lefebvre quantified the area of logging for a study site in the state of Para. They visually identified areas of selective logging and manually digitized them on each image in their study. Logged forests were identified by the patterns made by primary and secondary timber access roads and truck loading areas or patios (Stone and Lefebvre, 1998). I incorporated this method into my study, but only digitized areas of selective logging with obvious canopy degradation. If areas of logging with visible patios and logging roads did not have obvious canopy degradation, they were not digitized but captured in the texture analysis on TM band five.

Data set

This study used Landsat 5 Thematic Mapper (TM) satellite images and the1992 Landsat Pathfinder Humid Tropical Inventory data set derived from these images by the project at Michigan State University (MSU), supported by the U.S. National Aeronautics and Space Administration (NASA). The Basic Science and Remote Sensing Initiative (BSRSI) in the Department of Geography provided the Landsat TM images for this study. As one of the leading institutions of the NASA Landsat Pathfinder Project, BSRSI has the largest non-governmental Landsat imagery archive of the tropics consisting of 4000 scenes. The entire satellite data set is referenced by geographic location as well as the Landsat World Reference System path/row footprint (WRS2). The WRS2 tile system provides an organized spatial structure for data acquisition, cataloging, processing, and overall data management.

The deforestation GIS layer was derived from more than 200 Landsat TM images covering the Legal Amazon. The imagery was classified into seven thematic classes: forest, deforestation, regrowth, cerrado, cloud, cloud shadow, and water. This was done using an unsupervised image classification procedure. Although selective logging is visible in Landsat TM images, no attempt was made to classify the areas of selective logging automatically and it was not included in the 1992 estimate of deforestation.

Data Preparation

The first step in my research was to examine the more than 200 Landsat TM scenes that encompassed the Legal Amazon Basin at a 1:60,000 scale to identify indicators of selective logging. I identified selective logging areas by first observing a logged area that has been verified in a study done by Uhl (191994) (Figure 3.1). I found thirty scenes that contained selective logging indicators and canopy degradation. The scenes that contained visible selective logging are found mainly in a crescent along the eastern and southern Legal Amazon. These are the scenes that the automated method to detect logging patios identified and on which manual digitizing was done (Figure 3.2) to get a quantification of selective logging in the Legal Amazon Basin.

I then had to rectify the thirty images using nearest-neighbor resampling with the four points derived from ephemera data. These points were supplied with the images at the time of ordering and does not take into consideration correct the image to < 500m of the true ground (Chomentowski, personal communication). This was tested at BSRSI by collecting GPS ground points in the Amazon and testing them on several TM images.

Automated Detection of Logging Patios

In this step of my research I used an automated model to detect logging patios in the forest canopy. The patios were detected using a texture analysis on band five of the TM images. However, so that areas of deforestation and other land-uses did not interfere in the analysis, I masked out all land-uses except forest, using the 1992 deforestation data set. After the patios were detected, a buffer routine was used on them to obtain a measurement of the logged area.

The first step was to convert band five of the image to a grid using export in ERDAS IMAGINE. The image may include several bands of information. Each band is a set of radiance values for a specific portion of the electromagnetic spectrum (red, green, blue, near-infrared, short wave infrared, thermal infrared, etc.) or some other user-defined information created by combining or enhancing the original bands from other sources (ERDAS FIELD GUIDE, 1997). A grid, like a coverage, describes the distribution of one or more spatial variables. A grid generally describes a single characteristic or theme, such as land-use, soils or elevation (ESRI, 1994). Unlike a coverage, which stores geographic information in terms of lines, points, and polygons, a grid divides space up into discrete units, called cells (ESRI, 1994). A cell has a value describing its characteristics, a size that determines the resolution of the grid, and a position or location defined by a row and column in the grid. The ERDAS image is converted to a GRID format in order to extend all of the GRID GIS software capabilities to the image. This provides access to the actual pixel values in the image.

I used band five because in this middle-infrared (mid-IR) TM band, bare soil has a pattern in which high digital number (DN) values are found. This is consistent with relatively high visible reflectance from mineral matter in low organic soils and very high mid-IR DNs in dry soils that have little water to depress mid-IR reflectance (Mausel *et al.*, 1993). In the mid-IR, leaf spectra are dominated by water absorption, giving the forest canopy smaller DNs than bare soil, which is dominated by reflectance. Therefore, the texture analysis is able to distinguish the difference between logging patios and forest using DN values.

The 1992 deforestation vector coverage was rasterized using the POLYGRID command in GRID. The POLYGRID command creates a grid from polygons in an ARC/INFO coverage. The 1992 deforestation grid was reclassified into a forest/non-forest map and used to mask the band 5-grid (Figure 3.3). This was done in order to find selective logging sites and ensure that logging areas already classified as deforestation in the 1992 data set were not incorporated into this study and accounted for twice.

The band five grid was converted back into an image and submitted to a texture analysis in order to detect logging patios. Texture analysis detects spatial variation in neighboring pixels. According to Pratt (1991), many image portions of natural scenes are devoid of sharp edges over large areas. In these areas, the scene can often be characterized as exhibiting a consistent structure analogous to the texture of cloth. Image texture measurements can be used to segment the image and then classify its segments. I used a variance algorithm with a 5x5 window.

The algorithm is:

$$\textbf{Variance} = \frac{\Sigma(xij - M)^2}{n-1}$$

where:

xij = DN value of pixel (i,j)

n = number of pixels in a window

M = Mean of the moving window, where:

$$\textbf{Mean} = \frac{\Sigma x\ ij}{n}$$

Both a 3x3 and a 7x7 window were also tested. The 3x3 window included too much noise, while the 7x7 window excluded too much texture. I then analyzed the texture image to determine the threshold pixel values of the forest for removal. A portion of the undisturbed forest was selected and the statistics were then calculated for that area. Many randomly selected areas of undisturbed forest were tested to find the maximum value for removal. The texture image was then converted to a grided data set using the export option in ERDAS. Using a GRID command, the forest was removed from the image, leaving detected logging patios (Figure 3.4). Figure 3.5 is an example of the same image in Figure 3.4 displayed with a color composite of 4, 3, 2, with visible logging patios for comparison. The detected logging patio image was then converted into a polygon coverage. This coverage was then edited to remove all noise but the detected patios. The image with bands displayed at 4, 3, 2, was used to aid in the editing.

After identifying logging patios, I used a "buffer" routine to estimate the potential forest area affected by selective logging. In the case of Paragominas, studies within a section of logged forest indicated an average extraction radius of 180m (Souza and Barreto, 1999). Because this is the only basin-wide detection of selective logging, the 180 m buffer was utilized for the entire basin. Figure 3.6 is an example of buffered logging patios.

Digitizing Maps

In this step of my study I relied on visual interpretation at a scale of 1:60,000 to identify the location and extent of selective logging from the 1992 images. These areas were verified and digitized manually on each image at a scale of 1:30,000. The areas were generally found in or around areas of high land-use change and were identified by the characteristic logging patios and logging roads along with obvious canopy disturbance around the areas. Logged areas leave a characteristic pattern of white points, which are the log landings or patios, embedded in the red hues of the forest canopy. In the areas around the patios canopy degradation may be evident and, if so, was digitized. As stated earlier in this study, I will refer to the digitized areas as the areas of canopy degradation because these areas not only include selective logging, which is a precursor to fire, but also selective logging areas that have been burned. These burned areas may go beyond the area of selective logging but are also considered deforestation and result from selective logging.

After identifying areas of logging, I digitized these areas into vector GIS layers using ERDAS IMAGINE. The digitizing was done on the very edge of canopy disturbance. I separated the logging areas into two separate vector coverages obvious logging and subtle logging. Obvious selective logging includes spectrally bright patios, roads, and obvious canopy disturbance (Figure 3.7). Subtle logging refers to areas in and around highly logged areas that exhibit obvious canopy disturbance and faded patios and roads, or no patios and roads (Figure 3.8). Logging patios that did not have canopy disturbance were not digitized but were captured in the first step of this research. Because of the 10% overlap of the satellite sensor, some areas of selective logging were in more then one scene, so digitizing was done along with adjacent scenes so that logging areas would not be counted twice.

These areas were digitized on the computer screen with the polygons registered to the Universal Transverse Mercator (UTM) raster coordinates of the images. Each x-y coordinate of the polygons digitized was recorded (Table 3.1).

Chapter 4

Results

Analysis of Total Logging Detected in 1992 Landsat TM Images

Thirty Landsat TM scenes with less than 20% cloud cover found to contain selective logging were used to detect selective logging using an automated model following Souza and Barreto (1999). These thirty scenes represent 20% (~1,015,399 km²) of the area of the Legal Amazon and 64% (151,127 km²) of the deforestation. The analysis for the 1992 deforestation estimate showed that 67% (~3,351,158 km²) of the Legal Amazon was identified as forest and 5% (~237,664 km²) was identified as deforestation due to agriculture.

Using the TM band five-texture analysis on the masked images and incorporating Souza and Barreto's (1999) 180 m radius, I found 1834.001 km² of cryptic logging that was not detected as deforestation in the 1992 deforestation estimate (Table 4.1). In order to verify that this estimate did not include areas previously counted in the 1992 deforestation estimate, I took the 1992 deforestation data and the 1992 cryptic logging found in the analysis with ARC/INFO intersect computes the geometric overlay of two coverages, but only those features common to both coverages will be preserved in the output coverage (ARC/INFO, 1994). For the 1992 logging, I found that 26.863 km² was already included in the

1992 deforestation estimate as different classes (deforestation, cerrado, secondary growth, water, cloud, cloud shadow). I subsequently subtracted 26.863 km^2 from the amount of logging, giving the total cryptic deforestation found of 1834.001 km^2. Of the 26.863 km^2, 9.55 km^2 is deforestation as agriculture in the 1992 estimate (Table 4.1).

Analysis of Canopy Degradation Digitized in 1992 Landsat TM Images

The same 30 scenes I used above were interpreted for canopy degradation by means of visual analysis. As discussed in Chapter 3, I digitized canopy degradation into obvious logging and subtle logging. The amount of canopy degradation by obvious logging is 3349.616 km^2 (Figure 4.1) while the amount of canopy degradation due to subtle logging is 1269.359 km^2 (Figure 4.2). The total digitized canopy degradation area for the Legal Amazon Basin is 4618.984 km^2 (Figure 4.3). Figure 4.4 shows that canopy degradation due to obvious logging is much greater than that due to subtle logging.

In order to verify that this estimate did not include areas that had been counted in the 1992 deforestation estimate, the same procedure as discussed above was used. The 1992 deforestation data and the 1992 canopy degradation estimate found in the analysis were intersected in ARC/INFO. I found that 393.724 km^2 of obvious logging was already included in the 1992 deforestation estimate as different classes (deforestation, cerrado, secondary growth, water, cloud, cloud shadow). I thus subtracted 393.724 km^2 from the amount of obvious logging to get the total, 3349.616 km². Of that overlap, 214.464 km² is deforestation as agriculture in the 1992 estimate (Table 4.1). I found that 82.844 km² of subtle logging is already included in the 1992 deforestation estimate as different classes (deforestation, cerrado, secondary growth, water, cloud, cloud shadow). I thus subtracted 82.844 km² from the amount of subtle logging to get the total 1269.359 km². Of that overlap, 43.766 km² was deforestation as agriculture in the 1992 estimate (Table 4.1).

Analysis of Logging and Canopy Degradation in 1992 Landsat TM Images

I combined the above two analyses, cryptic logging and total canopy degradation (obvious logging + subtle logging) to estimate how much selective logging was missed in the 1992 deforestation estimate (Figure 4.5). In ARC/INFO I used the union command, which computes the geometric overlay of two polygon coverages but all polygons from both coverages will be split at there intersections and preserved in the output coverage (ARC/INFO, 1994). After combining cryptic logging and canopy degradation, and accounting for the overlap in the 1992 deforestation estimate with the intersection command, the total deforestation missed in the 1992 estimate of deforestation was 5308.906 km² (Table 4.1). Because the texture analysis on TM band five detects logging patios, some logging patios that were digitized into the canopy degradation layers were also detected. This means that part of the total logging estimate of 1834.001 km² is also included in the canopy degradation estimate of 4618.964 km². The union command accounted for this.

Using the data from the 1986 and the 1992 deforestation data supplied by BSRSI, I estimated the rate of deforestation to be ~18,000 $km^2 y^{-1}$. In Stone and Lefebvre (1998) study, they found that areas of selective logging and surface fires are visible in Landsat TM images but are covered over by regrowing vegetation within one to five years. They found that logging sites in a 1988 Landsat TM image were not visible in the same 1991 Landsat TM image. If I assume that the amount of selective logging found in 1992 was the result of two years of logging activity, then the new rate of deforestation is ~20,655 $km^2 y^{-1}$ with selective logging accounting for ~13% of this rate.

Comparison of 1991 and 1997 Landsat TM

In this study, I compared selective logging on the 1991 and 1997 Landsat TM images for path 226 row 63. I used this scene because of data availability. I found that in 1991 there was 5.187 km^2 of selective logging, and in 1997 there was a total of 81.589 km^2 of selective logging. In 1997, cryptic logging accounted for 17.514 km^2 and total canopy degradation accounted for 74.275 km^2 of the overall total. The 1997 Landsat TM image had 20% cloud cover; therefore, logging could be even greater. I found no spatial overlap when comparing the logging areas from 1991 and 1997. Those areas that were selectively logged in 1991 were not selectively logged in 1997. Also, there were no apparent visual clues in the 1997 imagery indicating the logging sites in 1991. The area selectively logged in 1991 was classified as forest in 1997. Selective logging in 1997 was more widely distributed geographically then it was in 1991. In the six-year comparison, logging increased 16-fold.

Analysis of Basin-wide Verification

To verify that all selective logging in the Legal Amazon was captured, I took a random 5% sample of the images where selective logging was not found. This encompassed 103 images in the western Legal Amazon; five of these images were selected for the verification. Images in eastern Amazon that did not include logging were not used in this verification because the dominant land-cover is cerrado. I ran the automated model on these images to detect logging patios and did a visual analysis to digitize areas of canopy degradation. I did not detect any logging patios in the scenes sampled; in two of the scenes, however, I found a small area of canopy degradation with logging indicators. I digitized these areas and found that 1.08 km^2 was missed in path 231 row 67 and 7.581 km^2 was missed in path 225 row 65. This equals 8.661 km^2 that was missed in my estimate of selective logging. Using this estimate of logging missed, I calculated that using the methods in this study, I captured 99.8% of visible selective logging for 1992.

Analysis of Accuracy Assessment of Logging Patios

I conducted an accuracy assessment on the automated model for detecting logging patios by dividing the 30 images in this study into four regions of logging (Figure 4.7). I used the extent of logging to define the regions and then took a random sample from each region. Two of the regions were regions of high logging and two were of low logging. Image path 226 row 63 and image path 002 row 67 were not included in the random sample. I took the random scene from each region (four scenes) and in ARC/INFO built a grid over the image with 18,000 km^2 by 18,000 km^2 cells. The grid cells were numbered starting with 1, and a random 5% sample was taken from the grid cells for each of the four images. I opened the grid over the images and counted all of the patios within the grid specified in the random sample. I then overlaid the detected logging patio coverage and counted how many patios were detected to get a percent accuracy.

The four scenes used in this analysis were path 222 row 63, path 223 row 64, path 226 row 68, and path 230 row 68. In scene path 222 row 63, four cells were analyzed. Only one cell contained logging patios. In this cell I counted one patio and the analysis captured 1 patio. In scene path 223 row 64, four cells were also analyzed. Only one cell contained logging patios, 17 were counted and 16 were captured. In scene 226 row 68, five cells were analyzed. Two of the cells contained logging patios; in the first cell, nine were counted and five were captured; in the second cell, 27 were counted and 24 were captured. In scene

230 row 68, four cells were analyzed. Only one cell contained logging patios, two were counted and one was captured. These analyses show that 84% of the logging patios detected were captured in the TM band five-texture analysis.

In this analysis, when counting logging patios, I counted all patios that were visible. Some of the logging patios that were counted were not highly visible and were within areas of canopy degradation where the texture analysis did not detect them. To verify that these areas were included in the estimate of selective logging, I overlaid the canopy degradation layers onto the images. So although this analysis shows that only 84% of the logging patios were detected, some of the patios that were excluded were quantified in the digitizing of canopy degradation.

Chapter 5

Discussion

The integration of remote sensing and GIS information has provided important insights regarding selective logging in the Legal Amazon Basin for 1992. I have found that although selective logging is difficult to capture using an automated method, it is possible to quantify selective logging using a visual interpretation combined with an automated detection of logging patios. An important issue was quantified in this study: the extent of selective logging in the Legal Amazon Basin. Results at the basin level show that ~13% of the rate of deforestation from 1986 to 1992 is due to selective logging.

In the 30 Landsat TM scenes where selective logging is found, 19% (~649,499 km^2) of the area is forest and 64% (~151,127 km^2) of the area is deforestation due to agriculture. This indicates that selective logging occurs within a proximity of high deforestation. Furthermore, while doing the visual inspection of the Landsat TM images it is evident that the process of selective logging is only occurring in areas of urbanization.

The rate logging identified in this study as ~2655 km^2 yr^{-1} varies significantly from the Nepstad et al (1999) study where it is estimated that 10,000 to 15,000 km^2

yr^{-1} of forest logging is not included in deforestation mapping programs. It also varies, although not as significantly, from a study done by Uhl and Holdsworth where they cite from IMAZON (Instituto do Homen e Meio Ambiente da Amazonia) an estimate that ~8,000 km^2 yr^{-1} is selectively logged.

The difference in logging estimates 2,655 km^2 yr^{-1} verses 15,000 km^2 yr^{-1} respected from my study and the Nepstad *et al* (1999) study may differ for several reasons. The first is that the Nepstad *et al* (1999) estimate is based on interviews of 1,393 wood mills operating in the Brazilian Amazon and did not use direct observation satellite imagery. The second reason may be because the Nepstad et al estimate is for 1996 and 1997, while my study was done on 1992 Landsat TM imagery and logging rates may have increased. As my analysis on the 1991 and the 1997 Landsat TM image comparison shows, selective logging in one image increased by 16-fold in six years. Nonetheless, this may be an isolated incidence and further investigation in other areas may have a different result. Souza and Barreto (1999) found in their study area that selective logging in 1984 was estimated at 2,089 ha and, in 1996, at 662 ha. The study area Souza and Barreto used has been selectively logged since the early 1980s this fact may help explain the low level of logging activity detected in 1996. If this is an accurate explanation of the decrease in selective logging for their area, then the Nepstad *et al* (1999) study estimate of selective logging at 10,000 to 15,000 km^2 yr^{-1} for 1996 and 1997 may be an overestimate of selective logging.

Using my data and the data available from the study done by Nepstad *et al* (1999) I conducted a sensitivity analysis. Using my data I considered the possibility that logging encompasses a larger radius extraction around a patio then 180 m. To test this assumption, I doubled the extraction radius to 360 m, thereby calculating cryptic logging for a larger area.

The area captured using a buffer radius of 360 m is 7336 km^2. It is not likely that this estimate is higher because the overlap of buffers, and other land classes, that would decrease this value are not figured into this estimate. Adding this estimate to the area of canopy degradation is 10,811 km^2. With the assumption that selective logging is visible for two years the rate of selective logging is ~5,406 $km^2\ yr^{-1}$. Thus the rate of selective logging per year based on satellite data might range from ~2,655 to ~5,406 $km^2\ yr^{-1}$ (Table 5.1).

Table 5.1: Sensitivity analysis calculating a possible lower bound annual logging rates for Nepstad et al (1999) data and upper bound estimate for the data in this study.

Nepstad *et al* (1999)			**This Study**				
Date	Reported Estimate Km^2	Based on High Intensity	Total Canopy Degradation	180 m Radius Buffer	Total	360 m Radius Buffer	Total
1992	______	______	1,737 $Km^2\ yr^{-1}$	917 $Km^2\ yr^{-1}$	2,655 $Km^2\ yr^{-1}$	3,668 $Km^2\ yr^{-1}$	5,406 $Km^2\ yr^{-1}$
96/97	10,000-15,000	6,177 Km^2	______	______	______	______	______

The data used in the Nepstad *et al* (1999) study calculated the selective logging rate by determining the log production (m^3) in the logging centers. Their estimate was calculated using a range of logging intensities, most of which were high intensity logging (low-intensity, 19(14-24); moderate intensity, 28(24-32) m^3 ha^{-1}; high intensity, 40(35-45) m^3 ha^{-1}). I calculated a high intensity logging estimate on roundwood production with their data to determine the rate if it was calculated with high intensity logging; using their estimate of 45 m^3 ha^{-1} for volume per area.

Table 5.2: Calculation of a lower bound estimate of the Nepstad et al (1999) data.

	Roundwood Production (10^6 m^3)	Low Logging Intensity %	Med. Logging Intensit y %	High Logging Intensity %	Logging 96-97 (km^2yr^{-1})	Assuming 100% Intensity 45 m^3ha yr^{-1}
Total	27.8	49	41	10	9,730-15,090	6,117 km^2

Thus if we assume that all logging is closer to the high intensity logging this calculation gives a possible lower rate of 6,117 km^2 y^{-1} (Table 5.2). Taking into account my upper bound estimate of 5,406 km^2 y^{-1} there is not much difference in the two estimates. If we also consider the state of Rondonia, where in this study selective logging was not identified whereas, Nepstad et al (1999) estimates between 1,320-1,920 km^2 y^{-1} logged in 1996 and 1997 in Rondonia. Subtraction of the Rondonia estimate from the lower bound estimate of the Nepstad *et al (1999)* study is 4,497 km^2 y^{-1}, which is lower than the upper bound estimate in this study. Indicating that the Nepstad *et al* (1999) study did not consider the possibility of counting areas already included in deforestation mapping programs. For instance, in many cases ranchers allow logging on their property before they themselves clear-cut the land for pasture. These instances are included in deforestation estimates. This further indicates that the estimate by Nepstad *et al* (1999) is an overestimation.

The logging estimate in the study done by Uhl and Holdsworth's (1997) paper does not state what year or years it's estimate represents. IMAZON's estimate is ~8000 km^2 yr^{-1}. The different estimates show the varying results in this area of concern. It is unknown if any of the above estimates are credible numbers.
My study is by no means an overestimate of selective logging, but a significant indicator that selective logging is evident in Landsat TM imagery and that a large portion of it can be captured as deforestation. More work needs to be done to capture cryptic deforestation.

Areas of new logging may be easy to identify in Landsat TM imagery and captured in this study, but as secondary growth fills in logging roads and patios, the logging sites become cryptic and harder to identify in satellite imagery. If areas of cryptic deforestation cannot be identified, then there is no way of knowing how much logging was not accounted for as deforestation. Some cryptic deforestation may not be visible in Landsat TM imagery; however, because of the degradation of the forest, the loss of biodiversity and the increased susceptibility to fire and carbon release into the atmosphere, the areas that have been missed should be considered deforestation. Also, small logging sites are excluded from this study due to the resolution of Landsat TM data (30 m), i.e., they cannot be visually identified.

In the study conducted by Stone and Lefebvre (1998), Lefebvre visited the sites of selective logging, found in their study in Landsat TM images, several years after logging to verify their classification. He found that the intensity of selective logging varied greatly, and the extent of damage to the forest was also highly variable. It was evident that soil compaction by heavy machinery impeded the establishment of new vegetation in roads and patios for several years following harvest. At one site in their study identified as logged, he found that former access roads still had no trees and little other vegetation rooting in the densely packed soil several years after it had been harvested. However, he found that the surface of the ground was covered with vines and other creeping growth that hid the soil from the satellite. From the ground, Lefebvre identified that dramatic changes in the forest canopy were still evident five years after logging; those trees not logged exhibited some canopy expansion, while fast-growing disturbance-following species (e.g. *Cecropia spp.*), together with vines and understorey growth, combined to form a multilayered and closed canopy. A view of this altered forest canopy from a satellite image would be composed of mixed pixels of partially shaded but vigorously growing vegetation interspersed with the occasional large canopy of a remaining broadleaf tree. The spectral mixture of partially shaded vigorous growth with the texture provided by these emergent, residual trees, makes distinguishing this from an unlogged forest very difficult using satellite data (Stone and Lefebvre, 1998). Lefebvre found that when viewed on the ground, there was no mistaking a logged forest from an unlogged forest.

Automated Detection of Logging Patios

Logging patios can be identified in Landsat TM images. The vicinity around these patios is where selective logging occurs, within 180 m in the state of Para according to the study done by Baretto and Souza (1999). The reason I used an automated model to detect logging patios was so I could quantify the area around the patios to obtain an estimate of selective logging. Although Souza and Barreto (1999) determined the size of the buffer on only 82.5 hectares it was incorporated basin-wide. While visually inspecting the Landsat TM images it was evident that logging patios generally occur in symmetrical patterns and if the size of the buffer was increased, as in the sensitivity analysis, a considerable amount of overlap would occur between buffer zones. Also, as shown in the sensitivity analysis even if the buffer was increased in size the selective logging estimate for 1992 would not be as high as current estimates found in studies such as Nepstad *et al* (1999). In future research it would be beneficial to further test the accuracy of the 180 m buffer, such as measuring the distance between patios to determine the spatial variability.

Some patios in Landsat TM images have evident canopy degradation around them while others do not. I used the automated model to capture areas of logging that were not evident with canopy degradation to capture the whole of logging impacts I digitized in the areas of degradation.

Legal Amazon Basin Digitizing Maps

Areas identified as obvious logging may be areas of recent logging. These areas have highly visible patios, and the canopy disturbance is identified as lighter shades of red and darker shades of gray. Areas identified as subtle logging may be areas of older logging that burned. These areas had either faded patios or no patios, and the canopy disturbance is identified by shades of gray in contrast to the surrounding undisturbed forest. Secondary roads and patios are clearly discernible in some of these areas.

I was very conservative in my digitizing; consequently, the digitizing of the logged areas may underestimate the selective logging. I digitized the logged areas right on the perimeter of where canopy disturbance was identified. In areas where the canopy disturbance was vast over large distances, I could not determine the edge of logging; therefore, digitizing was done as close to the logging patios and roads as possible. These areas may have been areas of a different terrain or forest type, possibly even areas of large fire disturbances. If primary and secondary roads and logging patios were not evident in the areas of canopy degradation, it was difficult to determine if they were logged areas. If these areas occurred where there was not evident logging, then they were not included in this estimate. This shows that there will be oversights in any large-scale inventory of selective logging in the Legal Amazon Basin using satellite imagery.

Considerations about the accuracy of the method

During this research project, remote sensing and geographic information systems were combined to provide a quantified estimate of selective logging. I considered three potential problems with the accuracy of this methodology: logging patio detection, selective logging digitizing, and total area affected by logging.

There were two effects that I considered in the detection of logging patios: (1) vegetation recovery and (2) topography. Regrowing vegetation in logging patios quickly covers the bare soil making detection of the patios more difficult with time. In areas of high topography, logging patios may not be detected using a texture analysis because they will be camouflaged by the topography. Visual interpretation is difficult for defining the limits between logged and unlogged forest because disturbance in the forest canopy must be visible, and delineation is considered subjective because it is interpreter dependent.

This methodology is conservative and is expected to be an underestimate of the area affected by selective logging.

Chapter 6

Conclusion

The objective of this research was to conduct the first basin-wide study to quantify the amount of selective logging in the Legal Amazon Basin for 1992 using Landsat TM images. Selective logging is a recent trend, which has researchers concerned. It may have irreversible influences on ecological systems, biodiversity, and carbon release into the atmosphere. This trend, is, in fact, so recent, that to conduct this research I had to rely on manuscripts in review.

I quantified the amount of selective logging in the Legal Amazon Basin using automated model to detect logging patios and by digitizing in selective logging with obvious canopy degradation. This estimate was then included in the deforestation rate from 1986-1992 for a rate of ~20,655 km^2y^{-1}, with selective logging accounting for ~13% of the deforestation rate in the Legal Amazon Basin.

Since selective logging is difficult to detect and regrowth covers the ground in one to five years, the estimate found in this study should be considered conservative. This estimate is a starting point for future studies that need to be conducted to automate the detection of cryptic deforestation. I have shown that selective logging is difficult to detect using statistical classification techniques but can be quantified using visual interpretation techniques; visual interpretation, however, is a time-consuming undertaking, especially for large areas. Furthermore, visual interpretation is difficult for defining the limits between logged and unlogged forest since disturbance in forest canopy must be visible and delineation is considered subjective because it is interpreter dependent. Further research in this area is important. Integrating this study with high-resolution satellite information, such as IKONOS with 1 m resolution, would add to the accuracy of estimating logging. Including ground verification using a Global Positioning System (GPS) to reference ground points in satellite imagery would also increase accuracy. Although the methods used in this study are time-consuming it would be beneficial to do this analysis of the 1996 Landsat TM data, to help researchers understand the trend of selective logging, and its impacts on carbon release, forest biomass, hydrology, biodiversity, and sustainable development.

The need to monitor selective logging is immense, and integrating remote sensing and GIS is a useful scientific method for monitoring selective logging and land cover change on a region-wide level. I am hopeful that this research will provide some insight into the detection of selective logging and will help advance future research related to this important issue.

Figure 1.1: This is a map of Brazil's Legal Amazon. This study area is an administrative area within the country of Brazil that includes $5x10^6$ km^2 of the nine states of Acre, Amapa, Amazonas, Para, Rondonia, Roraima, plus parts of Mato Grosso, Maranhao, and Tocantins.

This study area is an
cludes $5x10^6$ km² of
ndonia, Roraima,

Figure 1.1

Figure 1.2: Landsat TM color composite image of Para, Brazil, for path 222 and row 63, acquired on 24 July 1991. Areas of tropical forest, deforestation, regrowth, logging patios, and canopy degradation.

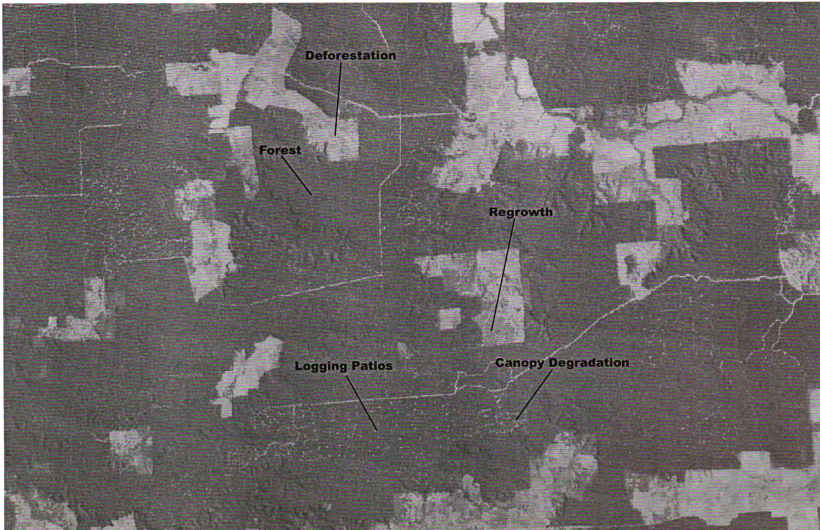


Figure 1.2

Selective Logging in Para, Brazil 1991

Scale = 1:334,000

Figure 1.3: This image is a close-up view of figure 1.2, showing an example of cryptic logging and obvious canopy degradation.

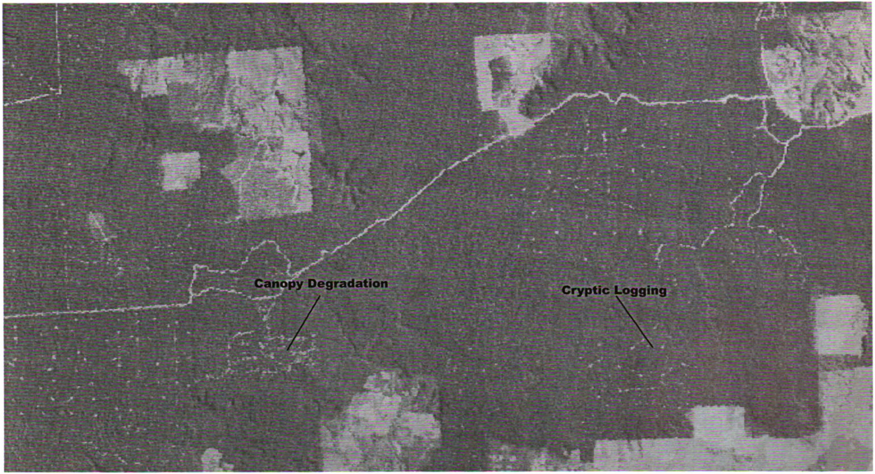


Figure 1.3

Scale = 1:170,000

Selective Logging in Para, Brazil 1991

6 3 0 6
Kilometers

Figure 3.1: Landsat TM color composite image of southern Para state, Brazil, for path 223 and row 65 acquired on 6 June 1993. A selective logging area of Mahogany that Christopher Uhl (199) used as a study site.

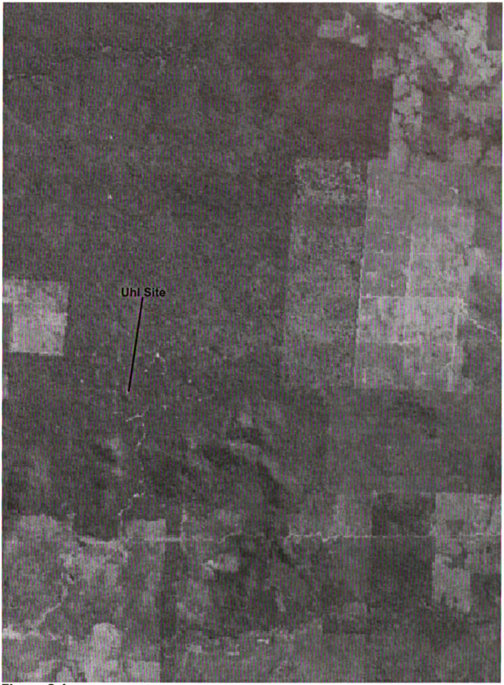


Figure 3.1

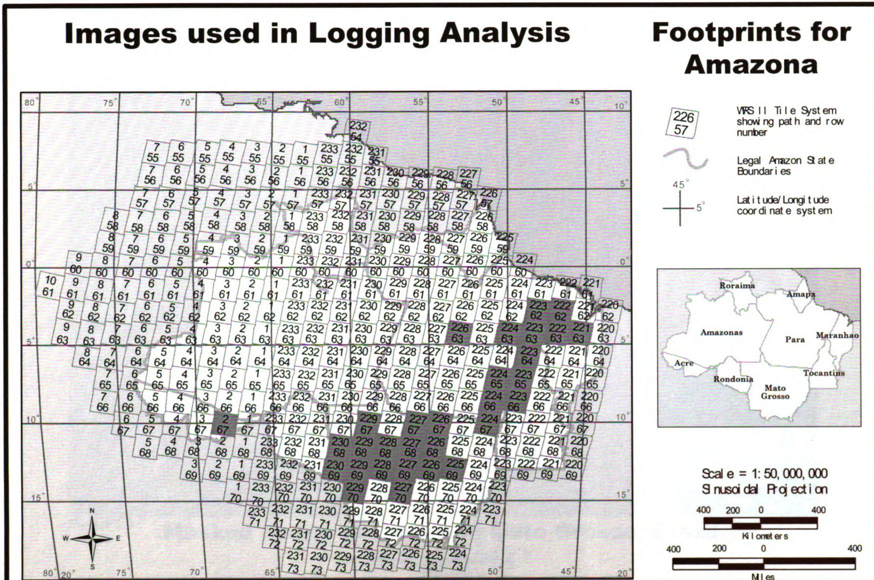
Christopher Uhl Study Site in Para, Brazil 1993

Scale = 1:118,000

2.6 1.3 0 2.6

Kilometers

Figure 3.2: The thirty images that contain visible selective logging and were used in the logging analysis. These images are highlighted in gray and found in a crescent along the eastern and southern Legal Amazon.



Images used in Logging Analysis
Footprints for Amazona
226 57
WRS II Tile System showing path and row number
Legal Amazon State Boundaries
45°
5°
Latitude/Longitude coordinate system
Roraima
Amapa
Amazonas
Para
Maranhao
Acre
Rondonia
Tocantins
Mato Grosso
Scale = 1: 50,000,000
Sinusoidal Projection
400 200 0 400
Kilometers
400 200 0 400
Miles
N
W
E
S

Figure 3.2

Figure 3.3: Band five of a Landsat TM image in the state of Mato Grosso, Brazil, for path 227 and row 69, acquired on 5 July 1992. All land cover but forest has been masked out of the image.

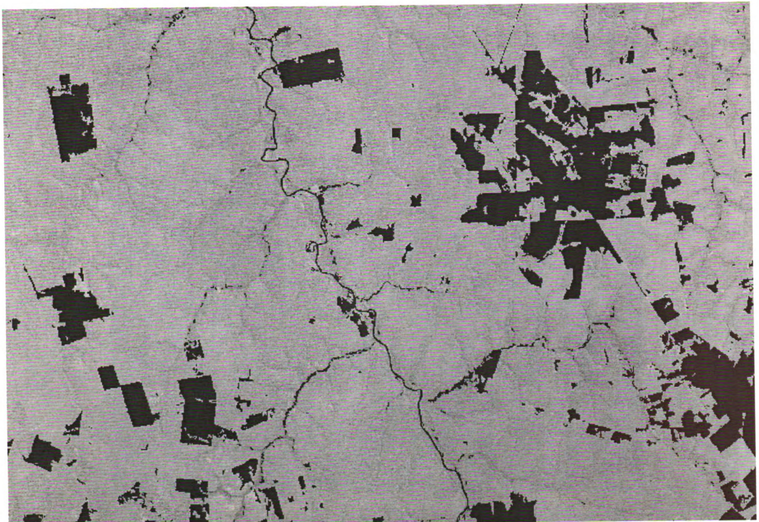


Figure 3.3 **Masked Image of Band 5 in Mato Grosso, Brazil**

12.8 6.4 0 12.8

Kilometers

Figure 3.4: An example of logging patios that were detected using the texture analysis on band five of a Landsat TM image. Mato Grosso, Brazil, 19 May 1992.

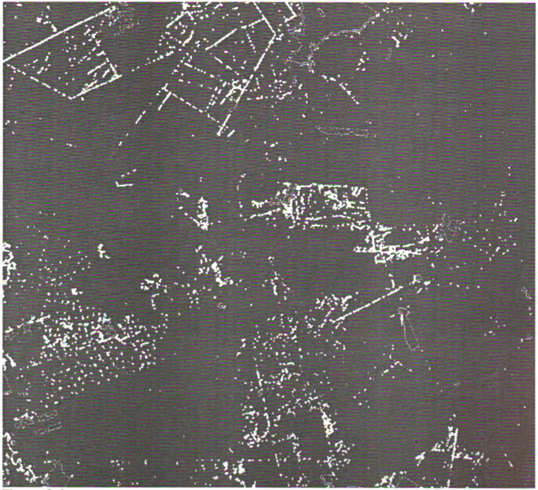


Figure 3.4

Logging Patios Detected Using Automated Model in Mato Grosso, Brazil 1992

6.8 3.4 0 6.8

Kilometers

Scale = 1:388,000

Figure 3.5: Landsat TM color composite image of Mato Grosso state, Brazil, for path 226 and row 69 acquired on 19 May 1992. This image is the same image as in figure 3.5 showing the visible logging patios that were detected using the automated method.

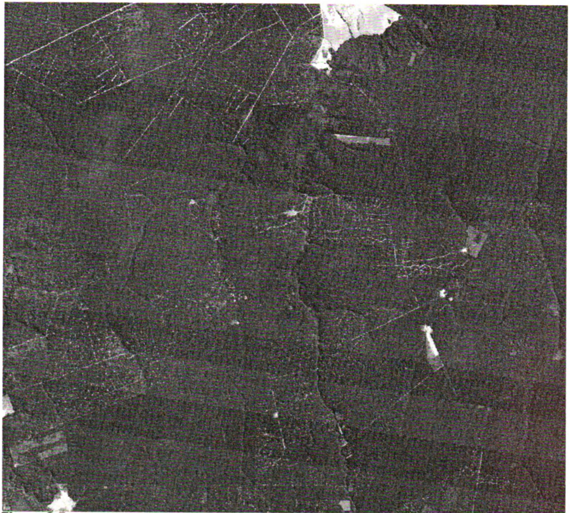


Figure 3.5
Visible Canopy Degradation and Logging Patios in Mato Grosso, Brazil 1992

Scale = 1:388,000

Figure 3.6: Landsat TM color composite image of Mato Grosso state, Brazil, for path 226 and row 69 acquired on 19 May 1992. Logging patios that have been detected with the automated method and buffered using the 180m buffer specified by Souza and Barreto (1999).

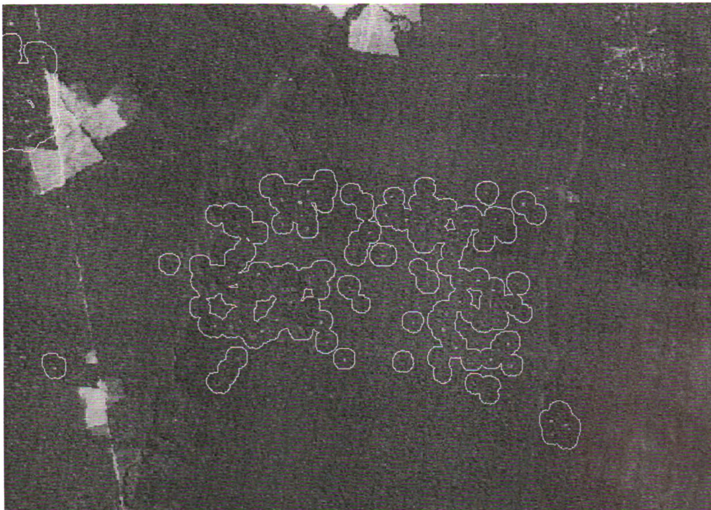


Figure 3.6

Logging Patios Buffered with 180m in Mato Grosso, Brazil 1992

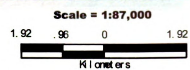


Figure 3.7: Landsat TM color composite image of Mato Grosso state, Brazil, for path 226 and row 69 acquired on 19 May 1992. Areas of obvious selective logging that have been digitized.

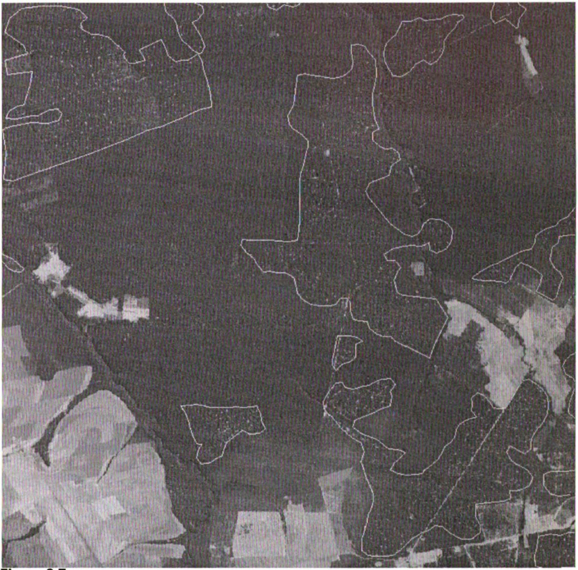


Figure 3.7

Obvious Logging in Mato Grosso, Brazil 1992

Scale = 1:173,900

3.86 1.93 0 3.86

Kilometers

Figure 3.8: Landsat TM color composite image of Para state, Brazil, for path 222 and row 62 acquired on 24 July 1991. Areas of subtle selective logging that have been digitized.

Figure 3.8
Canopy Degradation Layer B in Para, Brazil 1992

4 2 5 0 4
Kilometers
Scale = 1:184,000

Table 3.1: x-y raster coordinates for each polygon that was digitized around areas of selective logging. x-y coordinates for row A is obvious logging polygons. x-y coordinates for row B is subtle logging polygons.

Table 3.1					
IMAGES	**x-coordinates**	**y-coordinates**		**x-coordinates**	**y-coordinates**
Zone 23					
t2210630711922r.img					
t221063A	391,470	9,514,197	**t221063B**	388,675	9,515,297
	382,280	9,507,978		387,165	9,514,625
	370,983	9,504,268		385,167	9,511,646
	371,402	9,494,012		376,220	9,510,454
	362,052	9,490,831		377,999	9,504,545
	359,618	9,495,237		370,194	9,502,858
	360,819	9,494,154		360,835	9,477,184
	370,479	9,486,290		401,336	9,516,324
	375,632	9,485,686			
	372,644	9,483,193			
	389,959	9,486,735			
	378,546	9,505,775			
Zone 19					
t0020670830922r.img					
t002067A	615,373	8,919,463	**t002067B**	645,674	8,922,841
	614,328	8,916,779		631,903	8,914,480
	633,088	8,850,559		631,631	8,913,267
Zone 21					
t227067080692r.img					
t227067A	649,879	8,880,748			
	642,134	8,875,573			
	655,103	8,852,917			
	657,816	8,854,147			
Zone 21					
t226068051992r.img					
t226068A	682,940	8,784,744	**t226068B**	742,430	8,771,264
	716,952	8,781,605		740,689	8,769,438
	715,597	8,779,779		701,469	8,773,443
	743,162	8,779,501		672,431	8,754,447
	790,199	8,769,631		769,230	8,756,656
	762,701	8,767,301		778,873	8,753,417
	749,482	8,775,614		775,903	8,750,354
	752,906	8,775,084		784,839	8,752,188
	745,914	8,768,596		659,492	8,637,444
	732,131	8,765,937		664,570	8,636,957
	668,653	8,771,743		673,331	8,643,973
	663,562	8,767,999		668,883	8,635,396
	665,304	8,768,386		677,879	8,636,000
	670,975	8,756,867		708,301	8,632,266
	681,880	8,757,212		715,812	8,639,542
	690,101	8,756,841		717,650	8,630,361
	703,960	8,758,087		721,292	8,627,541
	713,897	8,760,544		727,032	8,627,063
	715,412	8,753,745		734,501	8,628,002
	741,968	8,764,583		736,960	8,629,001
	760,673	8,761,478		742,222	8,628,858
	795,646	8,617,865		758,074	8,629,446
	663,437	8,645,466		754,659	8,627,794
	659,610	8,642,806		752,611	8,628,875
	671,476	8,646,096		752,510	8,631,091
	686,758	8,632,417		752,678	8,640,305

	702,275	8,633,055		756,077	8,638,845
	727,183	8,632,031		730,372	8,635,354
	729,231	8,632,551		663,084	8,650,879
	739,435	8,626,400		694,017	8,646,860
	739,041	8,631,301		717,750	8,649,562
	744,102	8,629,119		776,755	8,647,539
	743,548	8,632,652		771,015	8,642,294
	738,135	8,637,125		804,533	8,677,910
	751,067	8,636,554		746,678	8,669,107
	747,727	8,638,845		750,740	8,677,994
	749,900	8,632,835		721,820	8,673,513
	756,195	8,629,018		724,061	8,674,878
	769,311	8,653,254		712,648	8,673,437
	795,637	8,663,577		712,279	8,679,253
	774,514	8,677,852		714,998	8,679,387
	771,846	8,678,825		708,234	8,662,628
	768,984	8,676,710		705,221	8,658,189
	763,437	8,677,482		684,325	8,666,035
	765,644	8,678,011		696,569	8,680,161
	743,044	8,677,659		695,948	8,679,522
	709,853	8,675,326		703,202	8,601,712
	701,134	8,670,895		704,659	8,681,452
	697,475	8,665,599		723,200	8,681,779
	683,628	8,668,906		725,605	8,681,737
	652,779	8,681,015		727,384	8,681,124
	655,372	8,678,892		738,798	8,677,961
	708,150	8,683,986		731,094	8,686,965
	701,058	8,682,056		685,038	8,693,125
	764,587	8,694,434		651,629	8,705,739
	763,395	8,692,420		679,054	8,710,472
	738,059	8,700,854		730,783	8,712,452
	713,907	8,696,994		732,747	8,709,683
	708,133	8,701,459		782,630	8,707,123
	708,561	8,699,965		795,755	8,717,009
	701,184	8,691,564		784,283	8,723,740
	701,612	8,694,569		780,607	8,721,751
	699,153	8,696,818		666,357	8,733,038
	689,964	8,697,153		704,558	8,732,669
	690,459	8,700,208		730,934	8,738,023
	686,943	8,700,275		745,914	8,746,658
	682,722	8,695,727		745,688	8,742,689
	655,724	8,710,673		801,352	8,748,622
	660,768	8,701,408		793,858	8,752,248
	661,179	8,699,436		794,186	8,750,124
	673,079	8,702,675		796,149	8,753,204
	673,524	8,700,703		684,770	8,651,027
	670,285	8,698,840		711,884	8,652,336
	673,524	8,700,703		768,086	8,638,839
	670,285	8,698,840		795,750	8,767,571
	673,792	8,706,729		791,512	8,764,080
	682,831	8,713,686		785,982	8,760,673
	687,438	8,712,746		786,703	8,762,628
	687,916	8,707,492		695,875	8,755,646
	689,838	8,704,614		697,403	8,753,305
	701,830	8,706,108		811,477	8,739,785
	712,480	8,714,147		816,596	8,739,374
	721,745	8,714,173		792,871	8,745,836
	717,566	8,720,299		669,999	8,742,420

	721,183	8,721,314		748,146	8,736,110
	725,706	8,707,769		749,817	8,736,370
	728,702	8,713,216		740,140	8,724,763
	752,393	8,709,993		652,720	8,722,330
	750,203	8,717,202		668,472	8,717,932
	750,253	8,720,567		702,393	8,680,151
	759,157	8,713,065		727,359	8,662,721
	760,030	8,710,883		744,924	8,630,478
	766,013	8,714,928			
	771,594	8,714,005			
	786,540	8,717,806			
	792,155	8,715,817			
	794,974	8,719,292			
	798,692	8,719,644			
	810,248	8,729,648			
	771,753	8,725,401			
	723,658	8,727,625			
	692,465	8,728,481			
	666,693	8,729,421			
	658,620	8,726,786			
	696,745	8,735,346			
	690,946	8,740,280			
	713,563	8,735,975			
	741,685	8,742,160			
	805,070	8,757,669			
	803,476	8,756,947			
	673,994	8,750,175			
	776,327	8,775,930			
	688,044	8,651,758			
	668,944	8,783,890			
	666,659	8,714,228			
	794,256	8,764,919			
	778,613	8,772,070			
	744,885	8,772,397			
	733,334	8,745,953			
	736,532	8,750,099			
	692,725	8,747,573			
	724,405	8,740,222			
	670,847	8,678,338			
	776,419	8,662,016			
	781,874	8,658,600			
	675,781	8,640,431			
Zone 22					
t2230630528912r.img					
t223063A	736,313	9,616,571	**t223063B**	837,622	9,595,764
	845,583	9,596,673		827,952	9,594,189
	823,676	9,588,011		823,951	9,598,240
	805,770	9,593,480		818,999	9,599,565
	861,555	9,589,929		875,060	9,511,979
	849,293	9,574,215		869,183	9,590,429
	838,022	9,574,040		859,713	9,578,400
	840,665	9,576,824		833,079	9,576,366
	837,014	9,565,987		730,894	9,584,835
	864,173	9,572,381		863,481	9,569,122
	859,438	9,575,399		870,792	9,572,340
	863,239	9,561,994		845,575	9,557,810
	858,821	9,562,136		836,664	9,559,318

	856,470	9,556,501		840,106	9,553,558
	817,140	9,556,784		835,955	9,551,016
	861,764	9,532,676		833,879	9,551,366
	834,329	9,538,778		808,362	9,562,203
	827,635	9,533,885		852,185	9,546,806
	832,596	9,535,044		859,179	9,540,921
	801,318	9,522,014		865,907	9,542,621
	803,994	9,518,546		837,872	9,542,738
	818,316	9,525,649		839,673	9,544,780
	819,908	9,521,597		831,528	9,537,278
	815,590	9,518,205		835,988	9,535,377
	826,543	9,519,238		839,723	9,528,308
	852,594	9,501,207		825,060	9,527,691
	856,345	9,499,865		827,327	9,526,791
	850,818	9,502,274		835,905	9,516,987
	858,713	9,507,151		846,742	9,526,282
	836,797	9,503,683		851,819	9,512,719
	836,238	9,514,337		842,541	9,509,535
	811,722	9,497,723		807,946	9,501,190
	825,026	9,494,997		803,969	9,500,815
	819,533	9,491,921		805,436	9,499,131
	829,419	9,494,397		808,679	9,497,181
	832,596	9,492,254		844,633	9,499,357
	838,631	9,494,613		855,045	9,498,398
	839,856	9,490,112		849,443	9,488,253
	835,663	9,487,077		849,243	9,481,384
	846,625	9,494,088		833,329	9,475,407
	854,345	9,495,889		838,814	9,472,031
	842,240	9,472,447		815,756	9,480,392
	843,241	9,472,072		810,463	9,481,901
	845,066	9,475,640		810,947	9,477,524
	837,664	9,475,415		777,185	9,460,560
	831,403	9,471,747		786,480	9,466,079
	775,776	9,467,654		833,838	9,450,207
	823,893	9,459,860		819,099	9,451,874
	844,066	9,466,379		813,297	9,455,067
	821,108	9,439,578		800,351	9,451,724
	847,991	9,542,424		802,044	9,453,774
	835,829	9,488,973		855,973	9,572,807
	801,285	9,468,311		818,227	9,552,872
	844,756	9,466,180		823,259	9,557,912
	797,415	9,442,241		821,971	9,557,419
				848,710	9,544,873
				853,039	9,524,111
				854,786	9,522,690
				849,077	9,520,977
				833,665	9,510,437
				814,131	9,505,740
				825,273	9,478,065
Zone 22					
t2260630720912r.img					
t226063A	195,441	9,596,697			
	192,710	9,599,362			
Zone 22					
t2230640810922r.img					
t223064A	693,189	9,407,304	**t223064B**	693,364	9,440,195

	740,556	9,366,382		693,398	9,440,251
	669,535	9,335,230		690,809	9,440,669
	670,090	9,422,306		669,660	9,405,383
	671,186	9,423,754		702,048	9,317,019
Zone 22					
t2230650602932r.img					
t223065A	698,158	9,271,176	**t223065B**	710,824	9,203,491
	695,693	9,271,460			
	789,689	9,271,653			
	640,115	9,244,691			
	694,473	9,242,184			
	663,225	9,213,192			
	660,854	9,214,796			
	709,312	9,200,960			
	710,382	9,202,572			
	621,508	9,185,302			
	658,396	9,195,387			
	677,813	9,177,782			
	707,675	9,164,448			
	599,985	9,138,151			
	713,857	9,128,337			
Zone 22					
t2240630622922r.img					
t224063A	682,561	9,582,450			
	663,743	9,545,879			
Zone 20					
t2290700711922r.img					
t229070A	827,164	8,450,345	**t229070B**	886,450	8,344,131
	826,659	8,442,729		832,975	8,344,264
	829,300	8,417,184		831,485	8,344,247
	783,623	8,422,424		788,717	8,488,556
	789,541	8,416,579		789,693	8,490,406
	778,548	8,421,770			
	786,346	8,410,959			
	787,306	8,409,767			
	842,876	8,406,224			
	863,769	8,399,154			
	858,140	8,401,481			
	857,238	8,400,024			
	858,819	8,399,237			
	812,603	8,368,146			
Zone 22					
t2240650716922r.img					
t224065A	567,697	9,169,913	**t224065B**	470,651	9,244,802
	588,930	9,170,371		556,814	9,169,755
	538,362	9,171,445		548,929	9,144,526
	575,332	9,142,935		547,139	9,144,201
	573,167	9,137,765			
	573,017	9,135,333			
	560,103	9,147,124			
	595,341	9,127,831			
Zone 21					
t2260690519922r.img					

t226069A	658,669	8,630,114	**t226069B**	666,363	8,630,215
	664,383	8,628,797		662,377	8,615,556
	668,134	8,626,774		716,298	8,622,386
	666,388	8,624,987		719,185	8,621,723
	660,968	8,622,537		717,288	8,620,313
	664,374	8,621,060		728,021	8,622,973
	658,358	8,618,190		736,588	8,602,894
	685,696	8,628,646		717,171	8,614,641
	682,810	8,629,938		714,385	8,611,159
	710,458	8,616,588		716,374	8,607,442
	714,620	8,622,747		676,139	8,608,784
	713,227	8,619,265		665,163	8,611,822
	729,867	8,619,315		664,836	8,605,310
	783,880	8,607,920		668,176	8,600,166
	782,688	8,606,644		666,648	8,599,042
	750,517	8,604,689		656,873	8,606,770
	737,997	8,603,481		686,401	8,601,752
	712,824	8,607,777		705,642	8,585,835
	710,257	8,603,380		702,067	8,586,195
	712,380	8,601,006		736,907	8,592,153
	715,291	8,600,091		741,127	8,589,644
	693,533	8,604,328		769,254	8,587,219
	693,911	8,611,855		800,175	8,592,967
	685,520	8,605,587		720,824	8,579,281
	672,279	8,605,788		718,119	8,583,275
	670,022	8,604,169		667,529	8,573,273
	664,752	8,608,558		674,687	8,567,911
	662,478	8,606,451		672,665	8,566,208
	667,479	8,608,969		695,598	8,554,083
	663,527	8,603,733		713,823	8,545,465
	668,620	8,597,876		714,024	8,541,572
	670,122	8,595,191		689,371	8,551,624
	679,420	8,596,508		652,694	8,495,320
	665,918	8,597,507		802,266	8,594,257
	706,699	8,596,365		801,275	8,591,513
	709,971	8,597,456		717,272	8,557,930
	703,401	8,591,238		718,558	8,558,336
	706,598	8,588,469			
	701,731	8,582,814			
	709,166	8,585,684			
	745,977	8,593,747			
	726,594	8,574,918			
	713,152	8,573,158			
	711,113	8,572,761			
	709,149	8,568,692			
	704,442	8,569,757			
	705,558	8,570,957			
	700,355	8,574,028			
	692,719	8,571,016			
	699,767	8,585,096			
	690,278	8,581,219			
	686,174	8,579,726			
	678,329	8,585,918			
	678,958	8,582,503			
	675,434	8,580,850			
	671,918	8,577,477			
	665,339	8,577,477			
	672,220	8,583,393			

	682,810	8,573,567			
	663,401	8,585,306			
	667,420	8,569,548			
	677,087	8,562,088			
	682,759	8,565,579			
	686,216	8,559,101			
	693,298	8,559,503			
	694,238	8,566,283			
	695,530	8,562,659			
	693,038	8,556,189			
	691,889	8,553,621			
	704,761	8,563,305			
	722,180	8,564,991			
	722,357	8,562,642			
	711,482	8,530,731			
	714,654	8,531,796			
	713,580	8,530,370			
	616,246	8,695,001			
	792,952	8,613,807			
	793,487	8,614,887			
	743,567	8,586,623			
	668,657	8,594,569			
	684,405	8,554,851			
Zone 22					
t2270680806922r.img					
t227068A	662,464	8,763,233	**t227068B**	643,676	8,773,579
	652,836	8,767,595		643,575	8,779,313
	650,044	8,767,645		602,673	8,770,220
	609,627	8,771,222		609,376	8,774,666
	552,059	8,749,476		516,121	8,765,857
	600,116	8,759,856		512,578	8,769,735
	615,159	8,736,689		525,348	8,767,060
	626,008	8,748,724		523,660	8,762,079
	661,093	8,755,025		517,225	8,760,491
	660,742	8,758,068		519,448	8,760,174
	668,364	8,742,288		624,236	8,748,924
	670,353	8,743,692		624,854	8,747,102
	623,534	8,716,029		659,839	8,755,627
	561,520	8,727,161		596,405	8,711,348
	581,712	8,717,550		577,517	8,718,870
	512,193	8,700,400		490,965	8,710,496
	519,849	8,701,654		486,686	8,711,666
	536,664	8,690,354		478,646	8,697,441
	540,559	8,678,169		478,345	8,694,132
	537,951	8,678,954		546,476	8,672,251
	540,743	8,684,721		563,442	8,697,191
	558,578	8,678,386		562,924	8,692,527
	619,756	8,700,851		561,988	8,690,270
	608,122	8,704,278		553,112	8,684,972
	643,208	8,705,047		643,764	8,654,892
	642,728	8,656,229		644,006	8,652,368
	546,642	8,746,549		547,802	8,661,645
	554,098	8,745,362		553,869	8,654,708
	523,739	8,698,161		505,102	8,754,258
	527,868	8,703,745		506,708	8,752,297
	524,968	8,701,338		599,878	8,711,894
	522,159	8,670,653		590,433	8,697,668

				561,512	8,696,774
				538,701	8,699,206
				519,861	8,675,434
Zone 21					
t2270700705922r.img					
t227070a	417,838	8,395,184			
	477,519	8,395,885			
Zone 22					
t2250690621922r.img					
t225069a			**t225069b**	165,772	8,603,052
				165,714	8,600,018
				161,650	8,599,852
				169,529	8,589,279
				168,380	8,600,871
Zone 21					
t2280680618922r.img					
t228068a	395,043	8,772,461	**t228068b**	411,831	8,799,281
	323,210	8,768,179		463,884	8,729,472
	326,602	8,766,832		433,226	8,726,271
	475,283	8,761,967		435,438	8,727,368
	426,499	8,730,844		400,232	8,719,877
	428,619	8,733,696		387,385	8,714,073
	420,304	8,732,773		362,482	8,669,321
	421,427	8,735,825		361,243	8,663,817
	435,147	8,732,657		399,899	8,664,673
	409,744	8,717,249		412,630	8,661,172
	397,014	8,721,190		415,806	8,633,616
	368,801	8,707,728		449,091	8,634,099
	353,851	8,710,738		478,468	8,634,872
	378,197	8,702,190		462,021	8,633,175
	461,456	8,701,567		340,254	8,794,241
	349,277	8,664,108		331,525	8,741,229
	348,346	8,661,596		326,174	8,738,902
	363,837	8,661,821		330,426	8,721,955
	416,945	8,655,909		312,205	8,710,883
	375,170	8,644,401		332,333	8,776,749
	372,019	8,644,875		342,228	8,783,062
	360,137	8,652,500		362,243	8,725,841
	359,605	8,635,205		470,017	8,694,350
	409,653	8,632,502		386,659	8,660,150
	411,366	8,634,182		376,249	8,638,381
	412,172	8,631,795			
	417,178	8,630,615			
	465,675	8,615,921			
	382,975	8,646,264			
	358,413	8,647,095			
	352,152	8,658,603			
	469,889	8,784,995			
	349,999	8,761,898			
Zone 21					
t226067051992r.img					
t226067a	735,056	8,884,969	**t226067b**	732,586	8,889,978
	733,477	8,882,659		737,501	8,881,877
	733,367	8,881,398		737,233	8,880,903

	720,620	8,812,092		732,351	8,884,885
	721,486	8,809,193		734,762	8,881,844
	725,578	8,811,101			
Zone 21					
t2270690705922r.img					
t227069a	518,690	8,628,913	**t227069b**	532,380	8,636,382
	526,627	8,591,277		530,320	8,636,340
	509,656	8,587,459		533,661	8,615,600
	492,927	8,589,176		529,039	8,617,359
	474,959	8,587,610		544,185	8,593,295
	470,714	8,581,071		501,542	8,573,694
	519,226	8,580,393		495,807	8,576,667
	521,620	8,567,013		493,412	8,578,517
	507,429	8,572,472		477,471	8,569,969
	505,896	8,572,087		479,162	8,572,933
	496,008	8,548,743		484,085	8,570,303
	505,201	8,553,466		496,594	8,552,109
	505,185	8,560,080		502,556	8,567,884
	510,066	8,565,991		505,921	8,568,470
	512,687	8,549,020		502,731	8,564,451
	536,189	8,535,305		499,684	8,563,630
	592,287	8,495,099		534,540	8,545,587
	522,006	8,497,318		527,214	8,554,931
	507,340	8,588,935		529,097	8,534,505
	499,904	8,575,500		530,320	8,533,245
	517,936	8,616,999		525,296	8,536,193
				523,195	8,512,950
				472,329	8,611,936
				471,250	8,607,817
				475,515	8,604,788
				489,879	8,636,842
				480,711	8,639,187
				464,225	8,607,646
				547,065	8,587,811
				511,757	8,579,187
				493,546	8,586,279
				519,243	8,561,772
				482,285	8,555,358
				488,087	8,561,512
				520,566	8,542,204
				494,903	8,510,471
Zone 21					
t2280690618922r.img					
t228069a	430,124	8,588,444			
	430,673	8,585,062			
Zone 21					
t2290690625922r.img					
t229069a	140,149	8,588,909	**t229069b**	167,306	8,585,172
	122,146	8,557,138		132,938	8,593,367
				103,920	8,514,235
				99,487	8,505,270
Zone 21					
t2290680711922r.img					
t229068a	320,892	8,770,800			

Zone 21					
t2290670703922r.img					
t229070a	342,489	8,854,024			
	314,794	8,814,204			
Zone 22					
t2240660716922r.img					
t224066a	552,837	9,085,874	**t224066b**	461,528	9,092,147
	572,387	9,093,808		591,427	9,072,597
	582,853	9,087,275		582,513	9,074,498
	585,694	9,085,874		456,075	9,071,846
	581,812	9,082,612		443,858	9,067,474
	582,473	9,081,141		445,799	9,063,662
	580,241	9,067,134		458,316	9,014,275
	538,019	9,068,795		547,754	9,005,230
	541,050	9,069,085		560,141	8,988,952
	539,189	9,064,893		561,501	8,985,600
	531,695	9,063,512			
	531,595	9,054,797			
	537,398	9,056,058			
	542,761	9,056,898			
	587,595	9,059,189			
	579,911	9,042,490			
	574,708	9,040,419			
	566,864	9,044,371			
	568,575	9,046,873			
	555,638	9,045,292			
	558,810	9,042,430			
	558,300	9,039,539			
	513,976	9,021,479			
	516,987	9,021,719			
	519,379	9,022,630			
	541,080	9,023,760			
	539,139	9,019,188			
	557,739	9,031,044			
	554,418	9,028,983			
	550,535	9,029,003			
	542,721	9,035,627			
	543,542	9,032,655			
	548,034	9,034,196			
	568,815	9,032,325			
	570,656	9,035,006			
	576,209	9,030,744			
	572,517	9,032,665			
	580,121	9,031,495			
	575,289	9,023,420			
	567,074	9,022,560			
	584,334	9,031,104			
	495,466	8,996,696			
	498,417	8,993,814			
	552,747	8,996,166			
	574,858	8,990,443			
	550,085	8,985,940			
	551,076	8,983,419			
	565,634	8,973,243			
	555,788	8,952,802			
	559,660	8,952,452			

Zone 20					
t2300690515922r.img					
t230069a	733,034	8,624,763	**t230069b**	751,109	8,638,205
	732,925	8,627,154		752,695	8,635,587
	734,436	8,627,112		755,866	8,519,069
	738,765	8,626,332			
	741,165	8,625,744			
	738,463	8,624,007			
	762,277	8,582,421			
	760,842	8,582,799			
	774,285	8,634,743			
	776,922	8,636,622			
Zone 20					
t2300680710922r.img					
t230068a	711,836	8,683,348	**t230068b**	683,043	8,772,092
				696,257	8,733,053
				727,700	8,688,077
Zone 22					
t2240670716922r.img					
t224067a	545,273	8,947,931			
	547,737	8,945,275			
	546,489	8,942,711			
	547,663	8,944,209			
	540,619	8,925,527			
Zone 22					
t2230660725922r.img					
t223066a	565,780	8,973,301	**t223066b**	561,557	8,985,503
	575,890	8,977,702		564,749	8,985,155
	594,112	8,992,086		565,742	8,982,459
	601,440	8,996,197		574,599	8,990,123
	603,117	8,994,471			
	604,546	8,992,520			
	597,814	9,004,643			
	594,683	8,999,849			
	605,229	9,001,836			
	600,062	9,000,321			
Zone 23					
t2220630724912r.img					
t222063A	196,289	9,608,239	**t222063B**	213,889	9,609,169
	212,942	9,618,364		220,658	9,611,653
	233,249	9,615,631		208,931	9,603,729
	230,110	9,606,229		218,789	9,592,268
	231,729	9,597,284		243,930	9,595,308
	202,020	9,603,763		241,945	9,596,337
	221,248	9,591,421		244,080	9,574,735
	225,101	9,593,455		213,200	9,569,602
	243,457	9,591,653		294,660	9,565,051
	247,551	9,585,391		300,192	9,558,664
	277,842	9,586,894		294,178	9,554,926
	296,296	9,591,603		244,384	9,582,282
	282,434	9,581,770		260,279	9,576,452
	279,926	9,581,014		308,122	9,561,014

	246,214	9,568,074		233,513	9,569,784
	235,151	9,573,132		192,969	9,553,423
	239,462	9,575,349		209,188	9,549,836
	205,733	9,574,685		220,267	9,551,970
	207,112	9,559,469		251,285	9,548,482
	215,234	9,567,343		247,647	9,543,300
	212,809	9,567,791		259,540	9,542,262
	235,849	9,562,908		284,603	9,544,678
	290,200	9,563,041		281,838	9,543,391
	195,411	9,596,555		330,246	9,539,546
	192,687	9,599,336		279,305	9,544,404
	195,545	9,455,632		244,915	9,533,525
	198,522	9,437,858		212,278	9,537,129
	204,042	9,435,286		195,519	9,521,849
	201,622	9,438,186		244,566	9,514,026
	312,673	9,569,269		250,911	9,523,261
	323,876	9,554,412		230,739	9,530,644
	336,649	9,547,286		246,501	9,527,330
	339,315	9,554,520		266,341	9,523,086
	274,355	9,536,980		271,748	9,524,963
	279,089	9,538,674		348,384	9,526,176
	187,206	9,532,354		194,763	9,497,823
	186,898	9,521,940		262,945	9,506,643
	187,696	9,521,226		254,831	9,494,136
	186,849	9,525,453		188,418	9,466,481
	210,608	9,516,866		193,310	9,476,015
	214,279	9,514,524		303,438	9,464,796
	219,395	9,518,660		178,876	9,464,289
	216,887	9,519,573		212,356	9,605,907
	253,087	9,524,639		220,717	9,601,918
	226,437	9,527,214		208,834	9,599,878
	247,822	9,527,388		207,335	9,596,947
	269,232	9,521,226		194,918	9,594,840
	271,756	9,521,193		193,719	9,592,808
	299,054	9,523,925		237,980	9,587,245
	201,955	9,502,823		242,605	9,577,762
	192,944	9,504,500		242,014	9,575,839
	191,807	9,496,702		228,940	9,562,847
	196,889	9,496,445		306,203	9,549,923
	202,486	9,493,090		345,685	9,533,026
	194,829	9,493,472		274,234	9,532,843
	248,968	9,503,545		235,160	9,535,833
	248,279	9,506,236		197,769	9,520,668
	252,796	9,502,989		262,850	9,517,437
	316,128	9,498,878		310,159	9,501,906
	317,963	9,498,529		258,653	9,495,177
	264,415	9,482,676			
	261,707	9,483,631			
	254,466	9,488,871			
	249,167	9,484,934			
	193,326	9,468,707			
	190,171	9,469,679			
	190,984	9,465,659			
	191,209	9,474,861			
	209,138	9,480,159			
	267,188	9,473,989			
	297,235	9,466,938			
	288,125	9,460,776			

	259,158	9,466,556			
	186,492	9,459,206			
	184,091	9,458,816			
	177,805	9,470,069			
	176,227	9,470,443			
	181,500	9,453,111			
	181,110	9,450,470			
	244,558	9,446,127			
	294,328	9,447,347			
	301,595	9,445,113			
	298,447	9,435,646			
	219,368	9,604,342			
	226,197	9,594,340			
	338,639	9,561,407			
	218,772	9,530,386			
	312,890	9,512,382			
	301,515	9,510,034			
	234,744	9,505,687			
Zone 23					
t2220620724912r.img					
t222062A	244,505	9,760,701	**t222062B**	228,895	9,729,108
	242,843	9,743,579		238,649	9,699,807
	247,065	9,741,476		237,301	9,697,429
	241,604	9,740,553		230,060	9,702,600
	238,994	9,728,036		233,725	9,694,038
	234,847	9,726,423		240,332	9,691,818
	224,108	9,708,885		239,777	9,693,949
	224,931	9,706,508		255,465	9,687,387
	242,119	9,706,342		258,786	9,688,417
	248,985	9,709,517		224,467	9,680,965
	254,504	9,704,413		223,736	9,668,404
	258,136	9,702,618		209,087	9,655,111
	262,101	9,712,467		209,007	9,650,407
	266,166	9,703,466		239,045	9,653,869
	271,003	9,706,275		238,535	9,646,857
	268,892	9,695,345		249,678	9,662,889
	265,625	9,698,844		248,427	9,656,300
	248,378	9,699,750		271,462	9,658,406
	222,978	9,685,282		265,278	9,644,972
	236,077	9,690,496		218,679	9,644,382
	232,694	9,687,422		215,579	9,639,308
	235,249	9,686,753		212,619	9,644,259
	239,336	9,689,166		206,127	9,639,740
	254,848	9,692,064		201,793	9,622,386
	263,173	9,685,422		227,312	9,633,803
	259,200	9,683,731		229,655	9,635,186
	248,304	9,684,938		231,117	9,624,412
	246,718	9,682,427		233,214	9,623,373
	276,571	9,680,613		243,344	9,628,975
	278,720	9,687,889		266,582	9,635,520
	292,973	9,683,123		265,093	9,628,341
	302,716	9,686,444		283,327	9,611,481
	308,045	9,683,440		259,878	9,619,673
	296,743	9,677,768			
	296,743	9,673,856			
	285,988	9,671,408			
	267,650	9,676,799			

	271,268	9,668,721			
	270,097	9,667,294			
	269,260	9,667,065			
	262,230	9,669,540			
	257,482	9,670,412			
	252,144	9,670,747			
	245,247	9,668,051			
	239,495	9,675,046			
	237,539	9,676,208			
	237,548	9,680,243			
	239,319	9,679,001			
	225,418	9,679,406			
	215,015	9,668,668			
	212,883	9,668,007			
	218,820	9,677,292			
	215,526	9,676,314			
	224,916	9,671,143			
	223,551	9,670,157			
	214,372	9,655,014			
	219,684	9,658,476			
	219,939	9,653,931			
	214,539	9,651,544			
	219,886	9,651,500			
	239,680	9,665,647			
	254,822	9,661,965			
	260,222	9,659,225			
	257,685	9,653,772			
	252,593	9,651,834			
	253,034	9,649,104			
	275,215	9,647,236			
	212,258	9,624,245			
	198,930	9,621,999			
	216,891	9,630,103			
	221,163	9,632,552			
	228,880	9,629,257			
	232,976	9,630,482			
	236,614	9,621,955			
	273,144	9,627,363			
	271,365	9,624,633			
	298,910	9,630,068			
	266,582	9,616,097			
	222,088	9,619,990			
Zone 22					
t2230620816912r.img					
t223062A	847,656	9,754,608	**t223062B**	848,157	9,757,894
	865,579	9,729,249		852,827	9,758,144
	860,065	9,724,441		850,292	9,755,818
	847,294	9,721,878		790,674	9,747,512
	834,452	9,722,532		791,975	9,745,277
	809,273	9,708,948		793,192	9,745,727
	814,063	9,708,303		808,261	9,752,323
	815,566	9,711,644		843,045	9,747,120
	875,443	9,693,968		900,744	9,742,917
	870,564	9,695,647		863,743	9,740,057
	870,564	9,698,378		858,072	9,740,173
	857,634	9,700,446		858,573	9,737,538
	851,934	9,697,980		863,626	9,714,931

	722,909	9,701,082		842,159	9,722,081
	746,798	9,688,453		844,554	9,723,486
	787,779	9,690,229		829,565	9,724,264
	804,607	9,688,621		751,022	9,736,310
	822,937	9,684,820		751,376	9,731,405
	859,384	9,685,448		757,103	9,716,063
	857,528	9,682,938		831,279	9,717,715
	873,366	9,679,270		879,322	9,691,670
	872,128	9,676,327		874,099	9,699,730
	815,265	9,680,437		863,564	9,705,731
	834,417	9,669,566		862,716	9,698,289
	846,207	9,669,275		841,461	9,697,141
	850,175	9,673,455		805,517	9,705,864
	859,481	9,669,107		770,784	9,700,181
	859,526	9,666,482		809,335	9,684,767
	871,651	9,669,142		881,647	9,687,657
	873,304	9,671,325		802,653	9,675,275
	852,915	9,659,694		808,725	9,668,002
	865,509	9,651,828		834,161	9,673,508
	858,271	9,647,348		858,191	9,644,882
	851,616	9,647,807		872,241	9,636,074
	717,792	9,632,155		877,644	9,634,923
	837,820	9,642,443		863,092	9,626,892
	839,737	9,649,911		858,189	9,627,417
	837,519	9,636,786		860,115	9,626,867
	843,688	9,634,108		848,440	9,630,261
	846,878	9,633,808		844,544	9,630,887
	849,053	9,641,329		854,203	9,609,346
	846,463	9,639,623		850,725	9,609,638
	846,967	9,637,299		854,269	9,615,234
	850,962	9,634,444		852,026	9,619,895
	853,975	9,636,857		733,199	9,682,888
	857,811	9,640,666		836,414	9,668,531
	865,661	9,629,869		733,550	9,651,156
	851,801	9,628,743		732,463	9,649,801
	854,720	9,631,303		718,884	9,645,846
	786,337	9,627,476		721,092	9,625,018
	838,166	9,628,285		783,619	9,624,700
	844,354	9,627,050		835,101	9,632,284
	863,576	9,618,644		840,603	9,615,193
	865,152	9,724,913		726,460	9,605,059
	866,699	9,683,206		841,192	9,754,281
	724,712	9,626,857		841,894	9,752,541
	728,609	9,627,393		892,632	9,744,080
	731,343	9,627,786		794,568	9,741,295
	728,667	9,620,026		829,122	9,720,573
	731,820	9,621,431		825,552	9,722,187
	732,932	9,632,736		824,189	9,719,687
				863,338	9,718,566
				776,679	9,709,603
				728,274	9,700,514
				730,248	9,700,765
				836,639	9,701,960
				848,755	9,700,372
				851,422	9,701,074
				854,424	9,704,059
Zone 22					

t2260630618972r.img					
t22606397A	231,840	9,637,858	**t22606397B**	245,821	9,601,483
	229,880	9,628,409		202,923	9,606,462
	201,494	9,615,239		198,090	9,606,778
	206,574	9,617,223		240,973	9,590,752
	197,997	9,609,264		213,143	9,592,790
	248,407	9,602,779		218,462	9,585,781
	199,742	9,600,054		196,399	9,592,342
	202,205	9,600,286			
	224,962	9,588,845			

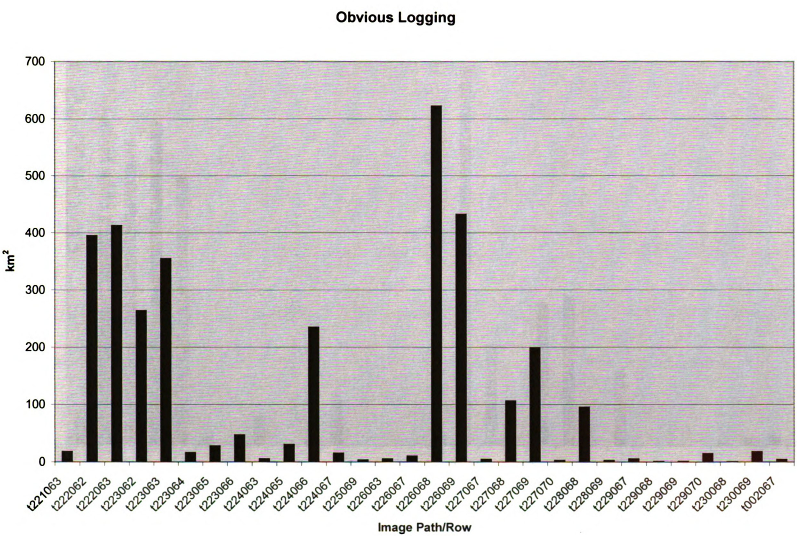


Figure 4.1: Obvious logging for each scene (units km²).

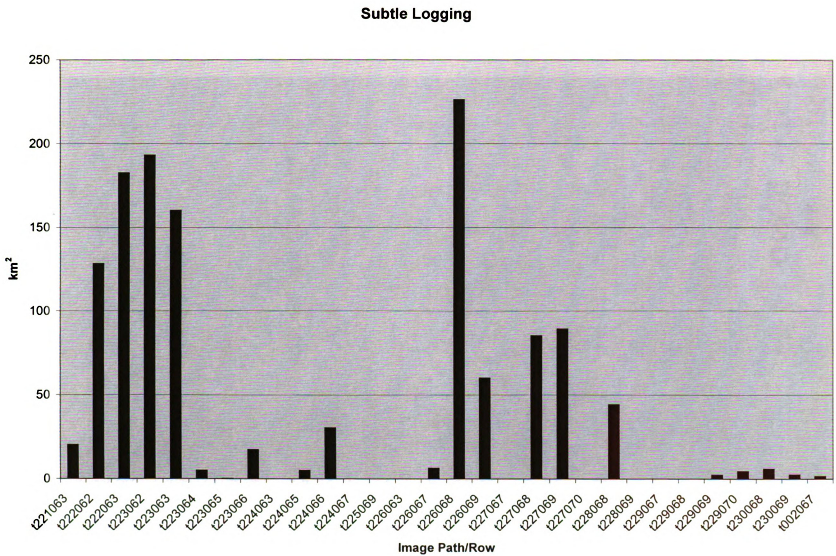


Figure 4.2: Subtle logging for each scene (units km²).

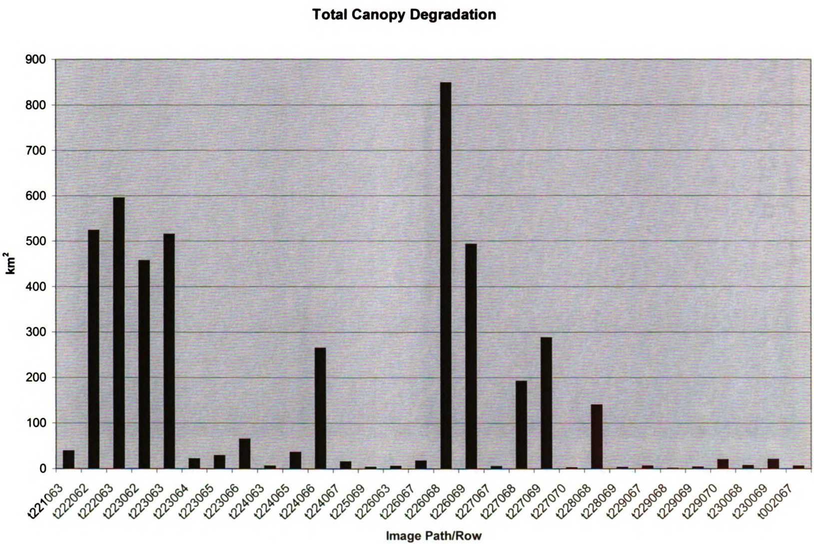


Figure 4.3: Total Canopy Degradation (units km²). Obvious logging and subtle logging combined.

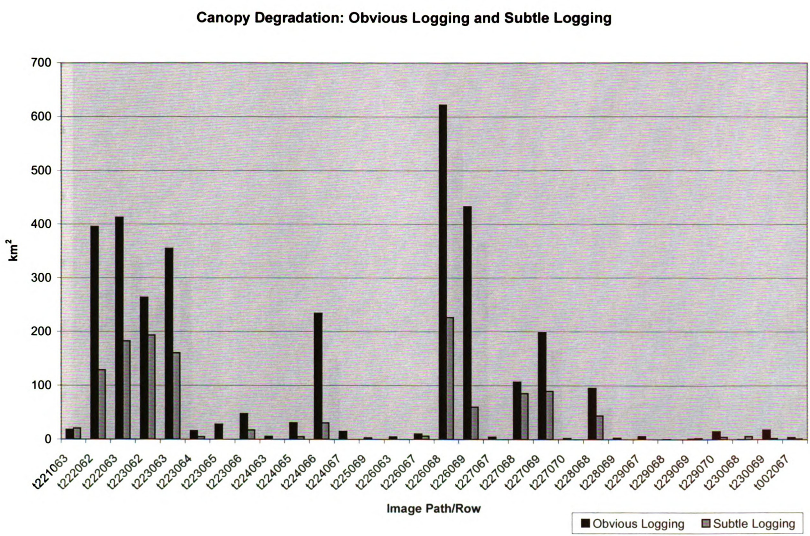


Figure 4.4: Obvious logging and subtle logging for each scene (units km²).

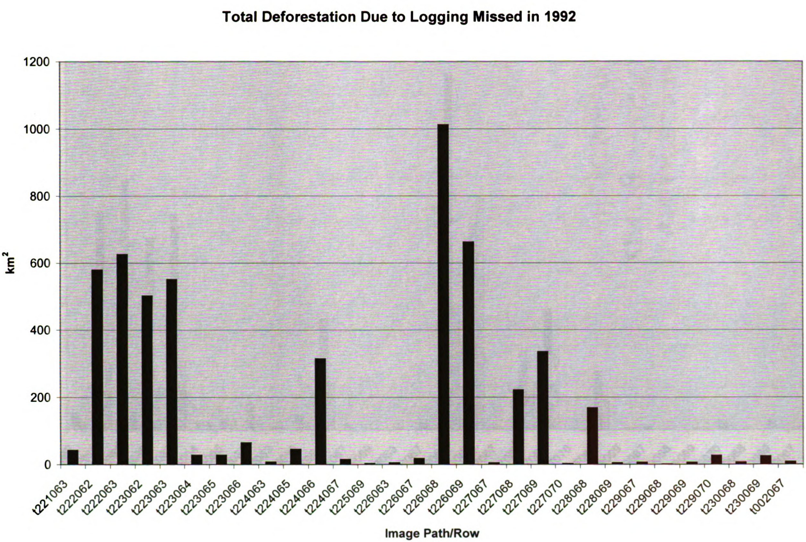


Figure 4.5: Total deforestation due to selective logging not included in the 1992 estimate of deforestation (units km²).

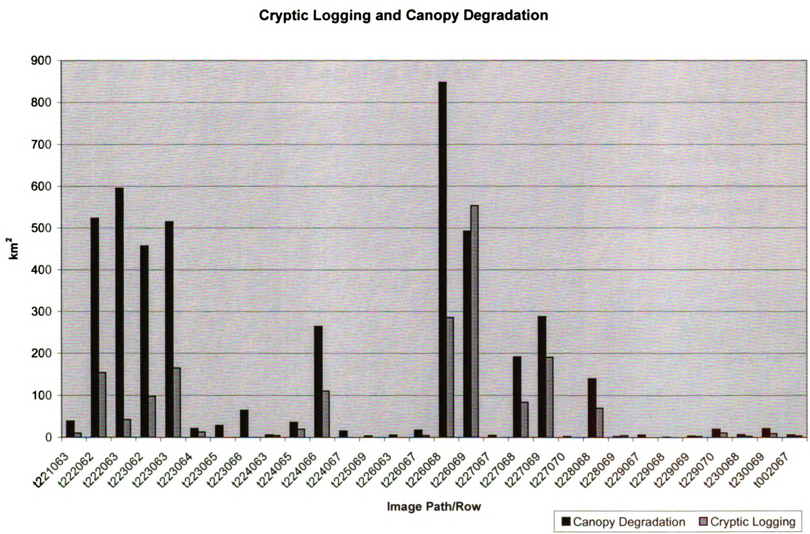


Figure 4.6: Cryptic deforestation captured compared to canopy degradation captured (units km²).

Figure 4.7: Images in study divided into four regions by extent of logging for the accuracy assessment of the detection of logging patios.

Four Regions Defined for the Accuracy Assessment of the Detection of Logging Patios

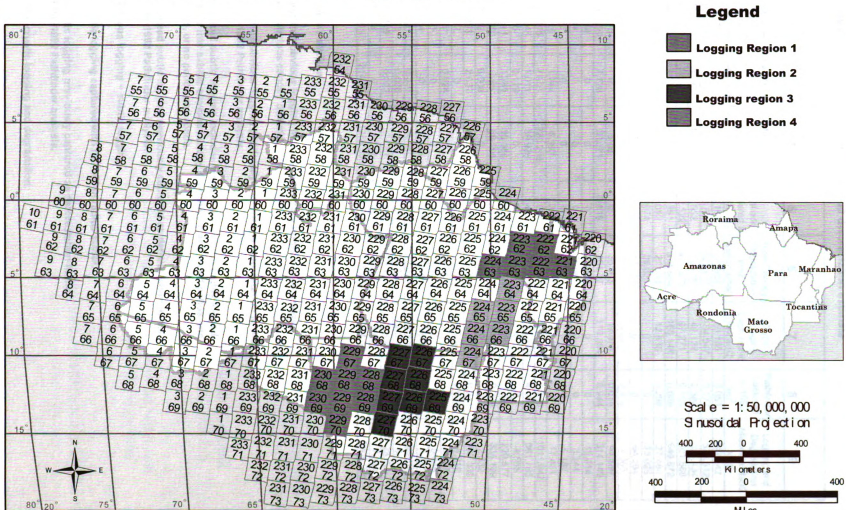


Figure 4.7

Table 4.1: Selective logging estimates for each method used in this study. Also, estimates of selective logging that was captured as agriculture in the 1992 deforestation estimate.

1	2	3	4	5	6	7	8	9
Image Path/Row	Obvious Logging km2 (digitized)	Pathfinder Captured in 1992 km2	Subtle Logging km2 (digitized)	Pathfinder Captured in 1992 km2	Total Canopy Degradation km2 (patio/buffer)	Cryptic Logging Captured in 1992 km2	Pathfinder Captured in 1992 km^2	Logging and Degradation Missed in 1992 km2
t221063	18.133	0.262	20.236	0.155	38.369	10.185	0.051	42.142
t222062	395.446	77.613	128.169	13.557	523.615	154.047	0.177	579.512
t222063	412.668	30.053	182.492	1.552	595.16	42.128	0.388	625.434
t223062	263.779	79.529	193.194	12.522	456.973	97.271	0.059	501.568
t223063	354.909	1.358	160.075	0.351	514.984	165.146	0.068	549.872
t223064	16.082	0.203	4.921	0.062	21.003	12.835	0.298	27.464
t223065	27.896	1.36	0.13	0.074	28.026	0	0	28.026
t223066	46.972	0.349	17.392	0.149	64.364	0	0	64.364
t224063	5.565	0.002	0	0	5.565	4.247	0.002	7.386
t224065	30.613	0	5.05	0	35.663	18.976	0.014	44.889
t224066	234.299	7.726	30.371	0.816	264.67	110.054	0.944	314.149
t224067	15.014	0	0	0	15.014	0	0	15.014
t225069	3.244	0	0	0	3.244	0	0	3.244
t226063	5.187	0	0	0	5.187	0	0	5.187
t226067	10.315	1.744	6.397	1.328	16.712	4.146	0.017	17.461
t226068	622.115	7.851	226.206	5.987	848.321	286.02	1.716	1011.942
t226069	432.645	1.011	59.928	1.413	492.556	553.295	4.085	661.785
t227067	4.665	0.179	0	0	4.665	0	0	4.665
t227068	106.641	1.341	85.086	0.515	191.727	83.551	1.23	220.577
t227069	198.362	0.85	89.195	0.157	287.557	190.664	0.204	334.169
t227070	2.332	0.008	0	0	2.332	0	0	2.332
t228068	95.353	2.637	44.007	4.121	139.361	69.671	0.241	167.339
t228069	2.622	0	0	0	2.622	3.938	0.024	4.219
t229067	5.697	0.024	0	0	5.697	0	0	5.697
t229068	0.645	0	0	0	0.645	0	0	0.645
t229069	1.234	0	2.268	0.546	3.502	2.555	0	5.711
t229070	14.937	0.336	4.387	0.273	19.324	10.443	0	26.102
t230068	0.413	0.006	5.89	0.005	6.32	2.314	0.001	6.473
t230069	17.715	0.022	2.453	0.182	20.168	8.836	0	23.724
t002067	4.118	0	1.512	0.001	5.638	3.689	0.031	7.814
TOTAL	3349.616	214.464	1269.359	43.766	4618.984	1834.001	9.55	5308.906

Column 1 = Image Path/Row

Column 2 = Digitized obvious logging includes spectrally bright patios, roads, and obvious canopy disturbance.

Column 3 = Digitized obvious logging previously captured as deforestation in the 1986-1992 Pathfinder analysis.

Column 4 = Digitized subtle logging includes areas in and around highly logged areas that exhibit obvious canopy disturbance and faded patios and roads, or no patios and roads.

Column 5 = Digitized subtle logging previously captured as deforestation in the 1986-1992 Pathfinder analysis.

Column 6 = Obvious logging + subtle logging.

Column 7 = Cryptic logging captured with the 180 m radius buffer.

Column 8 = Cryptic logging previously captured as deforestation in the 1986-1992 Pathfinder analysis.

Column 9 = Total cryptic logging and degradation.

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