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ACCURACY OF DIGITAL CLASSIFICATION VERSUS VISUAL INTERPRETATION OF DEFORESTATION IN AMAZON

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ABSTRACT: Tropical deforestation is a serious and looming global problem about which accurate information appears to be in short supply. The extent of tropical deforestation and the rate at which it is occurring are known for only a small portion of the tropical forests of the planet. It is critical to have reliable methods for continuous monitoring of changes in tropical forests. In addition to loss of a major portion of global biodiversity, tropical deforestation is closely associated with greenhouse gas fluxes to the atmosphere from biomass burning and/or decomposition. A variety of techniques for estimating tropical deforestation using Landsat and NOAA polar-orbiting meteorological satellite data were compared. Digital analyses of thematic mapper imagery were found to vary substantially among analysts and AVHRR 3.5-3.9 µm data were found to be inaccurate due to extreme radiometric sensitivity. Visual interpretation of Landsat thematic mapper images, coupled with digitizing the results into a geographic information system, was found to be the best tropical deforestation determination technique in terms of accuracy and cost.

INTRODUCTION

Tropical forests, including moist evergreen and seasonal forests, once covered ~24,500,000 km^2 of our planet's surface (Whittaker and Likens, 1975) and are now estimated to cover ~11,600,000 km^2 of which ~6,684,000 km^2 was estimated to be "undisturbed forest" as of 1980 (Guppy, 1984). Of the remaining total area of tropical forest, ~50% is contained within the Amazon Basin of South America and Brazil alone accounts for over 30% of the global total.

Tropical forests are home to the greatest diversity of plant and animal life on the earth and contain over half of our planet's plant and animal species. It is estimated they contain in excess of 5 million plant and animal species (Prance, 1982) and some workers feel the number of total species could go as high as 30 million (Erwin, 1986). One principal adverse effect of tropical deforestation (i.e., habitat destruction) would be mass extinctions comparable to what last occurred ~60-70 million years ago at the end of the Mesozoic era when the dinosaurs and many other species became extinct.

In addition to mass extinctions resulting from tropical forest habitat destruction, indirect and disruptive effects on precipitation patterns would also occur within South America. The impact on the water cycle and its chemical load with implications on biogeochemistry and soil degradation due to erosion as pointed out by Batista et al. (1988), Salati and Vose (1984), Commission on Ecology (1983), and Clement and Colon (1975), could be very significant. Salati and Vose (1983,

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1984) have reported that ~50% of the rainfall falling in the Amazon Basin is recycled. Tropical deforestation would disrupt longitudinal profiles of precipitable water and cause much drier conditions in the temperate zone of South America (Salati and Vose, 1984). Shukla et al. (1990) reported that widespread deforestation of the Amazon Basin would result in such substantially drier conditions that reestablishment of tropical forest vegetation would be impossible.

Widespread tropical deforestation in the Amazon Basin would also result in significant additions to global atmospheric CO_2 (Woodwell et al., 1983). The biological mass (biomass) of tropical forest vegetation contains several centuries-worth of accumulated carbon. The burning of large amounts of forest vegetation, and/or subsequent decomposition, releases this carbon into the atmosphere as CO_2 over a short period of time. Since the Amazon Basin now comprises ~50% of the remaining global tropical forest, the amount of CO_2 potentially to be released from deforestation is of global importance (Leslie, 1981; Houghton et al. 1985; Fearnside, 1990; and Kaufman et al. 1990).

SATELLITE REMOTE SENSING

Tropical deforestation has been studied with Landsat, meteorological satellites, space shuttle, and geostationary satellite data (Nelson and Holben, 1986; Tardin et al., 1979 and 1980; Tucker et al., 1984; Woodwell et al., 1983 and 1987; Nelson et al., 1987; Malingreau and Tucker, 1988; and Tardin and da Cunha, 1990).

Landsat multispectral scanner (MSS) and thematic mapper (TM) data can resolve areas 80-m and 30-m in size, respectively, and are collected every 16 days. This frequency of observation, coupled with the high probability of clouds and the frequent presence of smoke from forest-clearing fires, can result in useful data being collected only every 1 to 3 years for areas of interest. This frequency of observation is reduced if there is no Landsat receiving station operating in the area of interest.

Tropical forest area and deforestation have also been studied with NOAA polar-orbiting meteorological satellite data from the advanced very high resolution radiometer (AVHRR) sensor carried on the National Oceanic and Atmospheric Administration's (NOAA) satellites. These satellites record imagery twice every day (02:30 and 14:30 hours for NOAA-11 and 07:30 and 19:30 hours for NOAA-12). This high frequency of observation usually results in a series of images which can provide at least one cloud-free image of most tropical areas during each year's relative dry season. The 1-km ground resolution is suitable for identifying large-scale deforestation (Tucker et al., 1984; Malingreau and Tucker, 1988; and Cross, 1990) and is an useful survey tool.

Currently, there are two major initiatives underway to determine the extent and rate of deforestation in the Amazon Basin. One concerns the activities led by INPE (Brazilian Institute for Space Research) which includes the complete survey of the Brazilian Amazon Basin for 1975, 1978, 1988, 1989, and 1990, using techniques based on visual analysis of Landsat data (Tardin and da Cunha, 1990). The second one is led by NASA (C.J. Tucker, unpublished data, 1991) with the objective of assessing deforestation using 1985, 1988, and 1991 Landsat TM data for the entire Amazon Basin. These may be complemented by information on forest resources from the FAO Forest Resources Assessment 1990 Project (Committee on Forest, 1990).

The extent and rate of deforestation has been controversial because of the multitude of approaches to estimate these parameters without error bounds associated with deforestation figures. Further, a World Bank publication by Mahar (1989), based on projections of earlier assumed rates of deforestation, has increased the level of controversy regarding the extent of deforestation in the Brazilian Amazon. Due to the vastness of the area, satellite remote sensing, coupled with selective ground verification, seems to be the only means to provide the quantitative information needed.

There is no absolute independent way to assess the accuracy of any satellite remote sensing estimates for such a large region. Even though visual interpretation techniques are largely accepted, questions on how accurate these are versus digital analysis remain unanswered for deforestation studies in the Amazon region. Digital analysis is believed to be much less subjective. Once a pattern or assumed "signature" is known, computers can classify the whole scene objectively. However, land use classes are quite variable spectrally and there is usually no unique pattern for those classes. There is a great deal of analysts' decision in the digital approach. It remains important to investigate the variability of digital land use classifications performed by different analysts and to compare these results with visual interpretation estimates.

This work had the objective of assessing the variation in digital classification performance of major land use classes, with primary emphasis on deforestation, using Landsat TM data. Digital classifications done by five analysts, using a multispectral level-slicing technique, were compared with results of a robust classifier (modified maximum-likelihood decision rule) and with visual interpretations based on specific criterion. Comparisons were made using both estimations and evaluated in terms of mapping precision based on a pixel-by-pixel analysis. In addition, channel 3 of the AVHRR was also investigated to provide an independent estimation of deforestation. Further analyses of all five channels of AVHRR using the same techniques applied to the Landsat data were performed on the equivalent area of the TM scene for comparison. Field size distributions for the classes "others" and "clearings" were also investigated.

METHODS

STUDY AREA

The study site selected for this investigation, corresponds to the Landsat-5 scene (WRS: 227/67) centered at 10^{o} 08' S and 55^{o} 58' W. This area is dominated by a diversity of forest formations (IBGE and IBDF, 1988). Open ombrothermic forest is predominant, followed by a transition between "savanna" and "seasonal" forest and "savanna" and "ombrothermic" forest. There is also the occurrence of rain forest ("dense ombrothermic forest") in small proportions. There are two occurrences of "cerrado" ("savanna"), a typical vegetation of central plateau of Brazil, composed of grasses and woody species with great structural and density variations, from isolated trees to almost closed canopies. The cerrado occurs in the northeast and southwest of the scene.

This area is suffering great pressure from deforestation due to roads running to the east of the image and from the southeast towards Alta Floresta in a diagonal. Also, there are some clearings associated with the Teles Pires river which runs throughout the image. The clearing patterns are quite variable including the "fish bone" type typical of Rondonia to large fields similar to eastern Mato Grosso and south-eastern Para states.

PROCEDURES

Cloud-free Landsat Thematic Mapper (TM) data, acquired on July 18, 1988, were used in both digital and photographic forms. The digital analyses were based on TM bands 3, 4, and 5, using a systematic subsampling of every other line and pixel. Five independent classifications were performed by different "experienced" analysts using a simple classification method, the "multispectral level slicing technique" using the LAS (Land Analysis System) and IIS (International Imaging Systems) System 575 which run on VAX 11/780 and VAX 8200 computers of the Laboratory for Terrestrial Physics Computer Facility of NASA Goddard Space Flight Center. Five informational classes; water, forest, regrowth, clearings, and cerrado; were investigated. Post-classification analyses included the investigation of the classification performance for the combined clearing (regrowth plus clearing proper) and "other" (forest, water, shadow, and cerrado) classes. To minimize the imprecision, "deforestation" or "clearing" in the context of this paper, is used to mean the conversion of a forest canopy into a barren area or another vegetation community dominated by grass, shrub, or field crops. Once the field is abandoned and the native species begin to regrow and dominate the grasses it is called regrowth class.

The selection of the three thematic mapper bands was based on past experience and recommendations from the literature (Tardin and da Cunha, 1990; Chen et al. 1986; Stenback and Congalton, 1990). Additional bands would increase complexity resulting in analyst and computer time increases that would counteract any improvement in accuracies due to the added information. The sampling error introduced by selecting every other line and pixel should be very small (Bauer et al., 1978) and negligible compared to the error involved in spectral class assignment by the analyst.

In the "simple method" of classification, the thresholds for each class are established interactively, after displaying each band sequentially. Then, each sector (upper left, upper right corners, etc) of the scene is displayed (zoomed) and the threshold values refined. Finally, the refined thresholds are checked for the entire scene. Then, the individual classified bands are added, and the spectral classes of the composed image are assigned to the informational classes. The selection of this procedure was based on its simplicity and low cost. In terms of processing, it incorporates the efficiency of the simplest univariate method, "level slicing" (Swain and Davis, 1978) and yet, the procedure takes advantage of the multispectral information of TM data, allowing the analyst interactively assign informational classes to spectral classes. In comparison, the parallelepiped method, which has similar computational efficiency, may classify erroneously high correlated classes (Lillesand and Kieffer, 1979). The use of a more powerful algorithm, for instance the maximum likelihood classifier using just three TM bands for the entire Amazon Basin (over 250 scenes) would be prohibitive using current computer capabilities.

To provide a reference bench, a modified supervised classification of the entire scene was performed (Richards, 1986). The procedure involved clustering into unimodal spectral classes of a representative section of the scene, and then classifying the entire image based on the Bayes decision rule, also known as maximum likelihood decision rule. The resulting classified spectral classes were labeled using a color composite of the scene and the available vegetation map (IBGE and IBDF 1978).

The digital analyses were compared with visual interpretation results for the Alta Floresta scene. The visual interpretation is a major task led by NASA to assess the extent of deforestation and habitat fragmentation (C.J. Tucker, unpublished data, 1991). It involved delineating clearings using TM band 5, at the 1:250,000 scale, followed by the digitizing of the overlay using ARC/Info. Then, the results of each scene are integrated into a large file to compose the information for the entire Amazon Basin. To compare this information with the digital analysis, the scene had to be decomposed from the large archive and registered back to the TM image.

Areal extent estimates from the digital and deforestation analyses were also compared to deforestation estimates using AVHRR data. An image from 1988 day 190 (July 8, 1988) was selected using the 3.5 - 3.9 μm channel with 1.3 km (1.7 km^2 areal extent) spatial resolution from NOAA-9. The Alta Floresta area was free of clouds and minimal smoke was observed. The time of observation was 15:55 local solar time. Data were processed from 220^o-320^o Kelvin range with 10-bit radiometric resolution. Each radiometric level equals ~0.1^oK. Areas of undisturbed forest were selected adjacent to Alta Floresta TM scene and the mean and standard deviation were computed. The forest mean plus 3 standard deviations was used as the threshold between forest and non-forest (i.e., the 95% confidence limit).

In addition to the AVHRR channel 3 analysis, digital classifications using all five channels were performed based on the multispectral level slicing method and maximum likelihood classification for the Alta Floresta scene. The maximum likelihood classifications were performed using the same training set of different combinations of channels to verify the contribution of the AVHRR channels on the discrimination of five information classes (water, forest, cerrado, regrowth, and clearing). The maximum likelihood classifications were done on a Silicon Graphics Personal Iris 4D/20 (32 MB of memory and 1.2 GB of disk) using EASI/PACE software package from PCI. Training sites were selected based on the composite of AVRR channels 1, 2, and 3, using both Landsat TM and the vegetation map (IBGE and IBDF, 1988) as references.

Field size variation has a great impact on digital classification performance because it is associated with the diversity of the scene (Batista et al., 1985). Field size, defined as a cluster of adjacent pixels of the same class (e.g. clearings), was investigated for both the Bayes and deforestation classifications.

RESULTS

A visual inspection of the digital analyses indicated good agreement among all classification results (fig.1). Most particular features classified by one analyst as belonging to a certain class were usually assigned by the other analysts to the same class. This leads to the conclusion that this might be a simple technique that could be used to map these five informational classes, water, forest, regrowth, clearings, and cerrado. However, the density of the pixel assignments varies quite substantially, especially for highly variable spectral classes such as cerrado and regrowth. It is apparent that analysts 4 and 5 overestimated the cerrado class in detriment of forest. Before any conclusions regarding areal extent estimations for these classes could be drawn, the results have to be quantitatively examined.

AREA EXTENT ESTIMATIONS

Table 1 shows the areal extent estimations of each class by the different analysts and the Bayes classifier. Forest is by far the predominant class, followed by clearings which represents about 10% of the entire analyzed area. Analyst bias is readily apparent even for less variable spectral classes such as water. Water had the lowest frequency of occurrence and the the greatest variation in area estimates. For clearing, which was the major objective of this analysis, the area estimated by different analysts varied by 12%, excluding analyst 4 which did not classify clearing per se but rather clearing plus regrowth as a single class. When regrowth and clearing are considered as a single class, the estimations are more variable (36% between the largest and lowest estimations) because of the greater spectral heterogeneity of the regrowth class. In relation to the entire scene, the percent areal extent for clearings (clearing plus regrowth) varied from 14.4% to 19.5% (4,814 km^2 to 6,148 km^2).

Table 2 shows comparatively the results of Landsat TM digital analyses, visual interpretation estimations, and AVHRR analyses for deforestation (clearing plus regrowth) determination. As expected, the deforestation has a higher value than the digital TM estimations, because it includes not only the clearings but also fragmented forest patches. The digital classifications included some clearings in cerrado that were not separable spectrally. The upper bound of the 95% confidence interval is close to the deforestation "visual" estimate. The AVHRR analyses seem to have overestimated the deforestation area (~20%-50%).

Table 3 shows the results for the AVHRR channel 3 analyses. The AVHRR has three thermal bands which are useful for forest studies. Tucker et al. (1984) have reported that the greatest AVHRR spectral contrast between forest and deforested areas was in the 3.5-3.9 μm AVHRR channel. This channel is sensitive to temperatures in the 0° to 100° C range. We have found this channel is the most appropriate to detect cleared areas greater than 1 km since a substantially different radiation balance results in cleared areas being warmer than adjacent land where forest still stands which are cooler. AVHRR data have been used since 1982 to study areas like the Brazilian state of Rondonia. Variations as small as 0.1° C in the forest/deforestation threshold varied the estimated area by ±6%. This indicates that caution should be exercised for small area estimations of deforestation using AVHRR channel 3. Using the mean plus 3 standard deviations of the forest mean as the threshold value, results were similar to the Landsat TM (23% overestimation). This overestimation could be accounted by water and clearings within cerrado because they were not separated out from the non-forest category in the channel 3 thresholding analysis.

Due to the sensitivity of the AVHRR channel 3 thresholds, a more comprehensive analyses using several combinations of all five channels of the AVHRR were performed using both the maximum likelihood and multispectral level slicing techniques (Table 4 and 5). For the maximum likelihood classification of five information classes (water, forest, cerrado, regrowth, and clearings) a minimum of 3 channels are needed. In this case channels 1 and 2 should be selected along with either thermal channels 3 or 4. Other combinations resulted in overestimation of forest. At least the near infrared channel 2 should always be included in the three channel combination. Variation on the estimation of clearings were within 14% and for deforestation (clearings plus regrowth) were within 31% which were of the same magnitude of the TM variations.

The four channels combinations seem to improve the consistency of the classification results and seem to be just as good as all five channels (within 1% for deforestation). In this case the best combination of 4 channels was 1, 2, 3, and either 4, or 5. The use of a smoothing filter (3 x 3 pixels) did not change substantially the results for all classes, and due to the low resolution of the AVHRR it did not improve visually the classification map.

Results of the multispectral level slicing and the maximum likelihood techniques were very similar. However, clearing and regrowth were overestimated. Deforestation is in small proportion of the scene (less than 20%). The AVHRR sensor has a coarse spatial resolution (1.7 km^2). There is a large contrast between the spectral response of deforestation and forest in both reflective and thermal emission channels. A small proportion of clearing in a pixel dominated by forest makes this pixel distinct from a forest pixel and therefore, induces the analyst to assign it to clearing as opposed to forest. The maximum likelihood technique offers two parameters (threshold and a priori probability) that the analyst could use to minimize this bias. However, these parameters are interactively determined based on preliminary results by comparison with the color composite of the scene and therefore, the same bias trend persists. This explains the overestimation of the AVHRR (Table 5) in relation to the TM estimations (Table 1) for both clearings and regrowth classes.

Cerrado estimations by the AVHRR data are almost twice the TM estimations. This is consistent with the visual interpretation of the cerrado occurrence. The thermal channels, especially channel 3 are very helpful to separate cerrado from forest due to the contrast in evapotranspiration rates and hence temperature of these two cover types at the afternoon overpass of the NOAA satellite.

SIMPLE METHOD VERSUS BAYES CLASSIFICATION OF TM DATA

The overall coincidence with Bayes of the simple method (multispectral level slicing), on a pixel-by-pixel basis, of each analyst against the modified maximum likelihood classifier (Bayes) for the TM Alta Floresta scene, was very high for forest and clearings which are the primary classes of interest (Fig.2). This would also lead to the conclusion that the digital techniques used are adequate mapping tools for these two classes. From all pixels classified as clearing by Bayes, 88.2% were also classified as clearing by all analysts. Similarly, 86.8% for the forest class. This Table shows that regrowth is confounded with clearing and forest. In fact, this area has been continuously cleared since the sixties and the regrowth patterns vary quite substantially. Cerrado is quite variable spectrally and resulted in great confusion with forest, regrowth, and clearings. Based on just spectral information, cerrado cannot be accurately identified using TM bands 3,4, and 5.

Comparisons between all possible combinations of the classifications (Bayes plus five analysts) lead to similar conclusions (Fig. 2). The average represents the coincidence in a pixelwise basis between the classifications (n=15 for all classes, except for regrowth n=10). Again, cerrado and regrowth had the lowest average accuracies and the greatest standard deviations as opposed to forest and clearing. The class water had the greatest standard deviation as a result of a substantial overestimation by one of the analysts. But it represents only about 1% of the scene.

PIXELWISE COMPARISON BETWEEN DEFORESTATION AND DIGITAL ANALYSES OF TM DATA

Table 6 summarizes the comparisons between overall digital and visual interpretation classifications (two classes) in a pixelwise basis. Over 28% of the clearings identified by digital analysis was "natural" in the visual interpretation analysis. On contrary, only about 8% of forest in the digital analysis was considered clearing in the visual interpretation analysis. A visual comparison of classified maps of both analyses revealed that these 8% correspond mostly to small and irregular features. Many of these were later accounted for as "roads" in the visual interpretation analysis. The 28% is associated with the criterion of habitat fragmentation which in fact includes as clearings, areas of fragmented forest.

FIELD SIZE

Even though the criterion utilized to characterize the field is very convenient for digital processing once the digital classified image is available, it does tend to maximize the field size when compared to the traditional concept of field (Batista et al. 1985). Just one common single pixel connecting two fields of the same class will turn them into a single field. Fig. 3 shows the field size distribution for Bayes and visual interpretation classifications. As expected, small fields are much more frequent in the digital than in the visual interpretation analyses. Even though there are huge fields of clearings, small fields are more frequent for clearing than for "other" class, predominantly forest.

Looking at the misclassified fields, there is clear evidence that fields that are clearings in Bayes and "other" in the visual analysis tend to be small (less than 5 ha). On another hand, there is a high frequency of large (greater than 100 ha) fields classified as "other" in Bayes and as clearings in "visual" again in concert with the criterion of the visual interpretation.

Table 7 shows, quantitatively, the distribution of several classes of field sizes for the clearing class for both Bayes and visual interpretation classifications. Even though large fields (greater than 1000 ha) are responsible for the majority (90% of the total area cleared), there is a high frequency of small fields especially in the digital classification. This analysis of field size distribution becomes very important to explain the variation between the two approaches when several scenes of different complexity and clearing patterns are involved.

CONCLUSIONS

Visual inspection of the classification maps resulting from five independent digital analyses using a multispectral level slicing technique to classify Landsat TM bands 3, 4, and 5 into five classes (water, forest, regrowth, clearing, and cerrado) indicated a general agreement (82% coincidence with Bayes) among all classification results. Concentrations of any particular class seem to

(4.4% of the total clearings) correspond to the field size class of 0-10 ha. Small fields correspondent to single pixels tend to be mixed. The assignment of these pixels to a particular class tend to be subjected to high degree of analyst bias. The analysis of field size distribution is very important to explain the variation between digital and visual approaches when several scenes of different complexity and clearing patterns are involved.

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TABLE 1 AREA (km^2)

	BAYES	Analyst1	Analyst2	Analyst3	Analyst4	Analyst5
Water	693	285	277	526	352	2475
Forest	24933	25920	23765	24046	21371	19866
Cerrado	2161	1588	2992	3504	5242	4118
Regrowth	1640	1939	2444	1314	-----	2997
Clearings	3180	2875	3131	3217	5641	3151

TABLE 2 DEFORESTATION (CLEARINGS PLUS REGROWTH) AREA (km^2) DETERMINED BY TM DIGITAL ANALYSES, TM VISUAL INTERPRETATION, AND AVHRR ANALYSES

			95% Confidence Interval	
			Lower	Upper
TM Digital	5,255	(Average)	4,598	5,911
TM Visual	6,024			
AVHRR Channel 3*	6,463	(Median)	4,739	9,251
AVHRR (Maximum Likelihood)	7,189			
AVHRR (M. Level Slicing)	8,104			

* Non-forest class (includes water and clearings in cerrado)