EXTRACTING EARTH SURFACE FEATURE INFORMATION FOR LAND-USE/LAND COVER CLASSIFICATIONS IN AMAZÔNIA: THE ROLE OF REMOTE SENSORS

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RESUMO

Após décadas de desenvolvimento de sensores e técnicas de processamento, a ciência da informação geográfica tem feito inúmeras contribuições para a geração de dados sobre o uso e cobertura da terra (LULC). Este trabalho apresenta o estado da arte dos sensores mais utilizados e das recentes tendências em aplicações sobre LULC, particularmente na Amazônia. Técnicas de processamento também são discutidas, enfatizando alternativas aos convencionais métodos de classificação.

ABSTRACT

After decades developing sensors and processing techniques, geographic information science has consistently contributed to produce data about land-use and land cover (LULC). This paper presents the state of the art of the most used sensors and recent trends in LULC applications, particularly in the Amazon. Processing techniques are also discussed, emphasizing alternatives to the conventional methods of digital classification.

1. INTRODUCTION

The most commonly used remote sensing data for development of earth surface feature information in the Amazon Basin have been AVHRR, Landsat MSS, Landsat TM, SPOT, C-band Radar, L-Band Radar, and aerial photography. Other sensors, both existing and projected, which land surface focused researchers collectively have indicated an interest in using include: AVIRIS, airborne multispectral video or airborne multispectral digital camera, IKONOS, enhanced Landsat TM 7, and MODIS. The first part of this paper identifies common Amazon research themes associated with data acquired from each of these sensors and indicates why a given sensor is appropriate in addressing the themes identified. Recent trends are also briefly discussed, such as higher spatial resolution, higher spectral resolution, higher radiometric resolution, hyperspectral capability, and wavelengths not previously used by a given research group.

An alternate approach to improve the information content from spectral data is through the enhancement of original data. A third possibility is to implement different classification/analysis methods. A fourth way to improve the quality of information extraction using remote sensing is to integrate image classification with a GIS. The second part of this paper discusses the latter three ways of improving or potentially improving information extraction through remote sensing (enhancements, alternate analysis techniques, GIS support). The discussion is illustrated with related research or information from the literature concerning the Amazon.

2. THE STATE OF THE ART OF SOME SENSORS AND THEIR APPLICATIONS

After some decades developing sensors for aircraft and satellites, processing images derived from these sensors, and using different data analysis techniques for a variety of applications, remote sensing and geographical information science became a broad part of Earth Science. It is virtually impossible to list all the implications of every potential use of remote sensors for development of Earth surface feature information, even if we restrict the discussion to a particular application, such as land-use/land cover (LULC) change in the Amazon Basin.

I will address the subject focusing on two broad topics. First I will highlight the use of some commonly used sensors. Then I will focus on recent innovations. The discussion will be related to the objectives of the Indiana University/ACT (IU) research initiative within the LULC component of the Large-Scale Biosphere-Atmosphere Experiment in Amazônia (LBA).

The LBA experiment is one of the largest research efforts ever made to understand the relationships of human and environmental dimensions in the Brazilian Amazon (LBA 1996). Five out of seven study areas focused by the IU initiative are located along the LBA eastern transect. Our contribution is to provide data at local and landscape levels to inform regional models being built by LBA. The rationale behind this strategy is that our relatively little knowledge about these processes in Amazônia may be significantly improved by an integrated study at several temporal and spatial scales (Moran 1998). The following discussion about current and potential applications of remote sensing to the extraction of Earth surface feature information will focus on LULC applications and possible underlying factors related to the human dimensions of resource management in the region. The role of current and new sensors for this task is central as the variety of aerial and orbital data in distinct spatial, temporal, and spectral resolutions allows multiple applications.

2.1. MOST COMMONLY USED REMOTE SENSING DATA

The following paragraphs provide a brief description about the most commonly used remote sensing data for the extraction of Earth surface feature information and some of their major applications, particularly for LULC characterization in the Brazilian Amazon. I do not intend to cover all the characteristics of each sensor but rather give a general sense of its capabilities for the mentioned research field. Sources for the descriptions include Arnold (1997), Jensen (1996), Lillesand and Kiefer (1996), Szekielda (1988), and Richards (1986).

NOAA

The Advanced Very High Resolution Radiometer (AVHRR) flies onboard of the National Oceanic and Atmospheric Administration (NOAA) series of satellites, providing imagery in the visible, near infrared and thermal infrared wavelength bands. There is normally a pair of NOAA satellites in sun synchronous polar orbits, each orbit taking about 100 minutes, about 850 km above the planet's surface. The imagery data from a AVHRR sensor can be recorded or directly transmitted to a receiving station at a resolution of 1.1 km or 4 km. In either case, the across track swath width is about 3000 km. The along track swath length varies, but can be up to about 6000 km. The NOAA orbits are set up so that, twice daily, the current active pair of satellites provides coverage of almost the Earth's entire surface during a morning, afternoon, early evening and night pass. The series started in 1978 and continues up to date. The wavelength range of each band is:

- Band 1: 0,58 - 0,68 μm (red)
- Band 2: 0,72 - 1,10 μm (NIR)
- Band 3: 3,55 - 3,93 μm (MIR)
- Band 4: 10,3 - 11,3 μm (thermal)
- Band 5: 11,5 - 12,5 μm (thermal): on even numbered missions (e.g. NOAA 6, 8, 10, 12), channel 4 repeats

AVHRR was previously designed as a 'meteorological sensor' dedicated to applications such as cloud surface mapping, water surface delineation, and sea surface temperature monitoring. However, several researchers started using these images for a variety of other applications, based primarily on the wide range of wavelengths at the red and infrared portion of the electromagnetic spectrum. Several vegetation indices were derived, providing information on vegetation condition and density. The Normalized Difference Vegetation Index, for instance, has been widely used. This type of data is particularly useful to predict crop yields, to forecast vegetation fire danger zones, and to study vegetation dynamics. LULC mapping also has been done based on AVHRR data, mainly at global and regional scales (Malingreau and Belward 1992).

Due to its high sampling frequency and relatively low cost, AVHRR has provided large composite images, useful in several applications. Many studies have shown the potential of this instrument to study global vegetation, deforestation, and LULC in large areas (Malingreau and Tucker 1990, Townshend 1990, Roessel 1993). Other applications include burning monitoring, based on the responses of the thermal bands (Miranda et al. 1994). For the IU sites in LBA, AVHRR images are being explored for a regional assessment at each site, allowing for a broader understanding of LULC patterns including the landscapes under investigation.

LANDSAT

The LANDSAT series is the most widely used in remote sensing, particularly for LULC assessment. The series began in 1972. LANDSAT 1, 2, and 3 were pioneering efforts in remote sensing of Earth resources. All three have been decommissioned or have failed. They were sun-synchronous polar orbit satellites with an 18-day repeat cycle. The instruments included a RBV camera (bands 1, 2, 3) and the Multispectral Scanner (MSS), with the following characteristics:

- 185 x 185 km image extent
- 56 x 79 m pixel size, 6-bit data (0-63, rescaled to 0-127 gray levels)
- Band 1: 0,5 - 0,6 μm (green)
- Band 2: 0,6 - 0,7 μm (red)
- Band 3: 0,7 - 0,8 μm (NIR)
- Band 4: 0,8 - 1,1 μm (NIR)

LANDSAT 4 and 5 are the real 'work horses' of the program. They have a 16-day repeat cycle (9:45 local sun time) and include the same MSS as LANDSAT 1-3 plus the Thematic Mapper (TM), with the following characteristics:

- 185 x 185 km image extent
- 30 x 30 m pixel size, 8-bit data (0-255 gray levels)
- Band 1: 0,45 - 0,52 μm (blue)
- Band 2: 0,52 - 0,60 μm (green)
- Band 3: 0,63 - 0,69 μm (red)

- Band 4: 0,76 - 0,90 µm (NIR)
- Band 5: 1,55 - 1,75 µm (MIR)
- Band 6: 10,4 - 12,5 µm (thermal)
- Band 7: 2,08 - 2,35 µm (MIR)

It is redundant to say that many LULC applications in Amazônia have been done using LANDSAT images, particularly TM. LULC changes from natural vegetation to agricultural crops and subsequent regrowth may be quantified and related to both biophysical and socioeconomic causes through the integrative use of these images (Brondizio *et al*. 2000, McCracken *et al*. 1999, Hall *et al*. 1996, Lucas *et al*. 1998). Amazônia-wide studies of deforestation (Alves 1999, INPE, 1996, Skole and Tucker 1993) and forest alteration (Nepstad *et al*. 1999) have been conducted using TM data. Case studies have tracked LULC changes (Adams *et al*. 1995, Brondizio *et al*. 1994). Early research has failed to discriminate land cover classes such as some successional vegetation stages using MSS scenes (Dwivedi and Sankar 1992, Singh 1987). Several other initiatives have improved significantly the accuracy of classified LULC using TM data and distinct classification techniques, particularly for secondary regrowth mapping in Amazônia (Steininger 1996, Foody *et al*., 1996, Moran *et al*. 1994, Li *et al*. 1994, Mausel *et al*. 1993). Ecological studies have used TM data as a basis for the calculation of landscape metrics (Frohn *et al*. 1996, Dale *et al*. 1993, Batistella and Soares Filho, 1999). LANDSAT images have also improved the quality of fieldwork techniques (Campbell and Browder 1995). The IU project is assessing the human dimension of LULC in the region, using LANDSAT data to help the definition of factors and conditions that cause these processes. The support of field data and GIS integration has improved considerably the understanding and manipulation of LANDSAT images spectral range. A constraint for LANDSAT applications, as of any optical system when working in Amazônia is the frequent occurrence of clouds and smoke. Trends for future research include the integration of other sources of data (e.g., radar) to overcome this problem.

SPOT

The SPOT series, developed by the French Centre National d'Etudes Spatiales (CNES), started in 1986. In general terms, the main innovation of SPOT 1, 2, and 3 was the addition of a 10-meter resolution panchromatic band. Other more specific characteristics include off-nadir revisit, stereoscopy, and pointable instruments. The satellite is sun-synchronous, with a 26-day repeat cycle (local time 10-11am). The orbit is 832km high and the two High Resolution Visible (HRV) scanners are capable of operating in panchromatic mode (10 m resolution, 0,51 - 0,73 µm) and multispectral mode (20 m resolution):

- Band 1: 0,50 - 0,59 µm (green)
- Band 2: 0,61 - 0, 68 µm (red)
- Band 3: 0,79 - 0,89 µm (NIR)

SPOT 4 presently in operation also carries the Vegetation instrument, which has the same multispectral bands as SPOT 1, 2, and 3 plus a blue band (0,43 - 0,47 µm) and a mid-infrared band (1,58 - 1,75 µm). Its images are 2,000 x 2,000 km wide with a 1km spatial resolution.

The use of SPOT HRV instrument has not been very common to monitor LULC in the Amazon. The high relative cost of its images and the low relative spectral resolution to work with surface feature discrimination are two potential explanations for this fact. However, the high geometric fidelity and spatial resolution of SPOT panchromatic data are still very useful for the location of specific features, such as property boundaries of settlements in Amazônia.

The Vegetation instrument, although still little explored, have shown great potential for the global change community, due to its capability of vegetation monitoring (Klersy and Tempat 1994). Possible applications for the LBA experiment include surface parameters mapping; agricultural, pastoral and forest production assessment; terrestrial regional monitoring and modeling.

RADAR

Active remote sensing systems have been used for a variety of applications, particularly to extract information about surface parameters such as topography, geomorphology, soil moisture, coastal and flooding monitoring, and more recently LULC (Lillesand and Kiefer 1996). Microwave sensing is a very broad research field in itself. Several platforms, instruments, wavelengths and polarizations are available. The main general characteristic of these instruments, from a remote sensing standpoint, is that microwaves are capable of penetrating the atmosphere under virtually all conditions. When studying a region like the Amazon, where clouds are abundant during the wet season and smoke during the dry season, radar capability is appealing. Several studies have been done using radar data for LULC evaluation. I will focus on comparative approaches, with important conclusions for the LBA experiment and our LULC questions within the IU sites.

JERS (L-band), SIR-C (C- and L-band), and RADARSAT (C-band) have been the core data used for LULC studies in Amazônia (Ahern 1998). A comparative study on deforestation and secondary regrowth mapping in Rondônia found the following results (Rignot *et al*. 1997):

- C-band has limited utility for mapping deforestation
- At L-band, multiple polarizations are required for a reliable classification
- Single polarization, L-band, single date, JERS-1 data underestimate the extent of deforestation

- With multiple polarizations, six classes of land cover are mapped with 90% accuracy, including one level of regrowth, but intermediate regrowth is not well separated from the forest
- LANDSAT TM identify deforested areas better
- Combining the two classifications, seven classes of LC are mapped with 93% accuracy, including two classes of regrowth

Saatchi et al. (1997) also achieved high accuracy using SIR-C (L-band HH and HV channels) to separate secondary succession classes. Thus, low frequency radar systems seem more appropriate for land cover mapping in the Amazon (Yanasse *et al*. 1997). Results from SIR-C/X-SAR clearly show the increased value of using multiparameter and interferometric capabilities to characterize Earth's surface and vegetation cover and to generate geophysical products compared with optical sensors or single-channel radar alone (Evans *et al*. 1997). The integration between optical data and low frequency microwave data to solve problems of separability between LULC classes in Amazonian sites is a promising field of research.

AERIAL PHOTOGRAPHY

Airborne aerial cameras are remote sensors used for many decades (Reeves 1975). At the 'satellite age' one could argue why still using aerial photography. The answer is based on several factors, including:

- Improved and scalable vantage point
- Definition of a situation at a point in time, including for the past, when satellite images were not available
- Information can be recorded beyond the visible spectrum, including ultra-violet and infra-red
- Stereoscopy is possible
- Spatial resolution and geometric fidelity may be controlled

As technology develops, some of these characteristics may also be achieved by satellite images but still the aerial photos from the past will be useful for the study of LULC change. A typical potential use of these data in the Amazon is to evaluate environmental conditions prior to settlement installation or road construction. Many study areas were colonized decades ago, when even MSS images were not available. The only data available for that time are aerial photos and maps. The integration of these data in a GIS environment may provide a way to go deep into the past to investigate the pristine state of land cover.

2.2. OTHER POTENTIAL SENSORS

After describing the most commonly used sensors for LULC research in Amazônia, I will discuss some other potential instruments that are likely to be used for such applications.

AVIRIS

The Airborne Visible Infrared Imaging Spectrometer (AVIRIS) is a hyperspectral optical instrument developed to acquire data with a wide spectral and spatial coverage. The instrument flies onboard the NASA ER-2 aircraft at approximately 20km above ground level. Possible applications of AVIRIS are broad, including ecology, oceanography, soils and geology, snow and hydrology, atmosphere, among others.

The sensor has 224 contiguous spectral bands (approximately 9.6nm each) in the 380 to 2500nm range of the spectrum. The spatial resolution of the produced images is 20m and the ground swath is about 11km wide. When data from each band is plotted on a graph, it yields a spectrum. Comparing the resulting spectrum with those of known substances reveals information about the composition of the area being viewed by the instrument. The peaks and valleys of a spectrum not due to the sun or the atmosphere reveal information about the chemical composition of the pixel being examined. Every substance has its own spectrum, and one can look for the spectrum of specific features in the AVIRIS pixel spectra.

Processing AVIRIS images is not trivial. For LULC studies in the Amazon, I see two potential applications of this type of data. The first one would be to use AVIRIS bands to identify narrow spectral thresholds related to subtle changes in ground features, such as specific intervals during secondary succession. Once these portions of the spectrum are identified, they could be used to 'calibrate' the classification of images from different sources. Also, the identified features could improve the accuracy of some classification procedures (e.g., spectral mixture analysis) informing specific wavelengths for the subpixel discrimination. Another potential application of AVIRIS is land cover change detection. If a set of images is acquired through time, changes in their digital number (DN) spectra could inform about distinct processes such as phenology and agricultural cycles.

AIRBORNE HYPERSPECTRAL VIDEO OR DIGITAL CAMERA

The rationale behind the use of airborne multispectral video or digital camera is the possibility of a user to develop a instrument for specific purposes. Moran (1998) describes one example of hyperspectral camera developed to fly in small planes over the vegetation canopy. The camera functions as a 'flying spectro-radiometer', providing data at high spectral resolution and allowing the detection of DNs of very specific features at very narrow bands. Moreover, the very high spatial resolution of such a camera provides precise measurements.

The potential applications of data generated by airborne hyperspectral cameras are similar to those commented for AVIRIS. The extra benefit would be the possibility of having control of the whole operation for a specific area, allowing data generation at required time lags depending on the research needs.

IKONOS

IKONOS is a commercial satellite with high spatial resolution (1m panchromatic and 4m multispectral). It was launched recently to a sun-synchronous orbit. The nominal swath width is 13 km wide but mosaics of up to 12,000 sq.km may be produced. The panchromatic band ranges from 0.45 to 0.90 µm. The multispectral bands are the same as LANDSAT's first bands:

- Band 1: 0,45 - 0,52 µm (blue)
- Band 2: 0,52 - 0,60 µm (green)
- Band 3: 0,63 - 0,69 µm (red)
- Band 4: 0,76 - 0,90 µm (NIR)

Scientific reports about the use of IKONOS images for LULC assessments are still very recent. But the potential of these images is vast. They provide very detailed data allowing the analysis of relatively small features on the ground. Because IKONOS multispectral bands are the same as the first LANDSAT bands, comparisons of features will be viable at different spatial scales for LULC classification.

The Amazonian areas under investigation by the IU project include mosaics of patches of forest, secondary vegetation, and agriculture, several of them smaller than 1 ha. Using high spatial resolution images allow a better analysis of these patches throughout the image. Visual operations such as collecting training samples, interpreting LULC classes, and defining areas of interest tend to become more accurate. Although of high cost to cover large areas, IKONOS products will also be very useful during fieldwork, when features have to be recognized on the ground.

LANDSAT TM 7

LANDSAT 7 is the newest version of the LANDSAT series. It has the same characteristics of LANDSAT 4 and 5 plus the addition of a 15-meter resolution panchromatic band (0.522-0.90 µm). Other improvements include a higher spatial resolution for the thermal band (60m) and the important onboard radiometric calibration capability.

The major benefit generated by LANDSAT 7 for the LBA research groups is to provide timely, high quality visible and infrared images of Amazônia, continually updating the existing LANDSAT database. As radiometric and spectral resolutions remain the same, comparisons for global- and regional-change detection and characterization are possible.

RADAR - Shuttle Radar Topographic Mission (STRM)

As commented above, radar systems provide a wide range of applications for LULC researchers. Besides data integration to produce higher accuracy for LULC classification, the interferometric measurement capabilities uniquely provided by Synthetic Aperture Radar (SAR) are required to generate global topographic maps, to monitor surface topographic change, and to monitor glacier ice velocity and ocean features (Evans *et al*. 1997).

A very expected mission of the Space Shuttle was concluded recently. After 36 months of preparation and 18 months for data processing, the first Global Digital Elevation Model will be available. Modified SIR-C/X-SAR instruments (C- and X-band) have acquired topographic data over 80% of Earth's land mass (between 60 degrees North and 56 degrees South) during an 11-day Shuttle mission (the largest rigid structure flown in space).

The digital topographic map products to be generated will have 30m resolution, 16m absolute vertical height accuracy, 10m relative vertical height accuracy and 20m absolute horizontal circular accuracy. Numerous applications are waiting for the outcome of this mission. The entire LBA experiment will be benefited by a 30m resolution DEM. In several areas of the Amazon, there are not detailed topographic maps available impeding the development of studies that include this physical variable. With existing DEMs for the whole basin, we will be able to generate slope and aspect maps, construct models of water circulation, overlay topographical data with other biophysical variables, integrate DEM with satellite data to improve LULC classification, create 3-D models, and so on.

MODIS

The Moderate Resolution Imaging Spectroradiometer (MODIS) is the key instrument aboard Terra (EOS AM-1) satellite launched recently. MODIS sampling frequency is of 1 to 2 days, acquiring data in 36 spectra bands at a radiometric resolution of 12 bits. Spatial resolution varies among bands: bands 1-2 (250m), bands 3-7 (500m), and bands 8-36 (1000m). These data will improve our understanding of global dynamics and processes occurring on the land, in the oceans, and in the lower atmosphere. The table below shows some characteristics and potential applications of MODIS bands.

MODIS will play a vital role for the LBA experiment in the development of validated, regional, interactive system models about the biophysical environment. For the IU project, MODIS may provide a scalable approach using the bands in different spatial and spectral resolution to monitor LULC (e.g. phenology, agriculture cycles) and landscape dynamics (e.g. vegetation indices and enhancements for change detection) with a very high temporal resolution.

Primary Use	Band	Bandwidth
Land/Cloud Boundaries	1	620 - 670
	2	841 - 876
Land/Cloud Properties	3	459 - 479
	4	545 - 565
	5	1230 - 1250
	6	1628 - 1652
	7	2105 - 2155
Ocean Color/ Phytoplankton/ Biogeochemistry	8	405 - 420
	9	438 - 448
	10	483 - 493
	11	526 - 536
	12	546 - 556
	13	662 - 672
	14	673 - 683
	15	743 - 753
	16	862 - 877
Atmospheric Water Vapor	17	890 - 920
	18	931 - 941
	19	915 - 965
Surface/Cloud Temperature	20	3.660 - 3.840
	21	3.929 - 3.989
	22	3.929 - 3.989
	23	4.020 - 4.080
Atmospheric Temperature	24	4.433 - 4.498
	25	4.482 - 4.549
Cirrus Clouds Water Vapor	26	1.360 - 1.390
	27	6.535 - 6.895
	28	7.175 - 7.475
	29	8.400 - 8.700
Ozone	30	9.580 - 9.880
Surface/Cloud Temperature	31	10.780 - 11.280
	32	11.770 - 12.270
Cloud Top Altitude	33	13.185 - 13.485
	34	13.485 - 13.785
	35	13.785 - 14.085
	36	14.085 - 14.385

OBS: bands 1 to 19 are in nm; bands 20 to 36 are in μm

3. THE ROLE OF SOME PROCESSING TECHNIQUES

A variety of image processing techniques has been described in the literature (among others, Erdas 1998, Arnold 1997, Jensen 1996, Lillesand and Kiefer 1996, Szekielda 1988, and Richards 1986). Although some procedures are generally recommended to keep control over the accuracy of image processing techniques, there is no general recipe to achieve good quality results in remote sensing. Depending on the feature being analyzed, the characteristics of the sensor and the image, facilities available, personnel's expertise, time and cost constraints, one could use different approaches when extracting information from the landscape through analysis of spectral data.

I discuss three groups of methods to develop improved quality information during image processing. The first group is related to the use of data enhancement or transformation. The second group concerns to the implementation of different classification/analysis techniques. The last group concerns to the integration of remote sensing classifications with the support of geographical information systems (GIS). For each group, I have discussed different methodological approaches. By no means I intend to cover all the implications of each enhancement technique, each alternate classification procedure, or each supportive GIS technique. Examples are particularly related to LULC studies in Amazônia.

3.1. ENHANCING THE ORIGINAL DATA

Several purposes are claimed for the use of enhancement or transformation techniques (Mausel 1998). Among others, they include:

- Improvement of the overall quality of classification, e.g. through the merging of principal component or ratio bands before classification
- Reduction or elimination of noise in the data, e.g. the separation of noise in the last principal components
- Data compression, e.g. a ratio band instead of two bands or a principal component band explaining most part of the variation of the data set
- Maximization of spectral differences, e.g. through the use of different ratios

Also, some limitations are often recognized. It is always an extra effort to enhance or transform data, sometimes there is no improvement in the quality of classifications, and enhanced or transformed data are generally difficult to interpret. This is the reason why the cost/benefit of using these techniques should be always evaluated based on a theoretical basis about the procedure to be taken and the expected results.

RATIOS

Ratios are generally used in remote sensing to compress data and also to focus on specific subsets of a multispectral image (Lillesand and Kiefer 1996). Any given ratio tends to enhance a subset of features in a scene and degrade other subsets. These enhancements result from the division of digital numbers (DN) values in one spectral band by the corresponding values in another band. Ratioed images represent the variations in the slopes of the spectral reflectance curves between the two bands involved. Ratios will show better results if the reflectance responses for the same feature in different bands shows opposite behavior.

Ratios are used in image processing with three main objectives: to minimize spectral differences for similar features, to maximize spectral differences for different features, and to subtract subfeatures that are a minority in a feature. Sometimes, even having a reliable reason why to use ratios, the output may be difficult to interpret. This is probably one reason why many researchers have avoided the use of ratios in their applications. Through an exploratory search in the journal *Photogrammetric Engineering and Remote Sensing* since 1994, I found just eleven articles making use of some kind of ratio (Ramsey III *et al*. 1998, Kloditz *et al*. 1998, Lyon *et al*. 1998, Michener and Houhoulis 1997, Stoms *et al*. 1997, Ramsey III *et al*. 1997, Gaston *et al*. 1997, Yin and Williams 1997, Niemann 1995, Teng *et al*. 1995, and Thenkabail *et al*. 1994). However, when dealing with LULC classifications, we may want to recognize several different features (e.g., vegetation, water, soil, infrastructure, and so on). Ratios may be useful to help the discrimination of some of these features.

Near-infrared/red (NIR/R) is one of the most commonly used ratios to enhance the variance of vegetation. Healthy vegetation will have higher values in the NIR band and consequently a higher value for the ratio itself. Typically lower ratios will be found for stressed vegetation, as NIR reflectance decreases when the red reflectance increases. A more complex ratio using these two bands is the Normalized Difference Vegetation Index (NDVI), frequently used to identify and differentiate vegetation features in relation of some aspects, such as phenology (greenness) and biomass estimations. Near-infrared/mid-infrared (NIR/MIR) ratios may also be used to depict photosynthetic activity. Its general result is very similar to the NIR/R ratio, except for its higher sensitiveness to moisture in plants (Thenkabail *et al*. 1994). Vegetated areas are brighter than areas with bare soil (as NIR reflectance decreases when the MIR reflectance increases). But water features are not well discriminated from other classes because water and moisture in plants have similar responses both in NIR and MIR bands.

'Water ratios' commonly use the visible bands because of their penetration in this feature. Blue wavelength penetrates deeper than green and green penetrates deeper than red. Thus, a ratio between red and blue, for instance, might be useful to understand the numerous variations in the composition of water bodies.

Using ratios to investigate soil responses is more complicated because it involves either green or brown biomass, water as their moisture content, minerals, and so on. Besides that, color is not frequently an appropriate indicator of soil type or fertility (Nicholaides III and Moran 1995), except for particular parameters, such as organic matter (dark). Multiple ratios could be used to minimize soil influence in LULC classification, rank the moisture content in different soils within a landscape, discriminate various minerals and so on. The use of ratios in mineralogy is also possible but most mineral absorption bands are very narrow. Possible use of narrower bands of hyperspectral sensors may improve the potential of such ratios.

Finally, cultural features, such as urban areas may be difficult to discriminate when using ratio approaches, as concrete and asphalt have high reflectance responses in all bands. The partial applicability of many ratios is a good reason why they are generally integrated with raw data to allow a reliable classification of different land cover features.

Few studies have used vegetation ratios to classify different LULC features Amazon. Steininger (1996) investigated several indices trying to discriminate distinct ages of secondary succession. Considerable changes in spectral reflectance were observed over the first 19 years of regrowth, and these can be summarized by indices related to canopy brightness and greenness. The NIR reflectance, the difference index, Kauth-Thomas greenness, and percentage leaf cover all increase over the first 4 years after abandonment, peak from 4 to 8 years, and decrease from 8 to 13 years. The Normalized Difference Vegetation Index (NDVI) rapidly rises over the first 4 years, and displays no apparent relation to stand age thereafter. The brightness of regrowth canopies decreases from 8 to 13 years. According to these studies, spectral indices of canopy brightness are significantly correlated with regrowth stand age. Based on field research in several areas of Amazônia, these spectral patterns can be explained in terms of temporal changes in canopy geometry and leaf area. NDVI was found to be poorly related to the age and biomass, probably due to the dense leaf cover and strong pigment absorption of many tropical forest successional stages.

PRINCIPAL COMPONENT ANALYSIS

Principal components analysis (PCA) is a linear transformation, which uses image data statistics to define a rotation of original images in such a way that the new axes are orthogonal to each other and point in the direction of decreasing order of the variances (Eklundh and Singh 1993). This multivariate statistical technique used in remote sensing may have several applications, including image encoding and image data compression, reduction of dimensionality, noise removal, image enhancement, and digital change detection (Dwivedi and Sankar 1992).

The use of PCA in remote sensing has been highly associated with the fact that interband correlation is a problem frequently found in the analysis of multispectral images (Lillesand and Kiefer 1996). Thus, one of the main functions of PCA is to determine the extent of this correlation and, through a mathematical transformation, remove it. The final bands are totally uncorrelated (Crosta 1993). It is beyond the scope of this paper to discuss all implications of PCA. Instead, I intend to highlight the potential of this technique to extract the information content of spectral data.

There are three main steps to compute a PC transformation: the calculation of covariance or correlation matrix using input image data sets; the calculation of eigenvalues and eigenvectors; and the calculation of the principal components (Richards 1996). Unstandardized PCs are calculated using the covariance matrix and standardized PCs are calculated using the correlation matrix. The final components may be reformatted as PC bands through the use of eigenvectors statistics and processed as any other band (Landgrebe and Biehl 1995). One approach when using PCA is to investigate the loading of eigenvalues and eigenvectors to understand how the data variance is been explained by each component. A second approach is to merge the PC bands with other bands before classifying the image.

Very few studies have been carried out using PC bands to support the discrimination of vegetation features in Amazônia. Batistella (1999) used standardized and unstandardized PC bands and raw Landsat TM bands to classify LULC. Results showed that the use of PC bands did not bring a significant improvement in LULC classification accuracy for features such as mature forest, secondary succession stages, agricultural lands, and water. Further research in this field, particularly focusing on the use of PC transformation for more specific and narrow wavelengths of hyperspectral sensors may improve the discrimination of tropical vegetation features.

3.2. IMPLEMENTING DIFFERENT CLASSIFICATION TECHNIQUES

An alternate approach to increase information content from original and enhanced data is to implement improved classification techniques and methods of analysis. The transformation of spectral data into information through the extraction of thematic features has been traditionally done in a very standard way. Many textbooks present techniques for *supervised* or *unsupervised* classification, but not always they indicate the need of emphasizing the specific characteristics of each application. Taking the risk of being simplistic, I will mention some of the most used techniques during standard classification procedures, before indicating two important techniques to classify features composed of highly mixed pixels.

The main difference between supervised and unsupervised classification is that the former requires the identity and location of some of the land cover to be known (Mausel *et al*. 1990), while the latter is based on automatic clustering of pixels with similar spectral characteristics according to some statistically determined criteria (Jensen 1996). Hybrid classification systems are also frequently appropriate.

The unsupervised classification requires only a minimal amount of initial input from the analyst. However, knowledge about the spectral characteristics of the terrain is necessary to label certain clusters as representing land cover classes. Two algorithms are widely used. In the chain method, clusters are built and a mean vector is associated with each cluster. Then, a minimum distance to means classification algorithm is applied to assign each pixel to one of the created mean vectors (Landgrebe and Biehl 1995). In the ISODATA method (Iterative Self-Organizing Data Analysis Technique), the analyst specifies the maximum number of clusters, the maximum percentage of pixels whose class values are allowed to be unchanged between iterations, and the maximum number of times ISODATA is to classify pixels and recalculate cluster mean vectors (iterations) (Erdas 1998).

The supervised classification requires much more input from the analyst, including the collection of training samples, the generation of graphic methods for feature selection, and the selection of appropriate classification algorithms. Three algorithms are widely used. The minimum distance to means algorithm assigns the pixel class based on its distance to the mean center of a given cloud of points. The parallelepiped algorithm assigns the pixel class based on multi-dimensional rectangular shapes. The Gaussian maximum likelihood algorithm assigns the pixel class assuming a Gaussian distribution of the clouds of points (Lillesand and Kiefer 1996). The following paragraphs discuss two different techniques to improve the information content during the classification process.

SPATIAL-SPECTRAL CLASSIFIERS

The classifiers mentioned above do not take in account the spatial relationships among pixels. They rely solely on spectral data and each pixel is processed independently of its neighbors. Accuracy and errors can vary to a considerable degree depending on the formation of statistical classes from training data (Ince 1987).

After examining the variance of several images in a wide range of spatial resolutions, Woodcock and Strahler (1987) found that spectral classifiers are appropriate just for combinations of environments and spatial resolutions with low local variance. However, certain environmental features show a high variance, which affects the performance of the classification. When separating classes that are spectrally different in a simple classification system such as forest/non-forest, several approaches have shown adequate results (Alves *et al*. 1999). But when willing to generate a more detailed LULC classification, the use of these algorithms is not always recommended. A typical example of this problem is the classification of distinct stages of secondary growth in areas of the Brazilian Amazon. Using just spectral classifiers, some land cover classes cannot be reliably separated in a spectrally complex tropical forest environment. Because of the presence of mixed groups of pixels, other classification techniques should be tested. One of these techniques is a group of algorithms so called spatial-spectral classifiers.

Spatial-spectral classifiers assume spatially homogeneous objects that are larger than the resolution cells in the image. The basic strategy of these classifiers is to combine neighboring pixels into larger units as part of the classification process. The algorithms are based on the idea that using information from surrounding pixels enhances the classification (Gonzáles-Alonso and Soria 1991, Landgrebe 1980). This type of classifier is useful for the case in which some statistical distances between spectral classes are not sufficiently large, but spatial-spectral variability for the ground cover classes are different from each other (Arai 1993). One of these classifiers is called ECHO (Extraction and Classification of Homogeneous Objects). It first segments the scene into statistically homogeneous regions, and then classifies the data using a maximum likelihood algorithm (Landgrebe and Biehl 1995). If the parameter values during the segmentation process are chosen properly, ECHO usually provides higher accuracy than a pixel classifier. Several works willing to classify land cover in the Brazilian Amazon have confirmed this. Li *et al*. (1994) achieved accuracy higher than 93% when discriminating between advanced secondary succession and mature forest. Moran *et al*. (1994), Mausel *et al*. (1993), and Batistella (1999) also attained accuracy higher than 85% for several land cover classes using the same spatial-spectral classifier. Using another algorithm, Foody *et al*. (1996) and Kartikeyan *et al*. (1994) confirmed the important role of using contextual information when classifying intermixing features.

SPECTRAL MIXTURE ANALYSIS

A different approach to classify intermixing features is based on spectral mixture analysis. Its rationale is that each pixel in a scene commonly consists of a mixture of materials that all contribute to its spectral identity. Its objective is to isolate the main spectral contributions in each pixel. The primary difference between this technique and traditional classifiers refers to how signatures are derived and applied during classification. It derives a specific signature for a component that is common to the training set pixels. The signature is a specific material shared by training pixels and is used to identify pixels in the scene that contain the signature as a fractional component of the overall pixel spectrum (Schroeder 1998).

In other terms, the rationale behind spectral mixture analysis is to transform encoded-radiances (DNs) in all bands into fractions of reference endmembers, which are reflectance spectra of well-characterized materials that mix to produce spectra equivalent to those of pixels of interest in an image (Adams *et al*. 1995). Radiometric corrected images are needed in order to control atmospheric and sun angle effects during signature derivation. This process can be done through the calculation of combined gains and offsets for each band willing to calibrate the scene to reflectance values.

Then, some operational steps are required. The first of them is a preprocessing technique, when the image is surveyed for possible backgrounds that will be removed during signature derivation and classification of the materials of interest. The process of signature derivation develops a signature file for materials of interest that occupy either a whole pixel or a set fraction of a pixel. Inputs are the material input fraction and the confidence level required. Finally, the classification is carried out.

Spectral mixture analysis applied to multispectral images is a relatively new technique. Adams *et al*. (1995) obtained good results when detecting land cover change in the Brazilian Amazon. Further research is needed to assess the potential of this technique for the discrimination of mixed features such as different stages of secondary succession of tropical ecosystems.

Both techniques mentioned above (i.e., spatial-spectral classifiers and spectral mixture analysis) are appropriate for image conditions where there is high local variance. But they have pretty much opposite rationale. While spatial-spectral classifiers take in account the neighborhood effect to carry out a cartographic generalization, the spectral mixture analysis goes deeper into the pixel data to detect possible fractions affecting the spectral response. But both methods show great potential to achieve a better sense of land cover when intermixing features are present. The use of these techniques should be done with caution, considering factors such as the scale of the study, spatial and spectral resolution, features of interest, and possible shortcomings of each procedure.

3.3. SUPPORTIVE GIS METHODS

Results obtained from the single use of image processing systems are not always sufficient, mainly in studies involving integrated analyses of higher number of variables within the landscape and their spatial relations (Myers *et al*. 1989). For those, data are generally integrated in a GIS (Lioubimtseva 1999, Ball 1994, Flamm and Turner 1994, Mladenoff and Host 1994, Coulson *et al*. 1991). Qualified as a potent set of algorithms for digital manipulations of spatial attributes (Burrough 1986), these information systems have stored an amount always crescent of geographic data (Burrough and McDonnel 1998, DeMers 1997). Worldwide, multiple applications of GIS have been performed in diverse fields, integrating primary data acquired through remote sensing techniques (Townshend 1990, Goodchild and Brusegard 1989).

It has been demonstrated that remotely sensed digital data can be geocoded in a GIS and integrated with numeric data collected in the ground not only to track past deforestation, but also to see future trends of new agroecological processes (Brondizio *et al*. 2000, Marble *et al*. 1983, Domon *et al*. 1989, Mladenoff and Host 1994, Lillesand and Kiefer 1996). These trends represent a major potential for research programs such as the Large-Scale Biosphere-Atmosphere Experiment in Amazônia (LBA), due to the immense area of study and the myriad of variables involved.

Some applications use GIS as a tool for remotely sensed image processing. Others use remotely sensed data as an information source to GIS (Lunetta *et al*. 1991). These applications include line extraction from images to form boundaries; per-polygon classification; use of Digital Elevation Models (DEM) to correct image illumination/aspect or to geometrically correct radar images; use of image, DEM or shading information as the basis of vector search and query; and multiple modeling studies (Hinton 1996).

Landscape ecology and ecosystem management needs new methods to derive detailed spatial environmental data (Sample 1994). Lioubimtseva (1999) suggests a method of validation for broad-scale maps using ‘maplets’ generated from high-resolution remote sensing data. In this case, remote sensing techniques are been used to inform GIS manipulations at broader scales.

The opposite approach is to use field ancillary data to inform the extraction of information from spectral data. He *et al*. (1998) provided an interesting method to map temperate forests age classes and dominant canopy species at the landscape scale associating field data with preliminary Landsat TM classifications. Studies in the Brazilian Amazon have attempted to discriminate stages of secondary regrowth using vegetation and structure data integrated in a GIS (McCracken *et al*. 1999, Lucas *et al*. 1998). Topographic features (DEM), soil maps and other layers of information could also be tested to improve the accuracy of remotely sensed data classification. For the LBA sites under investigation by the IU project, vegetation structure and soil data could be used to inform the selection of features and training samples, if they are accurately mapped through Differential Global Positioning Systems (DGPS) and integrated in a GIS/remote sensing environment. Finally, accuracy assessment also may be improved if reliable ancillary data is used as test fields in an integrative remote sensing/GIS-based approach (Richards 1996, Janssen and Wel 1994). For all these applications it is important to monitor the quality of data used and results produced, always taking in account the research question underlying the choice of methodological tools.

4. CONCLUSION

The generation of global-, regional- and local-scale data sets, the reworking of historical data sets, new data initiatives, and some programmatic aspects of land data base development are fundamental themes to the remote sensing/GIS community (Justice *et al*. 1995). Similarly, the constant development and test of new processing techniques are central to achieve good results during the extraction of Earth surface feature information. LBA scientists are aware of these trends, making the discussion above just a small sample of the variety of current and potential applications for the large ongoing experiment in Amazônia.

These enhanced capabilities in terms of data and methods generate positive possibilities for the IU team. From the application standpoint, the new approaches discussed have allowed a more integrative study about LULC change within and across research sites.

The use of multi-temporal and multi-resolution datasets together with adequate processing techniques may provide a better understanding about the dynamics of deforestation, abandonment, and secondary regrowth in Amazônia. The study of LULC change and its human dimensions through these tools may contribute to a more sustainable development of the Amazonian communities under investigation.

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