

ACT Publication No. 11-01



## **Remote Sensing Image Classification**

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In: **Advances in Environmental Remote Sensing**. Q. Weng, ed. Taylor & Francis, Inc.

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# 9

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## 9.1 Introduction

The classification of remotely sensed data has long attracted the attention of the remote sensing community because classification results are fundamental sources for many environmental and socioeconomic applications. Scientists and practitioners have made great efforts in developing advanced classification approaches and techniques for improving classification accuracy (Gong and Howarth 1992; Kontoes et al. 1993; Foody 1996; San Miguel-Ayanz and Biging 1997; Aplin, Atkinson, and Curran 1999; Stuckens, Coppin, and Bauer 2000; Franklin et al. 2002; Pal and Mather 2003; Gallego 2004; Lu and Weng 2007; Blaschke 2010; Ghimire, Rogan, and Miller 2010). However, classifying remotely sensed data into a thematic map remains a challenge because many factors, such as the complexity of the landscape under investigation, the availability of reference data, the selected remotely sensed data, image-processing and image classification approaches, and the analyst's experiences, may affect classification accuracy. Many uncertainties or errors may be introduced into the classification results; thus, much effort should be devoted to the identification of these major factors in the image classification process and then to improving them. This chapter provides a brief overview of the major steps involved in the process of image classification, discusses the potential techniques for improving land-cover classification performance, and provides a case study for land use/cover classification in a moist tropical region of the Brazilian Amazon with Landsat thematic mapper (TM) imagery.

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## 9.2 Overview of Image Classification Procedure

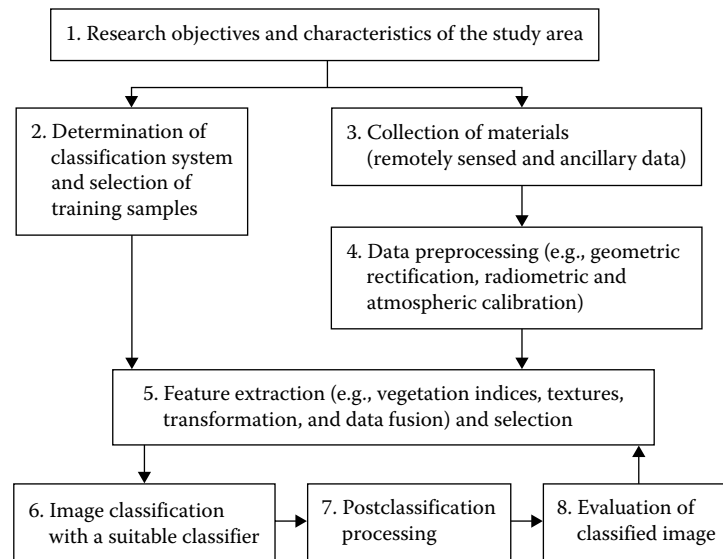
Classification of remotely sensed imagery is a complex process and requires the consideration of many factors. Figure 9.1 illustrates the major steps of an image classification procedure. Sections 9.2.1 through 9.2.8 provide brief descriptions for each step.

### 9.2.1 Nature of Remote Sensing Image Classification

Before implementing image classification for a specific study area, it is very important to clearly define the research problems that need to be solved, the objectives, and the location and size of the study area (Jensen 2005). In particular, clearly understanding the needs of the end user is critical. It is helpful to list some questions, such as the following: What is the detailed classification system and what are the most interesting land covers? What is the accuracy for each land cover or overall accuracy? What is the minimum mapping unit? What previous research work has been done and how can one maintain compatibility with it? What data sources are available and what data are required? What are the time, cost, and labor constraints? These questions directly affect the selection of remotely sensed data, selection of classification algorithms, and design of a classification procedure for a specific purpose.

### 9.2.2 Determination of a Classification System and Selection of Training Samples

A suitable classification system is a prerequisite for successful classification. In general, a classification system is designed based on the user's needs, the spatial resolution of the remotely sensed data, compatibility with previous work, available image-processing



**FIGURE 9.1**  
Major steps involved in the image classification procedure.

and classification algorithms, and time constraints. Such a system should be informative, exhaustive, and separable (Landgrebe 2003; Jensen 2005). In many cases, a hierarchical classification system is adopted to take different conditions into account.

A sufficient number of training samples and their representativeness are critical for image classifications (Hubert-Moy et al. 2001; Chen and Stow 2002; Landgrebe 2003; Mather 2004). Training samples are usually collected from fieldwork or from fine spatial resolution aerial photographs and satellite images. Different collection strategies, such as single pixel, seed, and polygon, may be used, but they will influence classification results, especially for classifications with fine spatial resolution image data (Chen and Stow 2002). When the landscape under investigation is complex and heterogeneous, selection of a sufficient number of training samples becomes difficult. This problem becomes complicated if medium or coarse spatial resolution data are used for classification, because a large volume of mixed pixels may occur. Therefore, selection of training samples must consider the spatial resolution of the remote sensing data being used, the availability of ground reference data, and the complexity of the landscapes under investigation.

### 9.2.3 Selection of Remotely Sensed Data

Remotely sensed data have different spatial, radiometric, spectral, and temporal resolutions. Understanding the strengths and weaknesses of different types of sensor data is essential for selecting suitable remotely sensed data for image classification. Some previous literature has reviewed the characteristics of major types of remote sensing data (Barnsley 1999; Estes and Loveland 1999; Althausen 2002; Lefsky and Cohen 2003). The selection of suitable remotely sensed data requires considering such factors as the needs of the end user, the scale and characteristics of the study area, available image data and their characteristics, cost and time constraints, and the analyst's experience in using the selected images. The end user's need determines the nature of classification and the scale

of the study area, thus affecting the selection of remotely sensed data. In general, at a local level, a fine-scale classification system is needed, thus high spatial resolution data such as IKONOS and QuickBird data are helpful. At a regional scale, medium spatial resolution data such as those from Landsat TM and Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) are the most frequently used data. At a continental or global scale, coarse spatial resolution data such as Advanced Very High Resolution Radiometer (AVHRR), Moderate Resolution Imaging Spectroradiometer (MODIS), and System Pour l'Observation de la Terre (SPOT) vegetation data are preferable.

Atmospheric condition is another important factor that influences the selection of remote sensing data. The frequent cloudy conditions in moist tropical regions are often an obstacle for capturing high-quality optical sensor data. Therefore, different kinds of radar data may serve as an important supplementary data source. Since multiple sources of sensor data are now readily available, image analysts have more choices to select suitable remotely sensed data for a specific study. In this situation, monetary cost is often an important factor affecting the selection of remotely sensed data.

#### 9.2.4 Image Preprocessing

Image preprocessing may include the examination of image quality, geometric rectification, and radiometric and atmospheric calibration. If different ancillary data are used, data conversions among different sources or formats and quality evaluation of these data are necessary before they can be incorporated into a classification procedure. The examination of original images to see any remote sensing system-induced radiometric errors is necessary before the data are used for further processing. Accurate geometric rectification or image registration of remotely sensed data is a prerequisite for combining different source data in a classification process.

If a single-date image is used for classification, atmospheric correction may not be required (Song et al. 2001). However, when multitemporal or multisensor data are used, atmospheric calibration is mandatory. This is especially true when multisensor data, such as TM and SPOT or TM and radar are integrated for an image classification. A variety of methods, ranging from simple relative calibration to the dark-object subtraction (DOS) method and complex physically based models (e.g., second simulation of the satellite signal in the solar spectrum [6S]), have been developed for radiometric and atmospheric correction (Markham and Barker 1987; Gilbert, Conese, and Maselli 1994; Chavez 1996; Stefan and Itten 1997; Vermote et al. 1997; Tokola, Löfman, and Erkkilä 1999; Heo and FitzHugh 2000; Song et al. 2001; Du, Teillet, and Cihlar 2002; Lu et al. 2002; McGovern et al. 2002; Canty, Nielsen, and Schmidt 2004; Hadjimitsis, Clayton, and Hope 2004; Chander, Markham, and Helder 2009). Topographic correction is important if the study area is located in rugged or mountainous regions (Teillet, Guindon, and Goodenough 1982; Civco 1989; Colby 1991; Meyer et al. 1993; Richter 1997; Gu and Gillespie 1998; Hale and Rock 2003; Lu et al. 2008a). A detailed description of atmospheric and topographic correction is beyond the scope of this chapter. Interested readers may check the references cited in this section to identify a suitable approach for a specific study.

#### 9.2.5 Feature Extraction and Selection

Selecting suitable variables is a critical step for successfully performing an image classification. Many potential variables may be used in image classification, including spectral signatures, vegetation indices, transformed images, textural or contextual information,

multitemporal images, multisensor images, and ancillary data. Because of the different capabilities of these variables in land-cover separability, the use of too many variables in a classification procedure may decrease classification accuracy (Price, Guo, and Stiles 2002). It is important to select only those variables that are most useful in separating land-cover or vegetation classes, especially when hyperspectral or multisource data are employed. Many approaches, such as principal component analysis, minimum noise fraction transform, discriminant analysis, decision boundary feature extraction, nonparametric weighted feature extraction, wavelet transform, and spectral mixture analysis (Myint 2001; Okin et al. 2001; Rashed et al. 2001; Asner and Heidebrecht 2002; Lobell et al. 2002; Neville et al. 2003; Landgrebe 2003; Platt and Goetz 2004), may be used for feature extraction, in order to reduce the data redundancy inherent in remotely sensed data or to extract specific land-cover information.

Optimal selection of spectral bands for image classification has been extensively discussed in the literature (Mausel, Kramber, and Lee 1990; Landgrebe 2003). Graphic analysis (e.g., bar graph spectral plots, cospectral mean vector plots, two-dimensional feature space plot, and ellipse plots) and statistical methods (e.g., average divergence, transformed divergence, Bhattacharyya distance, and Jeffreys–Matusita distance) have been used to identify optimal subsets of bands (Jensen 2005). In practice, divergence-related algorithms based on training samples are often used to evaluate class separability and select optimal bands.

### 9.2.6 Selection of a Suitable Classification Algorithm

In recent years, many advanced classification approaches, such as artificial neural networks, decision trees, fuzzy sets, and expert systems, have been widely applied in image classification. Cihlar (2000) discussed the status and research priorities of land-cover mapping for large areas. Franklin and Wulder (2002) assessed land-cover classification approaches with medium spatial resolution remotely sensed data. Published works by Tso and Mather (2001) and Landgrebe (2003) specifically focused on image-processing approaches and classification algorithms. In general, image classification approaches can be grouped into different categories, such as supervised versus unsupervised, parametric versus nonparametric, hard versus soft (fuzzy) classification, per-pixel, subpixel, and per-field (Lu and Weng 2007). There are many different classification methods available. For the sake of convenience, Lu and Weng (2007) grouped classification approaches as per-pixel, subpixel, per-field, contextual, and knowledge-based approaches, and a combination approach of multiple classifiers, and described the major advanced classification approaches that have appeared in the recent literature. In practice, many factors, such as the spatial resolution of the remotely sensed data, different data sources, classification systems, and the availability of classification software, must be taken into account when selecting a classification method for use. If the classification is based on spectral signatures, parametric classification algorithms such as maximum likelihood are often used; otherwise, if multisource data are used, nonparametric classification algorithms such as the decision tree and neural network are commonly used. Spatial resolution is an important factor affecting the selection of a suitable classification method. For example, high spectral variation within the same land-cover class in high spatial and radiometric resolution images such as those from QuickBird and IKONOS often results in poor classification accuracy when a traditional per-pixel classifier is used. In this circumstance, per-field or object-oriented classification algorithms outperform per-pixel classifiers (Thomas, Hendrix, and Congalton 2003; Benz et al. 2004; Jensen 2005; Stow et al. 2007;

Mallinis et al. 2008; Zhou, Troy, and Grove 2008). For medium and coarse spatial resolution data, however, spectral information is a more important attribute than spatial information because of the loss of spatial information. Since mixed pixels create a problem in medium- and coarse-resolution imagery, per-pixel classifiers have repeated difficulties in dealing with them. Subpixel-based classification methods can provide better area estimation than per-pixel-based methods (Lu and Weng 2006).

### 9.2.7 Postclassification Processing

Research has indicated that postclassification processing is an important step in improving the quality of classifications (Harris and Ventura 1995; Murai and Omatu 1997; Stefanov, Ramsey, and Christensen 2001; Lu and Weng 2004). Its roles include the recoding of land use/cover classes, removal of "salt-and-pepper" effects, and modification of the classified image using ancillary data or expert knowledge. Traditional per-pixel classifiers based on spectral signatures often lead to salt-and-pepper effects in classification maps due to the complexity of the landscape. Thus, a majority filter is often applied to reduce noise. Also, ancillary data are often used to modify the classification image based on established expert rules. For example, forest distribution in mountainous areas is related to elevation, slope, and aspects. Data describing terrain characteristics can be used to modify classification results based on the knowledge of specific vegetation classes and topographic factors. In urban areas, housing or population density is related to urban land-use distribution patterns, and such data can be used to correct some classification confusions between commercial and high-intensity residential areas or between recreational grass and crops (Lu and Weng 2006). As more and more ancillary data, such as digital elevation models (DEMs) and soil, roads, population, and economic data become available, geographic information systems (GIS) techniques will play an important role in managing these ancillary data and in modifying the classification results using the established knowledge or relationships between land cover and these ancillary data.

### 9.2.8 Evaluation of Classification Performance

The evaluation of classification results is an important process in the classification procedure. Different approaches may be employed, ranging from a qualitative evaluation based on expert knowledge to a quantitative accuracy assessment based on sampling strategies. A classification accuracy assessment generally includes three basic components: (1) sampling design, (2) response design, and (3) estimation and analysis procedures (Stehman and Czaplewski 1998). The error matrix approach is one of the most widely used in accuracy assessment (Foody 2002). In order to properly generate an error matrix, one must consider the following factors: reference data collection, classification scheme, sampling scheme, spatial autocorrelation, and sample size and sample unit (Congalton and Plourde 2002). After the generation of an error matrix, other important accuracy assessment elements, such as overall accuracy, omission error, commission error, and kappa coefficient, can be derived (Congalton and Mead 1983; Hudson and Ramm 1987; Congalton 1991; Janssen and van der Wel 1994; Kalkhan, Reich, and Czaplewski 1997; Stehman 1996; Smits, Dellepiane, and Schowengerdt 1999; Congalton and Plourde 2002; Foody 2002, 2004; Congalton and Green 2008). In particular, kappa analysis is recognized as a powerful method for analyzing a single error matrix and for comparing the differences among various error matrices (Congalton 1991; Smits, Dellepiane, and Schowengerdt 1999; Foody 2004). Many authors, such as Congalton (1991),

Janssen and van der Wel (1994), Smits, Dellepiane, and Schowengerdt (1999), Foody (2002), and Congalton and Green (2008), have reviewed the methods for classification accuracy assessment.

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### 9.3 Overview of Major Techniques for Improving Classification Performance

Different remotely sensed data will have variations in spatial, spectral, radiometric, and temporal resolutions, as well as differences in polarization. Making full use of these characteristics is an effective way of improving classification accuracy (Lu and Weng 2005; Lu et al. 2008b). Generally speaking, spectral response is the most important information used for land-cover classification. As high spatial resolution data become readily available, textural and contextual information become significant in image classification (Lu et al. 2008b). This section discusses some major techniques used for improving the performance of land-cover classification.

#### 9.3.1 Use of Spatial Information

The spatial resolution of an image determines the level of detail that can be observed on the Earth's surface, and spatial information plays an important part in improving land use/cover classification accuracy, especially when high spatial resolution images such as IKONOS and QuickBird images are employed (Sugumaran, Zerr, and Prato 2002; Goetz et al. 2003; Herold, Liu, and Clarke 2003; Hurtt et al. 2003; van der Sande, de Jong, and de Roo 2003; Xu et al. 2003; Zhang and Wang 2003; Wang et al. 2004; Stow et al. 2007; Mallinis et al. 2008; Zhou, Troy, and Grove 2008). A major advantage of these fine spatial resolution images is that such data greatly reduce the mixed-pixel problem, and there is the potential to extract much more detailed information on land-cover structures from these data than from medium or coarse spatial resolution data. However, some new problems associated with fine spatial resolution image data emerge, notably the shadows caused by topography, tall buildings, or trees, and the high spectral variation within the same land-cover class. These challenges may lower classification accuracy if classifiers cannot effectively handle them (Irons et al. 1985; Cushnie 1987). The huge amount of data storage capacity and severe shadow problems in fine spatial resolution images leads to challenges in selecting suitable image-processing approaches and classification algorithms. Spatial information may be used in different ways, such as in contextual-based or object-oriented classification approaches, or textural images (Blaschke 2010; Ghimire, Rogan, and Miller 2010).

#### 9.3.2 Integration of Different Sensor Data

Images from different sensors may contain distinctive features in reflecting land-cover surfaces. Data fusion or integration of multisensor data takes advantage of the strengths of distinct image data for improving visual interpretation and quantitative analysis. Many methods have been developed to integrate spectral and spatial information (Gong 1994; Dai and Khorram 1998; Pohl and van Genderen 1998; Chen and Stow 2003; Ulfarsson, Benediktsson, and Sveinsson 2003; Lu et al. 2008b; Amarsaikhan et al. 2010; Ehlers et al. 2010). Solberg, Taxt, and Jain (1996) broadly divided data fusion methods into four categories: (1) statistical,



(2) fuzzy logic, (3) evidential reasoning, and (4) neural network. Pohl and van Genderen (1998) reviewed data fusion methods, including color-related techniques (e.g., color composite, intensity, hue, and saturation [IHS], and luminance and chrominance), statistical/numerical methods (e.g., arithmetic combination, principal component analysis, high-pass filtering, regression variable substitution, canonical variable substitution, component substitution, and wavelets transforms), and various combinations of these methods. A recent review paper by Zhang (2010) further overviewed multisource data fusion techniques and discussed their trends. Li, Li, and Gong (2010) discussed the measures based on multivariate statistical analysis to evaluate the quality of data fusion results. In general, data fusion involves two major procedures: (1) geometric coregistration of two data sets and (2) mixture of spectral and spatial information contents to generate a new data set that contains the enhanced information from both data sets. Accurate registration between the two data sets is extremely important for precisely extracting information contents from both data sets, especially for line features such as roads and rivers. Radiometric and atmospheric calibrations are also needed before multisensor data are merged.

### 9.3.3 Use of Multitemporal Data

Temporal resolution refers to the time interval in which a satellite revisits the same location. A higher temporal resolution provides better opportunities to capture high-quality images. This is particularly useful for areas such as moist tropical regions, where adverse atmospheric conditions regularly occur. The use of remotely sensed data collected over different seasons has proven useful in improving classification accuracy, especially for crop and vegetation classification (Brisco and Brown 1995; Wolter et al. 1995; Lunetta and Balogh 1999; Oetter et al. 2000; Liu, Takamura, and Takeuchi 2002; Guerschman et al. 2003). For example, Lunetta and Balogh (1999) compared single- and two-date Landsat-5 TM images (spring leaf-on and fall leaf-off images) for wetland mapping in Maryland and Delaware, and found that multitemporal images provided better classification accuracies than single-date imagery by itself. An overall classification accuracy of 88% was achieved from multitemporal images, compared with 69% from single-date imagery.

### 9.3.4 Use of Ancillary Data

Ancillary data, such as topography, soils, roads, and census data, may be combined with remotely sensed data to improve classification performance. Harris and Ventura (1995) and Williams (2001) suggested that ancillary data may be used to enhance image classification in three ways: (1) preclassification stratification, (2) classifier modification, and (3) postclassification sorting. Since land-cover distribution is related to topography, topographic data have proven to be valuable in improving land-cover classification accuracy in mountainous regions (Janssen, Jaarsma, and van der Linden 1990; Meyer et al. 1993; Franklin, Connery, and Williams 1994), and topographic data are useful at all three stages of image classification as (1) a stratification tool in preclassification, (2) an additional channel during classification, and (3) a smoothing means in postclassification (Senoo et al. 1990; Maselli et al. 2000). In urban studies, DEM data are rarely used to aid image classification due to the fact that urban regions are often located in relatively flat areas. Instead, data related to human systems such as population distribution and road density are frequently incorporated in urban classifications (Mesev 1998; Epstein, Payne, and Kramer 2002; Zhang et al. 2002; Lu and Weng 2006). As discussed in Section 9.2.7, GIS techniques play an important role in the effective use of ancillary data in improving land use/cover classification performance.

## 9.4 Case Study for Land-Cover Classification with Landsat Thematic Mapper Imagery

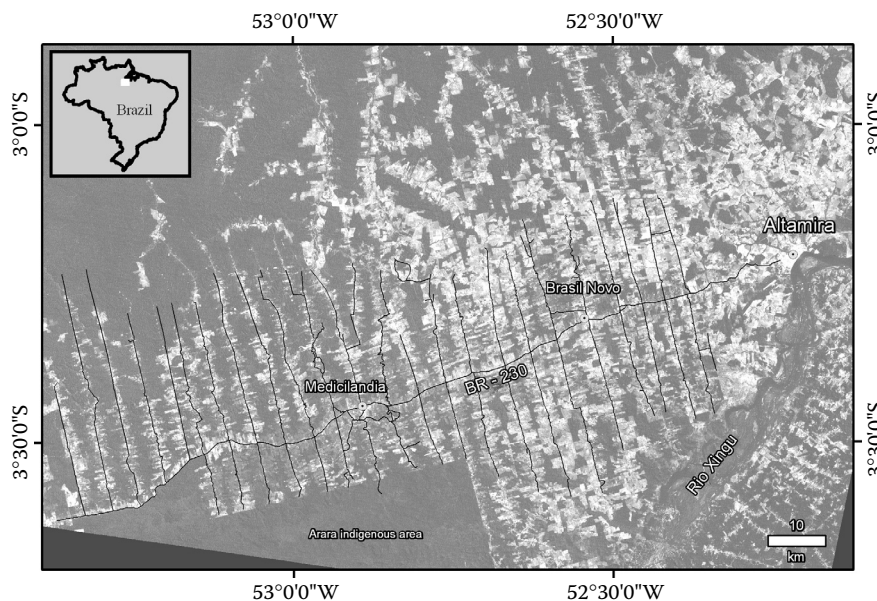
The previous sections have briefly reviewed major steps for image classification and potential measures for improving classification accuracy. The following section provides a case study in the moist tropical region of Brazil for showing how combination of remote sensing-derived variables and original spectral bands improved classification performance.

### 9.4.1 Research Problem and Objective

Landsat TM imagery is the most common data source for land-cover classification, and much previous research has explored methods to improve classification performance, including the use of advanced classification options such as neural network, extraction and classification of homogeneous objects (ECHO), object-oriented classifiers, decision tree classifier, and subpixel-based methods (Lu et al. 2004a, Lu and Weng 2007; Blaschke 2010). However, the role of vegetation indices and textural images in improving land-cover classification performance is still poorly understood, in particular in moist tropical regions such as the Brazilian Amazon. Therefore, we selected Altamira, Pará state, Brazil, as a case study to explore the role of vegetation indices and textural images in improving vegetation classification performance.

### 9.4.2 Study Area

Altamira is located along the Trans-Amazonian Highway (BR-230) in the northern Brazilian state of Pará. The city of Altamira lies on the Xingu River at the eastern edge of the study area (see Figure 9.2). In the 1950s, an effort was made to attract colonists from northeastern



**FIGURE 9.2**

Altamira of Para state, Brazil, was selected as the area for the case study.

Brazil, who came and settled along streams as far as 20 km from the city center. With the construction of the Trans-Amazonian Highway in 1970, this population and older caboclo settlers from earlier rubber boom eras claimed land along the new highway and legalized their land claims. Early settlement was driven by geopolitical goals of settling in the northern region of Brazil and by political economic policies aimed at shifting production of staples like rice, corn, and beans from the southernmost Brazilian states to the northern region. The uplands have a somewhat rolling topography, with highest elevation measuring approximately 350 m. Floodplains along the Xingu are flat, with the lowest elevation measuring approximately 10 m. Nutrient-rich alfisols and infertile ultisols and oxisols are found in the uplands of this area. The overall soil quality of this area is above-average fertility for Amazonia. The dominant native types of vegetation are mature moist forest and liana forest. Major deforestation in the area, began in 1972, which was concurrent with the construction of the Trans-Amazonian Highway (Moran 1981). Deforestation has led to a complex composition of different vegetation types in this area, such as different secondary succession stages, pasture, and agroforestry (Moran et al. 1994; Moran, Brondízio, and Mausel 1994; Moran and Brondízio 1998). Annual rainfall in Altamira is approximately 2000 mm and is concentrated during the period from late October through early June; the dry period occurs between June and September. The average temperature is about 26°C (Tucker, Brondízio, and Moran 1998).

### 9.4.3 Methods

After the research problems were clearly identified, research objectives were defined, and the study area was selected, the next step was to design a feasible classification procedure, which may include reference data collection for use as training samples, development of suitable variables from the selected remote sensing data, selection of a suitable classification algorithm, and evaluation of the classified image.

#### 9.4.3.1 Data Collection and Preprocessing

Sample plots for different land covers, especially for different stages of secondary succession and pasture, were collected during the summer of 2009 in the Altamira study area. Prior to fieldwork, candidate sample locations of complex vegetation areas were identified in the laboratory. In each sample area, the locations of different vegetation-cover types were recorded using a global positioning system (GPS) device, and detailed written descriptions and photographs of vegetation stand structures (e.g., height, canopy cover, species composition) were recorded. Sketch-map forms were used in conjunction with small field maps showing the candidate sample locations on A4 paper to note the spatial extent and patch shape of vegetation-cover types in the area surrounding the GPS point. Following the fieldwork, GPS points and field data were edited and processed using GIS and remote sensing software to create representative area of interest (AOI) polygons to be used for image classification. The AOI polygons were created by identifying areas of uniform pixel reflectance in an approximate  $3 \times 3$  pixel window size on the Landsat TM imagery. A land-cover classification system was designed based on our research objectives, compatibility with our previous research work (Mausel et al. 1993; Moran et al. 1994; Moran, Brondízio, and Mausel 1994; Moran and Brondízio 1998) and field surveys. The land-cover classification system included three forest classes (upland, flooding, and liana), three succession stages (initial, intermediate, and advanced stages, or SS1, SS2, and SS3), pasture, and four nonvegetated classes (water, wetland, urban, and burn scars).

A Landsat-5 TM image acquired on July 2, 2008 was geometrically registered to a previously corrected Landsat TM image with a geometric error of less than half a pixel. The nearest-neighbor resampling algorithm was used to resample the TM imagery to a pixel size of  $30 \times 30$  m. An improved image-based DOS model was used to perform radiometric and atmospheric correction (Chavez 1996; Lu et al. 2002; Chander, Markham, and Helder 2009). The gain and offset for each band and solar elevation angle were obtained from the image header file. The path radiance was identified based on clear water for each band.

#### 9.4.3.2 Selection of Suitable Vegetation Indices

Many vegetation indices have been used for different purposes, such as estimation of biophysical parameters (Bannari et al. 1995; McDonald, Gemmill, and Lewis 1998). Lu et al. (2004b) examined the relationships between vegetation indices and forest stand structure attributes such as biomass, volume, and average stand diameter in different biophysical conditions in the Brazilian Amazon. In this research, they found that vegetation indices with TM band 5 had higher correlation coefficients than those without band 5, such as normalized difference vegetation index (NDVI), in study areas like Altamira with complex forest stand structure. Therefore, in this research, different vegetation indices, including band 5, were designed, as well as other indices as summarized in Table 9.1. In order to identify suitable vegetation indices for improving vegetation classification performance, training sample plots for different vegetation types based on field surveys were selected for conducting separability analysis with the transformed divergence algorithm (Mausel, Kramber, and Lee 1990; Landgrebe 2003). Individual vegetation indices and a combination of two or more indices were explored. When different combinations of two or more indices

**TABLE 9.1**

Vegetation Indices Used in Research

Sl. No.	Vegetation Index	Equation
1	TC1	$0.304TM1 + 0.279TM2 + 0.474TM3 + 0.559TM4 + 0.508TM5 + 0.186TM7$
2	TC2	$-0.285TM1 - 0.244TM2 - 0.544TM3 + 0.704TM4 + 0.084TM5 - 0.180TM7$
3	TC3	$0.151TM1 + 0.197TM2 + 0.328TM3 + 0.341TM4 - 0.711TM5 - 0.457TM7$
4	ASVI	$((2NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - 2RED + BLUE)}) / 2$
5	MSAVI	$((2NIR + 1) - \sqrt{(2NIR + 1)^2 - 8(NIR - 2RED)}) / 2$
6	ND4_2	$(TM4 - TM2) / (TM4 + TM2)$
7	ND4_25	$(TM4 - TM2 - TM5) / (TM4 + TM2 + TM5)$
8	ND42_53	$(TM4 + TM2 - TM5 - TM3) / (TM4 + TM2 + TM5 + TM3)$
9	ND42_57	$(TM4 + TM2 - TM5 - TM7) / (TM4 + TM2 + TM5 + TM7)$
10	ND4_35	$(TM4 - TM3 - TM5) / (TM4 + TM3 + TM5)$
11	ND45_23	$(TM4 + TM5 - TM2 - TM3) / (TM4 + TM5 + TM2 + TM3)$
12	ND4_57	$(2 \times TM4 - TM5 - TM7) / (TM4 + TM5 + TM7)$
13	NDVI	$(TM4 - TM3) / (TM4 + TM3)$
14	NDWI	$(TM4 - TM5) / (TM4 + TM5)$

Note: ND = normalized difference; ASVI = atmospheric and soil vegetation index; MSAVI = modified soil adjusted vegetation index; TC = tasseled-cap transform. NIR, RED, and BLUE represent near-infrared, red, and blue band in TM image, that is, TM bands 4, 3 and 1. The ND number represents the TM spectral band.

are tested, standard deviation and correlation coefficients are used to determine the best combination of vegetation indices according to the following equation:

$$\text{Best combination} = \sum_{i=1}^n \text{STD}_i / \left| \sum_{j=1}^n R_{ij} \right| \quad (9.1)$$

where  $\text{STD}_i$  is the standard deviation of the vegetation index image  $i$ ,  $R_{ij}$  is the correlation coefficient between two vegetation index images  $i$  and  $j$ , and  $n$  is the number of vegetation index images.

#### 9.4.3.3 Selection of Suitable Textural Images

Many texture measures have been developed and textural images have proven useful in improving land-cover classification accuracy (Haralick, Shanmugam, and Dinstein 1973; Kashyap, Chellappa, and Khotanzad 1982; Marceau et al. 1990; Augusteijn, Clemens, and Shaw 1995; Shaban and Dikshit 2001; Chen, Stow, and Gong 2004; Lu et al. 2008b). Of the many texture measures, gray-level co-occurrence matrix (GLCM)-based textural images have been extensively used in image classification (Marceau et al. 1990; Lu et al. 2008b). Lu (2005) explored the roles of textural images in biomass estimation and found that textural images based on variance with TM band 2 and a window size of  $9 \times 9$  had a significant relationship with biomass. In another study, Lu and his colleagues (Lu et al. 2008b) explored textural images in vegetation classification and found that textural images based on entropy, second moment, dissimilarity, and contrast, with window sizes of  $7 \times 7$  or  $9 \times 9$ , exhibit better performance. Therefore, in our research, GLCM-based texture measures such as variance, homogeneity, contrast, dissimilarity, and entropy were explored with a window size of  $9 \times 9$  and Landsat TM bands 2, 3, 4, 5, and 7. Separability analysis with transformed divergence based on selected training sample plots of different vegetation classes was used for the selection of a potential single textural image or a combination of two or more textural images. The analysis of correlation and standard deviation of each textural image was used to identify the best combination according to Equation 9.1.

#### 9.4.3.4 Land-Cover Classification

Maximum likelihood classification (MLC) is the most common parametric classifier that assumes normal or near-normal spectral distribution for each feature of interest and an equal prior probability among the classes. This classifier is based on the probability that a pixel belongs to a particular class. It takes the variability of classes into account by using the covariance matrix. A detailed description of MLC can be found in many textbooks (e.g., Richards and Jia 1999; Lillesand and Kiefer 2000; Jensen 2005). In our research, MLC was used to conduct land-cover classification based on different scenarios, in order to explore the roles of vegetation indices and textural images in improving land-cover, especially vegetation classification in the moist tropical region. The scenarios included the consideration of six TM spectral bands, a combination of spectral and vegetation indices, a combination of spectral and textural images, and a combination of spectral indices, vegetation indices, and textural images. These classification results were analyzed based on accuracy assessment.

#### 9.4.3.5 Accuracy Assessment

Accuracy assessment is often required for a land-cover classification. A common method for accuracy assessment involves the use of an error matrix, for which the literature has provided the meanings of and calculation methods for overall accuracy, producer's accuracy, user's accuracy, and kappa coefficient (Congalton 1991; Smits, Dellepiane, and Schowengerdt 1999; Foody 2002; Congalton and Green 2008). In this study, a total of 338 test sample plots were used for accuracy assessment. An error matrix was developed for each classification scenario, and then producer's accuracy and user's accuracy for each class and overall accuracy and kappa coefficient for each scenario were calculated based on the corresponding error matrix.

#### 9.4.4 Results

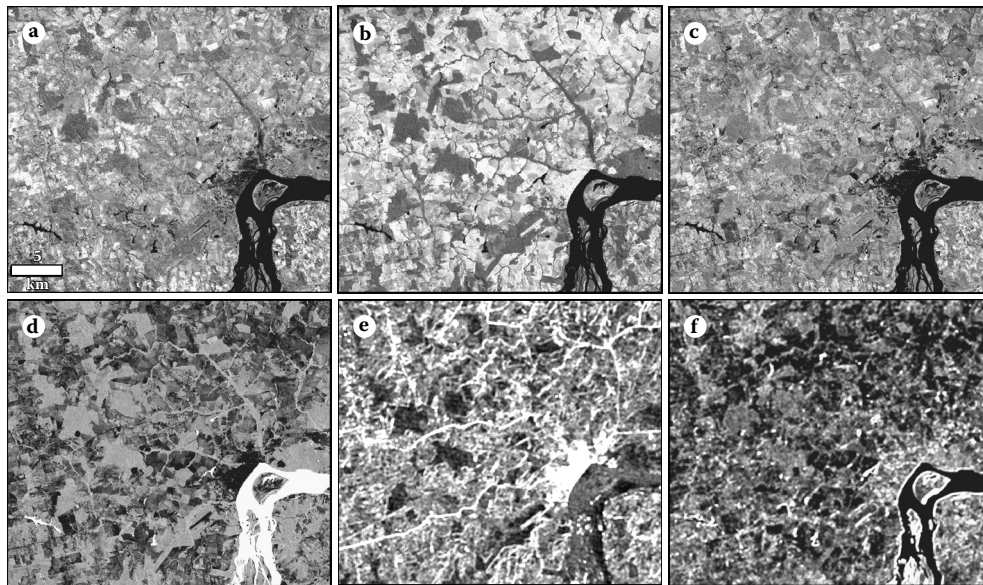
This section provides the analysis of the identified vegetation indices and textural images and compared the classified results with MLC based on different scenarios.

##### 9.4.4.1 Identification of Vegetation Indices and Textural Images

Since the classification of vegetation is especially difficult in our research, the selection of vegetation indices or textural images is essential to enhance vegetation separability, especially for different types of forest and secondary succession stages. Therefore, three forest types (upland forest, flooding forest, and liana forest), three succession stages (initial, intermediate, and advanced succession stages, or SS1, SS2, and SS3), and pasture were selected. The separability analysis indicated that the best single vegetation index includes ND4-25, TC2 (TC stands for tasseled cap), ND42-53, ND4-35, and TC3, and the best single textural images are from the dissimilarity on TM bands 2 or 3 (TM2-DIS, TM3-DIS), contrast on TM band 2 (TM2-CON), and homogeneity on TM bands 2 or 3 (TM2-HOM or TM3-HOM). However, no single individual vegetation index or textural image could separate the vegetation types. According to the separability analysis and the best combination model, a combination of two vegetation indices or two textural images provided the best results for vegetation separability. Three or more vegetation indices or textural images did not significantly improve vegetation separability; a similar conclusion was reached in our previous research (Lu et al. 2008b). Therefore, the best combination for two vegetation indices is TC2 and ND42-57, and the best combination for two best textural images is TM2-DIS and TM4-DIS (dissimilarity based on TM bands 2 and 4). Figure 9.3 provides the comparison of TM spectral bands, two selected vegetation indices, and two textural images, showing the different features for vegetation types, especially the textural images.

##### 9.4.4.2 Comparison of Classification Results

The comparison of accuracy assessment among different scenarios (see Table 9.2) indicated that although the incorporation of vegetation indices into spectral bands has a limited role in improving vegetation classification performance, it is helpful in improving the extraction and separability of pasture, water, and urban land covers; in contrast, the incorporation of textural images into spectral bands was valuable for improving vegetation classification performance, especially for upland forest, flooding forest, and intermediate and advanced succession classes. This research indicates that the incorporation of both

**FIGURE 9.3**

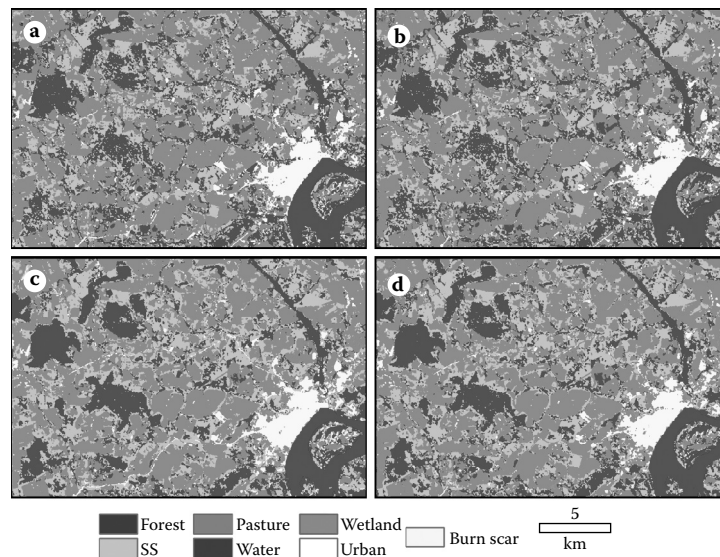
A comparison of thematic mapper (TM) bands 4 and 5, two vegetation indices, and two textural images. (a) and (b) TM bands 4 and 5; (c) and (d) the second component from tasseled cap transformation and the vegetation index based on bands 4, 2, 5, and 7; and (e) and (f) textural images based on dissimilarity on band 2 and band 4 and a window size of  $9 \times 9$  pixels.

**TABLE 9.2**

Comparison of Accuracy Assessment Results with MLC among Different Scenarios

Land-Cover Types	6SB		6SB and 2VI		6SB and 2TX		6SB and 2VI and 2TX	
	PA	UA	PA	UA	PA	UA	PA	UA
Upland forest	37.04	95.24	24.07	92.86	66.67	78.26	66.67	78.26
Flooding forest	93.75	50.00	100.00	41.03	100.00	66.67	100.00	69.57
Liana forest	95.45	66.67	95.45	63.64	81.82	66.67	84.09	69.81
SS1	84.00	61.76	80.00	64.52	92.00	57.50	92.00	58.97
SS2	67.86	90.48	67.86	86.36	78.57	95.65	82.14	92.00
SS3	89.66	74.29	86.21	75.76	79.31	85.19	86.21	89.29
Pasture	83.33	94.83	86.36	95.00	75.76	96.15	77.27	98.08
Water	68.18	100.00	95.45	100.00	72.73	100.00	95.45	100.00
Nonvegetated wetland	53.85	100.00	69.23	90.00	69.23	100.00	53.85	87.50
Urban	100.00	71.05	100.00	100.00	100.00	79.41	100.00	100.00
Burn scars	100.00	87.50	92.86	86.67	92.86	100.00	100.00	87.50
Overall accuracy		77.22		77.51		80.18		82.84
Kappa coefficient		0.7446		0.7485		0.7770		0.8071

6SB represents TM six spectral bands; 6SB and 2VI represent the combination of six spectral bands and two vegetation indices; 6SB and 2TX represent the combination of six spectral bands and two textural images; and 6SB and 2VI and 2TX represent the combination of six spectral bands, two vegetation indices, and two textural images. PA and UA represent producer's accuracy and user's accuracy.

**FIGURE 9.4**

(See color insert following page xxx.) Comparison of classification results among different scenarios with the maximum likelihood classifier: (a) six Thematic Mapper spectral bands, (b) combination of spectral bands and two vegetation indices, (c) combination of spectral bands and two textural images, and (d) combination of spectral bands, two vegetation indices, and two textural images.

vegetation indices and textural images into spectral bands provides the best classification performance. Figure 9.4 provides a comparison of classification results among the four scenarios. It indicates that the use of textural images can reduce the salt-and-pepper effect in the classification image, which is often produced with the per-pixel-based classification method.

#### 9.4.5 Summary of the Case Study

This study indicates the importance of textural images in improving vegetation classification accuracies. A critical step is to identify suitable textural images that can provide the best separability for specified classes. For the selection of a single textural image, one can select the textural image with the highest separability, but for the selection of two or more textural images, a method based on comparing the standard deviation and correlation coefficients between the images provides an easy way to identify a suitable combination.

### 9.5 Final Remarks

Image classification has made great progress over the past decades in the following three areas: (1) development and use of advanced classification algorithms, such as subpixel, per-field, and knowledge-based classification algorithms; (2) use of multiple remote sensing features, including spectral, spatial, multitemporal, and multisensor information; and (3) incorporation of ancillary data into classification procedures, including such data as topographic, soils, roads, and census data. Spectral features are the most important information



required for image classification. As spatial resolution increases, how to effectively use the spatial information inherent in the image becomes an important question to be considered. Thus, object-, texture-, or contextual-based methods have attracted increased attention (Lam 2008; Blaschke 2010; Ghimire, Rogan, and Miller 2010). Classification approaches may vary with different types of remote sensing data. In high spatial resolution data such as those from IKONOS and QuickBird, the high spectral variation within the same land-cover class poses a challenge. A combination of spectral and textural information and the use of per-field or object-oriented classification algorithms can reduce this problem. For medium and coarse spatial resolution data, mixed pixels are a problem, resulting in poor area estimation for classified images when per-pixel classifiers are used. Thus, subpixel features from spectral mixture analysis or fuzzy membership have been used in image classification. Moreover, image data have been integrated with ancillary data as another means for enhancing image classification in which GIS plays an important role. When multisource data are used in a classification, parametric classification algorithms such as MLC are typically not appropriate. Advanced nonparametric classifiers, such as neural network, decision tree, and evidential reasoning, or the knowledge-based approach appear to be the most appropriate choices.

The success of an image classification depends on many factors. The availability of high-quality remotely sensed imagery and ancillary data, design of a proper classification procedure, and skills and experiences of the analyst are most important. For a particular study, it is often difficult to identify the best classifier due to a lack of guidelines for classifier selection and the unavailability of suitable classification algorithms at hand. Comparative studies of different classifiers are thus frequently conducted. Moreover, the combination of different classification approaches has been shown to be helpful for improving classification accuracy. Future research is necessary to develop guidelines for the applicability and capability of major classification algorithms.

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## Acknowledgments

The authors wish to thank the National Institute of Child Health and Human Development at the National Institutes of Health (grant #R01 HD035811) and the National Science Foundation (grant #BCS 0850615) for their support for this research.

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