

ACT Publication No. 11-02



## **Land-Use and Land-Cover Change Detection**

D. Lu, E. Moran, S. Hetrick, and G. Li

In: **Advances in Environmental Remote Sensing**. Q. Weng, ed. Taylor & Francis, Inc. (Chapter 11)

---

**Anthropological Center for Training and Research on Global Environmental Change**  
Indiana University, Student Building 331, 701 E. Kirkwood Ave., 47405-7100, U.S.A.  
Phone: (812) 855-6181, Fax: (812) 855-3000, Email: [act@indiana.edu](mailto:act@indiana.edu), internet: [www.indiana.edu/~act](http://www.indiana.edu/~act)

# 11

## *Land-Use and Land-Cover Change Detection*

Dengsheng Lu, Emilio Moran, Scott Hetrick, and Guiying Li

### CONTENTS

11.1	Introduction .....	273
11.2	Overview of Change Detection Procedure .....	274
11.2.1	Nature of Change Detection Problems .....	275
11.2.2	Data Collection .....	276
11.2.3	Image Preprocessing .....	276
11.2.4	Image Processing and Classification .....	277
11.2.5	Selection of Change Detection Algorithms .....	278
11.2.6	Evaluation of Change Detection Results .....	279
11.3	Case Study for Detecting Urbanization with Multitemporal Landsat TM Images .....	279
11.3.1	Research Problem and Objective .....	279
11.3.2	Description of the Study Area .....	280
11.3.3	Methods .....	280
11.3.3.1	Data Collection and Preprocessing .....	281
11.3.3.2	Mapping of Impervious Surface Distribution .....	281
11.3.3.3	Detection of Urbanization .....	282
11.3.3.4	Evaluation of Urbanization Results .....	282
11.3.4	Results .....	282
11.3.5	Summary of the Case Study .....	282
11.4	Final Remarks .....	283
	Acknowledgments .....	284
	References .....	284

### 11.1 Introduction

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh 1989). Timely and accurate change detection of Earth's surface features provides the foundation for a better understanding of the relationships and interactions between human and natural phenomena in order to better manage and use resources. The advantages of repetitive data acquisition, its synoptic view, and a digital format suitable for computer processing have made remotely sensed data the major data sources for different change detection applications during the past decades (Lu et al. 2004; Kennedy et al. 2009). In general, change detection involves the application of multitemporal data sets to quantitatively analyze the temporal effects of the phenomena of interest. Good change detection research should provide the following information: area change and rate of change, spatial distribution

273

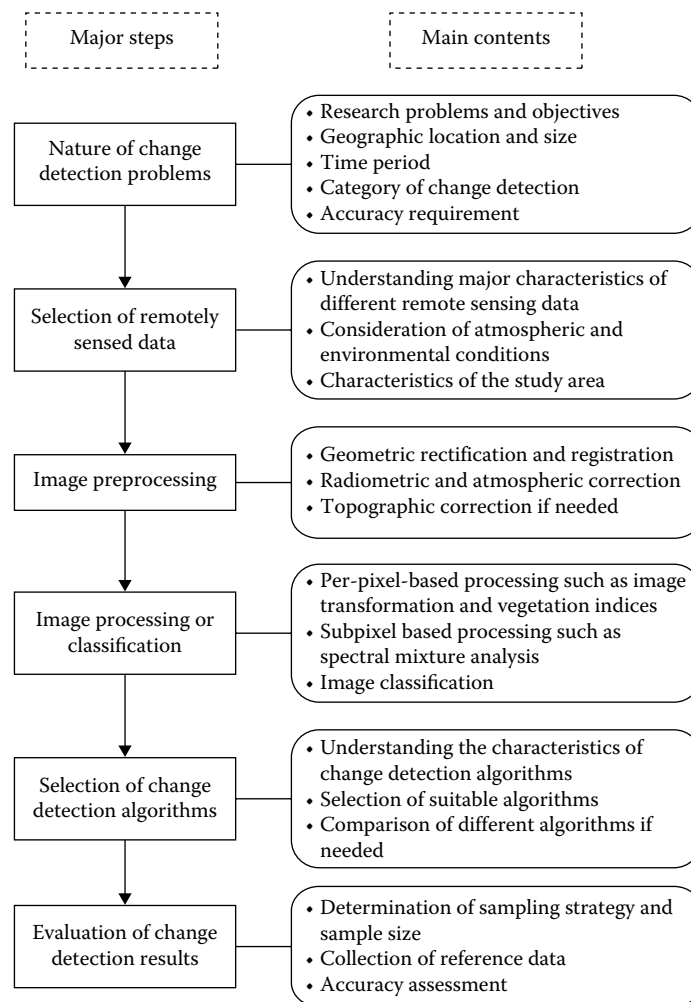
of changed types, change trajectories of land-cover types, and accuracy assessment of change detection results (Lu et al. 2004).

The objective of change detection is to compare spatial representation of two points in time by controlling all variances caused by differences in variables that are not of interest and to measure changes caused by differences in the variables of interest (Green, Kempka, and Lackey 1994). The basic premise in using remotely sensed data for change detection is that changes in the objects of interest will result in changes in reflectance values or local textures that are separable from changes caused by other factors, such as differences in atmospheric conditions, illumination, viewing angles, and soil moisture (Deer 1995). In practice, many factors, such as the quality of image registration, the quality of atmospheric correction or normalization between multitemporal images, the complexity of the landscape and topography under investigation, the analyst's skill and experience, and the selected change detection methods, can affect change detection results (Lu et al. 2004; Jensen 2005). Errors and uncertainties may come from different steps taken, such as in image preprocessing and selection of the change detection algorithm. It is important to understand the major steps in implementing the change detection procedure and to reduce errors or uncertainties in each step. Different authors have often arrived at different and sometimes controversial conclusions about which change detection techniques are most effective. Therefore, in this chapter, we describe the major steps used in the change detection procedure and provide a case study showing how to use change detection techniques to solve practical problems.

---

## 11.2 Overview of Change Detection Procedure

There are two categories of changes: changes between classes and changes within classes. A change between classes is a conversion of land cover from one category to a completely different category, for example through deforestation or urbanization. A change within classes is a modification of the condition of the land-cover type within the same category, for example through selective logging (Lu et al. 2004). The change detection procedure can be based on per-pixel, subpixel, or object-oriented methods, which require different image processing and change detection algorithms. The research objectives, remote sensing data used, and the geographical size of the study area can affect the design of the change detection procedure, including the use of different image processing methods and change detection techniques (Lu et al. 2004; Jensen 2005). In general, at a local scale, object-oriented methods are useful for reducing the spectral variation within the same land cover when very high spatial resolution images such as QuickBird or IKONOS are available. At a regional scale, per-pixel-based methods are often used when medium spatial resolution images such as Landsat Thematic Mapper (TM) images are available. For a national and global scale at which coarse spatial resolution images such as Moderate Resolution Imaging Spectroradiometer (MODIS) and Advanced Very High Resolution Radiometer (AVHRR) images are available, subpixel-based change detection techniques may provide better results than per-pixel-based techniques due to the mixed-pixel problem. However, in practice, per-pixel-based techniques are still the most common methods for land-cover change detection at different scales because the image processing techniques and change detection algorithms are mainly based on per-pixel data analysis. Therefore, this section mainly focuses on the per-pixel-based change detection procedure. Figure 11.1 illustrates the major steps and corresponding contents for

**FIGURE 11.1**

Major steps and corresponding main contents for a remote sensing-based land-cover change detection procedure.

the change detection procedure. The following subsections provide a brief description for each step.

### 11.2.1 Nature of Change Detection Problems

Before change detection is conducted in a specific study area, it is very important to clearly define the research problems that need solving, the objectives, and the location and size of the study area (Jensen 2005). These issues directly affect the selection of remotely sensed data and the selection of change detection algorithms. It is helpful to list some questions, for example, the kinds of change detection contents that are required: binary change and nonchange information, detailed “from-to” change trajectories, or the detection of continuous change. What is the accuracy overall and for each change detection trajectory? How large is the study area? What is the change detection period? What kinds of remote sensing

data and/or ancillary data are available? Based on these questions, one can identify specific research questions and objectives. After that, one can design a change detection procedure suitable for the specific study area and purpose.

### 11.2.2 Data Collection

Many remotely sensed data generated from both airborne and spaceborne sensors with different spatial, radiometric, spectral, and temporal resolutions, are available. In order to select suitable data sets for a specific study, it is important to understand the strengths and weaknesses of different types of sensor data. Some previous literature has reviewed the characteristics of the major types of remote sensing data (Barnsley 1999; Estes and Loveland 1999; Althausen 2002; Lefsky and Cohen 2003). For example, Barnsley (1999) and Lefsky and Cohen (2003) summarized the characteristics of different remote sensing data in spectral, radiometric, spatial and temporal resolutions, polarization, and angularity. The user's need, scale and characteristics of the study area, availability of various image data and their characteristics, cost and time constraints, and the analyst's experience in using the selected image may be the most important factors affecting the selection of remotely sensed data for a specific study area (Lu et al. 2004; Lu and Weng 2007). In general, at a local level, a fine-scale land-cover change scheme is required; thus, high spatial resolution data such as IKONOS, QuickBird, and SPOT 5 HRG (High-Resolution Geometric) data are helpful. At a regional scale, medium spatial resolution data such as Landsat TM and Terra Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) are the most frequently used data sources. On a continental or global scale, coarse spatial resolution data such as AVHRR, MODIS, and SPOT VEGETATION are preferable.

For a successful implementation of a change detection analysis using remotely sensed data, careful considerations of the remote sensor system, environmental characteristics, and image processing methods are important. The temporal, spatial, spectral, and radiometric resolutions of remotely sensed data have a significant impact on the success of a remote sensing change detection project. The important environmental factors include atmospheric conditions, soil moisture conditions, and phenological characteristics (Weber 2001; Jensen 2005). When selecting remote sensing data for change detection applications, it is important to use the same sensor, radiometric, and spatial resolution data with anniversary or very near anniversary acquisition dates in order to eliminate the effects of external sources, such as sun angle, seasonal, and phenological differences. However, in a specific study, selection of the same sensor data may be difficult, especially in moist tropical regions due to often cloudy conditions. Thus, the use of different sensor data for change detection is required (Lu et al. 2008a). Detailed descriptions about the considerations of remote sensing systems and environmental characteristics before implementing a change detection study are available in previous literature, such as Coppin and Bauer (1996), Biging et al. (1999), and Jensen (2005).

### 11.2.3 Image Preprocessing

Before implementing a change detection analysis, the following two conditions should be satisfied: (1) precise coregistration between multitemporal images and (2) precise radiometric and atmospheric calibration or normalization between multitemporal images. The importance of accurate geometric registration of multitemporal images is obvious, because largely spurious results of change detection are produced if there is misregistration (Townshend et al. 1992; Dai and Khorram 1998; Stow 1999; Verbyla and Boles 2000;

Carvalho et al. 2001; Stow and Chen 2002). Many textbooks have detailed the description of image-to-map rectification or image-to-image registration (e.g., Jensen 2005).

The same invariant objects could have different spectral signatures in different acquisition-date images due to different sun elevation angles and azimuth angles, vegetation phenological conditions, soil moisture, and atmospheric conditions. In such a case, the conversion of digital numbers to radiance or surface reflectance is a requirement for quantitative analyses of multitemporal images. A variety of methods, such as relative calibration, dark object subtraction, and 6S (second simulation of the satellite signal in the solar spectrum) have been developed for radiometric and atmospheric normalization or correction (Markham and Barker 1987; Gilbert, Conese, and Maselli 1994; Chavez 1996; Stefan and Itten 1997; Vermote et al. 1997; Tokola, Lofman, and Erkkila 1999; Heo and FitzHugh 2000; Yang and Lo 2000; Song et al. 2001; Du, Teillet, and Cihlar 2002; Lu et al. 2002; McGovern et al. 2002; Vicente-Serrano, Perez-Cabello, and Lasanta 2008; Chander, Markham, and Helder 2009). If the study area is rugged or mountainous, topographic correction may be necessary. More detailed information about topographic correction is available in Teillet, Guindon, and Goodenough (1982), Civco (1989), Colby (1991), Meyer et al. (1993), and Lu et al. (2008b).

#### 11.2.4 Image Processing and Classification

Change detection can be conducted using spectral bands or derived images such as vegetation indices and transformed images. For example, much previous research has indicated the usefulness of the visible red-band images in change detection analysis (Jensen and Toll 1982; Fung 1990; Chavez and Mackinnon 1994; Lu et al. 2005) because vegetation has low reflectance, but impervious surfaces or soils have high reflectance in this band. However, a single band cannot reflect all changed information due to the complex landscapes. For many situations, use of transformed images or vegetation indices can be more effective in extracting the differences of changed features than single spectral bands (Lu et al. 2005). Image transformation is often used to reduce data redundancy and the number of image channels so that the information contents are concentrated in a few transformed images (Jensen 2005). Different techniques have been developed to transform the multispectral data into a new data set. Principal component analysis (PCA), tasseled cap, minimum noise fraction, 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; Lu et al. 2008a) are among the most commonly used techniques. Vegetation indices are recommended for removing the variability, which is caused by canopy geometry, soil background, sun view angles, and atmospheric conditions when measuring biophysical properties (Elvidge and Chen 1995; Blackburn and Steele 1999). Many vegetation indices have thus been developed and applied to biophysical parameter studies (Anderson and Hanson 1992; Anderson, Hanson, and Haas 1993; Eastwood et al. 1997; Mutanga and Skidmore 2004). Vegetation indices are often used for land-cover change detection, especially for vegetation change.

For many applications, detailed land-cover change trajectories are required; thus, classification-based change detection techniques, such as postclassification comparison, are often used. Scientists and practitioners have made great efforts to develop 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).

Much previous literature has been specifically concerned with image classification (Tso and Mather 2001; Landgrebe 2003). Lu and Weng (2007) provided a comprehensive up-to-date review of classification approaches and techniques. Since classification results are the required data sets for detecting detailed land-use and land-cover “from-to” change trajectories, high classification accuracies are critical for change detection because individual classification accuracy will affect the change detection accuracy.

### 11.2.5 Selection of Change Detection Algorithms

For a given research purpose, when the remotely sensed data and study areas are identified, selection of an appropriate change detection method has considerable significance in producing a high-quality change detection product. Some techniques, such as image differencing, can only provide change or nonchange information, whereas other techniques, such as postclassification comparison, can provide a complete matrix of change directions. In general, change detection techniques can be roughly grouped into two categories: (1) those detecting binary change or nonchange information, such as using image differencing, image ratioing, vegetation index differencing, and PCA and (2) those detecting detailed “from-to” change trajectory, such as using the postclassification comparison and hybrid change detection methods (Lu et al. 2004). Previous literature has reviewed many change detection techniques (Singh 1989; Coppin and Bauer 1996; Yuan, Elvidge, and Lunetta 1998; Serpico and Bruzzone 1999; Coppin et al. 2004; Lu et al. 2004; Jensen 2005; Kennedy et al. 2009). Lu et al. (2004) grouped change detection methods into seven categories: (1) algebra, (2) transformation, (3) classification, (4) advanced models, (5) geographic information system approaches, (6) visual analysis, and (7) other approaches, and summarized the major characteristics, advantages, and disadvantages for the selected techniques. Due to the importance of monitoring changes among Earth’s surface features, the research of change detection techniques has long been an active topic, and new techniques are constantly appearing.

When implementing change or nonchange detection, one critical step is to select appropriate thresholds in both tails of the histogram representing the changed areas (Singh 1989). Two methods are often used for the selection of thresholds (Singh 1989; Yool, Makaio, and Watts 1997): (1) interactive procedure or manual trial-and-error procedure—an analyst interactively adjusts the thresholds and evaluates the resulting image until satisfied; and (2) statistical measures—selection of a suitable standard deviation from the mean. The two disadvantages of the threshold technique are (1) the resulting differences may include external influences caused by atmospheric conditions, sun angles, soil moistures, and phenological differences in addition to true land-cover change; and (2) the threshold is highly subjective and scene dependent, depending on the analyst’s familiarity with the study area and skill (Lu et al. 2004, 2005). When implementing the detailed “from-to” change detection, the results are mainly dependent on the classification accuracy for each date being analyzed (Jensen 2005). In other words, classification errors from the individual-date images will affect the final change detection accuracy. The critical step is to develop an accurate classification image for each date.

In practice, an analyst often selects several methods to implement change detection in a study area and then compares and identifies the best result through accuracy assessment (Muchoney and Haack 1994; Michener and Houhoulis 1997; Macleod and Congalton 1998; Yuan and Elvidge 1998; Mas 1999; Dhakal et al. 2002; Lu et al. 2005). Although a large number of change detection applications have been implemented and different change detection techniques have been tested, the question of which method is best suited for

a specific study area remains unanswered. No single method is suitable for all cases. The method selected depends on an analyst's knowledge of the change detection methods and skills in handling remote sensing data, the image data used, and characteristics of the study areas.

### 11.2.6 Evaluation of Change Detection Results

Accuracy assessment for change detection is particularly difficult due to problems in collecting reliable temporal field-based data sets; thus, much previous research on change detection did not provide a quantitative analysis of the research results. Standard accuracy assessment techniques have been developed mainly for single-date remotely sensed data. Previous literature has provided the meanings and calculation methods for these elements (Congalton, Oderwald, and Mead 1983; Congalton 1991; Janssen and van der Wel 1994; Kalkhan, Reich, and Czaplewski 1997; Biging et al. 1999; Smits, Dellepiane, and Schowengerdt 1999; Congalton and Plourde 2002; Foody 2002; Congalton and Green 2008). The error matrix-based accuracy assessment method is the most common and valuable method for the evaluation of change detection results. In addition, some new methods have been developed to analyze the accuracy of change detection (Morisette and Khorram 2000; Lowell 2001). Morisette and Khorram (2000) used "accuracy assessment curves" to analyze satellite-based change detection, and Lowell (2001) developed an area-based accuracy assessment method for the analysis of change maps. A monograph titled "Accuracy assessment of remotely sensed-derived change detection," edited by Siamak Khorram (Biging et al. 1999), is specifically focused on the accuracy assessment of land-cover change detection. This monograph describes the issues affecting the accuracy assessment of land-cover change detection, identifies the factors of a remote sensing processing system that affect accuracy assessment, presents a sampling design to estimate the elements of the error matrix efficiently, illustrates possible applications, and gives recommendations for accuracy assessment of change detection.

---

## 11.3 Case Study for Detecting Urbanization with Multitemporal Landsat TM Images

Section 11.2 briefly overviewed the major steps used in the change detection procedure. This section provides a case study for showing how to conduct a change detection for examining urban expansion based on multitemporal TM images in a complex urban-rural landscape.

### 11.3.1 Research Problem and Objective

Digital change detection in urban environments is a challenge due to three characteristics unique to urban areas: (1) urban land-use and land-cover changes usually account for a small proportion of the study area and are scattered in different locations; (2) impervious surfaces and similar spectral features between impervious surfaces and other nonvegetation land covers are complex; and (3) the spatial resolution of remotely sensed imagery is limited. Although many change detection techniques, such as PCA, image differencing, and postclassification comparison, can be applied to urban land-use and land-cover change detection (Singh 1989; Coppin and Bauer 1996; Coppin et al. 2004; Lu et al. 2004;



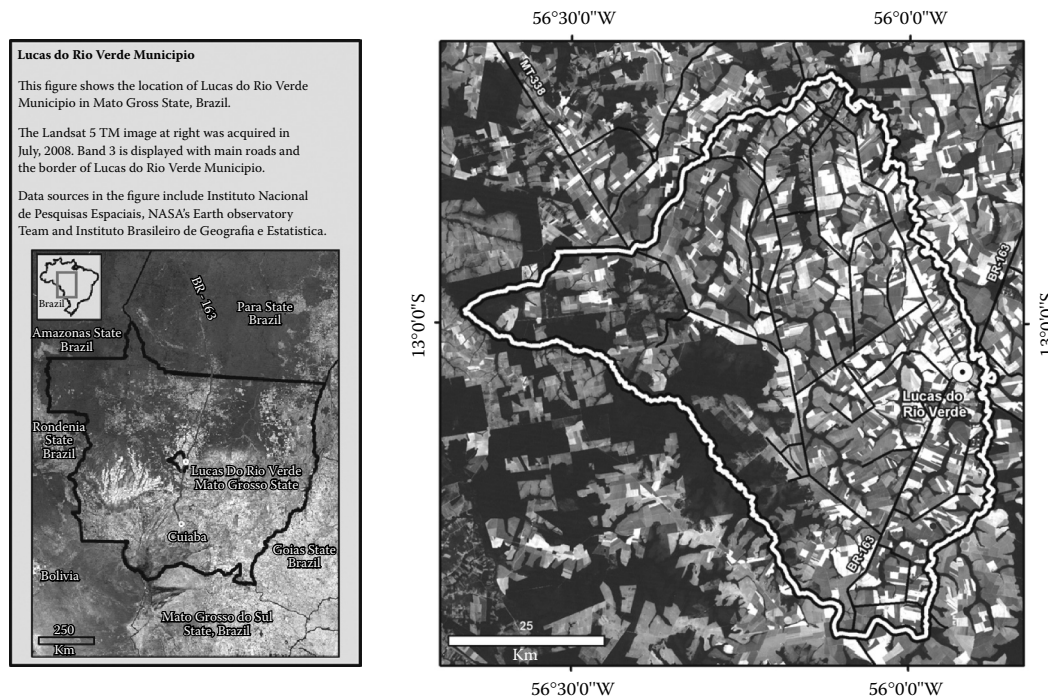
Kennedy et al. 2009), the detection results are often poor, especially in urban–rural frontiers. Therefore, this research aims to develop a change detection procedure suitable for detecting urbanization in a complex urban–rural frontier, based on the comparison of extracted impervious surface data sets from multitemporal Landsat TM images.

### 11.3.2 Description of the Study Area

Lucas do Rio Verde (hereafter called simply Lucas) in Mato Grosso state, Brazil, has a relatively short history and small urban extent. It was established in the early 1980s (Figure 11.2), and has experienced rapid urbanization. This region is connected to the city of Santarém, a river port on the Amazon River, and to the heart of the soybean growing area at the city of Cuiabá by highway BR-163, which runs through the county. The economic base of Lucas is large-scale agriculture, including the production of soy, cotton, rice, and corn, as well as poultry and swine. The county is at the epicenter of soybean production in Brazil, and it is expected to grow in population threefold in the next 10 years. Because it is, at present, a relatively small town, yet has complex urban–rural spatial patterns derived from its highly capitalized agricultural base, large silos and warehouses, and planned urban growth, Lucas is an ideal site for exploring techniques for detecting urbanization with remote sensing data.

### 11.3.3 Methods

After the research objectives were clearly defined, the next step was to select suitable remote sensing data and to design a feasible procedure for implementing change detection.



**FIGURE 11.2**  
Study area—Lucas do Rio Verde Municipio, Mato Grosso state, Brazil.

### 11.3.3.1 Data Collection and Preprocessing

Landsat images acquired on June 21, 1984, June 6, 1996, and May 22, 2008 were used in this research. Radiometric and atmospheric calibration was conducted using the image-based dark-object subtraction (DOS) method. The DOS model is an image-based procedure that standardizes imagery for the effects caused by solar zenith angle, solar radiance, and atmospheric scattering (Lu et al. 2002; Chander, Markham, and Helder 2009). The equations used for Landsat TM image calibration are

$$R_{\lambda} = \frac{PI \times D \times (L_{\lambda} - L_{\lambda, \text{haze}})}{[Esun_{\lambda} \times \cos(\theta)]} \quad (11.1)$$

$$L_{\lambda} = gain_{\lambda} \times DN_{\lambda} + bias_{\lambda} \quad (11.2)$$

where  $L_{\lambda}$  is the apparent at-satellite radiance for spectral band  $\lambda$ ,  $DN_{\lambda}$  is the digital number of spectral band  $\lambda$ ,  $R_{\lambda}$  is the calibrated reflectance,  $L_{\lambda, \text{haze}}$  is path radiance,  $Esun_{\lambda}$  is exo atmospheric solar irradiance,  $D$  is the distance between the Earth and sun, and  $\theta$  is the sun zenith angle. The path radiance for each band is identified based on the analysis of water bodies and shades in the images. The  $gain_{\lambda}$  and  $bias_{\lambda}$  are the radiometric gain and bias corresponding to spectral band  $\lambda$ , and they are often provided in an image header file or metadata file or calculated from maximal and minimal spectral radiance values (Lu et al. 2002). All TM images were geometrically coregistered into the UTM projection with geometric errors of less than one pixel, so that all images have the same coordinate system. The nearest neighbor resampling technique was used to resample the Landsat TM images into a pixel size of 30 m  $\times$  30 m during image-to-image registration.

### 11.3.3.2 Mapping of Impervious Surface Distribution

Per-pixel impervious surface mapping is often based on the image classification of spectral signatures (Shaban and Dikshit 2001; Dougherty et al. 2004; Jennings, Jarnagin, and Ebert 2004), but the spectral confusion between impervious surfaces and other land covers often results in a poor classification performance in the urban landscape (Lu and Weng 2005), especially in a complex urban–rural frontier. This research developed a method based on the combination of filtering images and unsupervised classification of Landsat spectral signatures for mapping per-pixel impervious surface distribution. The fact that the red-band image in Landsat TM has high spectral values for impervious surfaces, but has low spectral values for vegetation and water or wetlands provides the potential for rapidly mapping impervious surfaces. The minimum and maximum filters with a window size of 3  $\times$  3 pixels were separately applied to the Landsat red-band image. The image differencing between maximum and minimum filtering images was used to highlight linear features (mainly roads) and other impervious surfaces. Examining the difference image indicated that a threshold value of 13 can be used to extract the impervious surface image. The spectral signature of the initial impervious surface image was then extracted and was further classified into 60 clusters using an unsupervised classification method to refine the impervious surface image by removing the nonimpervious surface pixels. Finally, manual editing of the impervious surface image was conducted to make sure that all impervious surfaces, especially in urban regions, were extracted. The final impervious surface image was overlain on the TM color composite to visually examine the quality of the impervious surface results to assure that all urban area and major roads were properly extracted. The same method was applied to all three dates of TM imagery to generate a time series of impervious surface images.

### 11.3.3.3 Detection of Urbanization

Many change detection methods may be used for land-cover change detection (Lu et al. 2004), but most of them are not suitable for the detection of urbanization due to the unique characteristics of the urban landscape. Therefore, the change detection of urbanization in this research is based on the comparison of extracted impervious surface images in order to eliminate the impacts of spectral confusion between impervious surfaces and other land covers, such as between dark impervious surfaces and water or wetland, and between bright impervious surfaces and bare soils or harvested fields. Two methods were used in this research. The first method was to produce a color composite by assigning the 2008, 1996, and 1984 impervious surface images as red, green, and blue, for visual interpretation of impervious surface change. Another method was to produce the change detection result based on a comparison of extracted impervious surface images pixel by pixel. The total impervious surface area change was also calculated.

### 11.3.3.4 Evaluation of Urbanization Results

Accuracy assessment of change detection results is an important part of the change detection procedure for understanding the reliability and confidence in the results. In this research, quantitative assessment of the change detection was difficult due to the lack of high spatial resolution images or field survey data for Landsat TM imagery in 1996 and 1984. Therefore, the evaluation of change detection results was based on a cross-comparison between the TM color composite and urbanization images. No quantitative evaluation was conducted.

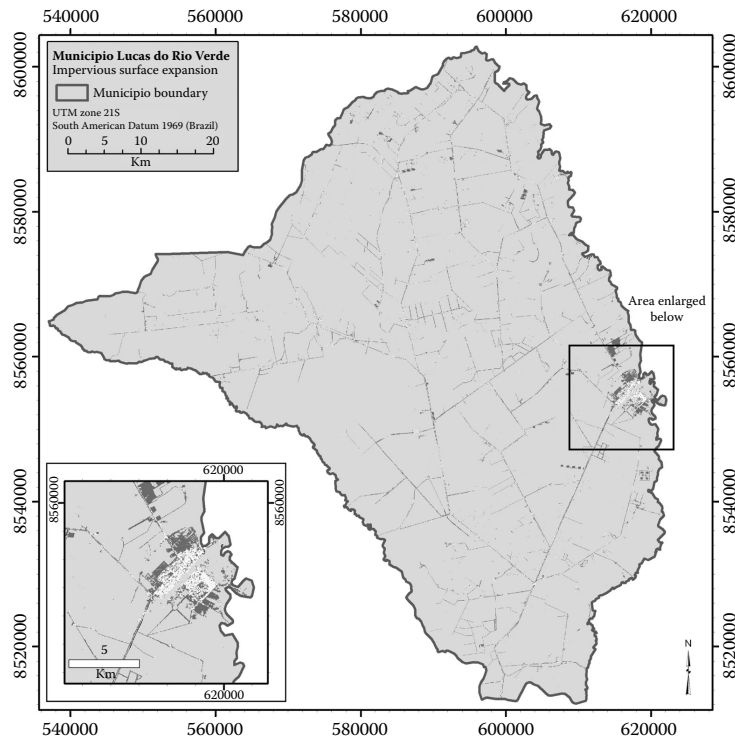
### 11.3.4 Results

Evaluation of the per-pixel impervious surface image based on overlaying it with the TM color composite indicated that a combination of filtering images and unsupervised classification methods developed in this research can effectively extract the pixel-based impervious surface image in a complex urban–rural frontier. Figure 11.3 shows where impervious surface change occurred between the TM acquisition dates. The impervious surface images of 2008, 1996, and 1984 were assigned as red, green, and blue in the color composite; thus, red indicates that impervious surfaces increased between 1996 and 2008, and yellow indicates that the impervious surface increased between 1984 and 1996. This figure shows that the major impervious surface increase between 1984 and 1996 was in central Lucas because it was established in the early 1980s, and then, the impervious surface rapidly increased in the north, northwest, and south parts of town, and more roads were constructed after 1996.

In per-pixel-based results, each extracted impervious surface pixel is assumed to be 100% impervious surface. Thus, the total impervious surface area for this study area can be calculated by multiplying the total pixel number of impervious surfaces and the TM pixel size (30 m by 30 m). This research indicates that the total impervious surface area in 1984 only accounted for 0.24% of the total study area, which gradually increased to 0.43% in 1996 and to 1.29% in 2008, implying rapid urbanization rate during the change detection periods.

### 11.3.5 Summary of the Case Study

The per-pixel-based method for mapping impervious surface distribution and monitoring its change is valuable for visual interpretation of urbanization. The method, based on the combination of filtering image differencing and unsupervised classification, can be successfully



**FIGURE 11.3**

(See color insert following page xxx.) Color composite of three dates of impervious surface distribution in 2008, 1996, and 1984 by assigning them as red, green, and blue, illustrating the spatial distribution and patterns of impervious surface changes.

used to map impervious surface distribution in the complex urban–rural frontier, which is often difficult for traditional classification methods. In addition, the detection of urbanization based on the extracted impervious surface images can eliminate the impacts of environmental conditions on remote sensing surface reflectance, which often results in a different reflectance for the same land covers. However, the areal extent of impervious surfaces is overestimated significantly, especially in the urban–rural frontier due to the mixed-pixel problem in Landsat TM images (Wu and Murray 2003; Lu and Weng 2006). From the view of area calculation of urbanization, fractional impervious surface distribution based on subpixel-based method, such as spectral mixture analysis, must be developed (Lu and Weng 2006).

#### 11.4 Final Remarks

Change detection has long been an active research topic, and many techniques have been developed in recent decades. The availability of more and more different types of sensor data and different ancillary data, along with a need for more detailed and accurate change detection information, provides new challenges for developing suitable change detection techniques for specific purposes. Change detection is a comprehensive procedure that requires careful design of different steps, including the statement of research problems

and objectives, data collection, preprocessing, selection of suitable change detection algorithms, and evaluation of the results. Errors or uncertainties may emerge from any of the different steps, thus affecting the change detection results. Understanding the relationships between the change detection stages, identifying the weakest links in the image processing chain, and then devoting efforts to improving them are keys to a successful change detection project. In addition, the designed change detection procedure should carefully take the spectral and spatial resolutions of the data, polarization, and angle features into account. Previous research on change detection is based mainly on per-pixel comparison. As high spatial resolution images such as QuickBird and WorldView become readily available, object-based or texture-based change detection methods may provide new insights and have recently attracted increasing attention (Lam 2008; Zhou, Troy, and Grove 2008; Blaschke 2010; Wu, Yang, and Lishman 2010).

---

### Acknowledgments

The authors thank the National Institute of Child Health and Human Development at NIH (grant # R01 HD035811) for the support of this research.

---

### References

- Althausen, J. D. 2002. What remote sensing system should be used to collect the data? In *Manual of Geospatial Science and Technology*, ed. J. D. Bossler, J. R. Jensen, R. B. McMaster, and C. Rizos, 276. New York: Taylor & Francis.
- Anderson, G. L., and J. D. Hanson. 1992. Evaluating handheld radiometer derived vegetation indices for estimating above ground biomass. *Geocarto Int* 7:71.
- Anderson, G. L., J. D. Hanson, and R. H. Haas. 1993. Evaluating Landsat Thematic Mapper derived vegetation indices for estimating aboveground biomass on semiarid rangelands. *Rem Sens Environ* 45:165.
- Aplin, P., P. M. Atkinson, and P. J. Curran. 1999. Per-field classification of land use using the forthcoming very fine spatial resolution satellite sensors: Problems and potential solutions. In *Advances in Remote Sensing and GIS Analysis*, ed. P. M. Atkinson and N. J. Tate, 219. New York: John Wiley & Sons.
- Asner, G. P., and K. B. Heidebrecht. 2002. Spectral unmixing of vegetation, soil and dry carbon cover in arid regions: Comparing multispectral and hyperspectral observations. *Int J Rem Sens* 23:3939.
- Barnsley, M. J. 1999. Digital remote sensing data and their characteristics. In *Geographical Information Systems: Principles, Techniques, Applications, and Management*, 2nd ed, ed. P. Longley, M. Goodchild, D. J. Maguire, and D. W. Rhind, 451. New York: John Wiley & Sons.
- Biging, G. S. et al. 1999. "Accuracy assessment of remote sensing-detected change detection," Monograph Series, ed. S. Khorram. Maryland: American Society for Photogrammetry and Remote Sensing.
- Blackburn, G. A., and C. M. Steele. 1999. Towards the remote sensing of Matorral vegetation physiology: Relationships between spectral reflectance, pigment, and biophysical characteristics of semiarid bushland canopies. *Rem Sens Environ* 70:278.

- Blaschke, T. 2010. Object based image analysis for remote sensing. *ISPRS J Photogramm Rem Sens* 65:2.
- Carvalho, L. M. T. et al. 2001. Digital change detection with the aid of multiresolution wavelet analysis. *Int J Rem Sens* 22:3871.
- Chavez Jr., P. S. 1996. Image-based atmospheric corrections—revisited and improved. *Photogramm Eng Rem Sens* 62:1025.
- Chavez Jr., P. S., and D. J. Mackinnon. 1994. Automatic detection of vegetation changes in the southwestern United States using remotely sensed images. *Photogramm Eng Rem Sens* 60:571.
- Chander, G., B. L. Markham, and D. L. Helder. 2009. Summary of current radiometric calibration coefficients for Landsat MSS, TM, ETM+, and EO-1 ALI sensors. *Rem Sens Environ* 113:893.
- Civco, D. L. 1989. Topographic normalization of Landsat Thematic Mapper digital imagery. *Photogramm Eng and Rem Sens* 55:1303.
- Colby, J. D. 1991. Topographic normalization in rugged terrain. *Photogramm Eng Rem Sens* 57:531.
- Congalton, R. G., R. G. Oderwald, and R. A. Mead. 1983. Assessing Landsat classification accuracy using discrete multivariate analysis statistical techniques. *Photogramm Eng Rem Sens* 49:1671.
- Congalton, R. G. 1991. A review of assessing the accuracy of classification of remotely sensed data. *Rem Sens Environ* 37:35.
- Congalton, R. G., and L. Plourde. 2002. Quality assurance and accuracy assessment of information derived from remotely sensed data. In *Manual of Geospatial Science and Technology*, ed. J. Bossler, 349. London: Taylor & Francis.
- Congalton, R. G., and K. Green. 2008. *Assessing the Accuracy of Remotely Sensed Data: Principles and Practice*, 2nd ed, 183. Boca Raton: CRC Press/Taylor & Francis Group.
- Coppin, P. R., and M. E. Bauer. 1996. Digital change detection in forest ecosystems with remote sensing imagery. *Rem Sens Rev* 13:207.
- Coppin, P. et al. 2004. Digital change detection methods in ecosystem monitoring: A review. *Int J Rem Sens* 25:1565.
- Dai, X. L., and S. Khorram. 1998. The effects of image misregistration on the accuracy of remotely sensed change detection. *IEEE Trans Geosci Rem Sens* 36:1566.
- Deer, P. J. 1995. Digital change detection techniques: Civilian and military applications, *International Symposium on Spectral Sensing Research 1995 Report*. Greenbelt, MD: Goddard Space Flight Center.
- Dhakal, A. S. et al. 2002. Detection of areas associated with flood and erosion caused by a heavy rainfall using multitemporal Landsat TM data. *Photogramm Eng Rem Sens* 68:233.
- Dougherty, M. et al. 2004. Evaluation of impervious surface estimates in a rapidly urbanizing watershed. *Photogramm Eng Rem Sens* 70:1275.
- Du, Y., P. M. Teillet, and J. Cihlar. 2002. Radiometric normalization of multitemporal high-resolution satellite images with quality control for land cover change detection. *Rem Sens Environ* 82:123.
- Eastwood, J. A. et al. 1997. The reliability of vegetation indices for monitoring saltmarsh vegetation cover. *Int J Rem Sens* 18:3901.
- Elvidge, C. D., and Z. Chen. 1995. Comparison of broad-band and narrow-band red and near-infrared vegetation indices. *Rem Sens Environ* 54:38.
- Estes, J. E., and T. R. Loveland. 1999. Characteristics, sources, and management of remotely-sensed data. In *Geographical Information Systems: Principles, Techniques, Applications, and Management*, 2nd ed., eds. P. Longley, M. Goodchild, D. J. Maguire, and D. W. Rhind, 667. New York: John Wiley & Sons.
- Foody, G. M. 1996. Approaches for the production and evaluation of fuzzy land cover classification from remotely-sensed data. *Int J Rem Sens* 17:1317.
- Foody, G. M. 2002. Status of land cover classification accuracy assessment. *Rem Sens Environ* 80:185.
- Franklin, S. E. et al. 2002. Evidential reasoning with Landsat TM, DEM and GIS data for land cover classification in support of grizzly bear habitat mapping. *Int J Rem Sens* 23:4633.
- Fung, T. 1990. An assessment of TM imagery for land-cover change detection. *IEEE Trans Geosci Rem Sens* 28:681.
- Gallego, F. J. 2004. Remote sensing and land-cover area estimation. *Int J Rem Sens* 25:3019.

- Ghimire, B., J. Rogan, and J. Miller. 2010. Contextual land cover classification: Incorporating spatial dependence in land cover classification models using random forests and the Getis statistic. *Rem Sens Lett* 1:45.
- Gilabert, M. A., C. Conese, and F. Maselli. 1994. An atmospheric correction method for the automatic retrieval of surface reflectance from TM images. *Int J Rem Sens* 15:2065.
- Gong, P., and P. J. Howarth. 1992. Frequency-based contextual classification and gray-level vector reduction for land-use identification. *Photogramm Eng Rem Sens* 58:423.
- Green, K., D. Kempka, and L. Lackey. 1994. Using remote sensing to detect and monitor land-cover and land-use change. *Photogramm Eng Rem Sens* 60:331.
- Heo, J., and T. W. FitzHugh. 2000. A standardized radiometric normalization method for change detection using remotely sensed imagery. *Photogramm Eng Rem Sens* 66:173.
- Janssen, L. F. J., and F. J. M. van der Wel. 1994. Accuracy assessment of satellite derived land-cover data: A review. *Photogramm Eng Rem Sens* 60:419.
- Jennings, D. B., S. T. Jarnagin, and C. W. Ebert. 2004. A modeling approach for estimating watershed impervious surface area from national land cover data 92. *Photogramm Eng Rem Sens* 70:1295.
- Jensen, J. R., and D. L. Toll. 1982. Detecting residential land use development at the urban fringe. *Photogramm Eng Rem Sens* 48:629.
- Jensen, J. R. 2005. *Introductory Digital Image Processing: A Remote Sensing Perspective*, 3rd ed., 526. Upper Saddle River, NJ: Prentice Hall.
- Kalkhan, M. A., R. M. Reich, and R. L. Czaplewski. 1997. Variance estimates and confidence intervals for the Kappa measure of classification accuracy. *Can J Rem Sens* 23:210.
- Kennedy, R. E. et al. 2009. Remote sensing change detection tools for natural resource managers: Understanding concepts and tradeoffs in the design of landscape monitoring projects. *Rem Sens Environ* 113:1382.
- Kontoos, C. et al. 1993. An experimental system for the integration of GIS data in knowledge-based image analysis for remote sensing of agriculture. *Int J Geogr Inf Syst* 7:247.
- Lam, N. S. 2008. Methodologies for mapping land cover/land use and its change. In *Advances in Land Remote Sensing: System, Modeling, Inversion and Application*, ed. S. Liang, 341. New York: Springer.
- Landgrebe, D. A. 2003. *Signal Theory Methods in Multispectral Remote Sensing*, 508. Hoboken, NJ: Wiley.
- Lefsky, M. A., and W. B. Cohen. 2003. Selection of remotely sensed data. In *Remote Sensing of Forest Environments: Concepts and Case Studies*, eds. M. A. Wulder, and S. E. Franklin, 13. Boston: Kluwer Academic.
- Lobell, D. B. et al. 2002. View angle effects on canopy reflectance and spectral mixture analysis of coniferous forests using AVIRIS. *Int J Rem Sens* 23:2247.
- Lowell, K., 2001. An area-based accuracy assessment methodology for digital change maps. *Int J Rem Sens* 22:3571.
- Lu, D. et al. 2002. Assessment of atmospheric correction methods for Landsat TM data applicable to Amazon basin LBA research. *Int J Rem Sens* 23:2651.
- Lu, D. et al. 2004. Change detection techniques. *Int J Rem Sens* 25:2365.
- Lu, D. et al. 2005. Land-cover binary change detection methods for use in the moist tropical region of the Amazon: A comparative study. *Int J Rem Sens* 26:101.
- Lu, D., and Q. Weng. 2005. Urban classification using full spectral information of Landsat ETM+ imagery in Marion County. *Indiana Photogramm Eng Rem Sens* 71:1275.
- Lu, D., and Q. Weng. 2006. Use of impervious surface in urban land use classification. *Rem Sens Environ* 102:146.
- Lu, D., and Q. Weng. 2007. A survey of image classification methods and techniques for improving classification performance. *Int J Rem Sens* 28:823.
- Lu, D., M. Batistella, and E. Moran. 2008a. Integration of Landsat TM and SPOT HRG images for vegetation change detection in the Brazilian Amazon. *Photogramm Eng and Rem Sens* 70:421.
- Lu, D. et al. 2008b. Pixel-based Minnaert correction method for reducing topographic effects on the Landsat 7 ETM+ image. *Photogramm Eng Rem Sens* 74:1343.

- Macleod, R. D., and R. G. Congalton. 1998. A quantitative comparison of change-detection algorithms for monitoring eelgrass from remotely sensed data. *Photogramm Eng Rem Sens* 64:207.
- Markham, B. L., and J. L. Barker. 1987. Thematic Mapper bandpass solar exoatmospheric irradiances. *Int J Rem Sens* 8:517.
- Mas, J. F. 1999. Monitoring land-cover changes: A comparison of change detection techniques. *Int J Rem Sens* 20:139.
- McGovern, E. A. et al. 2002. The radiometric normalization of multitemporal Thematic Mapper imagery of the midlands of Ireland—a case study. *Int J Rem Sens* 23:751.
- Meyer, P. et al. 1993. Radiometric corrections of topographically induced effects on Landsat TM data in alpine environment. *ISPRS J Photogramm Rem Sens* 48:17.
- Michener, W. K., and P. F. Honhoulis. 1997. Detection of vegetation associated with extensive flooding in a forested ecosystem. *Photogramm Eng Rem Sens* 63:1363.
- Morisette, J. T., and S. Khorram. 2000. Accuracy assessment curves for satellite-based change detection. *Photogramm Eng Rem Sens* 66:875.
- Muchoney, D. M., and B. N. Haack. 1994. Change detection for monitoring forest defoliation. *Photogramm Eng Rem Sens* 60:1243.
- Mutanga, O., and A. K. Skidmore. 2004. Narrow band vegetation indices overcome the saturation problem in biomass estimation. *Int J Rem Sens* 25:3999.
- Myint, S. W. 2001. A robust texture analysis and classification approach for urban land-use and land-cover feature discrimination. *Geocarto Int* 16:27.
- Neville, R. A. et al. 2003. Spectral unmixing of hyperspectral imagery for mineral exploration: Comparison of results from SFSI and AVIRIS. *Can J Rem Sens* 29:99.
- Okin, G. S. et al. 2001. Practical limits on hyperspectral vegetation discrimination in arid and semi-arid environments. *Rem Sens Environ* 77:212.
- Pal, M., and P. M. Mather. 2003. An assessment of the effectiveness of decision tree methods for land cover classification. *Rem Sens Environ* 86:554.
- Platt, R. V., and A. F. H. Goetz. 2004. A comparison of AVIRIS and Landsat for land use classification at the urban fringe. *Photogramm Eng Rem Sens* 70:813.
- Rashed, T. et al. 2001. Revealing the anatomy of cities through spectral mixture analysis of multispectral satellite imagery: A case study of the Greater Cairo region. *Egypt Geocarto Int* 16:5.
- San Miguel-Ayanz, J., and G. S. Biging. 1997. Comparison of single-stage and multi-stage classification approaches for cover type mapping with TM and SPOT data. *Rem Sens Environ* 59:92.
- Serpico, S. B., and L. Bruzzone. 1999. Change detection. In *Information Processing for Remote Sensing*, ed. C. H. Chen, 319. Singapore: World Scientific Publishing.
- Shaban, M. A., and O. Dikshit. 2001. Improvement of classification in urban areas by the use of textural features: The case study of Lucknow city. *Uttar Pradesh Int J Rem Sens* 22:565.
- Singh, A. 1989. Digital change detection techniques using remotely sensed data. *Int J Rem Sens* 10:989.
- Smits, P.C., S. G. Dellepiane, and R. A. Schowengerdt. 1999. Quality assessment of image classification algorithms for land-cover mapping: A review and a proposal for a cost-based approach. *Int J Rem Sens* 20:1461.
- Song, C. et al. 2001. Classification and change detection using Landsat TM data: When and how to correct atmospheric effect. *Rem Sens Environ* 75:230.
- Stefan, S., and K. I. Itten. 1997. A physically-based model to correct atmospheric and illumination effects in optical satellite data of rugged terrain. *IEEE Trans Geosci Rem Sens* 35:708.
- Stow, D. A. 1999. Reducing the effects of misregistration on pixel-level change detection. *Int J Rem Sens* 20:2477.
- Stow, D. A., and D. M. Chen. 2002. Sensitivity of multitemporal NOAA AVHRR data of an urbanizing region to land-use/land-cover change and misregistration. *Rem Sens Environ* 80:297.
- Stuckens, J., P. R. Coppin, and M. E. Bauer. 2000. Integrating contextual information with per-pixel classification for improved land cover classification. *Rem Sens Environ* 71:282.



- Teillet, P. M., B. Guindon, and D. G. Goodenough. 1982. On the slope-aspect correction of multispectral scanner data. *Can J Rem Sens* 8:84.
- Tokola, T., S. Löfman, and A. Erkkilä. 1999. Relative calibration of multitemporal Landsat data for forest cover change detection. *Rem Sens Environ* 68:1.
- Townshend, J. R. G. et al. 1992. The effect of image misregistration on the detection of vegetation change. *IEEE Trans Geosci Rem Sens* 30:1054.
- Tso, B., and P. M. Mather. 2001. *Classification Methods for Remotely Sensed Data*. New York: Taylor & Francis.
- Verbyla, D. L., and S. H. Boles. 2000. Bias in land cover change estimates due to misregistration. *Int J Rem Sens* 21:3553.
- Vermote, E. et al. 1997. Second simulation of the satellite signal in the solar spectrum, 6S: An overview. *IEEE Trans Geosci Rem Sens* 35:675.
- Vicente-Serrano, S. M., F. Pérez-Cabello, and T. Lasanta. 2008. Assessment of radiometric correction techniques in analyzing vegetation variability and change using time series of Landsat images. *Rem Sens Environ* 112:3916.
- Weber, K. T. 2001. A method to incorporate phenology into land cover change analysis. *J Range Manage* 54:A1.
- Wu, C., and A. T. Murray. 2003. Estimating impervious surface distribution by spectral mixture analysis. *Rem Sens Environ* 84:493.
- Wu, X., F. Yang, and R. Lishman. 2010. Land cover change detection using texture analysis. *J Comp Sci* 6:92.
- Yang, X., and C. P. Lo. 2000. Relative radiometric normalization performance for change detection from multi-date satellite images. *Photogramm Eng Rem Sens* 66:967.
- Yool, S. R., M. J. Makaio, and J. M. Watts. 1997. Techniques for computer-assisted mapping of range-land change. *J Range Manage* 50:307.
- Yuan, D., and C. Elvidge. 1998. NALC land cover change detection pilot study: Washington D.C. area experiments. *Rem Sens Environ* 66:166.
- Yuan, D., C. D. Elvidge, and R. S. Lunetta. 1998. Survey of multispectral methods for land cover change analysis. In *Remote Sensing Change Detection: Environmental Monitoring Methods and Applications*, eds. R. S. Lunetta and C. D. Elvidge, 21. Chelsea, MI: Ann Arbor Press.
- Zhou, W., A. Troy, and J. M. Grove. 2008. Object-based land cover classification and change analysis in the Baltimore metropolitan area using multi-temporal high resolution remote sensing data. *Sensors* 8:1613.

## ACT Publications 2010

No. 10-01

Mattos, L., E. Brondizio, A. Romeiro, and R. Orair. 2010. Agricultura de Pequena Escala e Suas Implicações na Transição Agroecológica na Amazônia Brasileira. *Amazônica* 2(2): 220-248.

No. 10-02

Mattos, L., E. Brondizio, A. Romeiro, and R. Orair. 2010. Influência da Origem da Família e de Variáveis Econômicas no Uso da Terra e no Desmatamento de Lotes Familiares da Amazônia Brasileira. *Novos Cadernos NAEA* 13(2): 27-62.

No. 10-03

Lu, D., S. Hetrick, and E. Moran. 2010. Land Cover Classification in a Complex Urban-rural Landscape with QuickBird Imagery. *Photogrammetric Engineering & Remote Sensing* 76(10): 1159-1168.

No.10-05

Lu, D., S. Hetrick, E. Moran, and G. Li. 2010. Detection of Urban Expansion in an Urban-rural Landscape with Multitemporal Quickbird Images. *Journal of Applied Remote Sensing* 4(041880): 1-17.

No.10-06

Mattos, L. and A. Cau. The Clean Development Mechanism and Agroforestry Activities in the Brazilian Amazon.

No.10-07

Muehlenbein, M.P., J.L. Hirschtick, J.Z. Bonner, and A.M. Swartz. 2010. Toward Quantifying the Usage Costs of Human Immunity: Altered Metabolic Rates and Hormone Levels during Acute Immune Activation in Men. *American Journal of Human Biology* 22: 546-556.

No.10-08

Muehlenbein, M.P., L.A. Martinez, A.A. Lemke, L. Ambu, S. Nathan, S. Alsisto, and R. Sakong. 2010. Unhealthy Travelers Present Challenges to Sustainable Primate Ecotourism. *Travel Medicine and Infectious Disease* 8: 169-175.

No.10-09

Tucker, C.M. 2010. Private Goods and Common Property: Pottery Production in a Honduran Lenca Community. *Human Organization* 69(1): 43-53.

No. 10-10

Tucker, C.M., H. Eakin, and E.J. Castellanos. 2010. Perceptions of Risk and Adaptation: Coffee Producers, Market Shocks, and Extreme Weather in Central America and Mexico. *Global Environmental Change* 20: 23-32.