APPLICATIONS PAPER

Application of Time Series Landsat Images to Examining Land-use/Land-cover Dynamic Change

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Abstract

A hierarchical-based classification method was designed to develop time series land-use/land-cover datasets from Landsat images between 1977 and 2008 in Lucas do Rio Verde, Mato Grosso, Brazil. A post-classification comparison approach was used to examine land-use/land-cover change trajectories, which emphasis is on the conversions from vegetation or agropasture to impervious surface area, from vegetation to agropasture, and from agropasture to regenerating vegetation. Results of this research indicated that increase in impervious surface area mainly resulted from the loss of cerrado in the initial decade of the study period and from loss of agricultural lands in the last two decades. Increase in agropasture was mainly at the expense of losing cerrado in the first two decades and relatively evenly from the loss of primary forest and cerrado in the last decade. When impervious surface area was less than approximately 40 km^2 before 1999, impervious surface area was negatively related to cerrado and forest, and positively related to agropasture areas, but after impervious surface area reached 40 km^2 in 1999, no obvious relationship exists between them.

Introduction

Deforestation has been recognized as an important contributor to carbon emissions, climate change, and loss of biodiversity (Skole *et al.*, 1994; Hirsch *et al.*, 2004; Fearnside, 2005). Since the 1970s, the Brazilian Amazon has experienced high deforestation rates (*http://www.obt.inpe.br/prodes/*) largely due to colonization projects initiated in the 1970s and 1980s, road construction, and land-use change (Moran, 1981; Laurance *et al.*, 2004). Deforestation has converted large areas of primary forest and cerrado/savanna to agricultural lands, pasture, successional vegetation, and agroforestry (Lucas *et al.*, 2000; Roberts *et al.*, 2002; Sano *et al.*, 2010). Mapping of land-use/land-cover distributions and monitoring of their changes over time are required for resource management, i.e., accurate examination of carbon and water cycling, and evaluation of environmental problems at different scales (Hirsch *et al.*, 2004; Fearnside, 2005; Sparovek *et al.*, 2010).

Research on mapping land-use/land-cover distribution and detecting its change in the Brazilian Amazon has attracted increasingly attention since the 1990s. Much research has explored methods to improve land-use/land-cover mapping performance based on remotely sensed imagery (Moran *et al.*, 1994; Brondízio *et al.*, 1996; Foody *et al.*, 1996; Rignot *et al.*, 1997; Lucas *et al.*, 2000; Roberts *et al.*, 2002; Vieira *et al.*, 2003; Salovaara *et al.*, 2005; Lu *et al.*, 2011a). In particular, mapping and monitoring of primary forest, cerrado/savanna, and secondary succession in the Brazilian Amazon have attracted increasing attention due to their important roles in carbon-related studies and environmental assessment (Roberts *et al.*, 2002; Ferreira and Huete, 2004; Brannstrom and Filippi, 2008; Sano *et al.*, 2010).

Previous literature has summarized a large number of techniques for mapping land-use/land-cover distribution and monitoring its dynamic change based on remote-sensing data (e.g., Singh, 1989; Tso and Mather, 2001; Coppin *et al.*, 2004; Lu *et al.*, 2004; Lu and Weng, 2007). In particular, the use of time-series Landsat images has attracted great interest for developing land-use/land-cover data due to public access with free (Masek *et al.*, 2008; Vogelmann *et al.*, 2009; Huang *et al.*, 2010; Thomas *et al.*, 2011). However, the limitations of remote-sensing data *per se* (spectral, spatial, and radiometric resolutions), atmospheric conditions, the complex vegetation composition and stand structure, and the lack of reference data that can be used for training samples during image classification make it difficult to develop high-quality time-series land-use/land-cover datasets (Lu and Weng, 2007). It necessitates developing a method to accurately map land-use/land-cover distribution from historical remote-sensing data without using training samples during the classification procedure. Therefore, the objective of this paper is to design a hierarchical-based classification method to develop time series land-use/land-cover datasets from Landsat images, and then to explore their dynamic change between 1977 and 2008 in Lucas do Rio Verde, Mato Grosso State, Brazil.

Study Area

The City of Lucas do Rio Verde (hereafter, Lucas) was established in 1982 with a total area of approximately 3,663 km^2. It has a relatively short history and small urban extent

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but has experienced rapid urbanization, especially in the past decade. The region is connected to Santarém, a port city on the Amazon River, and to the heart of Brazil's soybean-growing region at Cuiabá by means of the BR-163 highway, which runs through Lucas. The county is at the epicenter of soybean production in Brazil, and its economic base is large-scale agriculture, including the production of soy, cotton, rice, and corn as well as poultry and swine. The major vegetation types include primary forest (cerrado) and limited areas of regenerating vegetation that appeared in recent years. Deforestation began in the late 1970s with the construction of BR-163 highway and expanded rapidly, especially after the establishment of Lucas County, resulting in a large area conversion from primary forest and cerrado to agricultural lands. This study was able to examine the process of land-use/land-cover transformation in Lucas from the beginning, as the enhanced industrial infrastructure went into place and the urban expansion began pushing intensive agriculture outward into former agricultural fields and natural vegetation.

Methods

The satellite images used in this research were the same datasets as used in Lu *et al.* (2011b), except the 2007 TM image, thus land-use/land-cover change was examined for every six to seven years between 1977 and 1996 and for every three years between 1996 and 2008. The datasets included Landsat MSS images (08 - 09 July 1977), TM images (21 June 1984, 09 August 1990, 06 June 1996, 17 September 2002, 17 July 2005, and 22 May 2008), and an ETM+ image (10 August 1999). The 2004 and 2008 QuickBird images and 2009 land-use/land-cover survey data as well as Google Earth™ images were used to support the selection of sample plots for accuracy assessment. All Landsat images were geometrically rectified into UTM projection with 30 m spatial resolution. Since the image collection and preprocessing were described in Lu *et al.* (2011b), these processes were not repeated here.

Based on our research objectives, the characteristics of the study area, and selected remote sensing data, we designed a land-use/land-cover classification system consisting of primary forest, cerrado, regenerating vegetation, agropasture, water/wetland, and impervious surface area. Cerrado is shrub-dominated vegetation or a mixture of shrub and grassy vegetation. Regenerating vegetation consists of woody- or shrub-dominated vegetation which was regenerated after deforestation, including plantations and regrowth that appeared in recent years. Because agricultural lands and pasture during the dry season have similar spectral features on the Landsat images, they were merged as one class called "agropasture." Water and non-vegetation wetland were not the research focus in this study, and thus they were merged into one class (water/wetland). Impervious surface areas are generally the man-made materials such as roads, building roofs, and parking lots that water cannot penetrate.

Although many classification methods are available, as summarized in Lu and Weng (2007), they require many training samples for implementing image classification. For historical remote sensing data, land-use/land-cover classification is often difficult due to the lack of sufficient training samples that can be used for image classification. Therefore, we developed a hierarchical-based classification method consisting of stratification and cluster analysis with ISODATA (Jensen, 2005), as illustrated in Figure 1.

Previous research has indicated the difficulty in separating impervious surface area from other land-use/land-cover types (e.g., bare soils, crop residues, and wetland) based on Landsat multispectral images (Lu *et al.*, 2011b). Thus, a hybrid method consisting of thresholding, cluster analysis, and manual editing was used to map impervious surface area. This method was detailed in Lu *et al.* (2011b) and has proven to be effective for extracting impervious surface areas. Primary forest mapping was then conducted with the combination of thresholding on normalized difference vegetation index (NDVI) image and cluster analysis, as described in another research in Rondonia for mapping deforestation with MODIS and a limited number of TM images (Lu *et al.,* 2011c). After masking impervious surface area and forest classes from the Landsat multispectral bands, the remaining land-use/land-cover classes included cerrado, regenerating vegetation (e.g., plantation and other regenerated vegetation), agricultural land, pasture, water, and wetland. The cluster analysis was then used to classify the spectral signatures of remaining pixels into 50 clusters, and the analyst merged the clusters into cerrado, regenerating vegetation, agropasture, water/wetland, and mixed class (confused land covers). The mixed class was eventually classified through an iterative process of masking, cluster analysis, and recoding; that is, (a) masking out all classified

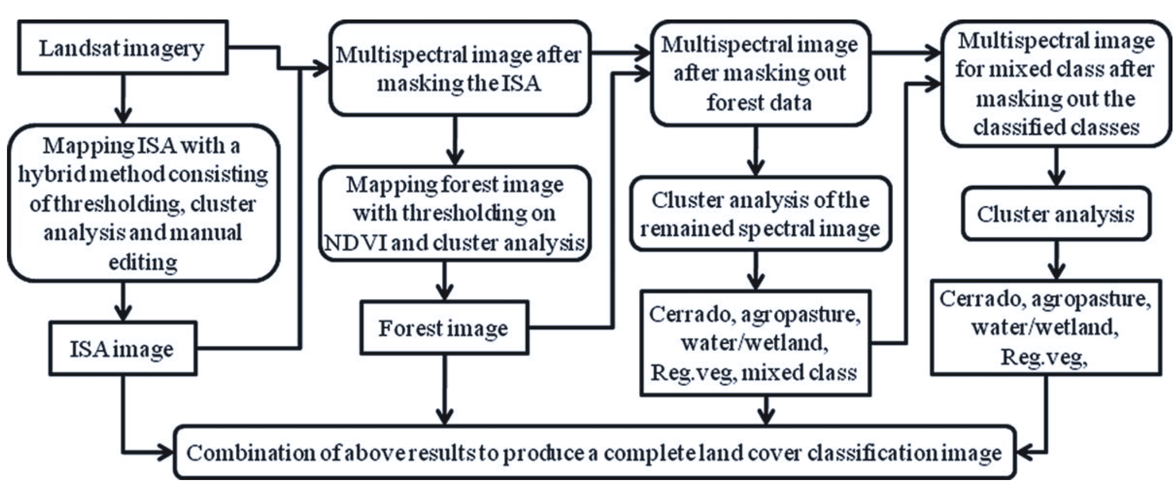

Figure 1. Hierarchical-based classification method for mapping land-use/land-cover distribution based on Landsat imagery (Note: ISA and Reg.veg represent impervious surface area and regenerating vegetation).

land-use/land-cover classes and remaining only the mixed pixels, (b) using cluster analysis to classify spectral signatures of the mixed pixels into 30 clusters, (c) merging each cluster into one of the land-use/land-cover classes, and (d) recoding the merged clusters into the same labels as the land-use/land-cover classification system. During the unsupervised classification, field survey data collected in 2009 and the 2008 QuickBird imagery were used to assist the cluster-merging process. This hierarchical-based classification method avoided the dilemma of the lack of training samples for historical remote-sensing data and made full use of analysts' experiences and knowledge for accurately mapping land-use/land-cover distribution.

In this research, the difficulty in land-use/land-cover classification was the separation of cerrado and regenerating vegetation, because cerrado ranges from grass-dominated to shrub-dominated vegetation. Fortunately, regenerating vegetation is very limited and mainly appeared after the 2002 Landsat images in this study area. Also, most regenerating vegetation was planted and few areas were regenerated from previous cerrado fields after deforestation. After all Landsat images were classified into thematic maps with the hierarchical-based method, the analyst can further modify the classified results to refine regenerating vegetation and cerrado classes by using the established rules based on bi-temporal classified images. For example, if a pixel was classified as regenerating vegetation in the 2008 classified image, but this pixel was classified as cerrado in the 2005 classified image, this pixel was corrected as cerrado in the 2008 classified image because of the misclassification between cerrado and regenerating vegetation. On the other hand, if a pixel was classified as cerrado in the 2008 classified image, but it was classified as agropasture in the 2005 classified image, this pixel was corrected to regenerating vegetation in the 2008 classified image because of the misclassification between cerrado and pasture or crops.

After classification, accuracy assessment for recent dates of the classified images was conducted with an error-matrix method. Different accuracy assessment parameters, such as overall classification accuracy, producer's accuracy, user's accuracy, and overall kappa coefficient, were calculated from the error matrix, as previous literature described (e.g., Congalton, 1991; Smits *et al.,* 1999; Foody, 2002; Congalton and Green, 2009). In this research, a total of 300 sample plots were selected with a stratified random sampling method with minimum number of 30 samples for the 2005 and 2008 classified images to independently develop an error matrix. The land-use/land-cover type for each test sample was identified from corresponding TM color composite by visual interpretation, which was supported by the 2004 and 2008 QuickBird images, the 2009 field survey, and Google Earth™ images. For the test samples in rural areas, the land-use/land-cover types including primary forest, cerrado, regenerating vegetation (mainly plantation) and agropasture can be easily identified. In urban-rural frontiers, QuickBird images and Google Earth™ images played an important role in distinguishing impervious surface area, agricultural lands, and wetland.

The total area for each land-use/land-cover class in the study area was calculated separately from the classified images between 1977 and 2008. Linear and nonlinear regression analyses were explored for the major land-use/land-cover classes (i.e., forest, cerrado, agropasture, and impervious surface area were used as dependent variable, respectively, and the year was used as independent variable) to understand the trends of land-use/land-cover dynamic change during the past three decades. The coefficient of determination (R^2) was used to identify the best regression model for the selected land-use/land-cover type. A scatterplot-based method was also used to examine the relationship between impervious surface area and forest, cerrado and agropasture. The analysis of total areas for major land-use/land-cover classes based on the entire study area provides overall trends, but cannot provide the detailed change trajectories and spatial patterns of their dynamic changes. Therefore, a post-classification comparison method was applied to detect land-use/land-cover change trajectories (Jensen, 2005; Lu *et al.*, 2004). In this research the most interesting change trajectories included the conversion from vegetation (i.e., forest, cerrado, and regenerating vegetation) or agropasture to impervious surface area, and the conversions from vegetation to agropasture and from agropasture to regenerating vegetation. Other changes are mainly caused by misclassification such as between cerrado and water/wetland because of the influence of different water levels during the change detection periods. Based on change detection results, the annual impervious surface area increase rate, annual agropasture change rates and annual deforestation rates of forest and cerrado were calculated, and the percentages of conversion from different land-use/land-cover classes to impervious surface area or agropasture were analyzed to understand how urban expansion affected deforestation and change of agricultural land in this region. According to the land-use/land-cover detection results, four stages were grouped for understanding which land-use/land-cover change dominated in different periods.

Results and Discussion

Analysis of Time-series Land-use/Land-cover Datasets

The hierarchical-based classification method effectively classified the Landsat images into six land-use/land-cover classes, as shown in Plate 1. The classification results showed that cerrado and forest accounted for the majority of the study area in 1977, but they decreased rapidly in 1984 and 1990; in contrast, agropasture became to occupy the majority after 1996. Since 2002, very limited forest areas remained in the western part of the study area. Plate 1 also indicates that there was no regenerating vegetation between 1977 and 1984, and very limited regenerating vegetation between 1990 and 1996. Obvious regenerating vegetation areas occurred in the western part of the county in 2002 and more appeared in 2008. Meanwhile, impervious surface area increased rapidly since 1990.

Accuracy assessment of the classification results from the 2005 and 2008 Landsat TM images indicated that an overall classification accuracy of approximately 93 percent for each classification result was obtained, as summarized in Table 1. Cerrado had a relatively low accuracy compared to other land-use/land-cover classes: a conclusion similar to other research results (e.g., Brannstrom and Filippi, 2008). This is because cerrado varies greatly in vegetation composition and vertical structure (dominant grass, shrub, or woodland). It has unclear boundaries with primary forest and is influenced by water, resulting in a high spectral variation in spectral signatures which may be similar to pasture, primary forest, regenerating vegetation, and water/wetland. Another major misclassification resulted from the similar spectral signatures between impervious surface area and agriculture (e.g., bare soils and crop residues). Although the accuracy assessments of other dates of land-use/land-cover classification results were not conducted, their accuracies were believed to be similar or even better than 93 percent because cerrado was mainly confused with regenerating vegetation, but there was no or very limited regenerating vegetation before 2002. Also, impervious surface area accounted for a very small proportion before 2002 as shown in Plate 1. Although the 1977 MSS

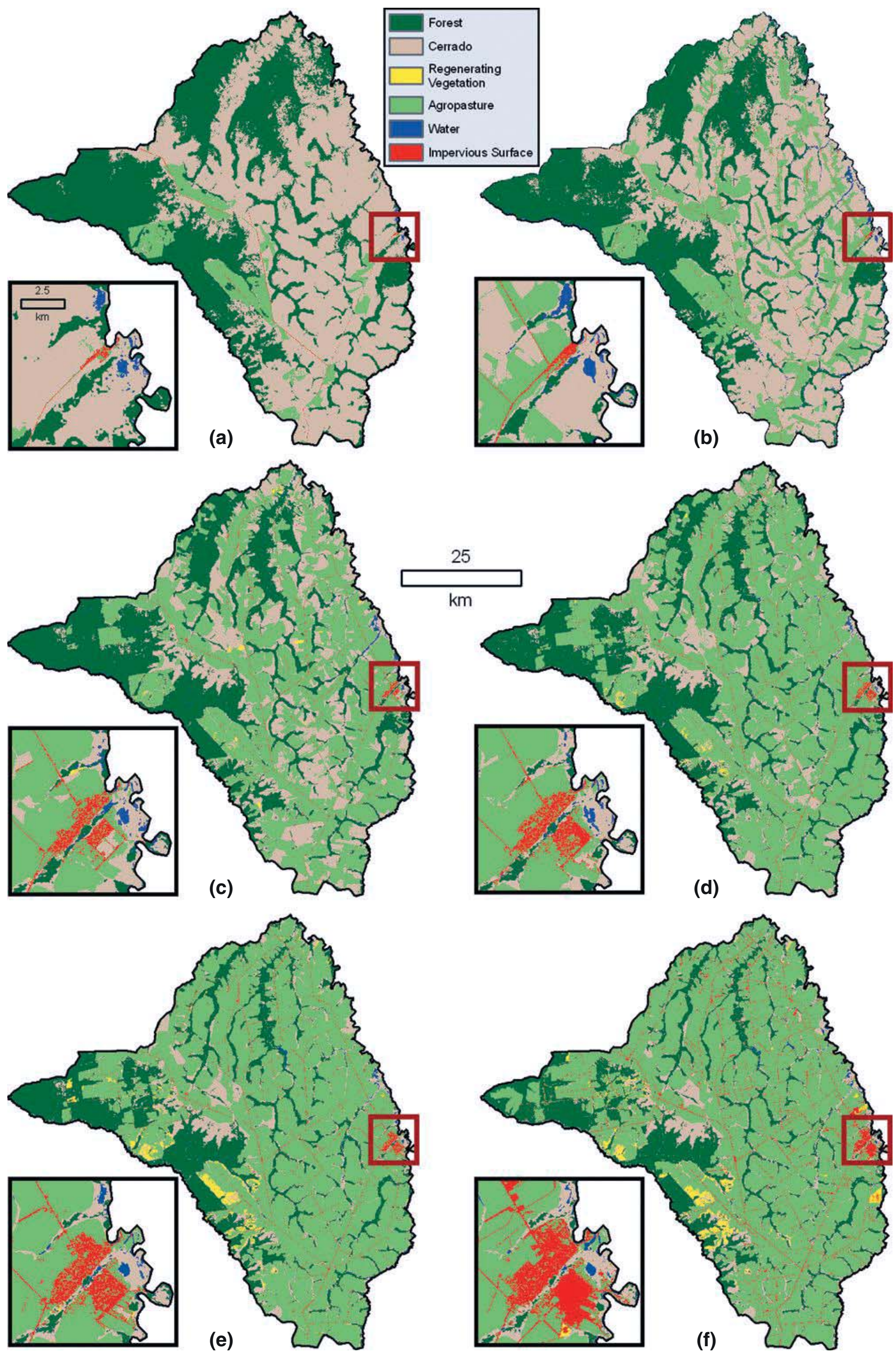

Plate 1. Comparison of time-series land-use/land-cover classification results for six-year intervals between 1977 and 2008 (therefore, the 1999 and 2005 classified images were not provided here): (a) 1977, (b) 1984, (c) 1990, (d) 1996, (e) 2002, and (f) 2008.

image has only four spectral bands with a relatively coarse spatial resolution of 60 m compared to the TM image with six spectral bands and 30 m spatial resolution, the classification accuracy was believed sufficiently high because forest and cerrado accounted for majority of the study area (the area of forest and cerrado accounted for 93.2 percent of the total study area, according to the classified image), other land-use/land-cover classes such as agricultural lands, impervious surface area and water accounted for a small proportion of the study area in 1977.

The high classification accuracy for each date of the Landsat image with the hierarchical-based method is due to the use of four key steps in the classification procedure: (a) stratification of land-use/land-cover classes reduced the

TABLE 1. ERROR MATRICES OF LAND-USE/LAND-COVER CLASSIFICATION RESULTS BASED ON THE 2005 AND 2008 TM IMAGES

Classification results based on Landsat TM in 2005										
	Forest	Cerrado	Agrop	Reg-veg	Wat/wet	ISA	RT	CT	PA	UA
Forest	49	3	0	0	0	0	52	55	89.1	94.2
Cerrado	5	34	0	0	2	0	41	42	80.9	82.9
Agrop	1	1	112	1	0	0	115	116	96.5	974
Reg-veg	0	2	0	29	0	0	31	30	96.7	93.5
Wat/wet	0	1	0	0	29	0	30	31	93.5	96.7
ISA	0	1	4	0	0	26	31	26	100.0	83.9
OCA = 93.0%; OKC = 0.91										

Classification results based on Landsat TM in 2008										
	Forest	Cerrado	Agrop	Reg-veg	Wat/wet	ISA	RT	CT	PA	UA
Forest	51	0	0	0	0	0	51	54	94.4	100.0
Cerrado	3	36	0	0	2	0	41	45	80.0	87.8
Agrop	0	3	107	1	0	2	113	109	98.2	94.7
Reg-veg	0	6	0	26	0	0	32	27	96.3	81.2
Wat/wet	0	0	0	0	30	0	30	32	93.7	100.0
ISA	0	0	2	0	0	31	33	33	93.9	93.9
OCA = 93.7%; OKC = 0.92										

Note: Agrop, Reg-veg, Wat/wet, and ISA represent agropasture, regenerating vegetation, water/wetland, and impervious surface area, respectively. RT, CT, PA, and UA represent row total, column total, producer's accuracy, and user's accuracy, respectively. OCA and OKC represent overall classification accuracy and overall kappa coefficient.

spectral confusion among different land-use/land-cover classes, (b) the analyst's knowledge and experience from field survey and QuickBird as well as Google Earth™ images were employed in merging the clusters into meaningful land-use/land-cover classes, (c) manual editing in each step further removed the misclassified classes that could not be automatically separated from the spectral signatures, and (d) post-processing based on the bi-temporal classified images further corrected misclassification between cerrado, regenerating vegetation, and agropasture. One advantage of this method is that it does not require training samples during image classification, which is critical for land-use/land-cover classification based on historical remote-sensing data. Generally, supervised classification methods rely heavily on the use of many representative training samples, which are often unavailable for historical image classification. On the other hand, unsupervised classification methods are often difficult in merging clusters into meaningful land-use/land-cover classes. The hierarchical-based classification method used in this paper not only overcomes the shortcoming of both supervised and unsupervised classification methods, but also includes the expert knowledge during the classification procedure; thus, this method can improve classification performance. The disadvantage is the requirement of human involvement, because the analyst's experience and knowledge or familiarity with the study area might affect the classification results.

The high accuracies of these land-use/land-cover classification results provided a reliable data source for further conducting land-use/land-cover change analysis. The land-use/land-cover changes over time for the entire study area, as well as the best regression models corresponding to the selected land-use/land-cover types are illustrated in Figure 2. The exploration of linear and nonlinear regression analyses indicated that forest area was linearly reduced from 1476.5 km^2 in 1977 to 652.1 km^2 in 2008, and cerrado areas were nonlinearly reduced from 1936.2 km^2 in 1977 to only 335.7 km^2 in 2008. Meantime, impervious surface area and agropasture were nonlinearly increased from only 7.1 km^2 and 236.3 km^2 in 1977 to 99.7 km^2 and 2480.6 km^2, respectively, in 2008. According to the regression models, remaining cerrado and primary forest areas that can be converted to agropasture may be depleted by 2013 and 2015, respectively, assuming the current deforestation rates continue but do not affect the preserved vegetation along waterways. Figure 2 also shows the decrease of agropasture from 2005 to 2008 due to the decreased deforestation rates of forest and cerrado and the increased urbanization rate during the same period. According to this trend, agropasture will continue to decrease as the City of Lucas continues to grow and expands into nearby agropasture lands in the near future.

The relationships of impervious surface area with forest, cerrado and agropasture areas during the periods of 1977 to 2008 may be better understood in a scatterplot, as shown in Figure 3. When impervious surface area was less than approximately 40 km^2 before 1999, impervious surface area had a positively linear relationship with agropasture area, and negatively linear relationships with forest and cerrado areas. After impervious surface area reached about 40 km^2 in 1999, no obvious relationships existed between impervious surface area and forest, cerrado and agropasture between 1999 and 2008. This implies that at the initial stage of population migration from other areas to Lucas, the increase of impervious surface area (e.g., roads, buildings) resulted in rapid conversion from primary forest and cerrado to agricultural lands. At the second stage, although impervious surface area continuously increased, its increased area was mainly due to the urban expansion at the expense of agriculture land. In particular, the increase of impervious surface area after 2005 has resulted in a slight decrease of agropasture area in 2008 due to the constraint of cerrado and forest areas.

Analysis of Land-use/Land-cover Change Trajectories and Rates

The above analysis of time-series land-use/land-cover datasets provided overall trends of dynamic change but did not show change trajectories. The major annual land-use/land-cover changes and detailed percentages of their changes

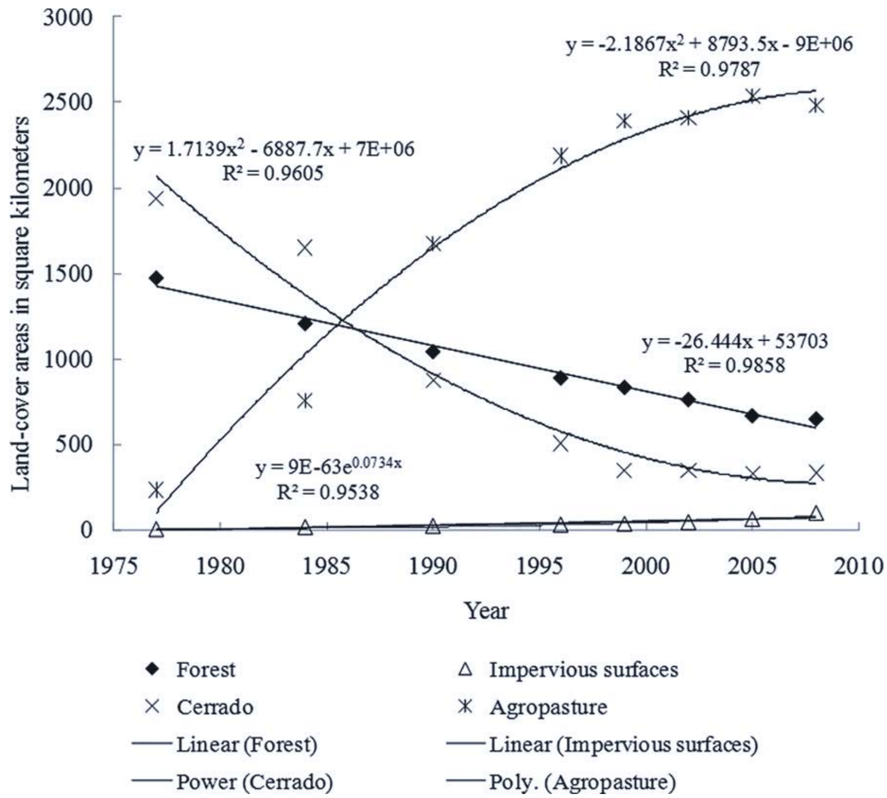

Figure 2. Comparison of major land-use/land-cover dynamic change from 1977 to 2008.

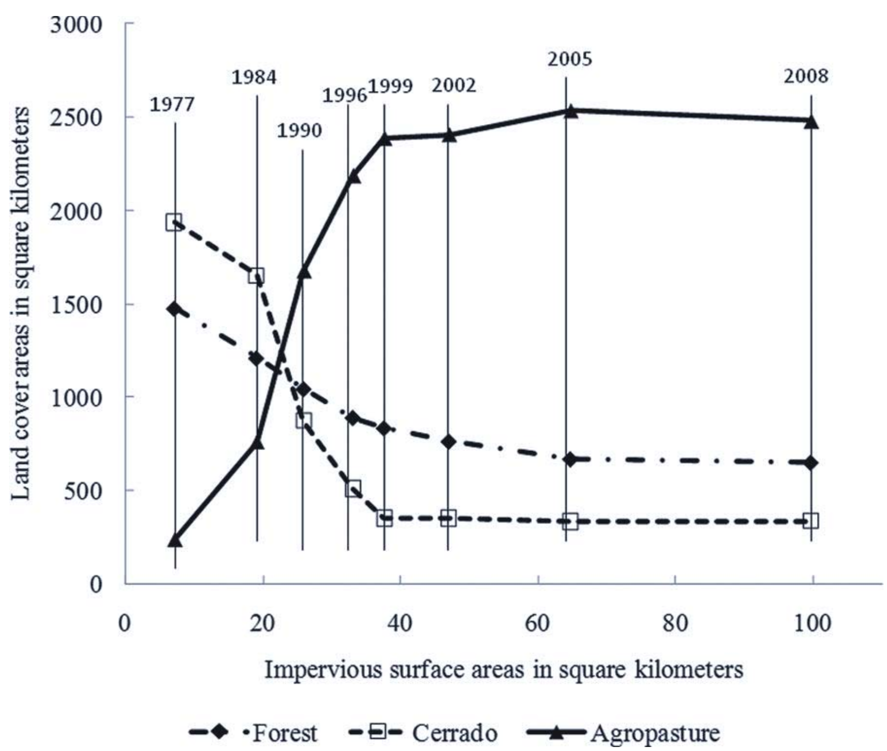

Figure 3. Relationship of impervious surface area with forest, cerrado, and agropasture.

from different land-use/land-cover classes to impervious surface area or agropasture are illustrated in Figure 4. The annual cerrado deforestation rate and annual agropasture growth rate reached the peaks during the period of 1984 to 1990, just after the establishment of the Lucas County. The cerrado deforestation rate was reduced from over 141 km^2/year during the period of 1984 to 1990 to approximate 8 km^2/year during the period of 2005 to 2008. The forest deforestation rate remained relatively constant, around 15 to 25 km^2/year in 1984 through 2005, and decreased to less than 4 km^2/year in 2005 to 2008. The highest agropasture expansion rate reached 157 km^2/year in 1984 to 1990, and then dropped significantly to less than 13 km^2/year in 2005 to 2008. The annual impervious surface area growth rate increased from only 2 to 3 km^2/year in 1977 to 1996 to over 13 km^2/year in 2005 to 2008. Initially, the increased impervious surface area was mainly at the expense of cerrado, accounting for 73percent in 1977 to 1984, but dropped to about 2 percent in 2005 to 2008. After 2002, the conversion from agropasture to regenerating vegetation became obvious. The detailed land-use/land-cover change trajectory images are illustrated in Plate 2. It indicated that the majority of the changed areas were from the conversion of vegetation (i.e., cerrado and forest) to agropasture during the first two decades (e.g., from 1977 to 1996), while the increase of road density and urban expansion were particularly noticeable during the last decade (from 1999 to 2008).

Implication of Urbanization, Deforestation, and Change of Agricultural Land

Based on the above analysis of major land-use/land-cover changes (see Figure 4), four development stages can be grouped for Lucas County:

1. The first stage between 1977 and 1984 represented the initial migration resulting in relatively high deforestation of cerrado and high agropasture expansion. Annual cerrado deforestation rate was approximately 75 km^2/year, annual agropasture expansion was less than 80 km^2/year, and annual increased impervious surface area was less than 2.4 km^2/year. At this stage, 92 percent of the increased agropasture area, and 73 percent of the increased impervious surface area were from cerrado deforestation.
2. The second stage between 1984 and 1999 represented high deforestation of cerrado, highly mechanized agricultural expansion, and a gradually increasing urbanization rate. Annual cerrado deforestation was 72 to 141 km^2/year, annual forest loss was 15 to 20 km^2/year, annual agropasture expansion was 75 to 157 km^2/year, and annual increased impervious surface area was only 2 to 4 km^2/year. During this stage, 75 percent to 90 percent of the increased agropasture area was from cerrado loss and 10 percent to 20 percent of which from forest loss. Meantime, 50 percent to 83 percent of the increased impervious surface area was converted from agropasture.
3. The third stage between 1999 and 2005 represented lower deforestation rates, slower agropasture expansion rates, and a relatively higher urbanization rate than previous stages. Deforestation was considerably lower and evenly from both cerrado and forest at 15 to 25 km^2/year. Annual agropasture expansion was 30 to 57 km^2/year and annual increased impervious surface area was 6 to 8 km^2/year. Of the increased agropasture area, 36 percent to 48 percent was from cerrado and 45 percent to 50 percent from forest, while 91 percent to 94 percent of the increased impervious surface area was converted from agropasture.
4. The fourth stage between 2005 and 2008 represented very low deforestation and agropasture expansion rates but a considerably high urbanization rate. Both forest and cerrado had very limited deforestation rates with less than 9 and 4 km^2/year, respectively. Annual agropasture expansion dropped to less than 13 km^2/year, and annual increased impervious surface area was over 13 km^2/year. Of the increased agropasture area, 63 percent was from cerrado loss

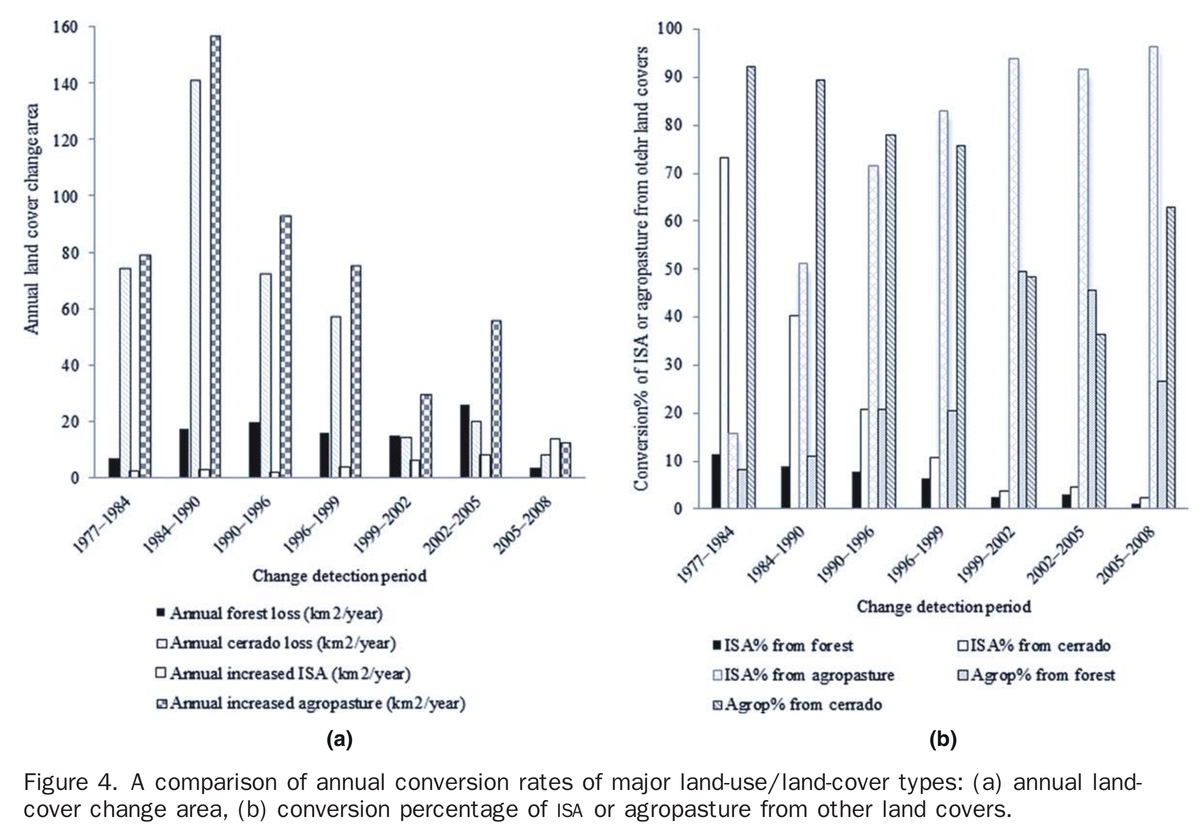

Figure 4. A comparison of annual conversion rates of major land-use/land-cover types: (a) annual land-cover change area, (b) conversion percentage of ISA or agropasture from other land covers.

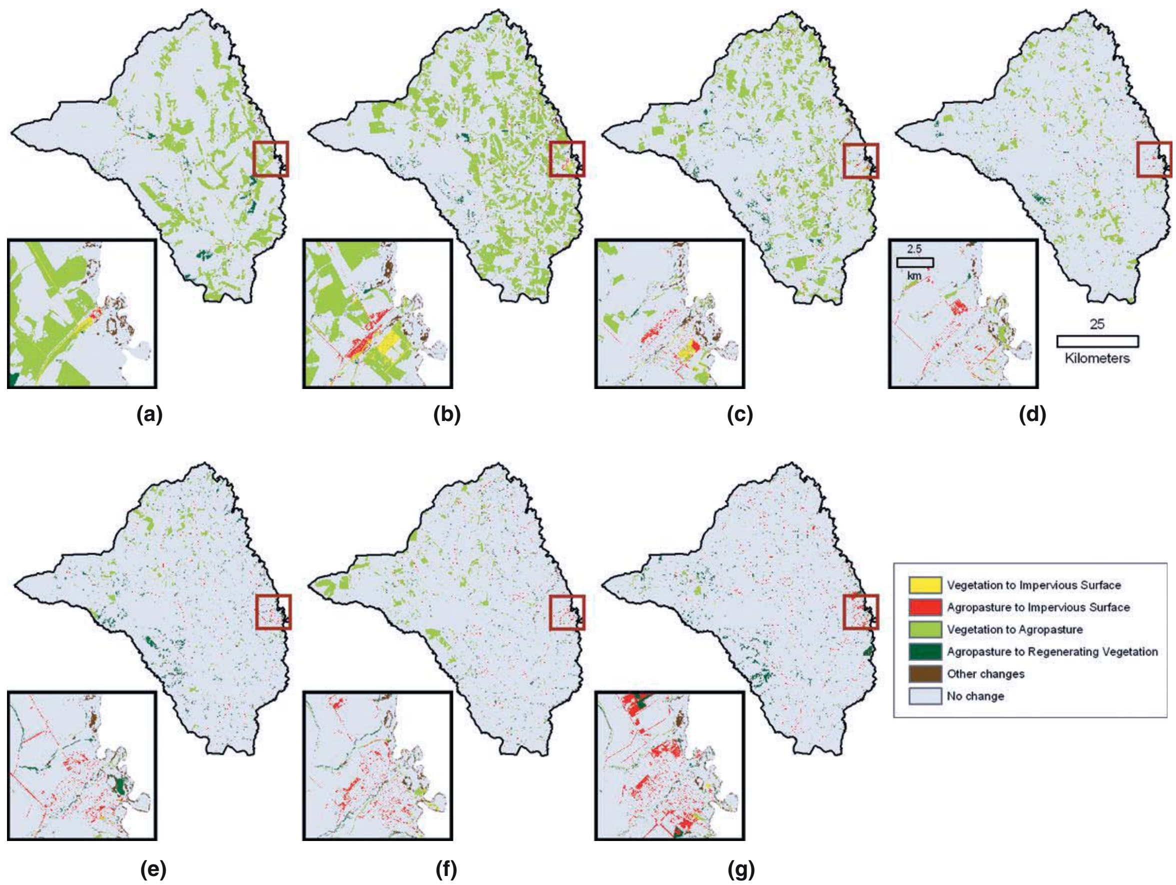

Plate 2. Comparison of land-use/land-cover changes during the different change detection periods: (a) 1977 to 1984, (b) 1984 to 1990, (c) 1990 to 1996, (d) 1996 to 1999, (e) 1999 to 2002, (f) 2002 to 2005, and (g) 2005 to 2008.

and 27 percent from forest loss. At this stage, over 96 percent of the increased impervious surface area was converted from agropasture.

Before 1980, deforestation in this area was very limited due to the constraints of roads and labor supply. Only one road (i.e., BR-163) ran through the county. When Lucas County was established in 1982, deforestation, especially of cerrado, increased because the major road ran through the cerrado landscape. However, the pioneer farmers claimed land beyond the edges of the highway and rapidly converted a large area of cerrado to agropasture. As cerrado continuously decreased and deforestation spread toward the limits of the county, deforestation of cerrado and forest occurred evenly between 1999 and 2005. After 2000, deforestation and agricultural expansion rates slowed due to the reduced supply of natural vegetation that could be converted. Meanwhile, urbanization rates increased faster, largely converting agricultural lands, accounting for over 91 percent. For example, between 1999 and 2005, impervious surface area increased by 42.2 km^2, and about 93 percent of area was converted from agricultural lands. Between 2005 and 2008, impervious surface area increased by 41 km^2, and over 96 percent of area was converted from agricultural lands. By 2005, the increased impervious surface area was slightly larger than increased agropasture. This may produce a new set of problems, such as housing for the rapidly growing population, transportation, urban and rural water pollution, planning and management of land resources, and environmental issues. Therefore, better understanding of land-use/cover changes and their interactions with human activities is valuable for making better decisions about the use of land resources.

Conclusions

Evaluation of land-use/land-cover classification results indicates that the proposed hierarchical-based classification method can be successfully used to develop time-series land-use/land-cover datasets from Landsat images. Overall, primary forest decreased linearly and cerrado nonlinearly, and agropasture and impervious surface area increased nonlinearly between 1977 and 2008 in Lucas County. At the initial stage, when impervious surface area was less than approximately 40 km^2 in this study area, impervious surface area was negatively related to cerrado and forest areas, and positively related to agropasture area. However, after impervious surface area reached a certain value (i.e., 40 km^2 in this study area in 1999), impervious surface area was not related to forest or cerrado areas; it was mainly converted from the loss of agropasture, especially in the past decade. The time-series land-use/land-cover datasets from 1977 to 2008 and the change detection results were valuable for better planning and managing the land resources, and may be useful for examining the impacts of population migration and changing economic conditions on land-use/land-cover change and for assessing shifts in environmental conditions due to this change.

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