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Spatiotemporal analysis of land use and land cover change in the Brazilian Amazon

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Abstract

This paper provides a comparative analysis of land use and land cover (LULC) changes among three study areas with different biophysical environments in the Brazilian Amazon at multiple scales, from per-pixel, polygon, census sector, to study area. Landsat images acquired in the years of 1990/1991, 1999/2000, and 2008/2010 were used to examine LULC change trajectories with the post-classification comparison approach. A classification system composed of six classes – forest, savanna, other-vegetation (secondary succession and plantations), agro-pasture, impervious surface, and water, was designed for this study. A hierarchical-based classification method was used to classify Landsat images into thematic maps. This research shows different spatiotemporal change patterns, composition and rates among the three study areas and indicates the importance of analyzing LULC change at multiple scales. The LULC change analysis over time for entire study areas provides an overall picture of change trends, but detailed change trajectories and their spatial distributions can be better examined at a per-pixel scale. The LULC change at the polygon scale provides the information of the changes in patch sizes over time, while the LULC change at census sector scale gives new insights on how human-induced activities (e.g., urban expansion, roads, and land use history) affect LULC change patterns and rates. This research indicates the necessity to implement change detection at multiple scales for better understanding the mechanisms of LULC change patterns and rates.

Keywords

land use and land cover change; spatiotemporal pattern; Brazilian Amazon; Landsat image

1. Introduction

Deforestation has been regarded as one of the most important factors affecting climate change, biodiversity, and other environmental conditions (Skole et al. 1994, Hirsch et al. 2004, Fearnside 2005). Monitoring of forest and savanna deforestation in the Brazilian Amazon has received much attention in the past three decades. Two systems, i.e., PRODES – Program for the Estimation of Deforestation in the Brazilian Amazon (http://www.obt.inpe.br/prodes/) and DETER – Real Time Deforestation Monitoring System (http://www.obt.inpe.br/deter/) have been developed to monitor annual deforestation using Landsat and MODIS data respectively. According to the INPE (National Institute for Space

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Research) report, a total area of 392,020 km^2 of forest was deforested in the Brazilian Amazon between 1988 and 2011 (http://www.mongabay.com/brazil.html). A large area of primary forest and savanna has been converted into secondary succession, agroforestry, pasture, agricultural fields, and infrastructures (Lucas et al. 2000, Roberts et al. 2002, Cardille and Foley 2003, Carreiras et al. 2006, Lu et al. 2012a). In addition to the monitoring of primary forest, timely detection of other land use and land cover (LULC) change, especially secondary succession and agriculture expansion, is also important for better management and planning of the deforested areas (Lu et al. 2012a).

Research on LULC change detection has attracted great attention in the past three decades (e.g., Singh 1989, Coppin et al. 2004, Lu et al. 2004a, Kennedy et al. 2009, Chen et al. 2012). Multitemporal remotely sensed data, especially time series Landsat images have been widely used for examining LULC change (Masek *et al.* 2008, Vogelmann *et al.* 2009, Huang *et al.* 2010, Thomas *et al.* 2011, Hansen and Loveland 2012). Although many change detection techniques have been developed, most of them are only used to detect binary change and non-change categories (Lu et al. 2004a). In practice, detailed "from-to" change trajectories are often required for better understanding LULC change patterns and rates. Post-classification comparison is the most common method to examine LULC change trajectories. Traditionally, LULC change detection is implemented at the per-pixel level, but analysis of LULC change at multiple scales may provide new insights on change patterns and rates. Therefore, this paper aims to analyze LULC change at different scales: per-pixel, polygon, census sector, and total study area using multitemporal Landsat images acquired in the years of 1990/1991, 1999/2000, and 2008/2010 within three study areas having different biophysical conditions in the Brazilian Amazon.

2. Methods

Altamira and Santarém in Pará State and Lucas do Rio Verde (hereafter, Lucas) in Mato Grosso State were selected for this research (Figure 1). The three study areas have different biophysical and socioeconomic conditions, as summarized in Table 1. This research employs multitemporal Landsat images to examine LULC change. Figure 2 provides a flow chart of this research, which includes image preprocessing, image classification using the hierarchical-based method, and change detection analysis at different scales.

2.1 Data collection and preprocessing

Landsat images used in this research were summarized in Table 2. All Landsat images with spatial resolution of 30 m were atmospherically calibrated with the improved image-based dark object subtraction method (Chavez 1996, Chander et al. 2009). The Landsat Thematic Mapper (TM) images that were downloaded from USGS (http://glovis.usgs.gov/) had been georeferenced already into Universal Transverse Mercator (UTM) coordinate system and their geometric accuracy met our research requirement, but the TM images obtained from Brazilian INPE had geometric errors that required implementing image-to-image registration based on the georeferenced images. Root mean square errors of less than 0.5 pixels were obtained.

In the moist tropical regions of the Brazilian Amazon, cloud cover is often a problem prohibiting the collection of cloud-free Landsat images (Asner 2001). In the Altamira and Santarém study areas, completely cloud-free Landsat images are not always available, thus, we used multiple Landsat images to remove the cloud/shadow problem, assuming that the clouds are located at different areas at various image acquisition dates. For example, in Altamira, we used the 2000 Landsat Enhanced Thematic Mapper Plus (ETM+) image as a reference image because of its relatively good quality for the majority of the study area. The cloud/shadow areas in this image were replaced with the 1999 Landsat TM image (see

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Figure 3). Because some clouds/shadows were still on both the 2000 ETM+ and the 1999 TM images, the 2003 TM image was used to replace the clouds/shadows because no other cloud-free Landsat images were available at the years close to 2000. Before implementing the replacement of clouds/shadows in a reference image, image-to-image normalization between the reference image and subject images was conducted by a regression-based method using pseudo-invariant objects such as road intersections and water which were selected from the multiple Landsat images (Heo and FitzHugh 2000, Yang and Lo 2000, Du et al. 2002). The reflectance values from the 2000 ETM+ images were used as a dependent variable and a regression model for each band was developed to calibrate the 1999 TM and the 2003 TM images. The same method was used in Santarém for replacement of clouds/shadows in the reference image. Because of the confusion of the spectral signatures among clouds, urban landscape, and agricultural lands, and between shadows and water bodies, automatically detecting clouds/shadows, especially the relatively light clouds/shadow, is often difficult. Therefore, we visually interpreted the clouds/shadows on the color composites by assigning near infrared, shortwave infrared and red wavelength band images as red, green and blue. The identified pixels having clouds/shadows in the reference image were then replaced with the spectral values of the same location from other spectrally normalized Landsat images.

Field surveys were conducted in Altamira in July–August 2009, in Santarém in 2010 and 1999, and in Lucas in 2009. The field surveys mainly collected sample plots in rural areas which documented different stages of secondary forest, pasture, and crop fields, as described in Li et al. (2011). QuickBird images for the three study areas were used to collect sample plots in urban and urban-rural frontiers. The reference data collected from field surveys and QuickBird images had two roles in this research, one was to support the identification of thresholds used in the hierarchical-based classification method, and another was to use as sample plots for accuracy assessment.

According to our project requirement and this research purpose, a classification system with six LULC classes – primary forest, savanna, other vegetation (e.g., secondary succession, plantations), agro-pasture (agricultural fields, pasture), impervious surface, and water, was designed for this study. In cases where clouds/shadows could not be completely removed from the multiple Landsat images, another class called cloud/shadow was included in preliminary classification results, but this class was removed from the final result through a post-processing procedure to accurately examine the LULC change patterns and rates in these study areas.

2.2 Development of LULC datasets and accuracy assessment

2.2.1 LULC classification with the hierarchical-based method—Many classification algorithms are available (Lu and Weng 2007, Tso and Mather 2009); however, developing an accurate classification result from remotely sensed data is still a challenge. Many factors, such as spatial and spectral resolution of the satellite imagery, available reference data, classification algorithm, and analyst's experience, may affect the classification (Lu and Weng 2007). In particular, a sufficient number of representative training samples are critical for the supervised classification algorithms. Many previous studies have documented the difficulty in LULC classification in the Brazilian Amazon due to the spectral confusion between different LULC types, such as among impervious surfaces, bare soils and non-vegetation wetland and the complex vegetation types and structures (Lu et al. 2004b, Lu et al. 2012b). In our previous research in the Brazilian Amazon basin, we have extensively examined LULC classification using different sensor data (e.g., Landsat, ASTER, SPOT, and radar) and different classification algorithms (e.g., maximum likelihood, neural network, decision tree, support vector machine, K-nearest neighbor) (Li et al. 2011, 2012a, b, Lu et al. 2012b). We found that the hierarchical-based classification method is valuable for LULC classification, especially when training sample data are not available for historical remote-sensing data (Lu et al. 2012a). The hierarchical-based method used four steps in the classification procedure: (1) stratification of LULC classes to reduce the spectral confusion among different classes; (2) use of the analyst's knowledge and experience to merge the clusters into meaningful LULC classes; (3) manually editing the classification results in each step to further refine the misclassified classes; and (4) post-processing based on the multi-temporal classified images to further correct misclassification. A detailed description of the hierarchical-based classification method is provided in Lu et al. (2012a). Therefore, this method is used in this research for LULC classification for the three study areas.

2.2.2 Refinement of LULC classification results—Even though the majority of clouds/shadows were removed from the reference image, some dispersed clouds/shadows still remained because some clouds were in the same location in different dates of images (Figure 3). It is important to further remove clouds/shadows in the classified images because of the requirement of accurately analyzing the LULC dynamic changes. A comparison of the multitemporal classification images and Landsat color composites among 1991, 2000 and 2008 in Altamira indicated that many clouds/shadows were located in forest areas. We employed three successive steps to replace the cloud/shadow pixels with the specific LULC types in the classification images:

1. Automatic replacement: If the pixels were classified as clouds/shadows in the prior-date classification image, but they were classified as forest in the posterior-date classification image, these pixels in the prior-date classification image were re-assigned as forest;
2. Visual editing: The classified image was overlaid on corresponding Landsat color composite, highlighting the pixels of clouds/shadows and assigning these pixels to a proper LULC class by visual interpretation of the color composite;
3. Majority filtering: Some single pixels of clouds/shadows in the classification images were removed using the majority filtering function, i.e., the pixel of the clouds/shadows was used as a center and a majority filter with a window size of 5 by 5 pixels was used to re-assign a LULC class to the center pixel.

In addition to the rules that were used for removal of clouds/shadows, other rules were used to correct the misclassification between primary forest and other-vegetation (mainly advanced succession) classes and between impervious surface and agro-pasture:

1. If the pixels in the prior-date classification image were forest, but were difficult to determine if they were primary forest or advanced succession in the posterior-date classification image, re-assign these pixels to forest in the posterior-date classification image;
2. If the pixels in the prior-date classification image were other-vegetation class, but were difficult to determine whether they were other vegetation or primary forest in the posterior-date image, re-assign these pixels to other vegetation in the posterior-date classification image;
3. If the pixels in the prior-date classification image were impervious surface, but were difficult to determine whether they were agro-pasture or impervious surfaces in the posterior-date classification image, re-assign these pixels to impervious surfaces;

In order to implement accurate analysis of agro-pasture dynamic change in rural areas, it is necessary to distinguish agro-pasture in rural area from grass in urban landscape, because the similar spectral features between grass in urban landscapes and pasture in rural landscapes during the dry season often results in misclassification. However, pasture is mainly distributed in rural landscapes, and so we were able to visually define the boundary of urban landscapes, and re-assign the classified agro-pasture in urban landscape as grass. After all above post-processing procedures were conducted on the classification images, accuracy assessments were implemented for the three study areas.

2.2.3 Evaluation of LULC classification results—Accuracy assessment is often required for better understanding the quality and reliability of a classification image. In general, overall classification accuracy and kappa coefficient are often used to assess the overall performance in a classification, while producer's accuracy and user's accuracy are used to evaluate the performance of each LULC class. These parameters are calculated from the error matrix, as described in previous literature (e.g., Foody 2002, Congalton and Green 2008). In this study, a total of 413 sample plots were collected from the 2009 field work and the 2008 QuickBird image in Altamira and they were used to evaluate the 2008 classification image. In Santarém, 546 sample plots were collected from the 2010 field work and the 2008 QuickBird image and were used for evaluating the 2010 classification image. Another 265 sample plots were collected in the 1999 field work and were used to evaluate the 1999 classification image. In Lucas, a total of 300 sample plots were collected from the 2008 QuickBird images and the 2009 field survey and were used to evaluate the 2008 classification image. The QuickBird images mainly covered the urban landscapes, thus, these images were primarily used to collect samples in the urban landscape, while field surveys were conducted in the deforested regions in rural areas. A detailed description of field data collection was provided in Li et al. (2011). Because reference data were not available for other dates of classification images, no accuracy assessments were conducted for these results, but we were confident that these results had similar classification accuracy based on our previous work using the hierarchical-based classification method (Lu et al. 2012a).

2.3 Analysis of LULC dynamic changes at multiple scales

In general, change detection is implemented at per-pixel level based on the classified images. However, change detection analysis can also be conducted at other scales such as polygon, census sector and overall scales, which are the foci of this research.

2.3.1 Analysis of LULC change at overall scale—The total area for each LULC class in each study area was calculated from the per-pixel based classification image. The proportion of each LULC type in a study area was calculated as:

$$\mathrm{A_i\%of\ \ LULC\ \ type}i\mathrm{=(area\ of\ the\ LULC\ typei/total\ study\ area)}*100,$$

Meanwhile, the change for each LULC type in a study area was calculated:

$$A_i = A_{it1} - A_{it2},$$

Where A_{it1} and A_{it2} represent a total area of the LULC type *i* at date *t1* and date *t2* respectively. The change analysis at overall scale provided the overall gain or loss for specific LULC types, but cannot provide the detailed LULC trajectories.

2.3.2 Analysis of LULC change at per-pixel scale—The post-classification comparison approach was used to examine the detailed LULC change trajectories at per-pixel scale. The major change trajectories in this research included

1. Deforestation of primary forest: the conversion from primary forest to other vegetation, or to agro-pasture, or to impervious surfaces;
2. Deforestation of savanna: the conversion from savanna to other vegetation, or to agro-pasture, or to impervious surfaces;
3. Deforestation of other-vegetation: the conversion from other vegetation to agro-pasture or to impervious surfaces;
4. Loss of agro-pasture lands: the conversion from agro-pasture to other vegetation or to impervious surfaces.
5. Other changes: water change and the changes due to the errors of image-to-image registration. These changes were not the foci of this research.

From above major LULC change trajectories, we can further examine (a) dynamic change of other vegetation class (gain due to the deforestation of primary forest and savanna, and loss from the conversion from other vegetation to agro-pasture and to impervious surfaces), (b) dynamic change of agro-pasture (gain due to the conversion from primary forest, savanna, and other vegetation to agro-pasture, and loss due to the conversion from agro-pasture to other vegetation or impervious surfaces), and (c) expansion of impervious surface areas (e.g., gain due to the conversion from primary forest, other vegetation, savanna, and agro-pasture to impervious surfaces).

The change and non-change areas were calculated from each change detection result. The percent of total changed area was calculated as: (total changed area/total study area)*100; and the annual percent of changed area was calculated as: percent of total changed area/ number of years during the change detection period. Meanwhile, the area and percent of each change trajectory were calculated from the change detection images for analyzing the change detection trends among the three study areas.

2.3.3 Analysis of LULC change at census sector scale—Census sectors as defined by Instituto Brasileiro de Geografia e Estatística (IBGE) are the minimum areal units created for the purpose of cadastral control of data collection. Many important variables related to population and economic conditions are organized at the census sector scale and are accessible for public use. These variables are critical for examining forces driving LULC change, thus, it is important to examine the LULC dynamic change at the sector scale but this has not been examined in previous research. Here we examined the LULC change at the sector scale as defined by the 2010 Brazilian census. Emphasis was placed on the LULC change in rural landscapes for examining the deforestation, regeneration and agriculture dynamic change. A pie graph was used to illustrate the proportions of each changed LULC type based on the percent of changed area at each census sector. Since some census sectors partially located outside of the classification image, only the census sectors within the study area were analyzed.

2.3.4 Analysis of LULC change at polygon scale—The classification system used in this research includes six LULC classes – primary forest, savanna, other vegetation, agro-pasture, impervious surface, and water. There is no savanna in Altamira and very limited savanna areas in Santarém, but savanna in Lucas accounts for a large proportion of land cover in the 1980s and 1990s. Impervious surface area and water account for a very small proportion in the three study areas and they are not the foci of this research. Therefore, the emphasis of LULC change at polygon scale in this research was on the dynamic change of forest, agro-pasture, and other-vegetation classes for Altamira and Santarém, and of forest, savanna and agro-pasture for Lucas. The classified images in raster format were converted into vector format shapefile polygons. The polygons with areas of less than 2 ha were merged to the nearest polygon by considering the minimum analysis size of these LULC types and the reduction of noise caused by the per-pixel based classification method. The areas of all polygons for each identified class were then calculated and the corresponding number of polygons with each polygon area range of less than 5 ha, [5-10), [10-30), [30-50), [50-100), [100-200), [200-500], and greater than 500 ha, was calculated (note: [5-10) means the area ranges of greater than or equal to 5 ha but less than 10 ha). The scale-bar graph for each polygon area range for these LULC types was used to examine the dynamic change of patch sizes at different dates and study areas for understanding the patterns of these LULC dynamic changes.

3. Results

3.1 Evaluation of LULC classification results

The classification accuracy assessment results for three study areas indicated that the hierarchical-based classification method effectively classified Landsat images into six-class thematic maps (see Table 3), providing the fundamental data sources for examining LULC change trajectories. Santarém and Lucas have higher overall classification accuracy (e.g., 91.7%-93.7%) than Altamira (i.e., 84%). The major problem causing relatively low accuracy in Altamira was the misclassification between advanced succession vegetation and primary forest due to their complex vegetation stand structure and species composition, and between initial succession (other vegetation) and dirty pasture (agro-pasture) due to the lack of a clear boundary between them. A similar situation was present in Santarém, but less so due to lower fertility conditions. For Lucas, some savanna (cerrado) was confused with other vegetation or agro-pasture due to the wide variation of savanna in species composition and density (Lu et al. 2012a). Although no accuracy assessment for other dates of classified images in the three study areas were implemented due to the lack of reference data, their classification results were believed to have similar accuracies, as our previous research had proven that the hierarchical-based classification method was reliable and stable (Lu et al. 2012a).

3.2 Analysis of LULC change at different scales

3.2.1 Analysis of LULC change at overall scale—A comparative analysis of the total area for each LULC class among the three study areas indicated that the composition of LULC classes varied considerably at different dates, as shown in Table 4. In Altamira and Santarém, forest accounted for the largest proportion of land covers but decreased rapidly in the past two decades. Other vegetation in Altamira had higher increasing rate than agro-pasture, but this trend was inversed in Santarém. There were no savanna areas in Altamira and very limited areas in Santarém, but savanna (or cerrado) in Lucas accounted for 23.9% of the study area in 1990, and rapidly decreased to only 9.5% in 1999. The continuous loss of forest and savanna in Lucas was largely a result of the increase in agro-pasture, which increased its proportion from 45.8% in 1990 to 67.7% in 2008. Figure 4 shows the LULC distributions in the three study areas, indicating the largest proportion of primary forest in Altamira and Santarém and of agro-pasture in Lucas, and indicating the obvious agro-pasture expansion and deforestation within the same periods.

Table 4 also indicates that loss of primary forest between 1991 and 2000 in Altamira resulted in expansion of both agro-pasture and other-vegetation classes, but its loss between 2000 and 2008 was mainly due to agro-pasture expansion. In Santarém, deforestation was mainly due to the conversion of primary forest to both agro-pasture and other-vegetation classes, especially other-vegetation over time. In Lucas, deforestation of primary forest and savanna between 1990 and 1999 was mainly due to agro-pasture expansion, but deforestation area between 1999 and 2008 was considerably decreased due to the constraint of available forest/savanna areas, and the limited deforestation of primary forest that did occur was due to the expansion of agro-pasture, impervious surfaces, and other vegetation. The results in Table 4 indicate the considerably different LULC change amounts in the three study areas during two detection periods. However, Table 4 only provides the overall information of LULC dynamic change, it does not provide detailed information about LULC change trajectories and the corresponding spatial patterns of change.

3.2.2 Analysis of LULC change trajectories at per-pixel scale—The detailed change trajectories for major LULC classes in Table 5 indicate that different study areas in both detection periods had considerably different change trajectories and amounts. Altamira and Santarém have much higher amounts of changed areas than Lucas, but the percentage of total changed area or average annual percentage of changed area in Altamira is much higher than in Santarém, as shown in Table 5, because Santarém has a large unchanged area of primary forest (see Figure 4 and Table 4). Major LULC change trajectories include deforestation of primary forest, dynamic change (gain or loss) of other-vegetation and agro-pasture in Altamira and Santarém, but in Lucas, the majority of change is the conversion of savanna to agro-pasture. The percent of gained areas for agro-pasture and other-vegetation classes in three study areas were much higher than the percent of their loss areas. As shown in Table 5, deforestation in Altamira is prone to agro-pastural expansion, in Santarém it is prone to expansion of other vegetation type; while in Lucas, deforestation is mainly due to agro-pasture expansion in the 1990s, but in the 2000s, expansion of other vegetation and impervious surface areas become another important factor resulting in deforestation. Figure 5 illustrates the spatial distribution of LULC change, indicating that the obvious changes in Altamira and Santarém were the conversion of forest to agro-pasture and other vegetation, and the transform between other vegetation and agro-pasture; but for Lucas, one obvious change was the conversion of savanna to agro-pasture between 1990 and 1999, and the expansion of impervious surface areas between 1999 and 2008. In the three study areas, impervious surface increase was mainly at the expanse of agro-pasture, although some conversion from forest and other vegetation, especially in rural regions, was observed.

3.2.3 Analysis of LULC change at census sector scale—Based on the percent of total changed area in a sector, we grouped census sectors into three groups in Altamira, five groups in Santarém, and two groups in Lucas (Figure 6). The patterns and rates of LULC changes illustrated in Figure 6 imply that the distance to the major urban areas, road expansion, and land use history may be related to the LULC change. For example, major deforestation in Altamira began in the early 1970s, coincident with the construction of the transamazon highway (see Figure 1) Moran, 1981). In the 1980s, major deforestation occurred close to the Altamira city and along the highway (Moran et al. 1994). Between 1991 and 2000, the sectors away from the urban area (A2 in Figure 6) had higher LULC change rates than in the areas close to the urban area (A1), and the sectors far away from urban (A3) had the lowest change rate. However, the changes between agro-pasture and other-vegetation had high proportion near the urban region (see A1), slightly decreased away from urban (see A2), and were lowest in rural regions (see A3). After entering the 2000s, the conversion of forest to other-vegetation or agro-pasture was reduced, while the conversions of other vegetation to agro-pasture increased considerably, especially close to the urban region compared to the conversions in the 1990s.

Santarém has a much longer land use history than the Altamira and Lucas study areas. During the 1990s, the S2 and S1 groups close to the Santarém urban region had higher LULC change rates than the S4 and S5 groups away from urban region, and the dynamic change between other vegetation and agro-pasture accounted for the high proportions in the S1 and S2 groups, while the conversion of forest and other vegetation to agro-pasture accounted for the largest proportion in the S4 group, and the conversion of forest to agro-pasture accounted for the large proportion in the S5 group (see Figure 6). The S3 group had lower LULC change rate than other groups because of the forest conservation policy close to the Tapajos River (see Figure 1). After entering the 2000s, LULC change in each sector group had higher rates than that in the 1990s. The conversion of agro-pasture to other vegetation accounted for a large proportion in the S1 group and some sectors in the S2 group where the sectors are relatively close to the urban region; on the other hand, the conversion of other vegetation to agro-pasture accounted for a large proportion in most of the sectors in the S2 and S4 groups where the sectors are relatively away from the urban region. In contrast, the conversion from forest to other vegetation accounted for the largest proportion in the S5 group. The S3 group in the 2000s had high LULC change rates due to the road expansion in the Belterra region close to the BR163 highway, resulting in higher conversion from forest and other vegetation to agro-pasture.

Lucas has a relatively short land use history because major deforestation was started after the county was established in 1982. Deforestation of forest and savanna was especially high in the 1980s, and reduced rapidly in the 1990s and 2000s (Lu et al. 2012a), because of the restriction of available forest and savanna resources. The percent of changed areas for those sectors near the Lucas city had higher values than the sectors away from the city (L1 versus L2) in 1990-1999, but inverse in 1999-2008. The proportion of impervious surface areas in 1999-2008 increased much higher than in 1990-1999, especially close to the urban area (i.e., the L1 sector group).

3.2.4 Analysis of LULC change at polygon scale—Considering the changes in patch sizes of forest class over time among three study areas, a common trend was that the number of polygons increased considerably but the average sizes decreased rapidly (See Table 6), implying increasingly fragmented forest landscape after deforestation. For the other-vegetation class, the number of polygons in both Altamira and Santarém increased, similarly to forest, but the average size of polygons was much smaller, implying that the other vegetation class was much more fragmented than forest. Altamira had a relatively small average size of other vegetation patch compared to Santarém; this may be because the good soil fertility in Altamira resulted in a relatively short rotation period between the dynamic change of other vegetation and agro-pasture (Lu et al. 2002). For agro-pasture, the number of polygons was highest in the year 2000/1999 for both Altamira and Santarém, but the average patch size increased gradually from 1991 to 2008/2010, implying an increase in large scale mechanized agriculture. In Lucas, the number of polygons in the year of 1999 had the lowest number but highest average size, implying that the rapid road expansion after 1999 had resulted in the replacement of agro-pasture. Overall, Lucas had much larger average sized polygons for agro-pasture than Altamira and Santarém. This might be expected considering the large scale mechanized agriculture found in the county.

The analysis of changes in numbers of polygons along different area ranges is helpful for understanding the fragmentation due to LULC change, as shown in Figure 7. When the patch size was greater than 30 ha, the number of polygons sharply decreased, especially in Altamira and Santarém, because deforestation, urbanization and road expansion often resulted in complex LULC composition. For forest, the number of polygons increased from the early 1990s to late 2000s, implying the increased fragmentation due to deforestation. However, it is also observed that the number of polygons in large patch size (e.g., greater than 500 ha) increases, especially in Santarém. This is because the forest in early 1990s having a huge size (thousands of ha) with a limited number of patches become a relatively small size of forest patches (less than a thousand ha) due to the road construction and deforestation, as shown in Figures 4 and 5. The increased numbers of polygons for the other-vegetation class in Altamira and Santarém implied that larger patch sizes appeared over time. The decreased number of relatively large patch sizes of savanna areas in Lucas may imply that a limited area of savanna remained due to its conversion to agro-pasture. Concerning agro-pasture in Altamira and Santarém, the number of polygons gradually decreased over time when patch size was less than 30 ha, but the numbers of polygons increased over time as patch size increased, implying the increased farming sizes over time because of the use of mechanization.

4. Discussion and summary

4.1 Improvement of LULC classification results

Development of accurate LULC classifications has been an active research topic in the past four decades since the first earth observation satellite was launched in the early 1970s. Great progress in improving LULC classification has been made, including incorporation of multiple sources of remote sensing data (e.g., optical sensor data, radar, LiDAR) and/or ancillary data (e.g., DEM, population density), development of advanced classification algorithms (e.g., neural network, support vector machine, random forest decision tree), and application of expert knowledge for post processing (Lu and Weng 2007, Lu et al. 2012b). However, classification is a complex procedure, the results of which may be affected by many factors such as the characteristics of the study area, selected data sources (e.g., remote sensing data, ancillary data, ground truth data), classification algorithms, and the analyst's experience (Lu and Weng 2007). Previous research has paid much attention to the application of multi-source remote sensing data and advanced classification algorithm, but misclassification often occurred due to the complex biophysical environments resulting in similar spectral or radiometric data and the constraint of remote sensing data and techniques. In the Brazilian Amazon, we have extensively examined the employment of different sensor data (e.g., optical sensor data, radar) (Li et al. 2011, 2012b, Lu et al. 2011) and different classification algorithms (Li et al. 2012a, Lu et al. 2012b). We found that no matter what remote sensing data or classification algorithms were used, there were still some misclassifications that could not be automatically separated from the remote sensing data. Incorporation of human knowledge during the classification procedure is necessary to improve LULC classification. Therefore, the hierarchical-based method that combined automatic classification and manual editing had proven valuable to provide reliable LULC classification (Lu et al. 2012a).

Post processing of the classification image has been regarded as an effective method to further improve classification accuracy. Ancillary data such as DEM is often used by relating expert knowledge of LULC distribution to topographic factors (e.g., elevation, slope, aspect) (Lu and Weng 2007). The key is to develop the expert rules that can be used to correct the misclassification. This research provides an alternative to conduct the post processing by establishing some reasoning knowledge based on the multitemporal classification results. This is especially valuable when good-quality ancillary data are not available such as in the Brazilian Amazon. Since a variety of sensor data with different spatial and spectral resolutions are available, more research should be focused on the combined use of the different source data or on the modeling of multi-scale remote sensing data to improve LULC classification.

4.2 The necessity of LULC change detection at different scales

The information for detailed LULC change trajectories is often required for change detection research, and often derived using the post-classification comparison approach at per-pixel level (Lu et al. 2004a, Kennedy et al. 2009, Hansen and Loveland 2012).

Concerning the application of LULC change detection results, analysis of LULC change at multiple scales may provide new insights for better understanding of the spatial patterns and rates of LULC change and the relationship between LULC change and socioeconomic variables collected at administrative units at varying scales of analysis.

At overall scale, the change detection results provide overall LULC change trends, but conceal the inner change trajectories and their spatial patterns, especially the dynamic changes between other vegetation and agro-pasture in this research. For example, the gain of agro-pasture lands can be due to the conversion from primary forest, other vegetation, and water/wetland, while the loss of agro-pasture lands can be due to the conversion from agro-pasture to other vegetation or to impervious surface areas. The change detection results at overall scale cannot reflect above change trajectories, but the change detection analysis at per-pixel scale can overcome these shortcomings. The per-pixel based change detection analysis is especially valuable when the information of detailed LULC change spatial patterns is required.

Although change detection studies at census sector and polygon scales are not common in previous research, their results indeed provide some new opportunities for analysis that the per-pixel based change detection results do not, such as the ability to relate the change results to human-induced activities. In order to better manage the deforested areas, it is required to understand the anthropogenic factors affecting deforestation or LULC change. Since the anthropogenic-relevant variables such as demographic and socioeconomic data are often organized and accessible at administration units (e.g., census sectors, township or county level), we need to examine the LULC change at the same scales corresponding to the administration units. At polygon scale, we may better understand how human-induced activities such as deforestation, road construction, and urbanization affect the fragmentation of the LULC distribution. Therefore, it is desirable to implement LULC change detection at multiple scales for better examining the LULC dynamic change in a specific study area.

4.3 A summary of research results

Through the analysis of LULC change at different scales based on three dates of Landsat images among three study areas in the Brazilian Amazon this research indicates the necessity to investigate LULC change at multiple scales for better understanding of the mechanisms of LULC change and the effective use of the LULC results in interdisciplinary research. The major conclusions can be summarized as follows:

1. Change detection at overall scale provides important information of overall LULC change trends but conceals inner LULC change within the study area and their spatial patterns.
2. Change detection at per-pixel scale provides the detailed LULC change trajectories and their spatial patterns. These results are often the fundamental data source for further examining LULC change at other scales such as different administration units.
3. Change analysis at the census sector scale provides valuable datasets for the analysis involving the linkage of LULC change and anthropogenic factors such as population density and socioeconomic conditions.
4. Change analysis at polygon scale can provide important data sources for examining how human and natural-induced factors affect LULC fragmentation within the study area.

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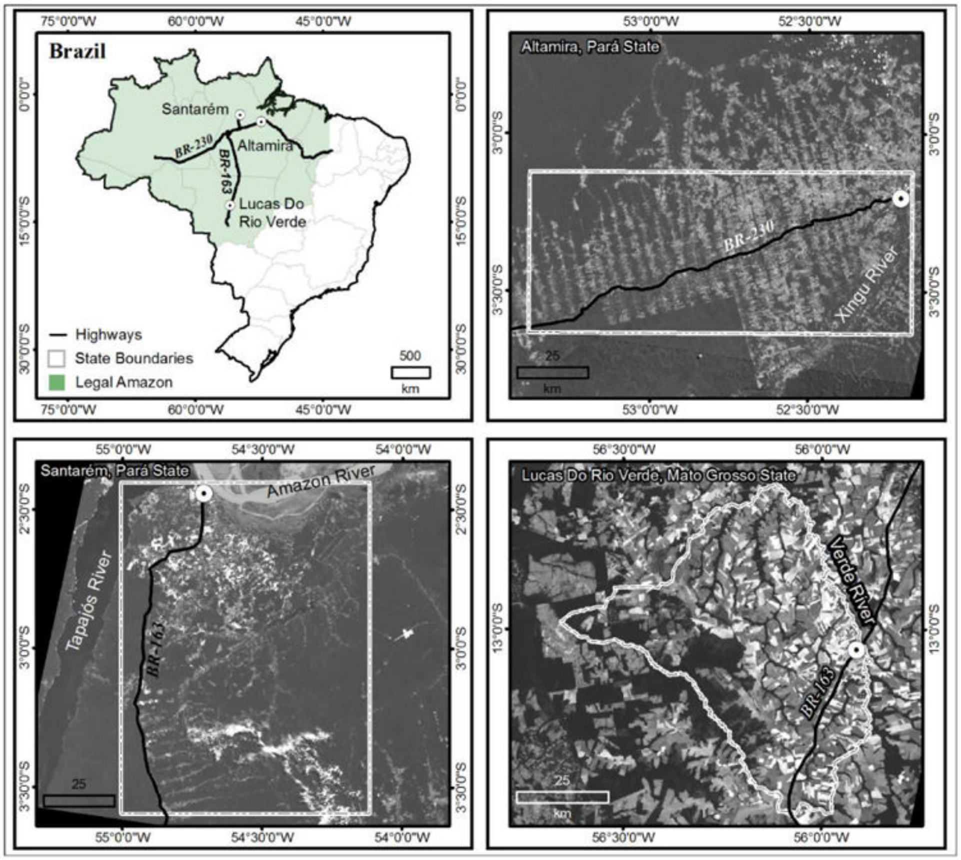

Figure 1.

Three study regions – Altamira and Santarém in Pará State and Lucas do Rio Verde in Mato Grosso State. Background images are red-band images from the Landsat 5 scenes acquired in July 2010 for Altamira and Santarém and in July 2008 for Lucas do Rio Verde. The dashed rectangles delineate the study areas in Altamira and Santarém and the dashed polygon delineates the boundary of the Lucas County. The white circle and black dot indicate the major urban location for each study area.

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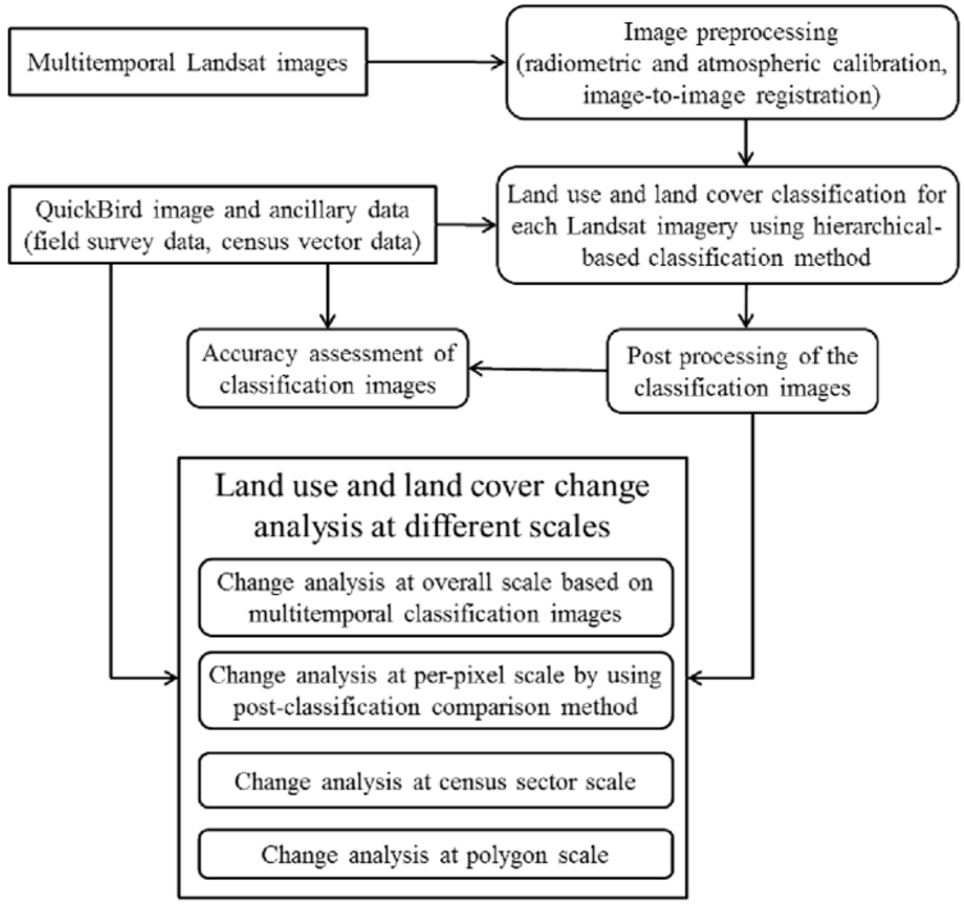

Figure 2. Flow chart of the research

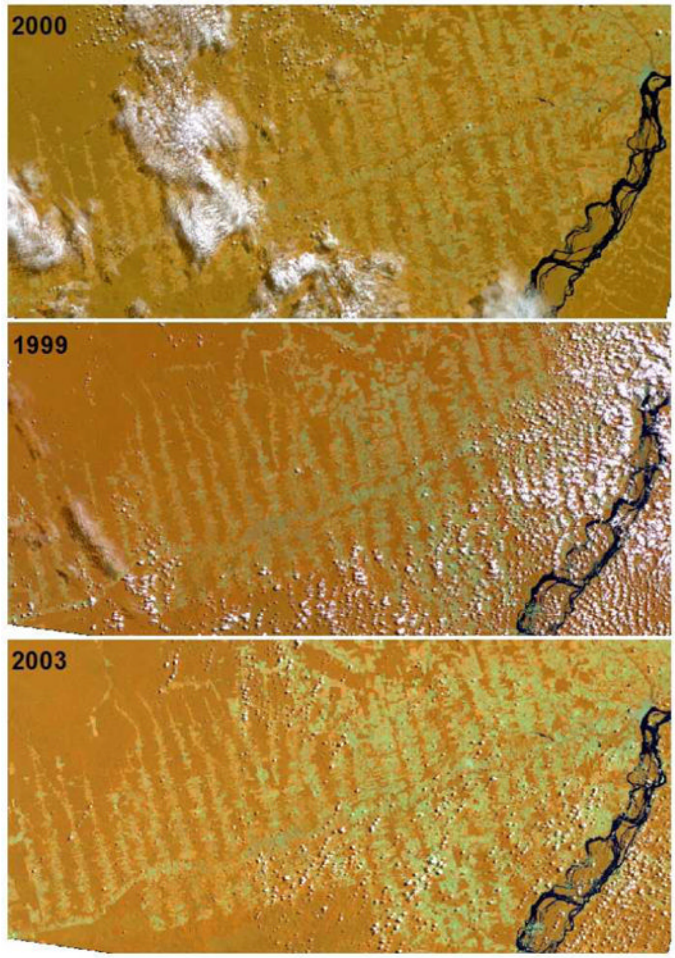

Figure 3.

A comparison of multiple Landsat images (near infrared, shortwave infrared, and red band images were assigned as red, green and blue in this color composite) in Altamira showing the cloud/shadow problem (note, the 2000 ETM+ scene image covers the entire study area, but both the 1999 and 2003 TM scene images lack a small part of data).

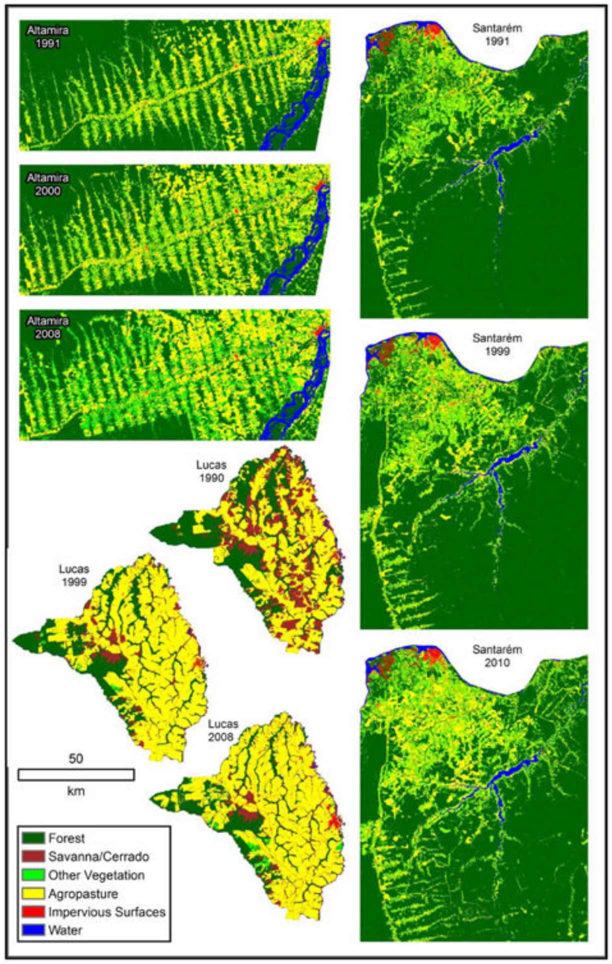

Figure 4. LULC maps of the three study areas derived from Landsat images

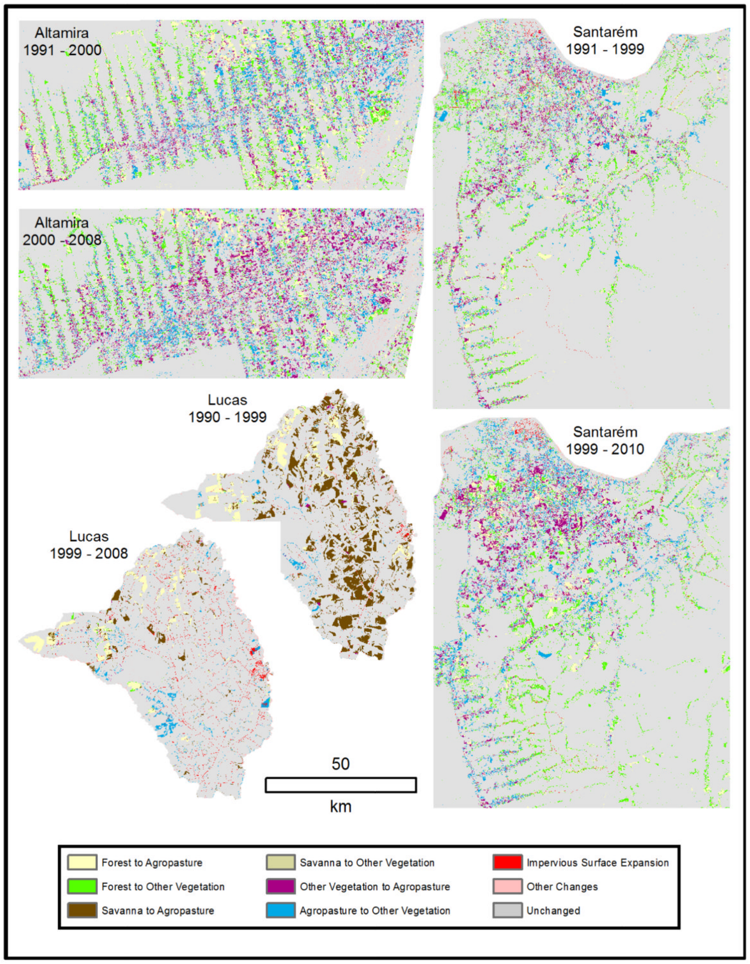

Figure 5. LULC change maps at per-pixel scale for the three study areas

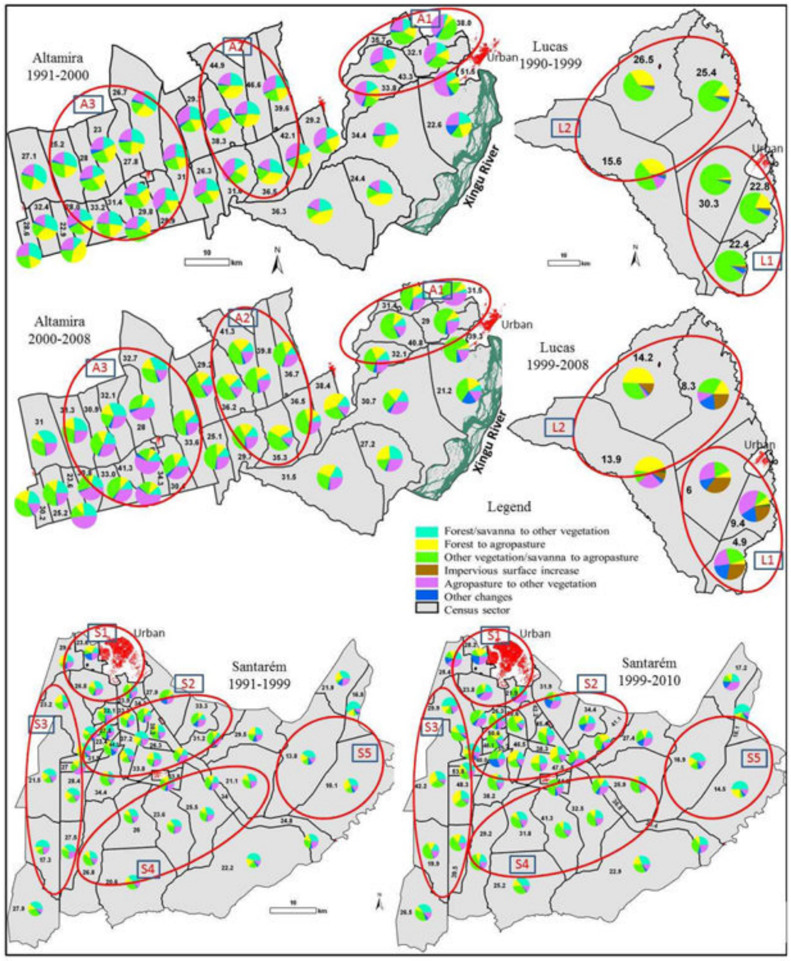

Figure 6. LULC change results at census sector scale for the three study areas in the Brazilian Amazon [note: the number in this figure represents the percent of total changed area accounting for total area in the sector, i.e., (total changed area/total area in a sector)*100]

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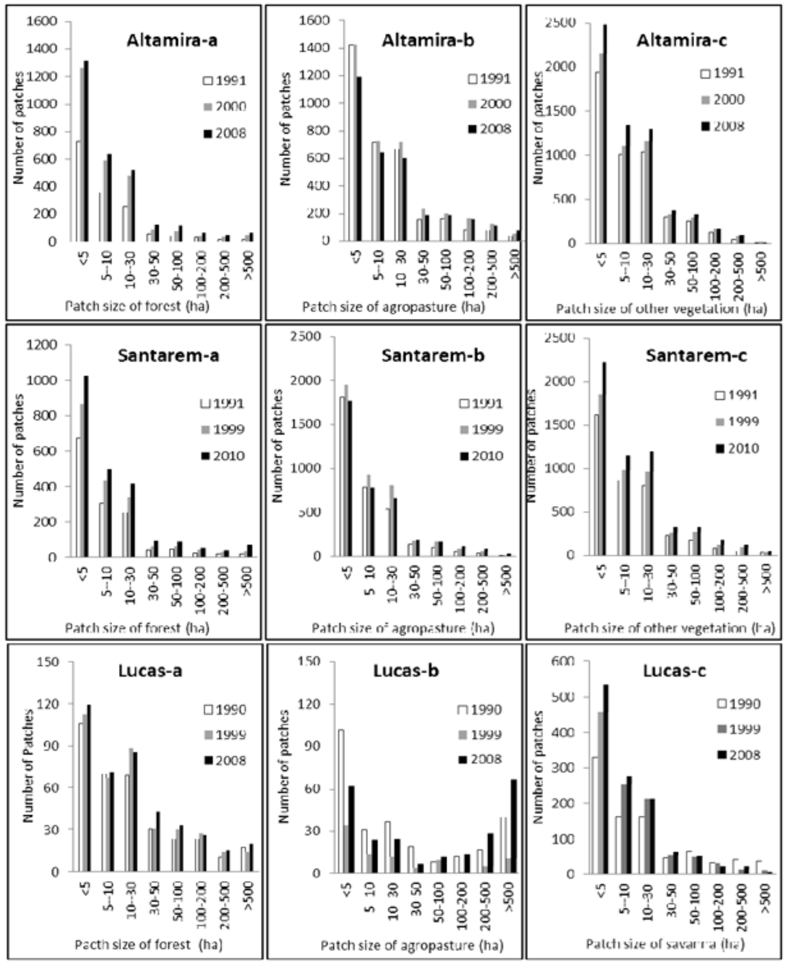

Figure 7.

Comparison of patch sizes of major LULC types among different dates at three study areas.

Table 1

Major characteristics of the three study areas in the Brazilian Amazon

Study areas	**Altamira**	**Santarém**	**Lucas do Rio Verde**
Geographic location	Located in the northern Pará State, Altamira is an important Transamazon hub that links to markets through the Transamazon Highway (BR-230). The extent of this study area is 7,512 km^2, covering the major deforested regions along the highway BR-230 and our traditional study area in the past two decades.	Located at the confluence of the Amazon River and the Tapajós River, Pará State, Santarém is linked to global markets through the export hub for agriculture commodities that originate in Mato Grosso State; reached by the east-west Transamazon (BR-230) Highway and its north-south link, the Cuiabá-Santarém (BR-163) Highway, both completed in the early 1970s. The extent of this study area is 12,078 km^2, covering our traditional study area in the past decade.	Located at the central area of Mato Grosso State, Lucas is connected to Santarém in north and to the heart of Brazil's soybean-growing region at Cuiabá via the BR-163 highway. The extent of this study area is 3,663 km^2, covering the Lucas county.
Biome	Amazon tropical moist forest - Liana forest	Amazon tropical moist forest and areas of tropical savanna thought to be edaphic	Tropical savanna (cerrado) and Amazon forest
Land use history	Deforestation since the early 1970s has led to a complex landscape consisting of different succession stages, pasture, agroforestry and agricultural lands. Because this region has better than average soils, the area has a strong and stable basis for agropastoral production, including cocoa and sugar cane.	Inhabited early by Tapajós indigenous communities. Different road networks extending out of the city of Santarém are associated with differing historical processes of settlement. The major roads and the landscape to the south of Santarém have a complex structure of agricultural settlements. Recent trend of small lot property aggregation into large industrial farms for export commodities.	Deforestation began in the late 1970s with the construction of BR-163 highway and expanded rapidly, especially after the establishment of Lucas County in 1982, resulting in a large area conversion from primary forest and savanna to agricultural lands.
Population growth	Altamira has a long history as a riverine settlement. Population in this Altamira county has grown from 1,000 in the early 1970′s to over 85,000 by 2000. The urban population in 2010 reached 76,695	Santarém was an important pre-historic occupation area. It is the third largest city in the Brazilian Amazon, after Belem and Manaus. The urban population in 2010 reached up to 204,129.	Lucas has a short-term history with relatively small urban extent, but the urban extent has grown quickly. The urban population in 2010 was 42,068.
Property Patterns	Homogeneous -Rectangular shaped Lots – Average 100 ha.	Heterogeneous – Often “irregularly” shaped lots – Average 44 ha; Trend of small holdings being aggregated into large farms for export of soy, rice, and corn.	Mixture of mostly fairly homogenous properties and a small number of relatively large holdings, Average 297 ha.
Length of dry months	3-4 months	4-6 months	6-7 months
Census Sectors	35 sectors with average size of 10,756 ha	42 sectors with average size of 8,277 ha	6 sectors with average size of 60,111 ha

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Table 2
Landsat images and other data sources used in research

Datasets	Altamira	Santarém	Lucas
Landsat images	Landsat 5 TM image on 20 July 1991 with Earthsat Orthorectified image.	Landsat 5 TM (L1G) on 11 July 1991, but clouds/shadows were replaced with a TM image (L1G) on 25 June 1991	Landsat 5 TM image (from INPE) on 9 August 1990
	Landsat 7 ETM+ images (L1G) on 4 July 2000, but clouds/shadows were replaced with two TM images on 19 August 1999 (L1G) and 22 August 2003 (L1G).	Landsat 5 TM (L1G) on 2 August 1999, but clouds/shadows were replaced with an ETM + image (L1G) on 10 August 1999	Landsat 7 ETM+ image (L1G) on 10 August 1999
	Landsat 5 TM image (from INPE) on 2 July 2008.	Landsat 5 TM image (from INPE) on 29 June 2010, but clouds/shadows were replaced with a TM image (L1G) on 12 July 2009	Landsat 5 TM image (from INPE) on 22 May 2008
QuickBird image	26 September 2008.	25 June 2008	20 June 2008
Field work	2009	1999 and 2010	2009
Census data	The 2010 Brazilian census sector data were used		

Note: TM represents Landsat Thematic Mapper sensor, and ETM+ represents Landsat Enhanced Thematic Mapper Plus sensor. The Landsat images from USGS are L1G products with good geometric accuracy, but the images from INPE have geometric errors that require conducting image-to-image registration using L1G products as reference images.

Table 3

Accuracy assessment results for the three study areas

Types	F	S	V	A	I	W	RT	CT	PA	UA
	Accuracy assessment for the 2008 classified image in Altamira									
F	126		31	1		2	160	131	96.2	78.8
S										
V	5		79	5			89	122	64.8	88.8
A			12	88	5	2	107	96	91.7	82.2
I				2	31	1	34	36	86.1	91.2
W						23	23	28	82.1	100
Overall accuracy: 84.0%; Kappa: 0.78										
Accuracy assessment for the 2010 classified image in Santarém										
F	168		11				179	172	97.7	93.8
S		15					15	15	100.0	100.0
V	2		152	28			182	165	92.1	83.5
A			1	122			123	150	81.3	99.2
I			1		29		30	29	100.0	96.7
W						15	17	15	100.0	88.2
Overall accuracy: 91.8%; Kappa: 0.89										
Accuracy assessment for the 1999 classified image in Santarém										
F	86		5	1			92	86	100.0	93.5
S		15					15	15	100.0	100.0
V			49	12			61	55	89.1	80.3
A			1	66			67	81	81.5	98.5
I				2	13		15	14	92.9	86.7
W					1	14	15	14	100.0	93.3
Overall accuracy: 91.7%; Kappa: 0.89										

Types	Accuracy assessment for the 2008 classified image in Altamira									
	F	**S**	**V**	**A**	**I**	**W**	**RT**	**CT**	**PA**	**UA**
Accuracy assessment for the 2008 classified image in Lucas										
F	51						51	54	94.4	100.0
S	3	36				2	41	45	80.0	87.8
V		6	26				32	27	96.3	81.2
A		3	1	107	2		113	109	98.2	94.7
I				2	31		33	33	93.9	93.9
W						30	30	32	93.7	100.0
Overall accuracy: 93.7%; Kappa: 0.92										

Note: LULC types – F, S, V, A, I and W represent Forest, Savanna, other vegetation (i.e., secondary succession vegetation and plantations), agro-pasture (i.e., agricultural and pasture lands), impervious surface areas, and water; RT, CT, PA, and UA represent row total, column total, producer's accuracy and user's accuracy.

Table 4

The statistical results of LULC types and corresponding changes at overall scale

LULC	Areas (km^2) of LULC types								
	Altamira			**Santarém**			**Lucas**		
	1991	**2000**	**2008**	**1991**	**1999**	**2010**	**1990**	**1999**	**2008**
F	5220.6	4332.5	3619.2	9948.8	9219.6	8406.8	1045.6	837.4	652.1
S				51.4	51.5	45.1	873.4	349.5	335.7
V	996.6	1355.3	1390.1	1191.4	1555.9	2019.7	12.7	25.9	72.4
A	1037.7	1555.9	2200.5	616.8	951.4	1281.5	1677.3	2389.8	2480.6
I	43.9	62.4	74.2	60.6	90.8	117.1	25.9	37.6	99.7
W	213.6	206.3	228.5	208.8	208.4	207.4	27.6	22.4	22.2
Total	7512.4			12077.6			3662.6		
	Percent (%) of each LULC type accounting for total study area (A_i%)								
	Altamira			Santarém			Lucas		
	1991	2000	2008	1991	1999	2010	1990	1999	2008
F	69.49	57.67	48.18	82.37	76.34	69.61	28.55	22.86	17.8
S				0.43	0.43	0.37	23.85	9.54	9.17
V	13.27	18.04	18.5	9.86	12.88	16.72	0.35	0.71	1.98
A	13.81	20.71	29.29	5.11	7.88	10.61	45.79	65.25	67.73
I	0.58	0.83	0.99	0.5	0.75	0.97	0.71	1.03	2.72
W	2.84	2.75	3.04	1.73	1.73	1.72	0.75	0.61	0.61

	Changed area in km^2 (and in percentage) for each LULC type					
	Altamira		Santarém		Lucas	
	1991-2000	2000-2008	1991-1999	1999-2010	1990-1999	1999-2008
F	-888.1(-99.2)	-713.3(-100)	-729.2(-99.9)	-812.8(-99.1)	-208.2(-28.2)	-185.3(-93.0)
S			0.1(0.0)	-6.4(-0.8)	-523.9(-71.1)	-13.8(-6.9)

LULC	Areas (km^2) of LULC types								
	Altamira			Santarém			Lucas		
	1991	2000	2008	1991	1999	2010	1990	1999	2008
V	358.7(40.1)		34.8(4.9)	364.5(50.0)		463.8(56.5)	13.2(1.8)		46.5(23.3)
A	518.2(57.9)		644.6(90.3)	334.6(45.9)		330.1(40.2)	712.5(96.6)		90.8(45.5)
I	18.5(2.1)		11.8(1.7)	30.2(4.1)		26.3(3.2)	11.7(1.6)		62.1(31.1)
W	-7.3(-0.8)		22.2(3.1)	-0.4(-0.1)		-1.0(-0.1)	-5.2(-0.7)		-0.2 (-0.1)

Note: (1) LULC types – F, S, V, A, I, and W represent Forest, Savanna, other vegetation (secondary succession vegetation and plantations), agro-pasture (i.e., agricultural lands and pasture lands), impervious surface areas, and water.

(2) A_i% of LULC type *i* = (area of the LULC type *i*/total study area)*100

(3) Negative in this table indicates overall area loss of a specific LULC type, and positive indicates the overall area gain of a specific LULC type during the change detection period.

(4) The changed area for LULC type *i* = the total area of type *i* in posterior date – the total area of type *i* in prior date;

(5) The % of changed area for LULC type *i* = the total changed area for type *i*/the total changed area for the study area at the change detection period;

Table 5

A summary of LULC change trajectories at per-pixel scale

LULC change		LULC change area in km^2						LULC change in percent					
		Altamira		Santarém		Lucas		Altamira		Santarém		Lucas	
		1991-2000	2000-2008	1991-1999	1999-2010	1990-1999	1999-2008	1991-2000	2000-2008	1991-1999	1999-2010	1990-1999	1999-2008
FD	F - V	473.5	383.4	464.7	565.5	2.2	5.3	25.0	19.4	32.3	29.9	0.3	1.3
	F - A	587.1	450.8	333.7	366.0	169.3	133.9	31.0	22.8	23.2	19.3	20.3	33.4
	F - I	6.5	5.7	11.1	15.8	1.9	2.4	0.3	0.3	0.8	0.8	0.2	0.6
TFD		1067.1	839.9	809.5	947.3	173.4	141.5	**56.4**	**42.4**	**56.3**	**50.0**	**20.7**	**35.3**
SD	S - V			0.7	0.7	4.1	4.7					0.5	1.2
	S - A					575.4	84.9					68.8	21.2
	S - I			0.5	1.0	3.9	2.3				0.1	0.5	0.6
TSD				1.2	1.7	583.4	91.9			0.1	0.1	**69.8**	**22.9**
VL	V - A	351.7	629.6	280.8	410.3	7.8	4.8	18.6	31.8	19.5	21.7	0.9	1.2
	V - I	6.5	8.1	11.5	12.8	0.1	0.2	0.3	0.4	0.8	0.7		
TVL		358.2	637.6	292.3	423.1	7.9	5.0	**18.9**	**32.2**	**20.3**	**22.3**	0.9	1.2
VG	F - V	473.5	383.4	464.7	565.5	2.2	5.3	25.0	19.4	32.3	29.9	0.3	1.3
	S - V			0.7	0.7	4.1	4.7					0.5	1.2
	A - V	415.7	432.9	271.7	450.4	34.2	73.5	22.0	21.9	18.9	23.8	4.1	18.3
TVG		889.2	816.3	737.2	1016.6	40.4	83.5	**47.0**	**41.2**	**51.3**	**53.7**	**4.8**	**20.8**
AL	A - V	415.7	432.9	271.7	450.4	34.2	73.5	22.0	21.9	18.9	23.8	4.1	18.3
	A - I	21.4	28.0	22.4	30.6	14.6	61.8	1.1	1.4	1.6	1.6	1.7	15.4
TAL		437.1	461.0	294.1	481.0	48.8	135.3	**23.1**	**23.3**	**20.5**	**25.4**	**5.8**	**33.8**
AG	F - A	587.1	450.8	333.7	366.0	169.3	133.9	31.0	22.8	23.2	19.3	20.3	33.4
	S - A					575.4	84.9					68.8	21.2
	V - A	351.7	629.6	280.8	410.3	7.8	4.8	18.6	31.8	19.5	21.7	0.9	1.2

LULC change		LULC change area in km^2						LULC change in percent					
		Altamira		Santarém		Lucas		Altamira		Santarém		Lucas	
		1991-2000	**2000-2008**	**1991-1999**	**1999-2010**	**1990-1999**	**1999-2008**	**1991-2000**	**2000-2008**	**1991-1999**	**1999-2010**	**1990-1999**	**1999-2008**
TAG		938.8	1080.4	614.5	776.4	752.5	223.6	**49.6**	**54.6**	**42.7**	**41.0**	**90.0**	**55.8**
IE	F - I	6.5	5.7	11.1	15.8	1.9	2.4	0.3	0.3	0.8	0.8	0.2	0.6
	S - I			0.5	1.0	3.9	2.3				0.1	0.5	0.6
	V - I	6.5	8.1	11.5	12.8	0.1	0.2	0.3	0.4	0.8	0.7		
	A - I	21.4	28.0	22.4	30.6	14.6	61.8	1.1	1.4	1.6	1.6	1.7	15.4
TIE		34.4	41.8	45.4	60.2	20.6	66.6	**1.8**	**2.1**	**3.2**	**3.2**	**2.5**	**16.6**
OC	WO	29.8	40.8	40.3	40.4	22.3	27.0	1.6	2.1	2.8	2.1	2.7	6.7
TCA (km^2)		1892.3	1979.3	1437.5	1893.6	835.9	400.7	**25.2**	**26.3**	**11.9**	**15.7**	**22.8**	**10.9**
ACA (km^2)		210.3	247.4	179.7	172.1	92.9	44.5	2.8	3.3	1.5	1.4	2.5	1.2

Note: (1) LULC change trajectory: F (or S) – V(or A, I) represent the conversion from forest (or savanna) to other vegetation (or agro-pasture, impervious surface); V – A (or I) represent the conversion from other vegetation to agro-pasture (or impervious surface); A – V (or I) represent the conversion from agro-pasture to other vegetation (or impervious surface); OC (WO) – Other changes (water change and others);

(2) LULC change aggregation: FD (SD) – forest (savanna) deforestation; VL (VG) – other vegetation loss (gain); AL (AG) – agro-pasture loss (gain); IE – Impervious surface expansion;

(3) TFD (TSD) – total area of forest (savanna) deforestation; TVL (TVG) – total area of other vegetation loss (gain); TAL (TAG) – total area of agro-pasture loss (gain); TIE – total area of impervious surface expansion; TCA – total changed area; ACA – annual changed area.

(4) Calculation: Annual changed area (ACA) = total changed area/number of years during change detection period % of total changed areas = (total changed area/total study area)*100 % of annual changed area = % of total changed areas/number of years during the change detection period % of change category *i* = (area of the change category *i*/total changed area)*100

Table 6

A comparison of average patch sizes (ha) of major LULC types

Study areas	LULC types	Number of polygons			Average size of polygons		
		1991	**2000**	**2008**	**1991**	**2000**	**2008**
Altamira	F	1519	2620	2900	346.1	165.9	125.0
	V	4717	5309	6103	20.7	25.2	22.4
	A	3314	3664	3158	30.7	42.3	69.9
Santarém		1991	1999	2010	1991	1999	2010
	F	1380	1877	2292	723.6	492.9	368.6
	V	3849	4589	5582	31.1	34.0	36.2
	A	3475	4185	3779	16.0	21.1	32.0
Lucas		1990	1999	2008	1990	1999	2008
	F	348	383	412	302.1	223.2	162.3
	S	878	1082	1189	98.3	23.0	26.0
	A	266	91	240	631.7	2633.6	1036.5

Note:(1) LULC types – F, S, V, and A represent Forest, Savanna, other vegetation (secondary succession vegetation and plantations), and agro-pasture (i.e., agricultural lands and pasture lands).
(2) Average size of polygons for a LULC class (unit: ha) = total area of the LULC type/number of polygons.