Satellite Monitoring of Urban Spatial Growth in the Atlanta Metropolitan Area

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Abstract

Monitoring growth and change along the metropolitan periphery is of critical concern both to those who study metropolitan dynamics and those who must manage resources and provide services in these rapidly changing environments. This research has been directed to assess urban spatial growth and land change along the outskirts of Atlanta, one of the fastest growing metropolitan areas in the United States in the past three decades. A time series of satellite images was used to trace the development of urban land uses for the period of 1973 to the present. An image processing and GIS-based method was developed to achieve the research goal. Results reveal that every week, more than one-hundred acres of forest, green space, and farmland in the Atlanta region were converted into urban uses. Between 1973 and 1999, the urban territorial extent has expanded by 247 percent for 13 metro counties while the population increased by 96 percent. The rate of urban growth was much higher in outer suburban counties. Concomitant with this high rate of urban growth was a far-reaching evolution in Atlanta's urban spatial form. The growth of high-density urban use (mainly commercial, transportation, industrial, and high-rise residential) is found to experience a clear transition from linearly concentrated form towards a multinucleated pattern. The spread of low-density urban use (mainly residential) exhibited a widely dispersed pattern, thus indicating a major feature of the suburbanization. In addition, Atlanta has few physical barriers to urban development; this growth in urban physical extent seems to be unlimited as the population and business continue to grow, particularly in the outer suburbs.

Introduction

Outward urban growth and concentration of human populations into large metropolitan areas continue to be one of the most significant forms of global change felt in both developing and developed counties alike (Turner *et al.*, 1993). Over the past decades, many American metropolises have experienced significant growth, predominantly in the form of suburbanization (Hartshorn, 1992). The accelerating urban growth has often been viewed as a sign of the vitality of regional economies. But such scattered growth, driven largely by technological advancement and population growth, has rarely been well planned, thus provoking concerns over the degradation of our environmental and ecological health. Monitoring growth and change brought on by metropolitan development is of critical concern, both to those who study metropolitan dynamics or urban climatology/meteorology and those who must manage resources and provide services in these rapidly changing environments.

Thematic assessments of urban growth involve procedures of monitoring and mapping which require robust methods and techniques. Conventional survey and mapping methods can not deliver the necessary information in a timely and cost-effective mode. Given their technological robustness, remote sensing technologies are increasingly affecting urban land-use change research (Geoghegan *et al.*, 1998; Civco *et al.*, 2000). But urban environments, given their heterogeneous surface covers with substantial inter-pixel and intra-pixel changes, are challenging the applicability and robustness of these methods and technologies (Michalak, 1993; Kam, 1995). Fortunately, substantial research efforts have been made to improve the performance of automated mapping in heterogeneous landscapes, and some strategies have been developed as a result of such efforts. Examples include

- the development of enhanced classification approaches ranging from knowledge-based expert systems (Moller-Jensen, 1990), artificial neural networks (Civco, 1993), fuzzy logic (Ji and Jensen, 1996), to genetic algorithms (Zhou and Civco, 1996);
- the use of pre-classification image transformations and feature-extraction techniques, such as median filtering (Sadler *et al.*, 1991) and various measures of image texture (Franklin and Peddle, 1990);
- the incorporation of spatially referenced ancillary data into the classification procedure (Ehlers *et al.*, 1990); and
- the application of post-classification spatial processing ranging from modal filtering (Booth and Oldfield, 1989) to contextual reclassification (Gong and Howard, 1992; Barnsley and Barr, 1996).

Nevertheless, the performance of these techniques can vary greatly with the changes in image characteristics and the circumstances for targeted studies (Campbell, 1996). For specific applications, an analyst must identify appropriate procedures in order to produce satisfactory results (Yeh and Li, 1996). Further efforts will certainly be maintained and will probably intensify in order to adapt these techniques to solve practical problems in a productive mode, thus reinforcing the absolute and comparative utility of current remote sensing and GIS techniques (Green *et al.*, 1994).

This research has been focused on Atlanta, Georgia as a case study area. For the past three decades, Atlanta has been one of the nation's fastest growing metropolises as it emerged to become the premier commercial, industrial, and transportation urban center of the southeastern United States. The metropolis' population increased 27 percent between 1970 and 1980, 33 percent between 1980 and 1990, and 40 percent between 1990 and 2000. The metropolis has expanded greatly as suburbanization consumes large areas of agricultural and forest land adjacent to the city, pushing the periurban fringe farther

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and farther away from the previous city core. This rampant suburban sprawl has provoked concerns over losses of large areas of primary forests, inadvertent climate repercussions, and the degradation of the quality of life in this region (Bullard *et al.*, 2000). The Sierra Club's 1998 Annual Report cited Atlanta as American's most sprawl-threatened large city. Starting from 1996, the author has been involved in various research projects focusing on the understanding of the dynamics of change in Atlanta through the use of geographic information technologies. This paper examines urban spatial growth and land change along the outskirts of the Atlanta, Georgia metropolitan region, as seen from satellite imagery, along with technical procedures identified in this specific application.

Study Area

The geographic area of Atlanta specified here consists of 13 counties in the Atlanta Metropolitan Statistical Area (Figure 1). This area includes ten counties under the Atlanta Regional Commission (ARC) as well as three additional counties, i.e., Coweta, Forsyth, and Paulding, which have shown growth patterns similar to the ARC counties. The City of Atlanta resides in the center of the study area. The total area is approximately 10,442 square kilometers, fitting within a whole scene (185 by 185 km) of Landsat MSS or TM imagery.

Physiographically, the Atlanta area is mainly in the foothills of the southern Appalachians in northern Georgia at an elevation of 300 to 350 m above sea level. The northwestern portion (approximately 15 percent of the total area) is in the Appalachian Mountains. It has an even terrain that slopes downward toward the east and south. The climate is generally characterized as mild. The Chattahoochee River traverses the study area.

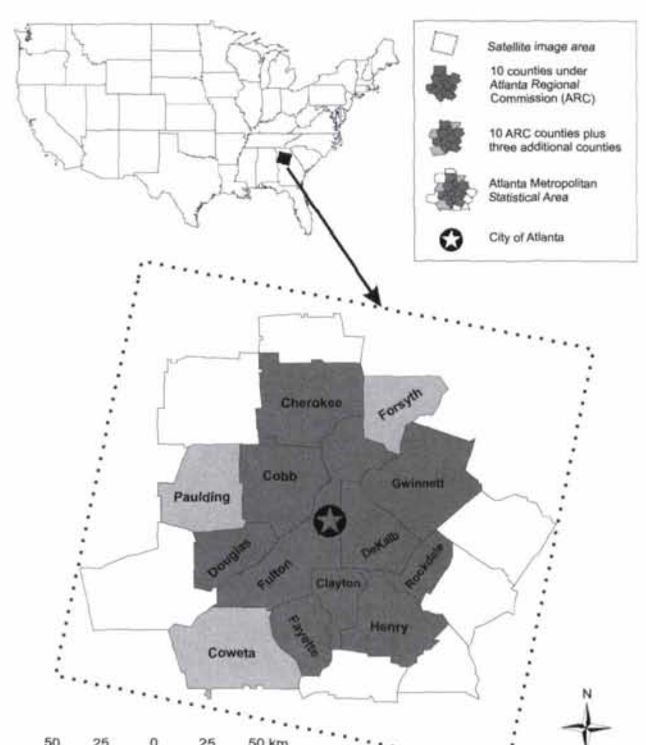

Figure 1. Location of the study area.

Research Methodology

Extracting meaningful urban land-change information from satellite data can be realized through either image-to-image comparison or map-to-map comparison (Green *et al.*, 1994). The research approach identified here is a map-to-map comparison change detection which can detect a full matrix of land-use/land-cover changes (Jensen *et al.*, 1995). The research methodology can be divided into three components as shown in Figure 2: (1) data acquisition and collection, (2) digital image processing, and (3) urban spatial change analysis.

Data Acquisition and Collection

Satellite Images

Ideally, high temporal and spatial resolution image data are most desired for this study. But fine-resolution data are costly and demand more processing time and computing resources. Given the budget constraints and the time availability, this study used a time series of Landsat images as the primary data for measuring and detecting spatio-temporal urban growth at six- to eight-year intervals beginning in 1973. The Landsat MSS data were used for the period before 1982 when TM data are not available. After that period, TM and ETM+ data were used. Eleven predominantly cloud-free scenes of Landsat images were acquired by three imaging sensor systems for Atlanta from 1973 to 1999. MSS data were obtained in 1973, 1979, and 1988; TM data were collected in 1987, 1993, 1997, and 1998; and ETM+ data were acquired in 1999. The specific dates, types of imagery, Landsat satellite series number, nominal spatial resolution of the various sensors, other environmental parameters, and the purposes for each scene are summarized in Table 1.

Because the study area spans two rows in the Worldwide Reference System (WRS), most of the scenes obtained have been centrically shifted so that the entire area is covered within one whole scene. But center shifting was not possible with the scenes acquired by Landsat 1 and Landsat 7. This is why both the north and south scenes for 1973 and 1979 were acquired. The two scenes were mosaicked together and further masked into one seamless scene with coverage similar to that of the center-shifted scenes for other years. Most of the scenes were acquired during the spring or earlier summer seasons (April–July) when vegetation is in the stage of vigorous growth. The 1998 and 1999 scenes are the two exceptions. The 1998 TM scene was acquired in the winter season. This scene was used

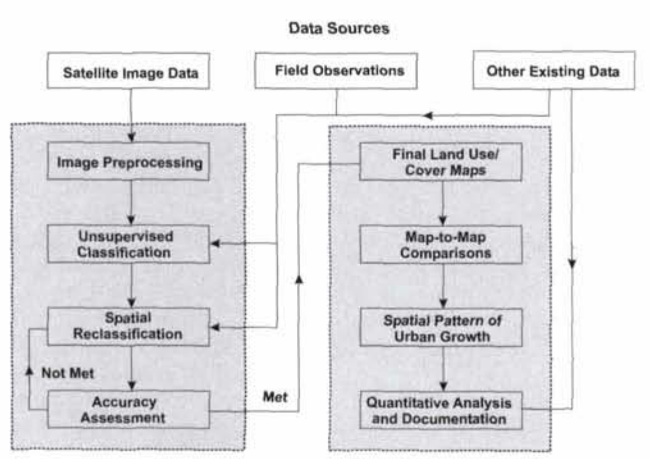

Figure 2. Working procedural route followed.

Table 1. Characteristics of the Satellite Data Used

Date	Type of Image	Landsat No.	Nominal IFOV (m)	Sun Elevation (degree)	Sun Azimuth (degree)	Scene Location	RMSE (Control Point No.)	RRN***	Purpose****
13 Apr 1973	MSS	1	57 by 79	54.16	129.37	north Atlanta	0.58 (13)	Yes	1
13 Apr 1973	MSS	1	57 by 79	54.83	127.39	south Atlanta			
11 Jun 1979	MSS	3	57 by 79	61.65	105.65	north Atlanta	0.46 (13)	Yes	1
11 Jun 1979	MSS	3	57 by 79	61.74	102.77	south Atlanta			
29 Jun 1987	TM	5	28.5 by 28.5	61.84	103.71	center-shifted	0.22 (13)	No	1
14 May 1988	MSS	5	57 by 79	61.61	115.51	center-shifted	0.51 (12)	ref.	4
31 Jul 1993	TM	5	28.5 by 28.5	57.00	110.00	center-shifted	0.40 (15)	No	1
29 Jul 1993	TM	5	28.5 by 28.5	61.00	106.00	center-shifted	ref.	No	2 and 4
02 Jan 1998	TM	5	28.5 by 28.5	27.00	150.00	center-shifted	0.27 (14)	No	3
09 Sep 1999	ETM+	7	28.5 by 28.5*	53.8	140.10	north Atlanta	0.52 (15)	No	1 and 4
09 Sep 1999	ETM+	7	28.5 by 28.5*	54.8	138.40	south Atlanta	0.44 (13)		

*The panchromatic band has a nominal IFOV (instantaneous field of view) of 15 m.
**The center of the north scene has been shifted by 50 percent. The scene size is approximately 185 by 185 km^2.
***RRN = Relative radiometric normalization.
****Code: 1 = land-use/land-cover mapping; 2 = reference data for geometric correction; 3 = reference data for ground truth in winter season; and 4 = land-use mapping accuracy assessment.

for improving landscape mapping, particularly for identifying vegetation, in combination with spring or summer scenes. The ETM+ scenes were acquired in later summer, and were the only scenes free from cloud available between April and September, 1999. Because of its high image quality, the 1988 MSS scene was used as the reference image for relative radiometric normalization of other MSS data, and no classification was attempted for this scene because a higher resolution scene for 1987 was available.

Reference Data

To facilitate satellite image-based change mapping, a range of reference data has been collected, including: (1) color infrared aerial photographs obtained with NASA's Advanced Thermal and Land Applications Sensor (ATLAS) on 11 May 1997; (2) contact prints of black-and-white and color aerial photographs for the period 1986 through 1988; (3) USGS digital orthophotos derived from National Aerial Photography Program (NAPP) photographs taken in January and February of 1993; (4) land-cover classification of Georgia 1988–1990 generated by ERDAS, Inc. for the Georgia Department of Natural Resources; and (5) USGS Level I and II land-use digital maps derived from the original source material from 1972 through 1976.

Field Surveys

Field surveys served two purposes. They helped establish the relationship between image signals and ground conditions. Representative spectral patterns for each land category on the satellite image(s) were selected, along with the aerial photos corresponding geographically to these image spectral patterns. These aerial photos were used as links by which the relationship between image signals and ground truth were established. Field work also helped obtain first-hand information about suburban sprawl throughout the study area, which is useful for understanding the dynamics of change. A Trimble GPS receiver was used for better positioning during the field surveys.

Digital Image Processing

The design of image processing procedures was based on a thorough understanding of image characteristics, landscape complexity, and the status of technological development. For facilitating such design, intensive experiments were carried out to address two important technological problems concerning multi-resolution data integration. Different relative radiometric normalization methods were assessed as applied to multi-date Landsat MSS images of Atlanta. The impacts of resolution on digital landscape change mapping for the data used in this research were evaluated. The results of these experiments were reported elsewhere (Yang, 2000; Yang and Lo, 2000). These experiments provided insights that have been used in the formulation of image processing procedures to ensure accurate results being extracted from the multi-date, multi-resolution satellite time series. The image processing procedures identified here involved a range of remote sensing and GIS methods and techniques, which include image preprocessing, image classification, GIS-based spatial reclassification, and accuracy assessment.

Image Preprocessing

Geometric rectification and radiometric normalization were attempted. Geometric rectification is critical for producing spatially corrected change mapping through time. The 1997 Landsat TM image, supplied by Space Imaging EOSAT, had already been accurately rectified and georeferenced to a UTM map projection (Zone 16), a NAD83 horizontal datum, and the GRS80 ellipsoid. This image was employed as the reference scene to which all other scenes were registered. The number of control points chosen can be seen in Table 1. Because the majority of the study area has relatively even terrain relief, only the first-degree polynomial equation was used in image transformation. The nearest-neighbor resampling method was needed to avoid changing the original pixel values of the image data. The TM and MSS images were resampled to 25 meters and 57 meters, respectively. The resultant root-mean-square errors (RMSEs) are around 0.5 pixel size and, thus, the accuracy of registration is excellent, as can be seen in Table 1.

The two Landsat MSS images used for image classification were acquired by two different Earth Resources Satellites, Landsat-1 and Landsat-3, at different dates. These MSS images were very different from each other in contrast though they were processed identically. To allow meaningful detection of land-use/land-cover change based on these images, a common radiometric response among them should be restored. To this end, the relative radiometric normalization (RRN) method is preferred over the absolute radiometric correction method because no *in situ* atmospheric data at the time of satellite overpasses are necessary. After careful evaluation of different RRN methods, it was decided that the method developed by Hall and his colleagues (1991) from the NASA Goddard Flight Center is most suitable for the Atlanta image scenes (see Yang and Lo, 2000). The Hall method of RRN using radiometric control sets (RCS) was applied to the MSS data only.

Radiometric normalization was not attempted on the Landsat TM images used in this study. These TM images acquired by the same sensor of Landsat 5 have been processed to a much higher degree of radiometric quality than that of the archival Landsat MSS data. It is also not appropriate to radiometrically normalize the higher resolution TM data with the MSS data. In addition, the author's early investigations have determined that application of radiometric normalization to the TM images does not enhance radiometric quality (Yang, 2000). For these reasons, radiometric normalization was not applied to the TM scenes.

Image Classification Scheme

Before image classification, a classification scheme must be established. Given the research objective and image resolution, a modified version of the Anderson scheme (Anderson *et al.*, 1976) was developed:

- *High-density urban use* consists of approximately 80 to 100 percent construction materials, which are typically commercial and industrial buildings with large open roofs as well as large open transportation facilities. It also contains a low percentage of residential development residing in the city cores;
- *Low-density urban use* consists of approximately 50 to 80 percent construction materials, which are residential development (single/multiple family houses and public rental housing estate) as well as local roads and small open (transitional) space as can always be found in a residential area; it also contains up to 20 percent of vegetation cover;
- *Cultivated/exposed land* contains the areas of sparse vegetation cover (less than 20 percent) that are likely to change or be converted to other uses in the near future, including clearcuts, all quarry area, cultivated land without crops, and barren rock or sand along river/stream beaches;
- *Cropland/grassland* is characterized by high percentages of grasses, other herbaceous vegetation, and crops, including lands that are regularly mowed for hay and/or grazed by livestock, golf courses and city parks, and regularly tilled and planted cropland;
- *Forest land* includes coniferous, deciduous, and mixed forests (90 to 100 percent); and
- *Water* consists of all areas of open water, including streams, rivers, lakes, and reservoirs.

Unsupervised Classification

The ISODATA (Iterative Self-Organizing Data Analysis) algorithm was used to identify spectral clusters from image data. To avoid the impacts of sampling characteristics (Vanderee and Ehrlich, 1995), the ISODATA algorithm was implemented without assigning predefined signature sets as starting clusters. Of all the clustering parameters, the number of classes is the most critical one. To find the optimum number, different numbers, namely, 20, 40, 60, and 80, were empirically tried out to determine if the resultant clusters could be better interpreted in relation to the classification scheme. Sixty was found to be the optimum class number for both the TM and MSS data. Another important reason for using such a large number of clusters for the 7-bit MSS data was that purer spectral clusters could be produced as a way to compensate for a high proportion of mixed pixels in the data. As for the ETM+ data, 80 clusters were used because these types of data may contain more information due to the incorporation of the 15-meter resolution panchromatic band. All the four bands of MSS data were used. For the TM and ETM+ data, the thermal band was not used in ISODATA clustering. Other important parameters specified include the convergence value, maximum number of iterations, and color scheme used for the output. The convergence value was specified as 0.990 for all the data.

The resultant clusters were assigned into one of the six land-use/land-cover classes through visual inspection of the original images and reference data as well as first-hand knowledge of the study area. The 1998 TM image acquired in the winter season (02 January 1998) was very helpful for cluster labeling, particularly for forest and cropland/grassland. To label the clusters, the original image as a false color composite and the clustered map were displayed side by side and then spatially linked together. A targeted spectral class was highlighted in color and its corresponding image pixels were examined by moving the cursor across the screen. The class assignment for individual clusters was based on an examination of the targeted cluster at two different levels of detail. At the large-scale level, the individual image color was mainly used in decision making. At the small-scale level, however, other image elements such as association and site were utilized to improve classification quality. Critical information for decision making in cluster labeling was noted in tabular format. The table included the following information: individual pixel characteristics, group pixel characteristics, class name assignment, and a remarks section of the table. Any spectral cluster containing more than one land-use/land-cover type was noted down in the remarks section of the table. This occurred when the spectral content of more than two different land-use/land-cover classes were similar. When this occurred, the cluster was initially labeled as one of the most likely land-use/land-cover classes. At a later stage, these clusters were split into smaller clusters for the correct land-use/land-cover labels using the spatial reclassification procedures.

Spatial Reclassification

The initial maps after the unsupervised classification came with an accuracy of about 60 to 70 percent. Unfortunately, this level of accuracy is not acceptable for this study. Further research efforts have been attempted for reducing image classification errors and improving accuracy. A close examination found two types of major misclassification errors: the boundary error and the confusion in spectral classes representing two or more land-use/land-cover types as described before. These errors can be substantially reduced with the use of spatial reclassification procedures described below.

The boundary errors occur at class boundaries due to the occurrence of spectral mixing within a pixel (Booth and Oldfield, 1989). These mis-classified areas are often small relative to the areas of correct classification. Within a class there are also some small areas of anomalous pixels representing the noise in the data. They are often in the form of salt and pepper. These small areas have to be removed and replaced with class values based on their surroundings. A modified 3 by 3 modal filter was used for reducing boundary errors.

Spectral confusion refers to the fact that several land-use/land-cover classes have very similar spectral responses, which is highly dependent upon imaging sensor characteristics (spatial, spectral, and radiometric resolutions) and scene content. For an image acquired with a broad spectral-band sensor, spectral confusion is inevitable. As image spatial resolution decreases (i.e., larger pixel size), the number of mixed pixels increases, and thus the spectral confusion tends to be more serious. Spectral confusion is likely to be more discernable for an image with lower radiometric resolution. On the other hand, spectral confusion tends to be more perceptible in an urban scene than that in a rural scene. Spectral confusion is the major barrier to achieving adequate accuracy using a per-pixel spectrally based classification method.

Defining spectral confusions requires the use of image spatial and contextural properties. To this end, an image interpretation method was employed because it allows an integrated use of spectral and spatial contents as well as human wisdom and experience, thus providing the most powerful means of determining the confusion in spectral clusters. Image interpretation can be incorporated effectively into a digital classification procedure with the use of on-screen digitizing, multiple zooming, AOI (area of interest) functionality, and other relevant GIS tools such as overlaying and recoding. In addition, several image processing programs permit advanced tools for spatial modeling through which some "manual" operations can be implemented automatically. With the use of this method, four major types of spectral confusion were identified:

- low-density urban (mostly residential)/forest (clearcuts, sparse forest, and wetlands);
- low-density urban (sparse residential)/cropland or grassland;
- forest (sparse forest and shrubs)/cropland or grassland; and
- high-density urban (large open roof buildings, air fields, and multilane highways)/cultivated or exposed land (large barren landmass, river beach, fallowed land).

These pairs of land-use/land-cover types were spectrally similar in varying degrees. Spectral confusions were found to be generally more serious for the MSS data than for the TM data. These spectrally confused clusters were first identified and AOI layers were created by on-screen digitizing. The AOI layers served as masks for splitting these confused clusters. Finally, GIS reclassification functionality was employed to recode the split clusters into their correct land-use/land-cover classes. This process was continued until acceptable accuracy was obtained.

Accuracy Assessment

Because of the limited availability of ground truth data, it was impossible to perform accuracy assessment for all five classified maps exhaustively. The strategy adopted here was to assess each of the three types of imagery covering the study area. To this end, the 1988, 1997/1998, and 1999 land-use/land-cover maps were chosen for accuracy assessment (see Table 1). The 1988 land-use/land-cover map was produced from the Landsat MSS data, the 1997/1998 land-use/land-cover map was produced from a summer 1997 and a winter 1998 Landsat TM image, and the 1999 land-use/land-cover map was based on the Landsat ETM+ data. The first two maps were produced by the author for other projects using the same method described in this paper. These years have excellent ground truth data, particularly for the most recent years. The accuracy assessment was carried out by using a standard method (Congalton, 1991). Test points were taken with a stratified random sampling scheme. Producer accuracy, user accuracy, and Kappa statistics were computed. Results revealed that the land-use/land-cover maps based on the TM or ETM+ images yielded slightly better accuracy than that of the land-use/land-cover map produced from the MSS images. The maps from the TM or ETM+ images exhibited a slightly higher kappa index of agreement for low-density urban, cropland or grass land, and forest than that of the map from the MSS data. This could be the result of higher spatial, spectral, and radiometric resolution of the ETM+ data. However, the land-use/land-cover map based on the MSS data is compatible in accuracy in every respect to the land-use/land-cover maps based on the TM or ETM+ data. Overall, these maps met the minimum 85 percent accuracy stipulated by the Anderson classification scheme (Anderson *et al.*, 1976). This is good evidence that the image processing approach adopted here has been effective in producing compatible land-use/land-cover data over time, despite the differences in spatial, spectral, and radiometric resolution of the three generations of Landsat data used in this project. Other maps for four different years were produced using the same procedures. It is anticipated that the same level of accuracy was maintained. Land-use/land-cover classification maps for each of the five dates are shown in Figure 3 (a color version of this figure may be accessed at www.asprs.org). Using the IMAGINE "summary" function, the statistics of each classification map for the 13 metro counties are summarized in Table 2. The land-use/land-cover changes during different periods were further computed (Table 3).

Change Detection

Procedures were developed to detect changes in the urban spatial pattern and to examine the nature of change. The spatial distribution of the major urban classes was extracted from each of the land-use/land-cover maps in the time series. Two maps depicting the change in each of the two urban uses are shown in Figures 4a and 4b (a color version of this figure may be accessed at www.asprs.org). The first map (Figure 4a) was produced with a GIS minimum dominate overlay function by which the smallest amount of high-density urban use in 1973 shows up fully while only the net addition in the following years in the time sequence was shown. For example, the magenta colored patches for 1992 on the map represent the net addition of high-density urban use between 29 June 1987 and 23 April 1992. Similarly, a second map showing the change in the low-density urban use from 1973 to 1998 (Figure 4b) was produced.

Analyzing land-use/land-cover conversion allows different combinations of changes to be revealed, thus providing further information concerning the nature of changes. A two-way cross-tabulation or matrix analysis was adopted to characterize land-use/land-cover conversion. This analysis produces a thematic layer that contains a separate class for every coincidence in two layers. It was used here to produce two land-use/land-cover conversion maps for the periods of 1973–1987 and 1987–1999. There are 16 possible combinations. But this study focused on the conversions of forest, cropland/grassland, or cultivated/exposed land into urban uses. Thus, the 16 combinations were further scrutinized and only nine were selected for further analysis. The remaining seven combinations were merged into a single unit (Table 4). These combinations of conversion are

- cultivated/exposed land into high-density urban use (C1),
- cultivated/ exposed land into low-density urban use (C2),
- cropland/grassland into high-density urban use (C3),
- cropland/grassland into low-density urban use (C4),
- forest into high-density urban use (C5),
- forest into low-density urban use (C6), and
- cultivated/exposed land or cropland/grassland or forest into water (three conversions are combined into one (C7).

The C0 is designed for all other combinations which are not considered here. Please note that the C0 contains a large number of unchanged pixels, or approximately 75 percent of the total pixels in this unit. Figure 5 is the output maps (a color version of this figure may be accessed at www.asprs.org).

Results and Discussion

Based on Figure 4a, the spatial expansion of high-density urban is clearly visible. In 1973, the high-density urban use was small, occupying only 2.85 percent of the total land area for the 13 metro counties in Atlanta (Table 2). It was mainly located within the loop highway I285 as well as several highly concentrated areas, such as Fulton Industrial District, Marietta (Cobb), interstate highways I285 and I85 junction (within Gwinnett County), and Atlanta International Airport. The outward spread of high-density urban use is quite clear in the1979 and 1987 patterns, following major transportation routes such as I75 and I85 in a linear form. Between 1973 and 1979, the net addition of high-density urban was 8,292 hectares, or 27.90 percent increment (Table 2). The net addition became 16,265 hectares, or 42.79 percent increment, for the period between 1979 and 1987. These additions were mainly concentrated in some inner counties, such as Fulton, Cobb, DeKalb, and Clayton. Significant growth of high-density urban use took place by 1993 and 1999, with net addition of 19,844 and 33,197 hectares,

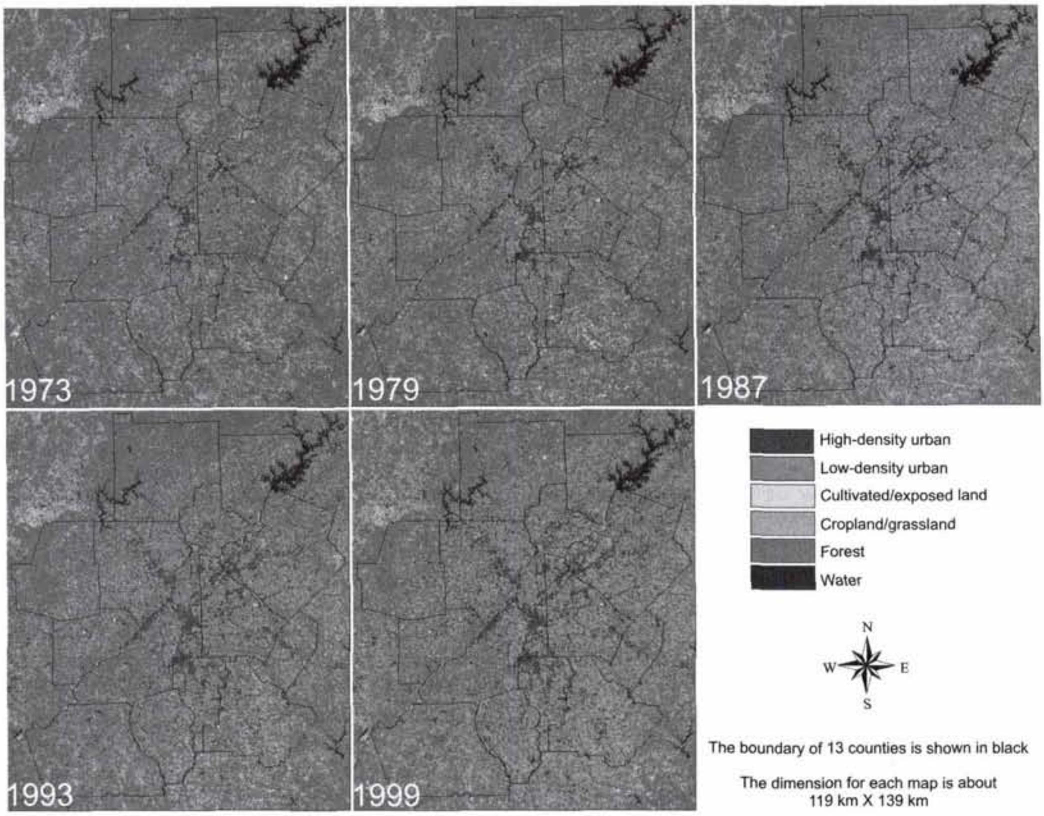

Figure 3. Land-use/land-cover maps in the Atlanta area: 1973–1999 (a color version of these maps can be found on the ASPRS website at www.asprs.org). They were produced from Landsat images. The boundary of the 13 counties in Atlanta is also shown.

Table 2. Land-Use/Land-Cover Statistics for 13 Metro Counties in Atlanta: 1973–1999

No	Land-Use/Land-Cover	1973		1979		1987		1993		1999	
		Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%	Area (ha)	%
1	High-density urban	29722	2.85	38015	3.64	54280	5.2	67633	6.48	87477	8.3
2	Low-density urban	76910	7.36	129174	12.37	177825	17.03	214484	20.54	282959	27.1
3	Cultivated/exposed land	14534	1.39	20595	1.97	15511	1.49	21132	2.02	5358	0.51
4	Cropland/grassland	159345	15.26	117365	11.24	117686	11.27	96700	9.26	101122	9.68
5	Forest land	750366	71.85	724967	69.42	663673	63.55	625984	59.94	545148	52.2
6	Water	13404	1.28	14166	1.36	15306	1.47	18348	1.76	22217	2.13
	In Total	1044281	100	1044281	100	1044281	100	1044281	100	1044281	100

Table 3. Land-Use/Land-Cover Changes During Different Periods

Periods		High-density urban	Low-density urban	Cultivated/exposed land	Cropland/grassland	Forest	Water
1979–	%	27.9	67.95	41.70	−26.35	−3.38	5.68
1973	ha	8292	52264	6061	−41980	−25399	762
1987–	%	42.79	37.66	−24.69	0.27	−8.45	8.05
1979	ha	16265	48651	−5084	321	−61294	1140
1993–	%	24.60	20.62	36.24	−17.83	−5.68	19.87
1987	ha	13353	36659	5621	−20986	−37689	3042
1999–	%	29.34	31.93	−74.65	4.57	−12.91	21.09
1993	ha	19844	68475	−15775	4422	−80836	3869
1999–	%	194.31	267.91	−63.14	−36.54	−27.35	65.75
1973	ha	57755	206049	−9176.76	−58222	−205217	8813

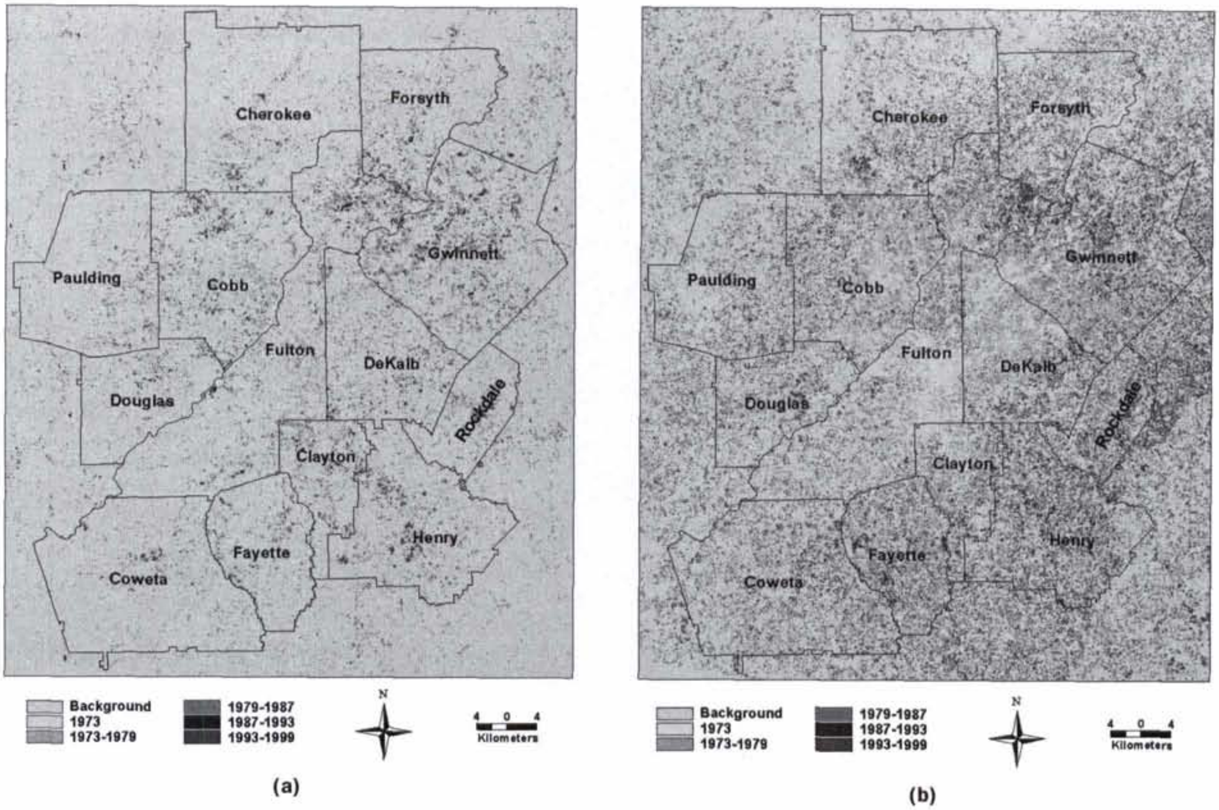

Figure 4. Change detection maps showing spatial growth of two major urban uses (a color version of these maps can be found on the ASPRS website at www.asprs.org). (a) Growth of high-density urban use in Atlanta: 1973–1999. (b) Growth of low-density urban use in Atlanta: 1973–1999.

TABLE 4. LAND-USE/LAND-COVER CONVERSION STATISTICS FOR DIFFERENT PERIODS

Maps		Nature of Change	Land Conversion Statistics			
			1973–1987		1987–1999	
Year A	Year B	Code*	Area(ha)	%	Area(ha)	%
3	1	C1	1669	0.16	3029	0.29
3	2	C2	1627	0.16	4709	0.45
4	1	C3	12094	1.16	11085	1.06
4	2	C4	31765	3.04	40127	3.84
5	1	C5	22621	2.17	28586	2.74
5	2	C6	79319	7.60	94559	9.05
3 or 4 or 5	6	C7	3653	0.35	6226	0.6
all other combinations		C0	891534	85.37	855960	81.86

*C1-converted from cultivated/exposed land(3) into high-density urban(1);
C2-converted from cultivated/exposed land(3) into low-density urban(1);
C3-converted from cropland/grassland(4) into high-density urban(1);
C4-converted from cropland/grassland(4) into low-density urban (2);
C5-converted from forest(5) into high-density urban(1);
C6-converted from forest(5) into low-density urban(2);
C7-converted from cultivated/exposed land(3) or cropland/grassland(4) or forest(5) into water(6); and
C0-all other combinations which are not considered here; note that approximate 75 percent of total pixels remain unchanged.

respectively. These new growth areas are highly concentrated in four areas: north (north Fulton), northeastern (Gwinnett), northwestern (Cobb), and southeastern (Henry) Atlanta. The linearly concentrated pattern of high-density urban use has been undergoing a transition toward a multinucleated pattern. The 1999 distribution shows further enhancement of this transition as the spread took place along more transportation routes and around more urban centers, particularly in some peripheral counties such as Coweta, Cherokee, Forsyth, Paulding, and Fayette. In 1999, the high-density urban use occupied about 87,477 hectares, or 8.38 percent of the total land area for the 13 counties in Atlanta, which is about a 194.31 percent increase in land when compared with 1973. The daily increment of high-density urban land was approximately six hectares or 15 acres for the period between 1973 and 1999.

The evolution of spatial pattern of low-density urban use, mainly residential, is clearly represented in Figure 4b. In 1973, the low-density urban use (in yellow) occupied about 76,910 hectares, or 7.36 percent of the total area for the 13 counties. Although the low-density urban land showed signs of spreading outward, its large share was clearly concentrated in the inner city core, namely, the city of Atlanta, as well as several inner counties such as Cobb, DeKalb, Clayton, and the western part of Gwinnett County. Additionally, a somewhat linear pattern can be seen, indicating the association between major transportation highways and low-density urban development. Thus, the spatial pattern of low-density urban use in 1973 may be perceived as a form of concentration mixed with some degree of dispersal. Significant growth of the low-density urban land occurred in 1979 and 1987, with a net addition of 52,264 and

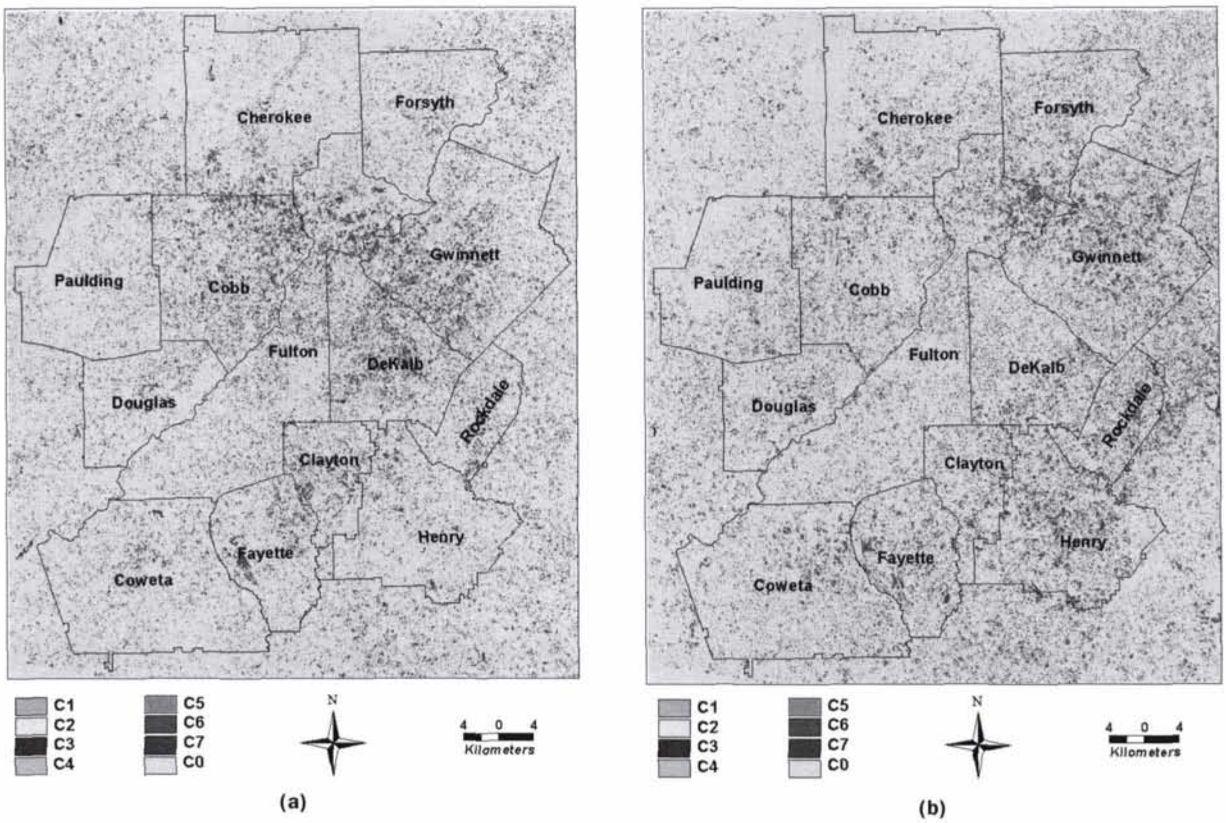

Figure 5. Land-use/land-cover conversions (a color copy of these maps can be found on the ASPRS website at www.asprs.org). (a) Land-use/land-cover conversion in the Atlanta Metropolitan Region: 1973–1987. (b) Land-use/land-cover conversion in the Atlanta Metropolitan Region: 1987–1999. Notes: C1-converted from cultivated/exposed land into high-density urban; C2-converted from cultivated/exposed land into low-density urban; C3- converted from cropland/grassland into high-density urban; C4-converted from cropland/grassland into low-density urban; C5-converted from forest into high-density urban; C6-converted from forest into low-density urban; C7-converted from cultivated/exposed land or cropland/grassland or forest into water; and C0-all other combinations which are not considered here; and approximately 75 percent of total pixels remain unchanged.

48,651 hectares, respectively (Table 3). Most of these new additions occurred outside the central city core, concentrating in four inner counties, namely, DeKalb (middle), Clayton (middle), Fulton (northern), and Cobb (northern), and in three exterior counties such as Gwinnett (western and southern), Rockdale (middle), and Fayette (Peachtree City). The growth directions in northern (northern Fulton), northwestern (Cobb), and northeastern (Gwinnett) Atlanta are quite visible. The spatial distribution pattern was becoming more and more dispersed at large. The low-density urban use continued to grow after 1987. Most of this growth, however, took place at the exterior of the metropolis, particularly in north Fulton, Gwinnett (eastern), Henry, Rockdale, Fayette, Forsyth, Coweta, Cherokee, and Douglas counties, as represented by the 1993 and 1999 distributions. The low-density urban use has become a widely spread-out pattern, indicating a major feature of the suburbanization process. In quantitative terms, the low-density urban use occupied 282,959 hectares or 27.10 percent of the total area for the 13 counties in 1999, indicating a 267.91 percent increase between 1973 and 1999. The daily increment of low-density urban use is approximately 22 hectares or 54 acres for the same period.

Another significant change is the continuing decline in cropland/grassland and forest in the Atlanta metropolitan area (Tables 2 and 3). The shrinking pattern of the spatial distribution of these two classes was proportional to the growth of two urban classes described above. Generally, the decline of cropland/grassland and forest land mainly took place in the interior of the metropolis before 1987 but in the exterior after 1987. In quantitative terms, cropland/grassland occupied 159,345 hectares or 15.26 percent of the total study area in 1973. It declined to 101,122 hectares (or 9.68 percent) by 1999. This represents a decrease of 36.54 percent, or a daily rate of six hectares (15 acres). Similarly, forest has declined from 750.366 hectares (or 71.85 percent) in 1973 to 545,148 hectares (or 52.20 percent) in 1999, thus representing a decrease of 27.35 percent, or a daily rate of 22 hectares (53 acres) in land area. The decline of forest and cropland/grassland is clearly the result of continued urban development of the city of Atlanta through the process of suburbanization.

Based on Figure 5, the nature of change is quite clear. From 1973 to 1987, the loss of forest land has contributed to the overwhelming share of the growth of both high-density and low-density urban uses in the metropolis. The high-density urban has experienced a net addition of 36,384 hectares, among which 62.17 percent came from the loss in forest land (C5) and 33.24 percent resulted from the loss in cropland/grassland (C3). The loss in cultivated/exposed land only contributed to 4.59 percent of the increase in high-density urban (C1) while, for the low-density urban use, approximately 70.37 percent (C6) and 28.18 percent (C3) of the increase came from the loss in forest land and cropland/grassland, respectively. The loss in cultivated/exposed land only accounted for 1.45 percent (C1) of the net addition in low-density urban land. The expansion of water area was mainly at the cost of forest land, cropland/grassland, or cultivated/exposed land (C7). The spatial distribution of land-use conversions is clearly evident from Figure 5. Overall, many of these conversions took place in some inner counties of the metropolis. The C6 (conversion from forest into low-density urban) was mainly concentrated in DeKalb (middle), Cobb (east), north Fulton, Gwinnett (west), Clayton, and Fayatte counties. The C5 (conversion from forest into high-density urban) shows a similar concentrating pattern. The C4 (conversion from cropland/grassland into low-density urban) and C3 (conversion from cropland/grassland into high-density urban) were primarily centralized in Cobb, Clayton, Gwinnett, north Fulton, DeKalb(north), and Rockdale counties. From 1987 to 1999, the magnitude of these conversions generally increased and forest and cropland/grassland conversions still overwhelmed the growth in two major urban uses. But the spatial distribution of these conversions has became more widely spread, mainly taking place in the exterior of the metropolis (Figure 5b).

Conclusions

Restless urban sprawl throughout the world has prompted concerns over the degradation of our environments and the quality of life. Understanding metropolitan dynamics and managing urban growth require rigorous use of technologies and methods in order to produce accurate mapping of land use/cover. Satellite remote sensing allows a retrospective, synoptic viewing of large regions, thus providing the potential for a geographically and temporally detailed assessment of urban development and landscape change.

By using Atlanta as a case site, this study has led to the following conclusions at the technological, theoretical, and application levels. At the technological level, the study has demonstrated the usefulness of satellite remote sensing, digital image processing, and GIS techniques for urban landscape change mapping. The methodology developed here to map land use/cover from a time series of satellite images was based on an adequate understanding of landscape features, sensor characteristics, and information extraction techniques. Several techniques were adopted to ensure accurate image classification results from the multi-temporal/multi-resolution satellite data. The MSS data were radiometrically normalized in order to establish a common radiometric response among these MSS images. An unsupervised image classification approach was employed, for which ISODATA clustering was used. A large (but manageable) number of clusters was extracted to ensure their spectral homogeneity. These clusters were labeled with reference to the ground truth data. To minimize problems of boundary errors caused by spectral confusion in the image classification, a spatial reclassification method was used to break down spectrally confused clusters to smaller ones for re-labeling. Accuracy assessment confirmed that the image processing procedures were effective in extracting land-use/land-cover maps and statistics of the Atlanta metropolitan area from Landsat MSS data which are compatible to those produced from Landsat TM/ETM+ data. Additionally, the combined use of post-classification comparison and GIS techniques has made possible the production of single-theme change maps, which emphasize spatial dynamics.

At the theoretical level, this study has examined the evolution of urban spatial form for the Atlanta metropolis. The growth of high-density urban use (commercial, transportation, industrial, and high-rise residential) is found to experience a clear transition from a linearly concentrated form towards a multinucleated pattern. The spread of low-density urban use (mainly residential) exhibited a widely dispersed pattern indicating a major feature of suburbanization. These findings on the evolution of Atlanta's urban physical form, which are based on biophysical measures, are compatible with those obtained from social and economic perspectives. Atlanta has been recognized as one of the few typical postmodern metropolises in North America (Hall, 1998). This study of Atlanta has led to the formulation of a new urban model, i.e., the urban realms model by Hartshorn and Muller (1989), which describes the nature of multinucleation in contrast to the conventional single, coherent entity in urban form. Fujii and Hartshorn (1995) further revealed the changing metropolitan structure of Atlanta, highlighting a multinucleating urban spatial form. Their studies were done by using census and economic data. The current study investigated the physical evolution of the urban spatial form, which should be a critical aspect for understanding postmodern urbanization characterized by physical fragmentation in Atlanta.

At the application level, this study has established a well-documented regional case study focusing on Atlanta. The project has revealed that every week, more than one-hundred acres of green space, forest, and farmland in the Atlanta region were converted into urban uses. Between 1973 and 1999, the urban territorial extent has expanded by 247 percent for the 13 metro counties while the population increased by 96 percent. The rate of urban growth was much higher in some outer suburban counties. The land-use/land-cover conversion analysis further reveals different combinations of changes. The loss of forest land has contributed to the overwhelming share of the growth of both high-density and low-density urban uses in the metropolis. These findings should be useful both to those who study urban dynamics and those who must manage resources and provide services in this rapidly changing environment. Given that many major metropolises in the nation face the growing problems caused by urban sprawl or restless suburban development, the technical framework developed in the current study focusing on Atlanta may be applicable to those metropolises with similar growth development styles. This can improve understanding of the variation in the nature-society dynamics of landscape, thereby facilitating a sophisticated approach to environmental management and sustainable development.

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