

LANDSAT IMAGE-BASED LULC CHANGES OF SAN ANTONIO, TEXAS USING ADVANCED ATMOSPHERIC CORRECTION AND OBJECT-ORIENTED IMAGE ANALYSIS APPROACHES

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ABSTRACT:

The City of San Antonio, Texas and its surrounding have been experiencing rapid land-use and land-cover (LULC) changes as a result of population growth and urban development in the last few decades. Current census data shows that San Antonio is the 8th largest city in the United States, surpassing Dallas and Detroit (U.S. Census Bureau). With such population increase comes increased pressure on the environment and natural resources. Multitemporal datasets consisting of Landsat TM images of 1985 and 2003 were used to perform change detection analysis, with the aim of achieving LULC characterization and pattern change between the two periods. Data pre-processing includes the use of Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASHTM) for atmospheric correction. Image classification was performed using the object-oriented approach (eCognitionTM). Change analysis shows that impervious surface (or urban area) increased in the study area by 33% between 1985 and 2003. The expected corresponding decrease in forest cover, even though observable especially within and around the city limits, is not reflected in the overall change information. The reasons for this are discussed in detail. While many subjective factors affect the classification accuracy using pixel-based supervised image classification, the work suggests that eCognition-based object-oriented classification is also affected by subjective factors such as the weight of shape (texture) and pixel value, levels of multiresolution segmentation, and selection of objects as training sites.

1. INTRODUCTION

Our natural environment is continually modified by both natural and anthropogenic activities. The challenges of understanding the various ecosystem processes and how changes may affect these processes in the coming decades are daunting. Changing climate, hydrologic regimes, vegetation redistributions, and urban growth are a few of the dynamics influencing landscape change.

Remotely sensed satellite images provide valuable datasets that can be used to analyze, evaluate, and monitor changes in ecosystems through change detection.

One of the major hurdles of any satellite image analysis is how to accurately compensate for atmospheric effects. Most atmospheric correction programs do not consider properties such as elevation, water vapour, and aerosol distribution. The FLAASH module in ENVI probably provides the most accurate means of compensating for atmospheric effects. The FLAASH model includes a method for retrieving an estimated aerosol/haze amount from selected "dark" land pixels in the scene. The method is based on observations by Kaufman et al. (1997), of a nearly fixed ratio between the reflectance for such pixels at 660 nm and 2100 nm (FLAASH User's Guide).

Object-based image classification, which is based on fuzzy logic, allows the integration of a broad spectrum of different object features such as spectral values, shape, and texture. Such classification techniques, incorporating contextual and semantic information, can be performed using not only image object attributes, but also the relationship among different image objects (Civanlar and Trussell, 1986; Driankov et al., 1993; Laliberte et al., 2004; Gitas et al., 2004). Franklin et al. (2000), for example, found that the incorporation of texture

in addition to spectral information increased classification accuracy on the order of 10-15%.

Several studies have investigated the ability of satellite imagery, including Landsat TM and ETM+, to perform change analysis. The aim of this work is to accurately characterize LULC changes in the San Antonio area between 1985 and 2003 using advanced atmospheric correction model and object-based image classification approach. Specific objectives are:

- to produce accurate and reliable results regarding LULC changes in the San Antonio area between 1985 and 2003,
- to evaluate the implications of current growth trends on available resources,
- to examine the advances of radiative transfer code based atmospheric correction and object-oriented classification methods.

2. STUDY AREA AND DATASET

The City of San Antonio and its surrounding environs lay at the confluence of four ecological regions. These ecoregions – Blackland prairie, Post oak savanna, South Texas plains, and Edwards Plateau – are each distinct in their soil, flora, and fauna. Also of note are the many springs, creeks, and rivers which arise in the immediate vicinity and to areas west and northeast of San Antonio as a result of fault lines along one of the nation's largest karst limestone aquifers (American Forests, 2002). The study area, lies within longitudes 98.82, 98.21W and latitudes 29.68, 29.17N and is situated mostly within Bexar County (Figure1).

Datasets for the study consist of two Landsat TM images of 10-05-1985 and 10-23-2003, provided by TexasView Remote Sensing Consortium. Both datasets (Path27/Row40) have zero cloud cover.

3. METHODOLOGY

Data pre-processing involved converting digital numbers to radiance, atmospheric correction using FLAASHTM, and co-registration. Image classification was done using object-oriented approach (eCognitionTM), followed by accuracy assessment and change detection (Figure 2).

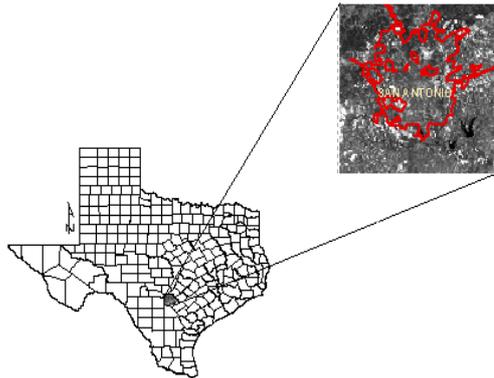


Fig 1. Study Area (red outline is the city limit)

3.1 Converting digital number to radiance

Conversion of the image DN values to spectral radiance is carried out using the equation,

$$L_{\lambda} = \left(\frac{LMAX - LMIN}{QCALMAX - QCALMIN} \right) * (DN - QCALMIN) + LMIN \quad (1)$$

where, DN = Digital Number for each pixel of the image

LMAX and LMIN = calibration constants (Table 1)

QCALMAX and QCALMIN = the highest and the lowest points of the range of rescaled radiance in DN.

For Landsat 4 and 5, the QCALMAX is 255 and the QCALMIN is zero.

Band	Prior to Aug. 1983		Prior to 15, Jan, 1984		After 15, Jan, 1984	
	LMIN	LMAX	LMIN	LMAX	LMIN	LMAX
TM1	-0.152	15.842	0.000	14.286	-0.150	15.210
TM2	-0.284	30.817	0.000	29.125	-0.280	29.680
TM3	-0.117	23.463	0.000	22.500	-0.120	20.430
TM4	-0.151	22.432	0.000	21.429	-0.150	20.620
TM5	-0.037	3.242	0.000	3.000	-0.037	2.719
TM6	0.200	1.564	0.484	1.240	0.1238	1.560
TM7	-0.015	1.700	0.000	1.593	-0.015	1.438

Table 1. LMAX and LMIN values for Landsat 4 and 5 TM (After Markham and Barker, 1986)

3.2 Atmospheric correction

Dark object subtraction (DOS) is perhaps the simplest and most widely used image-based relative atmospheric correction approach for classification and change detection applications (Spanner et al., 1990; Ekstrand, 1994).

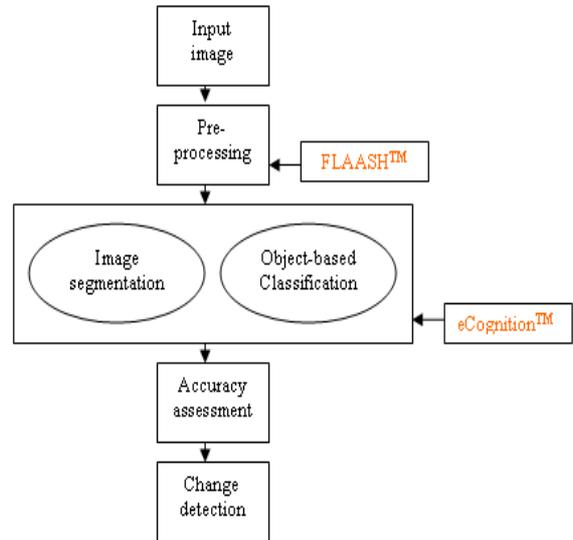


Fig 2. Methodology flow-chart

FLAASH is a more sophisticated algorithm based on MODTRAN that can compensate for atmospheric effects more accurately. Input into the FLAASH module includes the average elevation of the study area, scene centre coordinates, sensor type, flight date and time, and information about aerosol distribution, visibility, and water vapour conditions. Results shows that pixel spectral resolution is improved with FLAASH compared to simple DOS (Figures 3 and 4). Our classification is based on FLAASH atmospheric correction.

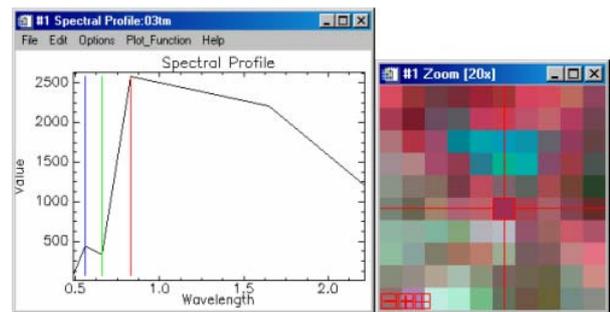


Fig 3. Pixel spectral profile after DOS

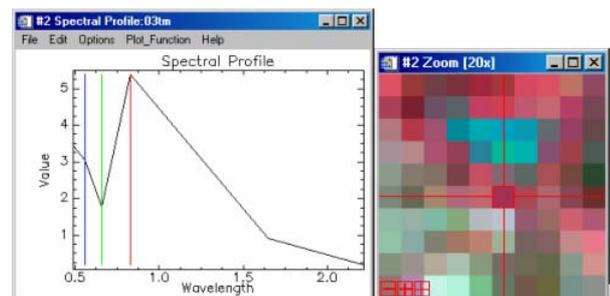


Fig 4. Pixel spectral profile after FLAASH

3.3 Image classification

A prerequisite to classification is image segmentation, which is the subdivision of an image into separated regions. Image objects resulting from segmentation represent image object primitives, serving as information carriers and building blocks for further classification or other segmentation processes (eCognition User Guide, 2002). During the segmentation procedure, image objects were generated based on several adjustable criteria of homogeneity such as colour, shape, and texture.

Four broad classes were delineated for classification: Clear-cut & Agriculture, Forest, Water, and Impervious surface (roads, streets, parking lots, buildings). The classification is based on the standard nearest neighbour approach. Nearest neighbour is a classifier used to classify image objects based on a given sample objects within a defined feature space (eCognition User Guide, 2002). Numerous sample objects or training areas were defined as initial information for the classification process.



Fig 5. Original image subset Fig 6. Classified image subset

In the classified image, red shows impervious surface, sky blue is water; green represents forest cover, while grey represents clear-cut and agriculture (Fig 6).

3.4 Accuracy assessment

It is important to be able to derive accuracy for individual classifications if the resulting data are to be useful in change detection analysis. There are a number of ways to do this in eCognition; the method used in this study is by generating error matrix based on samples. Original samples were deleted and new samples declared for the calculation of the error matrix. Table 2 shows the accuracy for the two datasets at 86% and 88%.

Year	1985	2003
Overall Accuracy	0.8624	0.8833
KIA	0.8050	0.8392

Table 2. Results of accuracy assessment

3.5 Change detection

The classified data is used as input image for change detection, using the change detection statistics tool in ENVI.

4. RESULTS AND DISCUSSION

Impervious surface increased in the study area between 1985 and 2003 by 33% (about 71 square miles) (Table 3).

		Initial State			Row Total	Class Total
		Impervious surface	Clear-cut & Agriculture	Forest		
Final State	Unclassified	0.05	0.02	0.02	96.71	100.00
	Impervious Surface	61.33	14.60	13.52	99.80	100.00
	Water	0.37	0.09	0.29	26.62	100.00
	Clear-cut & Agric.	10.41	32.96	13.86	99.94	100.00
	Forest	27.85	52.33	72.31	99.75	100.00
	Class Total	100.00	100.00	100.00		
	Class Changes	38.67	67.04	27.69		
Image Difference	33.18	-41.83	17.70			

Table 3. Change detection statistics (Area in percentage)

Most of the increases in impervious surface occur within or around the city limit, as a result of forest cover loss (Fig7) and also due to the development of some clear-cut and agricultural areas (Fig 8).

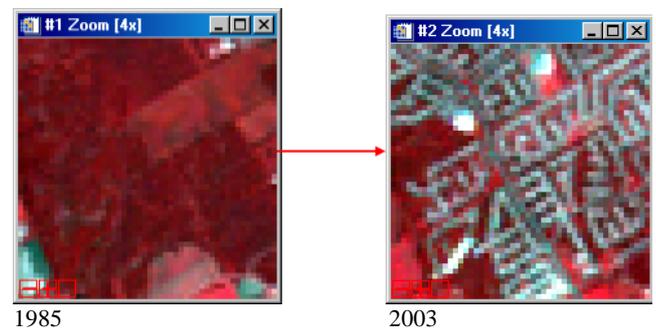


Fig 7. Forest cover change to mostly urban

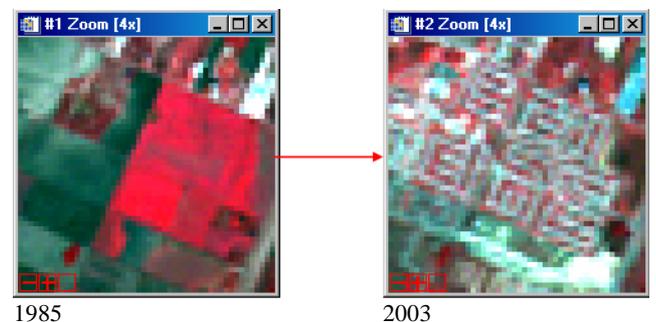


Fig 8. Clear-cut and agricultural land change to mostly urban

However, the resulting overall increase in forest cover (18%) and overall decrease in clear-cut and agriculture (-42%) are questionable (Table 3). The increase in forest cover is inconsistent with an earlier study by American Forests

(americanforests.org) in the same area between 1985 and 2001. American Forests concluded that forest cover, especially in the Greater San Antonio area, decreased with increasing impervious area. Detailed comparison found the major error comes from the misclassification of clear-cut and agriculture fields of 2003 image as forest cover (Figure 9).

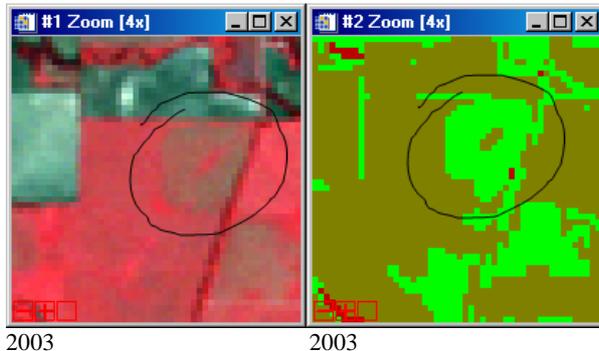


Fig 9. Left is the image, right is the classified result. Typical misclassification of agricultural field (grey) as forest (green) in the right side image.

The reason is that many cropped agriculture fields in 1985 was harvested land, fallow land, or even planned area for some new sub-divisions in the 2003 image. When we pick objects as training sites, we misrepresented them as forest. The second reason is that we might need to assign more weight to shape or texture than to the pixel value during image segmentation, because clear-cut and agriculture lands clearly have different shape compare with forest, even though they might have similar pixel value ranges. The third reason is that we need higher levels of multiresolution segmentation. After taking care of the above problems in future work, we can expect a reduction in forest cover with increasing impervious surface. The observed reduction in clear-cut and agricultural lands may also not be as significant.

5. CONCLUSIONS

This study demonstrated the potential for accurate LULC change assessment with advanced atmospheric correction and object-oriented image analysis using moderate resolution satellite data. Spectral resolution is clearly enhanced with FLAASH atmospheric model, thereby enhancing further analysis. Classification results show that impervious surface increased between 1985 and 2003 by about 33% (71% square miles), mostly within and around San Antonio city limits. With increasing urban population, increasing impervious surface with attendant vegetation loss especially in the Greater San Antonio area, will lead to increased atmospheric moisture and increased storm water flow; this portends significant economic and ecological implications in the near future.

Although the preliminary results in this study appears promising, more work is needed to improve classification results in eCognition before the proposed method can be considered sufficiently reliable in characterizing LULC changes in the study area.

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