Remote Sensing Image processing and Analysis (ES 6973)

Term Project

By

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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 from 1985 and 2003 respectively were used to perform change detection analysis, with the aim of achieving LULC characterization and pattern between 1985 and 2003. Data preprocessing includes the use of Fast Line-of-sight Atmospheric Analysis of Spectral Hypercubes (FLAASH™) for atmospheric correction. Image classification was performed using the object-oriented approach (eCognition™). Change analysis shows a reduction in forest cover (-23%) with corresponding increases in residential land cover (25%), roads and pavements (7%) between 1985 and 2003. Analysis also suggests increased pollution in Mitchell Lake, south of Loop 1604, between the two time frames.

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 vapor, 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). 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 (Song, C., et al., 2001; Ioannis, Z.G., et al., 2004; Alberti, M., 2004; Laliberte, A.S., et al., 2004; Moeller, S.M., et al., 2004). 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 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 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.

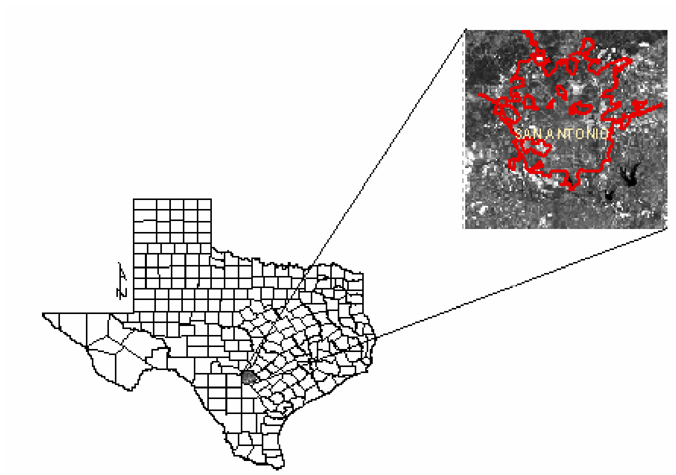


Figure1. Study Area

3. Methodology

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

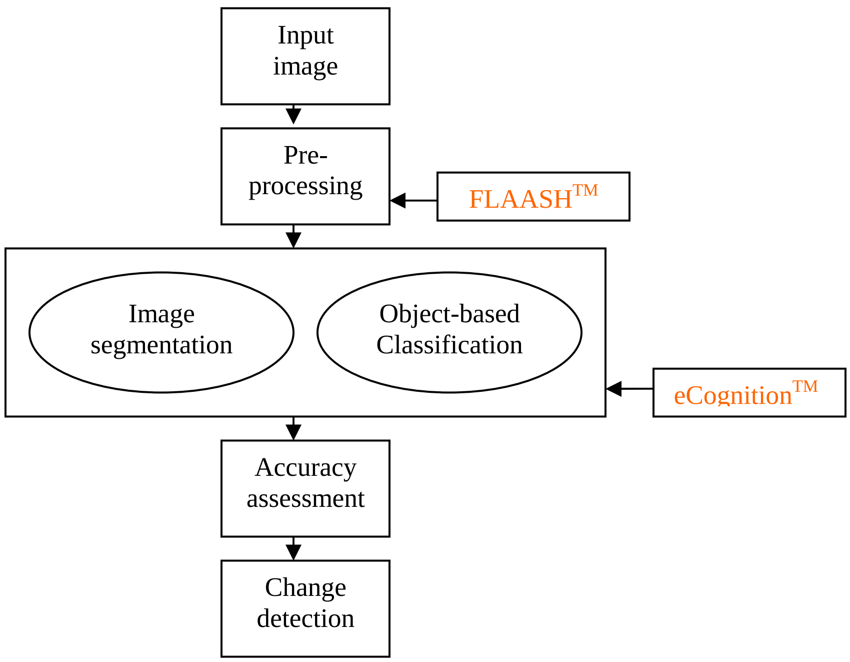


Figure2. Methodology flow-chart

3.1 Converting digital number to radiance

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

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

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.

	Prior to Aug. 1983		Prior to 15, Jan, 1984		After 15, Jan, 1984	
	$mW*cm^{-2}*ster^{-1}*\mu m^{-1}$		$mW*cm^{-2}*ster^{-1}*\mu m^{-1}$		$mW*cm^{-2}*ster^{-1}*\mu m^{-1}$	
Band	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

Table1. 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 absolute atmospheric correction approach for classification and change detection applications (Spanner et al., 1990; Ekstrand, 1994). FLAASH is a more sophisticated algorithm that can compensate for atmospheric effects more accurately. Input into the FLAASH module includes the average elevation of the study area, scene center coordinates, sensor type, flight date and time, and information about aerosol distribution, visibility, and water vapor conditions. Results shows that pixel spectral resolution is improved with FLAASH compared to simple DOS (Fig3 and 4).

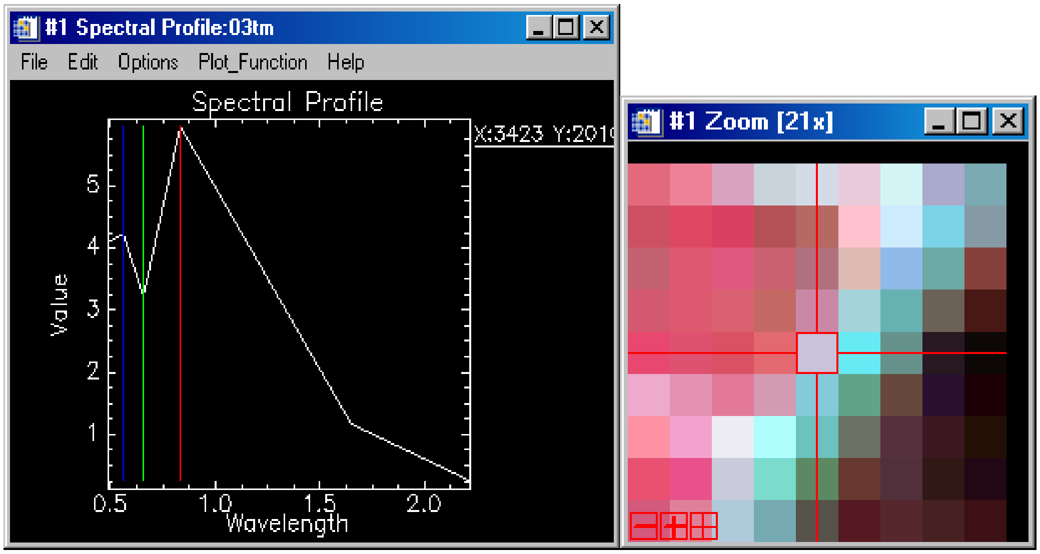


Figure3. Pixel spectral profile after DOS

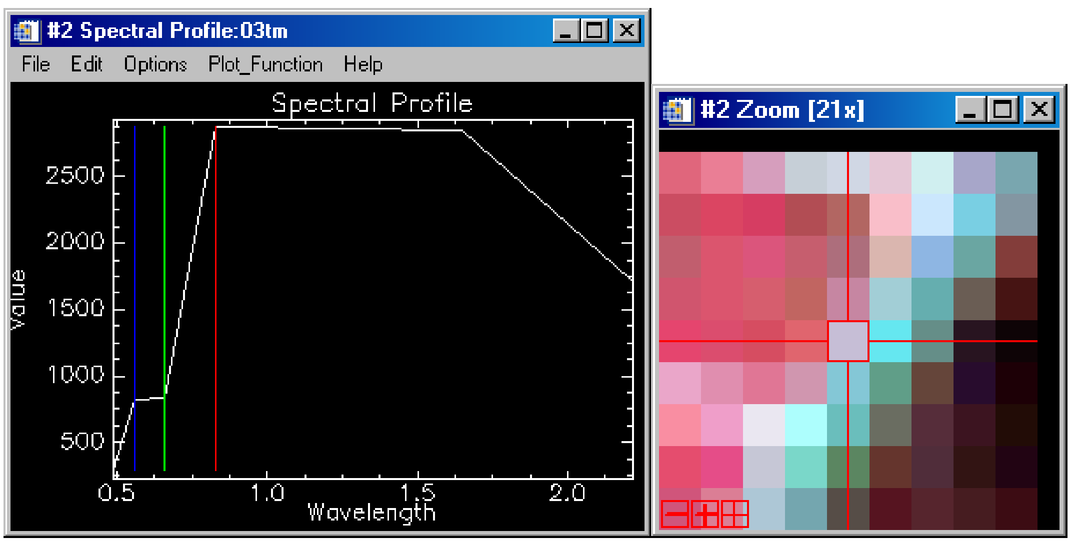


Figure4. Pixel spectral profile after FLAASH

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 color, shape, and texture (Fig5).

Multiresolution segmentation (Level 1)
Compactness = 0.7
Smoothness = 0.3
Shape factor = 0.8
Scale parameter = 25

Figure5. Multiresolution segmentation

Seven classes were delineated for classification: Fallow land, Cropland, Forest, Grass, Roads/Pavement, Residential, and Water. The classification was based on the standard nearest neighbor approach. Nearest neighbor 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.

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. To ensure more reliability, a more experienced colleague was asked to select the new samples without knowing what the old samples were. Table2 shows the accuracy for the two datasets:

1985 Image Classification Accuracy							
User Class	Fallow land	Forest	Grass	Roads/Pavement	Residential	Water	Cropland
Producer	0.99	0.975	0.6087	0.9833	0.9385	0.9583	0.75
User	0.9519	0.9512	0.7778	0.9156	0.9385	1	0.8333
Hellden	0.9706	0.9630	0.6829	0.9672	0.9385	0.9787	0.7895
Short	0.9429	0.9286	0.5185	0.9365	0.884	0.9583	0.6522
KIA Per Class	0.9861	0.9679	0.5888	0.98	0.9254	0.9556	0.7373
Totals							
Overall Accuracy	**0.9382**						
KIA	**0.9237**						
2003 Image Classification Accuracy							
Producer	0.9506	1	0.5833	0.8873	1	1	0.8
User	0.939	0.9474	1	0.9844	0.8364	1	0.6667
Hellden	0.9448	0.9730	0.7368	0.9333	0.9109	1	0.7273
Short	0.8953	0.9474	0.5833	0.875	0.8364	1	0.5714
KIA Per Class	0.933	1	0.5638	0.8584	1	1	0.7834
Totals							
Overall Accuracy	**0.9169**						
KIA	**0.8984**						

Table2. 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.

4.0 Results

4.1 LULC Changes

Results show a reduction in forest cover (-23%) with corresponding increases in residential land cover (25%), roads and pavements (7%) between 1985 and 2003. Active agricultural plots also seem to have doubled between the two time frames in consideration; since crop growing and harvesting cycle is a very dynamic process, the shift between many plots of fallow and croplands could be a temporary one (Table3). Increases in grass area are consistent with urban growth; new golf courses, and lawns in new residential areas are observable in the 2003 image.

Initial State (1985)

Final State (2003)

	Fallow land	Forest	Grass	Roads/Pavement	Residential	Water	Cropland (Active crops)	Row Total
Unclassified	0.015	0.017	0.000	0.031	0.007	0.000	0.000	99.329
Fallow land	39.835	9.920	18.694	11.529	4.030	0.920	24.219	99.993
Forest	15.659	58.989	16.217	11.625	12.182	16.804	13.325	99.999
Grass	21.676	8.876	30.598	8.507	5.638	1.217	32.651	99.998
Roads/Pavement	9.484	9.338	9.643	40.737	11.911	3.635	7.111	99.931
Residential	4.169	9.032	13.575	24.192	64.235	2.426	7.755	99.987
Water	0.229	0.847	0.192	0.390	0.244	74.438	0.211	99.964
Cropland (Active crops)	8.934	2.981	11.080	2.990	1.753	0.559	14.728	99.999
Class Total	100.000	100.000	100.000	100.000	100.000	100.000	100.000	
Class Changes	60.165	41.011	69.402	59.263	35.765	25.562	85.272	
Image Difference	**-18.556**	**-22.891**	**90.650**	**6.916**	**24.925**	**27.838**	**130.895**	

Table3. Change detection statistics (Area in percentage)

4.2 Mitchell Lake Pollution

Water level is clearly higher in Mitchell Lake in 2003 compared to the 1985 level; however the water is more polluted as indicated from the coloration in the 2003 image.

2003 **1985**

Figure6. Mitchell Lake (South of Loop 1604)

5. Conclusions

This study demonstrated the potential for accurate LULC change assessment using 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 a reduction in forest cover (-23%) with corresponding increases in residential land cover (25%), roads and pavements (7%) between 1985 and

2003. Many studies have shown that urban land use change has profound impact on both seasonal-averaged and minimum surface temperature changes within the spatial scale of the watershed. With increasing urban population, unsustainable replacement of forest cover with impervious cover (commercial and residential buildings, roads, and pavement) especially in the Greater San Antonio area is bound to have significant economic and ecological implications in the near future. Some of these implications may include: more flooding as a consequence of increased stormwater flow, and urban heat island (UHI) effect. Heat islands form as cities replace natural land cover with pavement, buildings, and other infrastructure (Fig.7). These changes contribute to higher urban temperatures in a number of ways:

- Displacing trees and vegetation minimizes the natural cooling effects of shading and evaporation of water from soil and leaves (evapotranspiration).
- Tall buildings and narrow streets can heat air trapped between them and reduce air flow.
- Waste heat from vehicles, factories, and air conditioners may add warmth to their surroundings, further exacerbating the heat island effect.

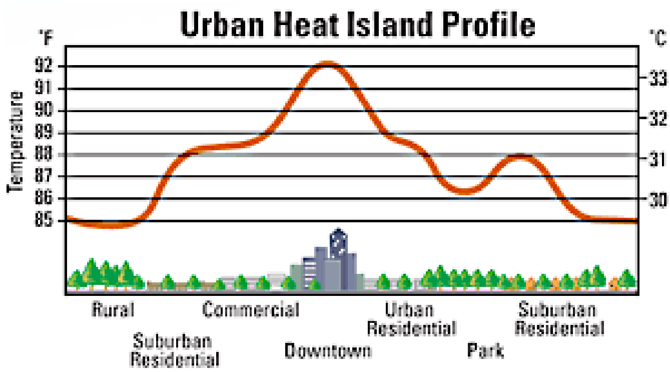
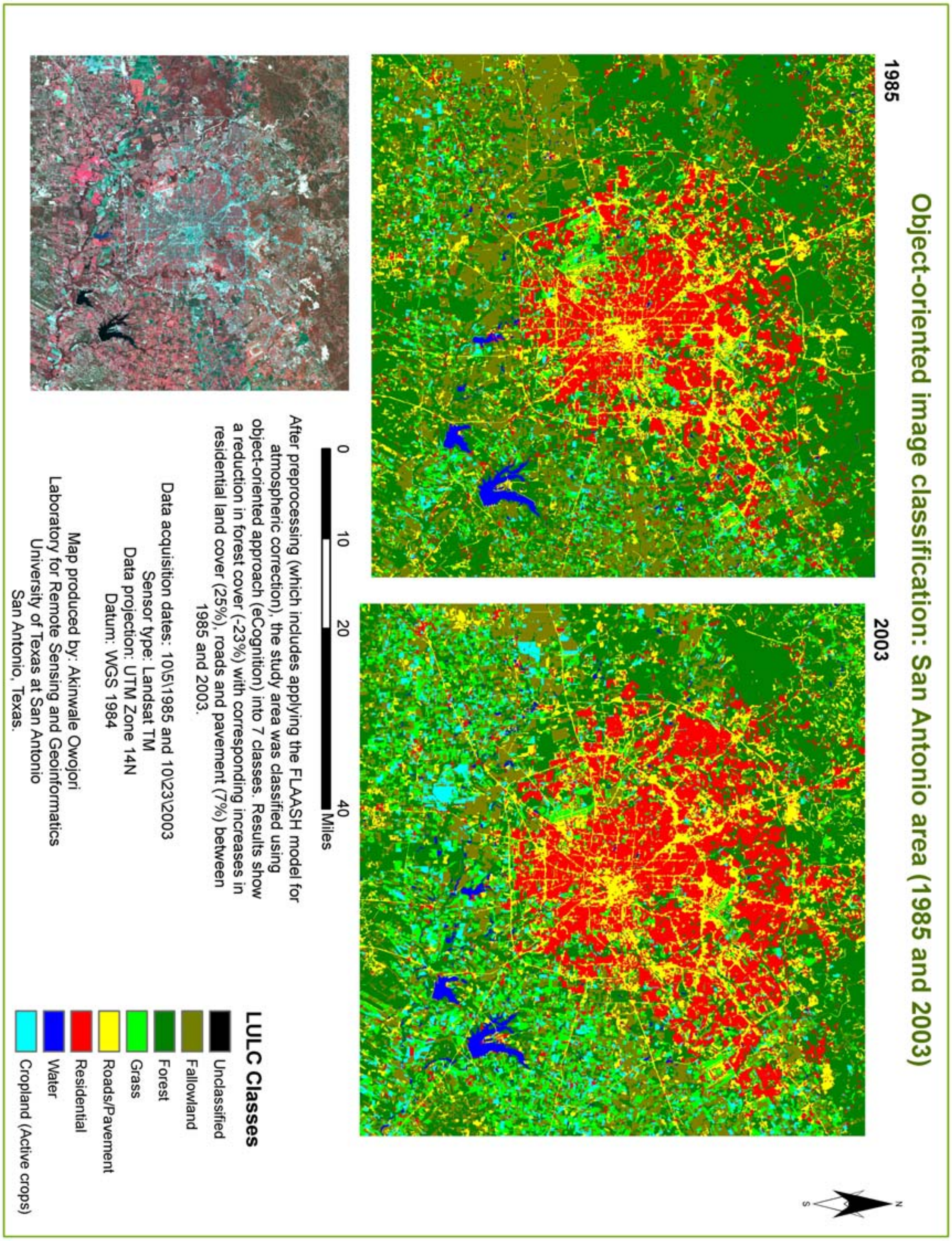


Figure7 (Source: www.EPA.gov)

Although results in this study can be considered fairly reliable in characterizing LULC changes in the study area, classification can be significantly improved with the use of higher resolution data.

Appendix


Object-oriented image classification: San Antonio area (1985 and 2003)
1985
2003
0 10 20 40
Miles
After preprocessing (which includes applying the FLAASH model for atmospheric correction), the study area was classified using object-oriented approach (eCognition) into 7 classes. Results show a reduction in forest cover (-23%) with corresponding increases in residential land cover (25%), roads and pavement (7%) between 1985 and 2003.
Data acquisition dates: 10\5\1985 and 10\23\2003
Sensor type: Landsat TM
Data projection: UTM Zone 14N
Datum: WGS 1984
Map produced by: Akinwale Owojori
Laboratory for Remote Sensing and Geoinformatics
University of Texas at San Antonio
San Antonio, Texas.
LULC Classes
Unclassified
Fallowland
Forest
Grass
Roads/Pavement
Residential
Water
Cropland (Active crops)
N
S

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U.S. Census Bureau (http://www.census.gov).