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Mapping and Assessing Urban Impervious Areas Using Multiple Endmember Spectral Mixture Analysis: A Case Study in the City of Tampa, Florida

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Mapping and Assessing Urban Impervious Areas Using Multiple Endmember
Spectral Mixture Analysis: A Case Study in the City of Tampa, Florida

by

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A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Arts
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ABSTRACT

The advance in remote sensing technology helps people more easily assess urban growth. In this study, the utility of multiple endmember spectral mixture analysis (MESMA) is examined in a sub-pixel analysis of Landsat Thematic Mapper (TM) imagery to map urban physical components in Tampa, FL. The three physical components of urban land cover (LC): impervious surface, vegetation and soil, were compared using the proposed MESMA with a traditional spectral mixture analysis (SMA). MESMA decomposes each pixel to address the heterogeneity of urban LC characteristic by allowing the number and types of endmembers to vary on a per pixel basis. This study generated 642 spectral mixture models of 2-, 3-, and 4-endmembers for each pixel to estimate the fractions of impervious surface, vegetation, soil, and shade in the study area with a constraint of lowest root mean square error (RMSE). A comparative analysis of the impervious surface areas (ISA) mapped with MESMA and SMA demonstrated that MESMA produced more accurate results of mapping urban physical components than those by SMA. With the multiyear Landsat TM data, we quantified sub-pixel %ISA and the %ISA changes to assess urban growth in the City of Tampa, Florida during the past twenty years. The experimental results

demonstrate that the MESMA approach is effective in mapping and monitoring urban land use/land cover changes using moderate-resolution multispectral imagery at a sub-pixel level.

CHAPTER 1: INTRODUCTION

Urbanization, a global phenomenon mainly driven by population growth and large scale rural to urban migration, is defined as outward expansion of built-up urban areas to the periphery, or the spreading of city suburbs (Black and Henderson, 1999; Herold *et al.*, 2003; Martinuzzi *et al.*, 2007; Burgess, 2008).

Urban sprawl and expansion of suburbs results in a rapid transformation of agricultural and forested lands to urban land uses, such as residential, industrial, and commercial areas. There is no universally accepted definition to describe urbanized areas. The standards distinguishing urbanized areas from suburban areas and rural areas vary from country to country. Referring to the United States Census Bureau, an urbanized area is defined as “one or more places (‘central place’) and the adjacent densely settled surrounding territory (‘urban fringe’) that together have a minimum of 50,000 persons” (U.S. Census Bureau, 1995).

Therefore, in this thesis, the urbanization process deals with the expansion of population and the transformation of land use and land cover (LULC) categories, although it also involves changes in the economic, social, and political structures of an area. This transformation of the land is often accompanied by a series of environmental and socio-economic issues, such as damage to ecological systems, regional climate alteration, over-consumption of fresh-water and energy resources, and effects to the population structure (Green *et al.*, 1994; Kalnay and

Cai, 2003; Xiao *et al.*, 2006). Therefore, not all the urban growth is beneficial to social and environmental systems. How to detect and understand changes in urban areas is very significant for fostering environmental and human sustainability of cities, and also for predicting growth pattern of cities around the world, so that their present and future resource needs can be met (Weng and Quattrochi, 2007). In addition, by predicting urban growth, urban planners and policymakers can better understand why this geographic phenomenon happens, and plans for and provide the infrastructure and services required by the expanding number of new urban residents. To reduce the negative environmental impacts due to the rapid urbanization, it is necessary to quantify and categorize urban growth; especially the transformation of LULC types, in a meaningful way for land use decision-makers.

Impervious surface area (ISA) is not only a major indicator for assessing the rate of urban growth, but also a key factor in evaluating the intensity of urbanization because of its impact on habitat quality (Stankowski and Trenton, 1972; Turner and Meyer, 1991; Arnold and Gibbons, 1996; Madhavan *et al.*, 2001; Alberti, 2005; Jat *et al.*, 2008; Pickett *et al.*, 2008). Impervious surfaces are mainly artificial features that do not allow water to pass through, such as parking lots, roads, sidewalks, and so on. Urban areas are composed of various materials, such as impervious surfaces, soils, vegetation (grass/turf, shrub and tree canopy), and water. In urban areas, the percentage of impervious cover varies because of different land uses. Therefore, characterization and quantification of the spatial pattern of impervious surfaces is significant when assessing urban LULC changes

and urban growth (Daniel *et al.*, 2002; Jarnagin, 2003; Wilson *et al.*, 2003; Yang *et al.*, 2003; Yuan and Bauer, 2007; Weng and Lu, 2008; Riva-Murray *et al.*, 2010).

With the advent of remote sensing, people can easily get information regarding the structural attributes of cities with a synoptic perspective in an efficient and economical way. Remote sensing can provide a way to understand global and regional environmental changes and human-environment interactions by mapping and monitoring LULC. Much research has been done to study urban LULC aimed at monitoring urban expansion and description of why urban sprawl has taken place in particular urban areas using remote sensing data (Seto *et al.*, 2002; Pauleit *et al.*, 2003; Seto and Liu, 2003). This data helps researchers investigate various urban phenomena in detail, extending their understanding beyond the rather limited knowledge of urban size and shape provided by traditional paper map sources.

Remote sensing techniques more effectively monitor LULC changes by providing multi-resolution and multi-temporal information in a timely and cost-effective manner (Treitz *et al.*, 1992; Chen *et al.*, 2000; Weng, 2002; Xian and Crane, 2005). Many studies have demonstrated that remote sensing data are capable of estimating and mapping impervious surfaces (Ridd, 1995; Phinn *et al.*, 2002; Small and Lu, 2006; Powell *et al.*, 2007, Franke *et al.*, 2009). It appears that most urban impervious land cover can be modeled using traditional classifications, which assume that the pixel size of remotely sensed data is smaller than the size of urban individual features, or that most pixels of the imagery only contain one type of urban land cover. Images with finer spatial resolution contain much more

spectral information than those with coarser resolution. This additional spectral information can be used to extract greater detail by using endmembers. However, most urban land surfaces are spatially and spectrally heterogeneous at some scale because of the complex mixture of land cover types in urban environments (Ward *et al.*, 2000; Small, 2002; Phinn *et al.*, 2010; Huang *et al.*, 2011). Using low spatial resolution images to unmix different endmembers in each pixel may be problematic due to increased spectral variances among materials and shadows (Barnsley and Barr, 1996; Dare, 2005). Per-pixel classifiers inaccurately estimate urban surface materials when using moderate to coarse spatial resolution satellite data (spatial resolution > 10 meters), such as Landsat and SPOT imagery. This limits their capability of detecting important spectral and spatial variations in urban features (Lu and Weng, 2004; Xian and Crane, 2005) (Figure 1). Firstly, in different urban areas, the physical composition and spectral signature of land-cover classes are diverse (Ridd, 1995; Small, 2005; Song, 2005; Powell *et al.*, 2007). Secondly, for moderate resolution remote sensing data, the percentage of mixed pixels in the imagery is very high due to complexity and heterogeneity of urban surface materials (Herold *et al.*, 2004; Wu, 2004; Small, 2005).

Figure 1. Per-pixel classification and sub-pixel classification. Map with high percentage of mixed pixels (there are 9 pixels in the image) (a), map by per-pixel based classification (b), fraction map of Land cover type I by sub-pixel classification (c), fraction map of Land cover type II by sub-pixel classification (d), and fraction map of Land cover type III by sub-pixel classification (e).

Ridd (1995) proposed a model for mapping the urban environment in terms of simple physical components: Vegetation, Impervious surface, Soil (V-I-S model) (Figure 2). Urban areas may be divided into these three parts, based on the percentage of the spatial unit occupied by vegetation, soil, and impervious surface, if water surfaces are ignored (or masked out). A spectral mixture analysis (SMA) technique has been developed to unmix images at sub-pixel scale to estimate the fraction abundance of these three physical components within a pixel. SMA assumes that ideally the spectral signal of a pixel can be modeled by a combination of spectra contributed by some endmembers, or components, or LULC types, or pure spectrally individual features. Mapping the urban environment

based on spectral mixture analysis (SMA) and V-I-S model for estimating ISA fractions has been conducted in different urban areas in the world (Rogan and Chen, 2003; Lee and Lathrop, 2005; Powell *et al.*, 2007; Pu *et al.*, 2008; Yang *et al.*, 2010). For example, Ji and Jensen (1999) demonstrated that sub-pixel analysis could effectively quantify urban imperviousness using Landsat Thematic Mapper (TM) imagery. Wu (2004) applied normalized spectral mixture analysis (NSMA) method to model heterogeneous urban composition with a constraint. Lu and Weng (2009) suggested that linear spectral mixture analysis (LSMA) and the V-I-S model could be an effective method to characterize urban environments, although spectral, spatial, and temporal variability of this model should be examined in the process of application. Powell *et al.* (2007) used multiple endmember spectral mixture analysis (MESMA) to effectively address the problems of spatial and spectral variability of different materials using moderate spatial resolution image for the urban area of Manaus, Brazil. Yang *et al.* (2010) also reported a pre-screened and normalized multiple endmember spectral mixture analysis (PNMESMA), which integrated normalized spectral mixture analysis (NSMA) and MESMA, for estimating ISA fraction, and demonstrated that PNMESMA performed better in estimating ISA fraction than other SMA- or NSMA-based methods in a case study in the Lake Kasumigaura Basin, Japan.

Figure 2 . V-I-S model illustrating the characteristics of urban landscape. (From Ridd, M. K., 1995)

Although simple SMA could provide a physically meaningful and plausible measure of fraction abundance for different materials on the ground in an urban environment, it cannot account for the subtle spectral variations nor can it account for differences in physical composition of materials represented in the pixels (Small, 2001; Rashed *et al.*, 2001; Weng *et al.*, 2004; Pu and Gong, 2011) and it is also limited by a maximum number of 6-7 endmembers within mixed pixels (Li and Mustard, 2003; Hung, 2002). Because of these issues, traditional SMA cannot account for the complexity and spectral heterogeneity of urban materials. However, the MESMA technique can overcome limitations of the

traditional SMA by allowing the number and type of endmembers to vary for each pixel in the image. MESMA evaluates each possible model (two-, three-, or four-endmember model) based on the criteria of fraction values of each endmember, root mean square error (RMSE), and shadow fraction. Therefore, in this study, MESMA is used to unmix images with every possible combination of two, three, and four endmembers applied to every pixel in terms of the fraction abundance of the four components: vegetation, impervious surface, soil, and photometric shade (Ridd, 1995; Adams and Gillespie, 2006; Powell *et al.*, 2007). It has advantages in modeling all the ground surface materials, comparing with the traditional SMA which assumes each endmember has a constant spectral signature and therefore uses a fixed number of endmembers to map entire areas, rather than considering the variety of number and type of land cover components in urban areas (Ridd, 1995; Song, 2005; Yang *et al.*, 2010). This study monitors and detects land cover changes in the past two decades at the sub-pixel level, using the percentage change of impervious surface to assess the degree of urban growth, in terms of LULC changes in the City of Tampa, FL.

Many researchers have used remote sensing derived data to explain the relationships between impervious surfaces and population density. An early paper by Stankowski and Trenton (1972) suggested that there could be a close relationship between the %ISA and population density in an area, and that the %ISA could be estimated by the population density. Lu *et al.* (2006) built a procedure of urban land-use classification based on the combination of impervious surface and population density. They also found a strong relationship

between impervious surface and population density ($R^2 = 0.782$). Therefore, census data can be used to explain and understand the phenomenon of urban ISA change.

CHAPTER 2: RESEARCH OBJECTIVES

Although some studies have shown that MESMA has the capability of mapping the physical components of land cover, most of them have applied the MESMA approach in a variety of environments for vegetation mapping (e.g., Roberts *et al.*, 1998a, 2003; Li *et al.*, 2005; Rosso *et al.*, 2005) using hyperspectral data and only a few (e.g., Power *et al.*, 2007; Yang *et al.*, 2010) have used it in an urban environment with moderate spatial resolution imagery. Because of the advantages of MESMA over SMA in mapping urban land cover at a sub-pixel level, it has great potential for use in studies which attempt to understand urban growth and LULC changes by mapping the urban environment using moderate spatial resolution satellite imagery. This study will focus on a comparative analysis between MESMA and SMA and their capability of mapping impervious surface area (ISA) using moderate spatial resolution Landsat TM imagery in the urban environment. The main goal of this study is to evaluate the performance of MESMA in mapping the physical components of urban land cover, focusing on changes in impervious surface in the City of Tampa, Florida for the years 1990, 2000, and 2010, . By assessing changes to %ISA, usually from natural, vegetated landscape into impervious surface, the spatial pattern and intensity of urbanization can be measured and assessed.

Specifically, four key research questions are addressed in this thesis:

1. Does MESMA have the capability to estimate ground component fractions?
2. Does MESMA perform better in mapping physical components, compared to the traditional SMA?
3. Can urban growth in Tampa, Florida be quantified by assessing urban LULC changes, especially %ISA change, but also including spatial pattern, density, and the rate of land cover changes?
4. Does population increase have an influence on %ISA changes thus on urban growth in the City of Tampa, Florida?

CHAPTER 3: METHODOLOGY

To answer the four key research questions, MESMA and SMA are respectively performed to assess urban LULC changes in the City of Tampa, Florida during the past two decades. All experimental procedures were implemented in ENVI 4.8, ArcGIS 10, SPSS 20, and VIPER Tools, a plug-in for the ENVI software package.

3.1 Study Area and Datasets

The region of the City of Tampa, Florida was chosen as the study area because of its rapid urbanization during the last century, particularly since World War II (Figure 3). The City of Tampa, part of the Tampa Bay Area, is located on the west coast of Florida, with elevations ranging from sea level to as high as 48 feet (about 15 meters). Its flat topography and geographic location along the coast provide numerous possibilities of urban expansion. Tampa has a humid subtropical climate, with a rainy season extending from June to September. The population of Tampa City was approximately 300,000 in 2010, and had an average increase rate of 0.81%/year during the 1990-2010 period (US Census Bureau, 2010).

The City of Tampa has been undergoing development since settlement in the 1800s (Xian and Crane, 2005). The recent pattern of urban LULC can be characterized as “suburban sprawl”, as impervious surfaces replace natural land

cover in peripheral areas, especially near The University of South Florida, and New Tampa. The dominant landscapes in the City of Tampa are residential and commercial areas, forest, and water. Increasing population and the development of New Tampa have caused rapid changes in the land cover structure during the past twenty years. Since the 1990s, artificial land cover, such as residential areas, commercial areas, and roads has increased quickly, replacing forests and croplands. This pattern of development changes the degree of imperviousness in the area. Therefore, ISA was chosen as the key indicator of urbanization in this study.

Figure 3. Location of the study area. The City of Tampa, a part of Hillsborough Country, is located on the west coast of Florida. The study area is presented in a Landsat-5 TM composite image (Bands 4, 3, 2 vs, R, G, B). The Landsat TM image was acquired on April 27, 2010.

Remotely sensed data provide a means for monitoring changes in urban land cover over time. Three scenes of the study area that were cloud-free or had low amounts of clouding were selected from Landsat-5 TM images (Path17/Row41), acquired on June, 7, 1990, June, 2, 2000, and April 27, 2010 . In order to validate the spectral unmixing results, references images comprising of 1-m spatial resolution DOQQ aerial photographs, acquired on March, 3, 2001, were selected

as reference images to compare with the TM image acquired in 2000. Additionally, 1990, 2000, and 2010 US Census data at the tract level and in shapefile format were collected and used to explore the relationship between urban growth and population change in the study area during the past two decades. The 1990 census data was normalized to 2000 tract boundaries allowing direct comparison between these two dates. However, because of changes in the 2000 and 2010 tract boundaries inconsistencies in the data required elimination of some of the tracts from the population analysis. In 2010 there are 143 tracts in the City of Tampa, but only 95 tracts covered by the study area could be used (see Appendix A3).

3.2 Data Pre-processing

Three scenes of Landsat-5 TM images were used in this study. A 900-km² region was chosen as the case study area and subset from the Landsat images. For all images, six bands (TM bands 1-5, and 7) were used, and the spatial resolution of all images is 30 m. The scenes were then geo-referenced to 7.5 min United States Geological Survey (USGS) topographic maps. Atmospheric correction were performed using the Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes (FLAASH) software package in ENVI 4.8. Although water is an important component of the urban environment, it was not used as a land cover type for evaluating MEMSA and SMA, therefore water bodies in the scene were masked out by setting a threshold value in Band 7.

3.3 Methods for Estimating ISA

3.3.1 Spectral mixture analysis and multiple endmember spectral mixture analysis

Conventional spectral mixture analysis (SMA), a linear spectral mixture analysis, is a technique for estimating the reflectance - R measured at pixel level - i and can be modeled as the linear sum of n endmembers, or spectrally 'pure' materials, weighted by fraction f_{ki} of each endmember within the field of view of pixel i . For a given wavelength, λ , the mixing equation for spectral images is given in equation (Adams *et al.*, 1993):

$$R_{i\lambda} = \sum_{k=1}^n f_{ki} * R_{k\lambda} + e_{i\lambda} \quad (1)$$

while $R_{i\lambda}$ is the measured value of reflectance at pixel i ; f_{ki} is the fraction of endmember k within pixel i ; $e_{i\lambda}$ is the residual error at pixel i and represents the difference between observed and modeled spectra. The modeled fractions should be constrained by the following:

$$\sum_{k=1}^n f_{ki} = 1, \text{ and } f_{ki} \geq 0 \quad (2)$$

In order to calculate the value of f_{ki} , a system of m or $m+1$ equations (corresponding m bands or wavelengths) is required, and the number of endmembers, n , should be less than the number of bands, m . In this study, for Landsat-5 TM image, the number of bands is 6, therefore, the number of endmembers cannot exceed 6.

SMA assumes that all pixels in the image are modeled by a fixed number of representative endmembers. SMA is based on the following assumptions in estimating the composition of each image pixel:

- Each pixel not only contains information about the proportion of each component but also spectrum of each component;
- Brightness of an image pixel is a linear sum of n pure endmembers;
- Spectral proportions of the endmembers are equal to proportions of the area covered by endmembers on the ground;
- Most of the pixels in the image are comprised by some measurable amount of the endmembers.

SMA is limited in that it cannot account for the absence of one or more endmembers of some pixels or spectral variation within pure materials. In the multiple endmember spectral mixture analysis (MESMA), the root-mean squared error (RMSE) of the residuals for each pixel across all bands was measured to evaluate the accuracy of every model instead of the residuals in the SMA model (Roberts *et al.*, 1998a). The RMSE for pixel i can be described by the following (Adams *et al.*, 1993, Roberts *et al.*, 1998a):

$$\text{RMSE}_i = (\sum_{\lambda=1}^m (e_{i\lambda})^2 / m)^{1/2} \quad (3)$$

where $e_{i\lambda}$ is the residual error of band λ at pixel i , and m is the total number of bands (6 for Landsat-5 TM image). MESMA has an advantage over conventional SMA when decomposing images since it allows the number and type of endmembers to vary pixel by pixel (Roberts *et al.*, 1998a). This technique uses whichever model has the smallest RMSE, assuring that the selected endmember is representative of that class. Based on the criteria of RMSE, fraction values, and residual threshold, a series of candidate models are tested to produce fraction images with the lowest error (Roberts *et al.*, 1998b). From Figure 4, in order to

select appropriate endmembers for constructing a spectral library in MESMA, the Purity Pixel Index (PPI) and manual selection were used. (2) The MESMA model (based on all combinations of final library endmembers) is applied to every pixel in the image, based on a set of criteria. (3) If all the criteria are satisfied, the 'best-fit' model is selected for each pixel; if not, the remaining pixels are unclassified. (4) Fraction cover derived from MESMA is produced.

Figure 4. Flowchart of the MESMA model.

3.3.2 Endmember selection

The selection of appropriate endmembers is very important for SMA because of the endmembers' effects on its spectral unmixed result (Tompkins *et al.*, 1998; Brandt *et al.*, 2005). For standard SMA, the key to endmember selection

is identification of extremely pure spectrum to represent each feature (i.e., endmember) on the ground (Adams *et al.*, 1995; Powell *et al.*, 2007). For MESMA, successful endmember selection relies on identifying a series of spectra that represent the spectral variations for each material in the scene (Roberts *et al.*, 1998b; Okin *et al.*, 2001). There are two sources of pure spectral signatures: (1) image endmember, selected from representative pixels from satellite sensor images (Elmore *et al.*, 2000; Small, 2001; Song, 2005), and (2) reference endmember, collected from reference images, and measured in the laboratory or on the ground with a spectroradiometer (Smith *et al.*, 1990; Adams *et al.*, 1995; Roberts *et al.*, 1998). In general, reference endmembers are of higher purity than image endmembers. Thus reference endmember spectra can be the optimal ones as the candidate endmembers for each group of interest, but they may not be appropriate for those interests within the image (Ballantine *et al.*, 2005). This is explained by the following reasons. (1) Reference endmembers may cause uncertainty arising from radiometric calibration and geo-registration, which could affect evaluation of the performance of SMA or MESMA, while image endmembers contains the same errors caused by atmospheric effects (Song and Woodcock, 2003; Chen and Vierling, 2005). (2) Reference endmembers measured in the field or laboratory cannot provide spectra of all the ground components, but image endmember could cover all potential types of ground surface materials (e.g., all vegetation types in the City of Tampa, Florida). In this study, all representative endmembers for SMA were selected from the images.

There are a variety of methods for extracting pure pixels from the image. In

this study, the endmembers were selected from images based on the PPI method and manual selection. Appropriate endmembers were effectively found by the PPI method, which identifies extreme pixels, or representative pure signatures, in data by searching for a set of vertices on a convex hull (Boardman *et al.*, 1995; Chaudhry *et al.*, 2006). Image endmembers can be collected by linking the PPI image with the image used to identify classes, avoiding the choice of edge pixels. In this study, the endmember collection was generalized into five groups: vegetation A (tree), vegetation B (shrubs and grasses), high albedo impervious surface (e.g. asphalt), low albedo impervious surface (e.g. concrete), and soil (Figure 5). In the study area, vegetation A pixels were mainly distributed in so-called urban forests, and vegetation B pixels were mainly distributed in residential areas and parks, etc. High albedo and low albedo pixels were found in the downtown, roads, and roofs. The soil pixels were found in low frequently bare lands.

Figure 5. Five major endmember reflectance spectra identified by PPI method

3.3.3 Building the spectral library

Identification of appropriate endmembers and their corresponding spectral signatures is of great importance for SMA (Sabot, 1992; Maas, 2000; Peddle and Smith, 2005; Cho *et al.*, 2009). For MESMA, the spectral library should contain enough spectra for each class of materials to represent spectral variation of materials on the ground; however, the number of endmembers in the library cannot be too great, because the total number of endmembers in the potential models is inversely proportional to the computational efficiency and accuracy (Powell *et al.*, 2007). Many studies show that 4-endmember models don't necessarily guarantee better performance than 3-endmember models (Fitzgerald *et al.*, 2005; Powell *et al.*, 2007). In order to construct a comprehensive and

representative spectral endmember library, three steps were used in this study following a procedure developed by Dennison and Roberts (2003). (1) All possible endmembers were collected to augment the number of spectra in the library. (2) A series of representative spectra for each class of materials were selected to reduce computation errors and complexity by eliminating spectra from other material classes. (3) Endmembers that represent materials on the ground in the study area were selected for use with MESMA.

Potential image endmember pixels were identified by PPI and manual selection, resulting in five different types of candidate image endmembers, including: Vegetation A, Vegetation B, High albedo, Low albedo, and Soil. In order to construct a final endmember spectral library, the collection of endmember spectra were reduced using the product *Viper Tools* user manual, by Dennison and Roberts (2003). Firstly, the procedure selected representative endmembers for each material class from the library to eliminate those spectra that might be confused with other material class, based on the criteria of the value of RMSE ($< 2.5\%$). Secondly, the most representative endmembers for each material class were identified using the Endmember Average RMSE (EAR), Minimum Average Spectral Angle (MASA), In_CoB (Count based Endmember selection), and Out_CoB (Roberts, 2003). EAR is the average RMSE of a spectrum when it models all other endmembers within a material class. For each class, spectrum with the lowest EAR is considered as a possible representative endmember for the spectra within that class. The MASA is used to calculate the spectral angle between a spectrum and all other spectra within that class. The lowest MASA

value of a candidate spectrum is usually considered as the more representative of the endmember of that class. CoB selects optimal endmembers by calculating the greatest number of spectra that candidate spectrum can be modeled within or out of their class. In this study, the final spectral library for MESMA consisted of optimal endmembers of the five classes: Vegetation A, Vegetation B, High albedo, Low albedo, and soil. Later, Vegetation A and Vegetation B were combined into a single vegetation class. High albedo and Low albedo were also combined into a single impervious surface class.

3.3.4 SMA Models

Spectral mixture models for simple SMA with V-I-S model could model land cover using three major physical components (vegetation, impervious surface, soil) in urban environments at the sub-pixel level. Three representative endmembers of their material classes, optimal endmembers, were used in this study. Traditional SMA model assume that the spectrum of an endmember is constant, without considering shade (i.e., shaded areas and shadow). Although shade is not a physical component, it is present in the images. For example, in highly urbanized downtown areas, tall buildings can create extensive shadows depending on solar angle and sensor position. Shadows are also a problem in forested areas because of the density of trees. Therefore, shade is a very important endmember in spectra mixture models.

Candidate endmembers by PPI and manual selection were used for SMA models. There were five different classes used in this study. For urban environments, the procedure of simple SMA was based on the following

assumptions: (1) tree, shrubs, and grass may coexist in a pixel; (2) High albedo and low albedo may coexist in a pixel, while they are spectrally distinct; (3) the soil category is not divided into different classes because there are so few areas with a high percentage of soil. The final vegetation fraction images by SMA were calculated as the sum of vegetation A and vegetation B fractions. The final impervious surface fraction images by SMA were also calculated as the sum of High albedo impervious surface and Low albedo impervious surface fractions.

3.3.5 MESMA Models

The final spectral library for MESMA was used to map V-I-S fractions in the study area. MESMA differs from the traditional SMA by allowing the combination of an unfixed number of endmembers. In this study, two-, three-, four-endmember models were applied to determine the best model for each pixel by setting some constraints, including: fractions, RMSE or residuals. Shadows are not physical components, but they are spectral components that should be considered when estimating the physical proportions (Peddle *et al.*, 1999; Fitzgerald *et al.*, 2005; Garcí'a-haro *et al.*, 2005). Photometric shade is defined as a spectrum whose reflectance value is equal to zero for each band (Adam and Smith, 1986). Shadows can partly account for the relationship between the endmembers that represent their class in the library collection and the endmembers that represent the materials of their class on the ground (Eddy, 2009). Therefore, the image is modeled by two endmembers, three endmembers, and four endmembers (i.e., one spectrum + photometric shade; two spectra + photometric shade; three spectra + photometric shade) for each pixel with a set of criteria (Table 1). Two

endmember models consisted of any material class spectrum and shade, such as vegetation-shade model, impervious surface-shade model, and soil-shade model. Three endmember models consisted of two different material classes and shade, such as vegetation-impervious-shade model, vegetation-soil-shade model, and so on. The allowable endmember fraction was between -0.05 and 1.05 (Dennison and Roberts, 2003; Hamada *et al.*, 2011; Shahtahmassebi *et al.*, 2011). The maximum allowable shade fraction is 0.8 (Roberts *et al.*, 1998a). The terrain is relatively flat in the study area, hence shaded areas were relatively scarce. The RMSE was constrained to 2.5%. Based on the above constraints, two-, three-, four-endmember models were applied to each pixel. If a two-endmember model could model a pixel well, then the two-endmember model was selected as the optimal one. If not, the pixels were left unclassified. For the remaining pixels, if a three-endmember model could model pixels well, the three-endmember model was selected. If not, the pixels were left unclassified. For those pixels that could not be modeled by two-, and three-endmember models, a four-endmember model was used. The results of optimal models by MESMA were to map a series of fraction abundance maps for each class of materials. Figure 6 presents a flowchart of MESMA for estimating the endmember fractions.

Table 1. Allowed models in the MESMA method.

2-emb	3-emb	4-emb
VegA _i + Shade VegB _i + Shade ImpH _i + Shade ImpL _i + Shade Soil _i + Shade	VegA _i + VegB _i + Shade VegA _i + ImpH _i + Shade VegA _i + ImpL _i + Shade VegA _i + Soil _i + Shade VegB _i + ImpH _i + Shade VegB _i + ImpL _i + Shade VegB _i + Soil _i + Shade ImpH _i + ImpL _i + Shade ImpH _i + Soil _i + Shade ImpL _i + Soil _i + Shade	VegA _i + ImpH _i + ImpL _i + Shade VegB _i + ImpH _i + ImpL _i + Shade Soil _i + ImpH _i + ImpL _i + Shade

Note: There are five components used in the study. (1). VegA_i: Tree; (2). VegB_i: Shrub and grass; (3). ImpH_i: High albedo; (4). ImpL_i: Low albedo; (5). Soil_i: Soil.

Figure 6. Flowchart of MESMA method developed in the study.

3.3.6 ISA estimation

Optimal results were produced by MEMSA when the fraction of shade-endmember in the model was converted to fractions that represent the

physical composition of the materials in each pixel. After shade normalization, tree canopy, shrubs and grass were combined into one vegetation class, and then low albedo impervious surface and high albedo impervious surface were combined into one impervious surface class. The sum of the fraction values of vegetation, impervious surface, and soil were equal to 1. The fraction value of each class within a pixel was between 0 and 1. Water pixels, already masked out in a prior step, were assigned a fraction value representative of water. Finally, a map comprised by four classes: vegetation, impervious surface, soil, and water was finally produced. A general procedure of estimating ISA fraction in the study is shown in Figure 7. In the figure, ISA was also estimated by using SMA.

Figure 7. Flowchart of estimating ISA fraction in the study.

3.3.7 Accuracy assessment

In order to evaluate whether MESMA performed better in mapping the physical components of urban land cover, the results of SMA and MESMA were both evaluated for the correlation between modeled fractions and reference fractions derived from a fine-resolution reference image (1 m resolution). DOQQ aerial photographs acquired in 1990, 2000, and 2011 were used as reference maps to assess accuracy. All the reference images were classified into four classes by visual interpretation: vegetation, impervious surface, soil and water. Since the spatial resolution of the aerial photograph is very high (1 m), the fractions of each material class interpreted from the aerial photographs corresponded with the actual fraction in the field (Anderson *et al.*, 1996; Stehman and Czaplewski, 1998; Carpenter *et al.*, 1999).

A random sampling technique was used to select a representative sample of the results from MEMSA and SMA images in this study. There are > 30 samples with the same window size (30 m × 30 m, which just matches the TM spatial resolution) and were randomly selected from homogenous patches on the Landsat image to eliminate errors from georeferencing process between modeled image and reference images. Within each sampled pixel/window, the fractions of materials were respectively extracted/interpreted from Landsat image and from the fine-resolution aerial photographs. The correlation between modeled fractions and reference fractions for each physical component (endmember) was calculated by the equation:

$$\tilde{y} = kx + \beta \quad (4)$$

Where the reference fraction $\tilde{y}$ is a dependent variable; the modeled fraction x is an independent variable. For an ideal model, the slope $k=1$, and the intercept $\beta=0$. RMSE was employed to estimate the accuracy of these two models (i.e., SMA and MESMA).

$$\text{RMSE} = \sqrt{\frac{\sum (f_m - f_i)^2}{N-1}} \quad (5)$$

where N is the number of the samples; f_m is the fraction of each endmember modeled by SMA or MESMA; f_i is the fraction of each endmember measured (interpreted) from the aerial photographs.

CHAPTER 4: RESULTS AND DISCUSSION

4.1 MESMA Model

In MESMA, representative spectra of every material class, were chosen from the final spectral (endmember) library. For the 1990 TM image, there were a total 19 endmembers in the final spectral library, including 5 vegetation A, 3 vegetation B, 4 high albedo, 4 low albedo, and 3 soil endmembers. Therefore, there were total 338 combination models, including 19 two-endmember models, 143 three-endmember models, and 176 four-endmember models (Table 2). There were total 219 combinations of endmembers for the 2000 TM image, modeled by using 17 different endmembers (5 vegetation A, 3 vegetation B, 4 high albedo, 2 low albedo, and 3 soil endmembers). The 2010 TM image could be modeled using 18 two-endmember models, 125 three-endmember models, and 108 four-endmember models. The details that how many pixels could be estimated by these models were summarized in Tables 3-5.

Table 2. Number of all combination models for the 1990, 2000, and 2010 reflectance images in the study area.

Model	1990	2000	2010
2-endmember	19	18	18
3-endmember	143	113	125
4-endmember	176	88	108
Total	338	219	251

Table 3. Number of pixels successfully modeled by each level of model complexity for the 1990 TM reflectance image.

Model	Pixels modeled	%Non-water area	%Total area
Water mask	133510	-	13.55
2-endmember	493880	57.13	49.39
3-endmember	366174	42.26	36.62
4-endmember	1002	0.12	0.10
Total		99.51	99.66

Table 4. Number of pixels successfully modeled by each level of model complexity for the 2000 TM reflectance image

	Pixels modeled	%Non-water area	%Total area
Water mask	133510	-	13.55
2-endmember	476388	55.10	47.64
3-endmember	387703	44.74	38.77
4-endmember	98	0.00	0.00
Total		99.84	99.96

Table 5. Number of pixels successfully modeled by each level of model complexity for the 2010 TM reflectance image.

Model	Pixels modeled	%Non-water area	%Total area
Water mask	133510	-	13.55
2-endmember	455104	52.64	45.51
3-endmember	402633	46.47	40.26
4-endmember	1428	0.16	0.14
Total		99.27	99.46

From the tables above, the two-endmember models partly explained the images, while the three-endmember models more comprehensively modeled these images, based on a series of criteria: (1) The fraction values of endmembers of major physical components were between -0.05 and 1.05; (2) the maximum fraction of shade was 0.8; and (3) RMS error was equal to 0.025. However, the

four-endmember models failed to model many pixels in the images, and also increased the cost of computation in this study. For the 1990 reflectance image, 13.55% of water areas were masked out by establishing a criterion. In non-water areas, 57.13% of the pixels were modeled by the two-endmember models, 42.26% of the pixels were modeled by the three-endmember models, but only 0.12% of the pixels were modeled by the four-endmember models. From the output of classification image, it was found that many of the pixels modeled by four-endmember models were adjacent to water. However, edge pixels with low reflectance value could be modeled by any spectra with shadows. The four-endmember models were not considered in the final MESMA results because they didn't improve the accuracy of models and increased computational cost and complexity. (Roberts *et al.*, 1998b; Halligan, 2002). As a result both the two- and three-endmember models were chosen as the optimal ones for the purposes of this study (57.13% of pixels modeled by two-endmember models, and additional 42.26% of pixels modeled by three-endmember models), although about 0.61% pixels in the study area remained unclassified. This number of unclassified pixels was so small that it would not greatly affect the accuracy of ISA estimation. Accordingly for the 1990 image 99.39% pixels of the land area was modeled by the MESMA method. For the 2000 image 99.84% pixels of non-water areas were modeled by the two- and three-endmember models in MESMA, and the remaining 0.16% were unclassified. A total of 99.11% of pixels were well modeled by the two- and three-endmember models for the 2010 image, leaving 0.89% of pixels in non-water areas unmodeled.

After the shadow/shaded fraction modeled by MESMA was accounted for the physical compositions of the materials in each pixel, vegetation A and vegetation B were combined into one vegetation class, and high albedo impervious surface and low albedo impervious surface were combined into one impervious surface class. Water pixels, had already been masked out, and were now assigned to a fraction value of water. The Final fraction maps of the four physical components were produced: vegetation, impervious surface, soil, and water using the 1990, 2000, and 2010 Landsat TM images (Figures 8-10). The brightness of the fraction maps for the three different years varied across the study area, with higher brightness indicating abundance of the material, and darkness a decreased amount. Comparing the images from 1990 to 2010, the impervious surface fraction maps became brighter (Figures 8B, 9B and 10B), implying that ISA increased, while the soil fraction maps became darker. For the vegetation fraction maps, the forest area in the upper right of the maps was bright, indicating a high percentage of vegetation in that area (Figures 8A, 9A, and 10A). The appearance of downtown areas, roads, airports, and some residential areas was very bright in the impervious surface fraction maps.

(A)

(B)

(C)

(D)

Figure 8. Fraction images generated by MESMA using Landsat-5 TM image acquired on June, 7, 1990. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

(A)

(B)

(C)

(D)

Figure 9. Fraction images generated from MESMA using Landsat-5 TM image acquired on June, 2, 2000. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

(A)

(B)

(C)

(D)

Figure 10. Fraction images generated from MESMA using Landsat-5 TM image acquired on April, 27, 2010. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

4.2 SMA Model

In the SMA method, all training samples of endmembers (vegetation A, vegetation B, high albedo, low albedo, and soil) were obtained by PPI and manual selection. A shadow/shaded endmember was not added in this method, since it might decrease the accuracy of the components estimation. Results of fraction maps of the four primary physical components are shown in Figures 11-13, created with corresponding Landsat TM images acquired in 1990, 2000, and 2010. The brightness in vegetation and impervious surface fraction maps modeled by SMA was very similar to that produced by MESMA, although there were some differences in the soil fraction maps.

(A)

(B)

(C)

(D)

Figure 11. Fraction images generated from SMA using Landsat-5 TM image acquired on June, 7, 1990. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

(A)

(B)

(C)

(D)

Figure 12. Fraction images generated from SMA using Landsat-5 TM image acquired on June, 2, 2000. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

(A)

(B)

(C)

(D)

Figure 13. Fraction images generated from SMA using Landsat-5 TM image acquired on April, 27, 2010. Vegetation fraction map (A); impervious surface fraction map (B); soil fraction map (C); and water (D). Brighter areas indicate higher fractions, while darker areas indicate lower fractions.

4.3 Comparison between MESMA and SMA

In order to compare the performance of mapping the physical components between MESMA and SMA, accuracy assessment analyses were done using fine-resolution aerial photographs as reference images. Reference DOQQ aerial photographs acquired on March, 13, 2001 were the only ones available for assessing the accuracy of three major physical components created from 2000 Landsat TM image. A total of 36 sample units (30 m x30 m) were utilized in the accuracy assessment which used stratified random sampling. The sample sites consisted of two subsets: one was selected from the homogenous patches in order to decrease georeferencing errors; the other subset was selected from mixed pixels in the image which had equivalent variation of the three physical materials (vegetation, impervious surface, and soil). Since the spatial resolution of the reference image was 1 m there were 900 small units (1 m x 1 m) in the reference image of each sampled pixel from the TM image. The component fraction was visually interpreted from the reference image with the help of grid lines in ENVI. RMSE (Eq. (5)) was employed to assess the accuracy of modeled fractions with measured (interpreted) fractions. Table 6 shows the comparison results of the fraction estimations between MESMA and SMA. From the table, it is obvious from the lower RMSE that MESMA produced higher levels of accuracy than SMA when mapping the three physical components (vegetation, impervious surface and soil) at the sub-pixel level in the study area. The general conclusion that MEMSA has higher accuracy than SMA is supported by the results displayed in Figures 14 – 19 below.

A closer examination of the results (Figures 14 - 19), indicates that MESMA has produced an overestimation in the low to medium levels (0-68%) of vegetation areas (Figure 14A), while there is slight underestimation of the dense vegetation areas (RMSE = 0.033 for vegetation from MESMA). The overestimation is mainly due to shade effects in the vegetated areas, while the underestimation of vegetated areas is due to the complexity and diversity of vegetation spectra. The result shown in Figure 14 (B) suggest that simple SMA was also sensitive to the vegetation endmember, although some underestimation and overestimation were found for all samples (RSME = 0.050).

Figure 16 shows that, compared to SMA (RMSE = 0.079), MESMA (RMSE = 0.024) improved the ISA estimation accuracy through varying the number and type of endmembers from pixel to pixel. The overestimation of low ISA areas was obvious in SMA because a limited number of endmembers were available in this study. There might be some confusion between shaded non-ISA surfaces and low-albedo surfaces in the SMA process. If there were a sufficient number of representative endmembers to decrease this confusion, the accuracy of SMA in estimating ISA could be improved.

SMA was less sensitive than MESMA when modeling the soil component as shown in Figure 18(B). The overall RMSE was 0.104 in SMA, and its coefficient of determination (R^2) was 0.8260, while for MESMA, the RMSE was reduced to 0.04, and the corresponding coefficient of determination (R^2) was improved to 0.985. The residual plots in the Figure 19(B) show obvious underestimation and overestimation in the samples. It is possible that due to their similar spectral

signatures the shaded non-ISA surfaces (such as shaded soil) were confused with ISA surfaces. Photometric shade was not considered as an endmember to model material surfaces so shadow and shaded areas were difficult to accurately model in SMA. MESMA allowed the addition of a “photometric shade” endmember, improving its performance in this area.

Table 6. Comparison of fraction estimation accuracy between MESMA and simple SMA. (n=36)

	Components	Intercept	Slope	R ²	RMSE
MESMA	Vegetation	0.032	0.953	0.986	0.033
	Impervious	0.015	0.970	0.992	0.024
	Soil	-0.130	0.985	0.970	0.040
SMA	Vegetation	0.035	0.951	0.970	0.050
	Impervious	0.030	0.915	0.918	0.079
	Soil	-0.050	0.983	0.826	0.104

Notes: R²: Coefficient of Determination; RMSE: Root Mean Square Error;

Figure 14. Measured vegetation fraction values from aerial photographs against their modeled values by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

Figure 15. Residual plots with vegetation fraction values modeled by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

Figure 16. Measured impervious fraction values from aerial photographs against their modeled values by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

Figure 17. Residual plots with impervious fraction values modeled by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

Figure 18. Measured soil fraction values from aerial photographs against their modeled values by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

Figure 19. Residual plots with soil fraction values modeled by MESMA (A) and SMA (B) from the 2000 Landsat TM image.

4.4 Assessment of Urban Growth

In order to assess the patterns and intensity of urban growth in the City of Tampa, Florida during the past twenty years, ISA distribution maps derived from the TM images acquired in 1990, 2000, and 2010 were analyzed. From these ISA fraction images it is obvious that the %ISA in the study area consistently increased during the study period; from 14.08% in 1990 to 20.63% in 2000, and from 20.63% in 2000 to 27.31% (Table 7). This result indicates great changes to the landscape in the whole study area during the past two decades, especially near the University Square area. The average rate of the ISA fraction increase was 0.655%/year in the period of 1990-2000, and 0.668%/year in the period of 2000-2010. The consistent change rate in the study area during the two decade periods indicates a trend of steady increase. At the pixel scale of analysis, the result indicates an increase in the percentage of the number of pixels with an ISA fraction greater than 0, which has grown from 0.83% of the whole study area in the period between 1990-2000 to 0.71% in the period between 2000-2010.

Table 7. Percentage of ISA (%ISA) and the percentage of number of pixels with ISA fraction > 0 (%pixel-based ISA fraction > 0) in 1990, 2000, and 2010 TM images.

	1990	2000	2010
%ISA	14.08	20.63	27.31
% pixel-based ISA fraction > 0	49.4	50.23	57.24

The ISA fraction images were consistent with urban LULC distribution in the

study area. During the past twenty years, the percentage of low percent impervious surface decreased, while the percentage of moderate to high percent impervious surface increased (Figure 20). The percentage of areas with 0-10% ISA fraction decreased from 44.38% to 34.6%. The percentage of high percent impervious surface, such as 70-80%, 80-90%, and 90-100% ISA fraction, continuously increased. By calculating the ISA change for each pixel and then visualizing the ISA fraction maps, three regions with high percentages of impervious surface were identified: Tampa International Airport, downtown Tampa, and University Square (see Figure A4 in Appendices for their locations). After checking pixel counts for these areas of increased ISA during the past two decades, University Square underwent the greatest change among the three regions. Figures 21 - 23 demonstrate the %ISA changes in the study area from 1990 to 2010.

Figure 20. %ISA changes from 1990 to 2010

Figure 21. Distribution map of %ISA in the study area in 1990.

Figure 22. Distribution map of %ISA in the study area in 2000.

Figure 23. Distribution map of %ISA in the study area in 2010.

4.5 Urban Growth Analysis

In order to understand the relationship between urban growth and population augmentation, census data were used to evaluate the impact of human activities (population increase) on urban growth. Ninety-four tracts within the City of Tampa covered by the study were selected for urban growth case analysis (Figure 24).

Population and the %ISA of the 94 tracts were used to test the relationship between urban landscape composition change and population change.

Figure 24. Ninety-four tracts in the City of Tampa covered by the study area.

Table 8 suggests that the average population, population density (person/mile²), and %ISA in the 94 tracts have consistently increased from 1990 to 2010. The population in the 94 tracts was 387,473 in 1990, increasing to 426,290 in 2010. The average population in the 94 tracts increased from 4,122.05 in 1990 to 4,535.3 in 2010; an increase rate of 0.5%/year, although population levels in some tracts did decrease (Figure 25). The rapid population increase resulted in an obvious expansion of impervious surfaces during the past two decades, especially in and surrounding the University Square area. However, it was also found that the %ISA of some tracts increased while the population slightly

decreased (e.g. Downtown). These decreases of population and increase of impervious surface areas occurred in areas with especially high levels of ISA. This can be explained by the conversion of downtown residential areas to commercial purposes. Although the %ISA in these downtown areas increased greatly, the population decreased due to decreased residential space.

From Table 8 and Figure 26, it is evident that population density significantly increased from 1990 to 2010. The average increase rate of population density was 0.15%/year from 2000 to 2010, down slightly from 0.19%/year from 1990 to 2000. The greatest decrease of population density among the 94 tracts was tract “004000” (see A3), an area located in Downtown Tampa, where the population density declined from 11,731 (person/mile²) in 1990 to 875 (person/mile²) in 2010. In addition, the population density of some tracts in and surrounding the University Square area, such as ‘000100’, ‘000300’, and ‘010803’, were very high, and consistently increased from 1990 to 2010. According to the definition of urbanized areas by U.S. Census Bureau, these tracts can be considered as urbanized areas because the population density of the contiguous tracts is higher than 1,000 persons per square mile (see A3).

The results shown in the Figure 27 suggest that the number of tracts with relatively low %ISA (e.g. lower than 20%) decreased while the number of tracts with relatively high %ISA (e.g., higher than 44%) increased. It was also found that the %ISA increased for every tract from 1990 to 2010. To further demonstrate the increase of %ISA, the results of pixel-based %ISA of the 94 tracts are shown in Figure 28. The proportion of low to middle pixel-based %ISA (e.g., 0-20%, and

20-40%) went down from 1900 to 2010, while the proportion of high-pixel-based %ISA (e.g., 60-80%, and 80-100%) went up from 1990 to 2010. Therefore, population increases in these areas were directly associated with increased %ISA. Also, increased population directly relates to increased %ISA because anthropogenic activity causes increases in %ISA unless a geological process.

Table 8. Population, population density and the percentage of ISA in the 94 tracts from 1990 to 2010.

	POP		POPD		%ISA	
	Mean	Stdev	Mean	Stdev	Mean	Stdev
1990	4122.05	1911.42	4366.61	2093.90	21.21	7.02
2000	4329.03	2207.36	4451.51	2004.86	33.40	9.92
2010	4535.30	2392.90	4520.03	2077.68	42.39	11.37

Note: POP: Population; POPD: Population Density; Stdev: Standard Deviation.

Figure 25. Population changes in the 94 tracts from 1990 to 2010.

Figure 26. Population density changes in the 94 tracts from 1990 to 2010.

Figure 27. %ISA changes in the 94 tracts from 1990 to 2010.

Figure 28. %ISA changes (per-pixel based) in the 94 tracts from 1990 to 2010.

CHAPTER 5: CONCLUSIONS

In this study, impervious surface distribution together with vegetation and soil cover, have been directly derived from Landsat TM reflectance images by applying MESMA and SMA models. The experimental results demonstrated that MESMA had a higher capability of mapping physical components for estimating impervious surface and provided better performance than the traditional SMA. This can be explained by two reasons: (1) The MESMA approach allows the number and type of endmembers to vary in each pixel of the image. This gives it an advantage over SMA when modeling urban environments, because different types of land cover occur as complex features in a small area (Powell *et al.*, 2007; Myint and Okin, 2009). (2) Shade information and the specific information of the model can be easily traced in MESMA (Myint and Okin, 2009). In addition, MESMA was successfully applied in the study area of the City of Tampa and improved the accuracy of mapping physical components. This success was because (1) there were a sufficient number of spectra available to build a representative spectral library with the optimal number of endmembers present for each class; (2) the terrain of Tampa is relatively flat so that urban materials could be modeled with minimal shadow effects; and (3) photometric shade was considered as a fixed endmember for every model, which effectively decreased

the confusion between areas of low albedo and shade.

The urban environment of the City of Tampa, Florida, and its twenty-year change were assessed using ISA as an indicator. The results showed that Tampa has experienced great changes in the %ISA during the past twenty years. From 1990 to 2010, the %ISA expanded at an average rate of 0.66% per year. Some natural and protected landscapes were rapidly transformed into impervious surfaces. Specifically, the lower percentage of (0-10%ISA) impervious surface decreased by up to 10%, while the higher percentage (90-100%ISA) impervious surface increased by up to 5%. In order to understand the relationship between human activity and the landscapes' transformation, an urban growth case study was done. It found that overall population, population density, and the %ISA of areas within the study area all increased during the past two decades. At the tract level, every tract showed an increase of impervious surface area, and the population and population density of most tracts also increased. This underscores the linkage between increased population and the expansion of impervious surfaces, as rural and peripheral areas urbanized. However, the positive relationship between the population growth and increased %ISA did not always occur. For example, as some already urbanized areas in downtown Tampa increased their population density without increasing the %ISA. Therefore, human activity (notably by population increase) is the most important factor driving, the increase of the %ISA area and urban growth outward from the city center to peripheral areas.

The findings of this study in the City of Tampa show how important increases

in population numbers and density are in driving urban expansion into peripheral areas. In particular, the increase of population is consistent with the rapid transformation of landscapes in urban areas. Such a rapid urbanization (urban growth) in the urban environment may increase the numerous burdens on cities to provide services such as education, transportation, infrastructure, and physical security. Because of this, managed development through urban planning is essential to improve our living environment and our quality of life; promoting society's goals for a healthy and sustainable state in the economic, social, and political issues. Application of remote sensing techniques in the urban environment can provide a meaningful and efficient way of mapping and monitoring the changes in urban landscapes, especially the transformation of urban land use and land cover types. It is very significant for fostering the goals of environmental and human sustainability in cities, and can be applied in managing cities around the world.

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APPENDICES

A1. Accuracy assessment

A1.1 Vegetation accuracy assessment (MESMA Vs. Reference image)

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Actual ^b	.	Enter

a. Dependent Variable: Modeled

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.993 ^a	.986	.986	.032775652

a. Predictors: (Constant), Actual

b.

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.550	1	2.550	2373.796	.000 ^b
	Residual	.035	33	.001		
	Total	2.585	34			

a. Dependent Variable: Modeled

b. Predictors: (Constant), Actual

Coefficients^a

Model	Unstandardized Coefficients		Standardized Coefficients	t	Sig.
	B	Std. Error	Beta		
1 (Constant)	.032	.010		3.233	.003
Actual	.953	.020	.993	48.722	.000

a. Dependent Variable: Modeled

A1.2 Vegetation accuracy assessment (SMA Vs. Reference image)

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Actual ^b		.Enter

a. Dependent Variable: Modeled

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.985 ^a	.970	.969	.049905032

a. Predictors: (Constant), Actual

b. Dependent Variable: Modeled

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.694	1	2.694	1081.731	.000 ^b
	Residual	.085	34	.002		
	Total	2.779	35			

a. Dependent Variable: Modeled

b. Predictors: (Constant), Actual

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.035	.014		2.436	.020
	Actual	.951	.029	.985	32.890	.000

a. Dependent Variable: Modeled

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.03512889	.93866795	.42254244	.277440507	36
Residual	-.096949980	.176878929	0E-9	.049186936	36
Std. Predicted Value	-1.396	1.860	.000	1.000	36
Std. Residual	-1.943	3.544	.000	.986	36

a. Dependent Variable: Modeled

A1.3 Impervious accuracy assessment (MESMA Vs. Reference image)

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Actual ^b		.Enter

- a. Dependent Variable: Modeled
b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.996 ^a	.993	.992	.024198452

- a. Predictors: (Constant), Actual
b. Dependent Variable: Modeled

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.599	1	2.599	4438.274	.000 ^b
	Residual	.019	33	.001		
	Total	2.618	34			

- a. Dependent Variable: Modeled
b. Predictors: (Constant), Actual

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.015	.007		2.284	.029
	Actual	.970	.015	.996	66.620	.000

- a. Dependent Variable: Modeled

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.01486625	.98474050	.35211869	.276474574	35
Residual	-.077801391	.065435007	0E-9	.023839937	35
Std. Predicted Value	-1.220	2.288	.000	1.000	35
Std. Residual	-3.215	2.704	.000	.985	35

a. Dependent Variable: Modeled

A1.4 Impervious accuracy assessment (SMA Vs. Reference image)

Variables Entered/Removed^a

Mode	Variables Entered	Variables Removed	Method
1	Actual ^b	.	Enter

a. Dependent Variable: Modeled

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.958 ^a	.918	.915	.079323458

a. Predictors: (Constant), Actual

b. Dependent Variable: Modeled

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	2.314	1	2.314	367.736	.000 ^b
	Residual	.208	33	.006		
	Total	2.522	34			

a. Dependent Variable: Modeled

b. Predictors: (Constant), Actual

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	.030	.021		1.416	.166
	Actual	.915	.048	.958	19.176	.000

a. Dependent Variable: Modeled

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	.03021498	.94536179	.34843714	.260873835	35
Residual	-.40781328	.099747948	0E-9	.078148231	35
Std. Predicted Value	-1.220	2.288	.000	1.000	35
Std. Residual	-5.141	1.257	.000	.985	35

A1.5 Soil accuracy assessment (MESMA Vs. Reference image)

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Actual ^b		.Enter

a. Dependent Variable: Modeled

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.985 ^a	.970	.969	.039703448

a. Predictors: (Constant), Actual

b. Dependent Variable: Modeled

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.754	1	1.754	1112.846	.000 ^b
	Residual	.054	34	.002		
	Total	1.808	35			

a. Dependent Variable: Modeled

b. Predictors: (Constant), Actual

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.013	.010		-1.289	.206
	Actual	.985	.030	.985	33.359	.000

a. Dependent Variable: Modeled

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.01253854	.95232528	.22528803	.223878171	36
Residual	-.078043655	.086562894	0E-9	.039132145	36
Std. Predicted Value	-1.062	3.247	.000	1.000	36
Std. Residual	-1.966	2.180	.000	.986	36

A1.6 Soil accuracy assessment (SMA Vs. Reference image)

Variables Entered/Removed^a

Model	Variables Entered	Variables Removed	Method
1	Actual ^b		.Enter

a. Dependent Variable: Modeled

b. All requested variables entered.

Model Summary^b

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.909 ^a	.826	.821	.104081133

a. Predictors: (Constant), Actual

b. Dependent Variable: Modeled

ANOVA^a

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1.750	1	1.750	161.577	.000 ^b
	Residual	.368	34	.011		
	Total	2.119	35			

a. Dependent Variable: Modeled

b. Predictors: (Constant), Actual

Coefficients^a

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-.005	.025		-.191	.850
	Actual	.983	.077	.909	12.711	.000

a. Dependent Variable: Modeled

Residuals Statistics^a

	Minimum	Maximum	Mean	Std. Deviation	N
Predicted Value	-.00486249	.95892680	.23269922	.223628843	36
Residual	-.198932692	.496338367	0E-9	.102583485	36
Std. Predicted Value	-1.062	3.247	.000	1.000	36
Std. Residual	-1.911	4.769	.000	.986	36

a. Dependent Variable: Modeled

A2. ISA fraction distribution data

Table A 1. ISA fraction distribution data in the study area from 1990 to 2010

% ISA	1990	2000	2010
0-10	44.379	42.198	34.599
10-20	15.842	6.412	5.047
20-30	8.544	6.916	6.645
30-40	6.199	6.693	7.507
40-50	4.496	6.901	7.314
50-60	3.167	6.370	6.842
60-70	1.228	4.035	6.415
70-80	0.55	2.310	4.273
80-90	0.228	1.524	1.282
90-100	1.818	3.089	6.526

A3. Population and Population density (person/mile²) (94 census data by tract in the City of Tampa Florida from 1990-2010)

Tract	POP90	POP00	POP10	Area	POPD90	POPD00	POPD10
000100	6546	7754	9401	2.63	2488.97	2948.29	3574.52
000200	7118	8074	7621	1.15	6189.57	7020.87	6626.96
000300	6444	7228	8376	1.13	5702.65	6396.46	7412.39
000400	4562	4772	4793	1.52	3001.32	3139.47	3153.29
000500	3906	3859	3779	1.15	3396.52	3355.65	3286.09
000600	5821	6712	6547	1.03	5651.46	6516.50	6356.31
000700	6223	6308	5724	0.82	7589.02	7692.68	6980.49
000800	3135	3675	3264	1.02	3073.53	3602.94	3200.00
000900	5011	6614	7024	0.87	5759.77	7602.30	8073.56
001000	7408	7372	8457	2.20	3367.27	3350.91	3844.09
001100	2345	2345	2166	0.65	3607.69	3607.69	3332.31
001200	3269	2798	2879	0.54	6053.70	5181.48	5331.48
001300	5023	5440	5706	1.51	3326.49	3602.65	3778.81
001400	3790	4187	4462	0.93	4075.27	4502.15	4797.85
001500	2542	2554	2412	0.58	4382.76	4403.45	4158.62
001600	2141	1991	1923	0.51	4198.04	3903.92	3770.59
001700	4177	4272	4187	1.02	4095.10	4188.24	4104.90
001800	3521	3334	4129	0.93	3786.02	3584.95	4439.78
001900	3024	2647	2831	0.76	3978.95	3482.89	3725.00
002000	2532	2638	2729	0.50	5064.00	5276.00	5458.00
002100	2820	2939	2701	0.51	5529.41	5762.75	5296.08
002200	1800	1870	1580	0.50	3600.00	3740.00	3160.00
002300	2972	3160	3057	0.56	5307.14	5642.86	5458.93
002400	3821	4066	3792	0.93	4108.60	4372.04	4077.42
002500	5371	6293	6637	1.02	5265.69	6169.61	6506.86
002600	2426	2091	1784	6.52	372.09	320.71	273.62
002700	5984	6592	6888	1.36	4400.00	4847.06	5064.71
002800	2927	2913	2792	0.66	4434.85	4413.64	4230.30

002900	2308	2218	1922	0.51	4525.49	4349.02	3768.63
003000	3525	3526	2914	0.52	6778.85	6780.77	5603.85
003100	3631	2498	2673	0.51	7119.61	4898.04	5241.18
003200	2317	2569	2463	0.32	7240.63	8028.13	7696.88
003300	3400	1987	2063	0.32	10625.00	6209.38	6446.88
003400	3048	2388	3009	0.52	5861.54	4592.31	5786.54
003500	2722	2398	2416	0.63	4320.63	3806.35	3834.92
003600	3725	3753	4333	1.59	2342.77	2360.38	2725.16
003700	1842	3137	2014	3.56	517.42	881.18	565.73
003800	1370	1411	1047	0.83	1650.60	1700.00	1261.45
003900	1842	1660	1975	0.67	2749.25	2477.61	2947.76
004000	1877	1479	140	0.16	11731.25	9243.75	875.00
004100	1312	1176	1835	0.25	5248.00	4704.00	7340.00
004200	1499	1530	1055	0.40	3747.50	3825.00	2637.50
004300	3437	2988	3052	0.29	11851.72	10303.45	10524.14
004400	2266	2261	2071	0.37	6124.32	6110.81	5597.30
004500	3800	4076	4244	0.73	5205.48	5583.56	5813.70
004700	2609	2676	2245	0.71	3674.65	3769.01	3161.97
004800	4201	4300	3886	0.99	4243.43	4343.43	3925.25
004900	3158	3438	3982	0.70	4511.43	4911.43	5688.57
005000	3357	3184	5505	0.72	4662.50	4422.22	7645.83
005100	1454	2420	4667	1.05	1384.76	2304.76	4444.76
005300	2297	2203	3809	3.37	681.60	653.71	1130.27
005400	5634	5436	5465	1.36	4142.65	3997.06	4018.38
005500	1436	1597	1931	0.37	3881.08	4316.22	5218.92
005700	3792	4220	3670	0.68	5576.47	6205.88	5397.06
005800	4263	4356	4363	1.14	3739.47	3821.05	3827.19
006000	4609	4959	5271	1.27	3629.13	3904.72	4150.39
006100	6165	6652	6612	0.99	6227.27	6719.19	6678.79
006200	3373	3268	3526	0.66	5110.61	4951.52	5342.42
006300	3432	3531	3733	0.74	4637.84	4771.62	5044.59

006600	3796	3647	3736	0.78	4866.67	4675.64	4789.74
006700	4577	4903	5381	1.13	4050.44	4338.94	4761.95
006800	7296	7284	7503	1.40	5211.43	5202.86	5359.29
006985	4916	4999	5214	1.21	4062.81	4131.40	4309.09
007085	9903	6142	6656	1.38	7176.09	4450.72	4823.19
010203	2218	2019	1977	1.64	1352.44	1231.10	1205.49
010204	3625	3853	5024	1.71	2119.88	2253.22	2938.01
010401	4352	5206	5350	1.03	4225.24	5054.37	5194.17
010402	3091	4291	5094	4.07	759.46	1054.30	1251.60
010500	7744	7578	7152	1.68	4609.52	4510.71	4257.14
010600	3241	2666	3231	1.04	3116.35	2563.46	3106.73
010700	9322	9611	8831	2.43	3836.21	3955.14	3634.16
010803	4785	7775	9402	0.76	6296.05	10230.26	12371.05
010804	7835	10054	11651	2.97	2638.05	3385.19	3922.90
010805	2627	3643	4943	0.74	3550.00	4922.97	6679.73
010806	6095	8554	7506	1.03	5917.48	8304.85	7287.38
010807	7483	7741	8202	0.99	7558.59	7819.19	8284.85
010808	2786	3023	2956	0.41	6795.12	7373.17	7209.76
010900	3062	2541	5160	2.42	1265.29	1050.00	2132.23
011003	3643	4537	4520	2.03	1794.58	2234.98	2226.60
011203	3612	3420	3008	0.84	4300.00	4071.43	3580.95
011204	6252	6194	6029	1.60	3907.50	3871.25	3768.13
011205	2391	2666	2697	0.91	2627.47	2929.67	2963.74
011206	2802	2798	2852	0.78	3592.31	3587.18	3656.41
011301	3529	3108	3041	1.12	3150.89	2775.00	2715.18
011302	7475	8262	8061	2.36	3167.37	3500.85	3415.68
011603	3995	3911	4107	1.25	3196.00	3128.80	3285.60
011605	6123	6043	6748	3.21	1907.48	1882.55	2102.18
011801	7808	11277	12387	2.23	3501.35	5056.95	5554.71
011802	6528	6734	6670	1.27	5140.16	5302.36	5251.97
011901	3971	4224	4746	0.82	4842.68	5151.22	5787.80

011902	6544	6482	7183	1.36	4811.76	4766.18	5281.62
011903	6833	7625	7604	1.05	6507.62	7261.90	7241.90
012001	3031	2692	2511	2.84	1067.25	947.89	884.15
012002	3822	3633	3652	1.92	1990.63	1892.19	1902.08
SUM	392767	412436	432180	116.28	3377.77	3546.92	3716.72

Census data sources (All the tract number based on the criteria of tracts in 1990):

1990 census data :

(<http://www.census.gov/geo/www/ezstate/FL.pdf>)

2000 census data :

(http://www.census.gov/geo/www/cenpop/tract/tract_pop.txt)

2010 census data :

(http://www.census.gov/geo/www/2010census/centerpop2010/tract/CenPop2010_Mean_TR12.txt)

**A4. ISA fraction changes (94 census data by tract in the City of Tampa
Florida from 1990-2010)**

Tract	%ISA-90	%ISA-00	%ISA-10	%ISAC (90-00)	%ISAC (00-10)
000100	24.21	35.50	44.62	11.29	9.12
000200	26.13	42.93	54.03	16.80	11.10
000300	16.21	28.66	42.04	12.45	13.38
000400	28.60	39.98	50.47	11.38	10.49
000500	10.87	22.18	31.33	11.31	9.15
000600	19.79	33.11	43.74	13.32	10.63
000700	15.15	24.01	36.19	8.86	12.18
000800	14.69	23.12	27.83	8.43	4.71
000900	17.27	26.83	35.77	9.56	8.94
001000	14.92	24.12	30.25	9.20	6.13
001100	11.34	17.04	25.10	5.70	8.06
001200	17.82	25.14	39.19	7.32	14.05
001300	18.49	27.90	39.26	9.41	11.36
001400	13.64	25.05	34.74	11.41	9.69
001500	12.55	24.43	33.23	11.88	8.80
001600	21.36	33.11	50.46	11.75	17.35
001700	14.82	24.03	32.90	9.21	8.87
001800	20.11	28.00	40.13	7.89	12.13
001900	21.83	32.97	46.71	11.14	13.74
002000	14.08	26.52	37.58	12.44	11.06
002100	13.71	27.13	38.38	13.42	11.25
002200	24.91	35.61	53.90	10.70	18.29
002300	18.21	29.99	37.44	11.78	7.45
002400	19.82	33.12	39.93	13.30	6.81
002500	23.12	42.79	48.43	19.67	5.64
002600	26.38	39.89	46.17	13.51	6.28
002700	23.80	41.55	51.44	17.75	9.89
002800	15.52	28.09	35.36	12.57	7.27
002900	17.91	29.93	41.88	12.02	11.95
003000	26.20	39.27	49.45	13.07	10.18
003100	22.94	37.02	51.85	14.08	14.83
003200	27.77	44.46	57.32	16.69	12.86
003300	33.09	48.26	66.44	15.17	18.18
003400	21.30	32.82	43.90	11.52	11.08
003500	24.12	36.14	45.08	12.02	8.94
003600	20.94	31.56	40.79	10.62	9.23
003700	26.18	34.92	41.12	8.74	6.20
003800	35.14	49.01	59.14	13.87	10.13

003900	40.79	54.14	68.74	13.35	14.60
004000	34.15	45.68	52.87	11.53	7.19
004100	30.30	44.16	55.55	13.86	11.39
004200	26.97	41.89	49.95	14.92	8.06
004300	25.18	40.21	49.37	15.03	9.16
004400	29.51	47.85	61.28	18.34	13.43
004500	25.60	42.14	56.43	16.54	14.29
004700	35.00	51.91	57.56	16.91	5.65
004800	27.53	43.27	55.59	15.74	12.32
004900	34.48	53.47	65.71	18.99	12.24
005000	37.04	53.93	61.47	16.89	7.54
005100	34.32	50.03	52.01	15.71	1.98
005300	25.68	31.12	34.90	5.44	3.78
005400	18.27	30.74	32.02	12.47	1.28
005500	33.14	55.38	59.95	22.24	4.57
005700	27.49	44.68	52.01	17.19	7.33
005800	27.24	36.77	48.73	9.53	11.96
006000	19.52	33.43	38.39	13.91	4.96
006100	10.41	17.81	19.88	7.40	2.07
006200	22.37	35.76	48.95	13.39	13.19
006300	18.85	32.26	47.16	13.41	14.90
006600	27.67	34.21	52.16	6.54	17.95
006700	17.91	27.08	36.31	9.17	9.23
006800	16.72	28.89	35.65	12.17	6.76
006985	11.54	21.33	25.23	9.79	3.90
007085	26.71	33.19	47.41	6.48	14.22
010203	7.54	8.86	15.98	1.32	7.12
010204	11.27	16.68	24.29	5.41	7.61
010401	15.02	21.65	29.91	6.63	8.26
010402	15.92	23.72	30.20	7.80	6.48
010500	20.25	29.04	36.55	8.79	7.51
010600	13.64	22.49	25.93	8.85	3.44
010700	16.28	24.09	31.69	7.81	7.60
010803	22.88	43.07	49.77	20.19	6.70
010804	10.96	20.07	29.69	9.11	9.62
010805	27.07	38.94	52.46	11.87	13.52
010806	28.68	51.90	58.56	23.22	6.66
010807	24.75	37.53	47.85	12.78	10.32
010808	22.56	46.92	54.65	24.36	7.73
010900	13.90	23.60	29.97	9.70	6.37
011003	12.28	16.89	23.97	4.61	7.08

011203	12.43	19.69	22.92	7.26	3.23
011204	17.65	27.15	34.24	9.50	7.09
011205	12.21	22.15	28.06	9.94	5.91
011206	18.53	29.54	38.09	11.01	8.55
011301	15.45	28.14	29.95	12.69	1.81
011302	15.64	28.95	31.33	13.31	2.38
011603	14.76	28.16	33.16	13.40	5.00
011605	24.65	39.89	45.21	15.24	5.32
011801	19.13	32.97	36.98	13.84	4.01
011802	23.69	41.64	51.28	17.95	9.64
011901	21.18	33.51	36.74	12.33	3.23
011902	18.29	35.98	41.42	17.69	5.44
011903	18.39	33.82	41.95	15.43	8.13
012001	21.89	29.72	39.67	7.83	9.95
012002	17.26	25.69	33.47	8.43	7.78
SUM	15.57	23.87	30.11	8.30	6.24

A5. ISA fraction (94 census data by tract in the City of Tampa Florida from 1990-2010)

Figure A 1. %ISA of the 94 tracts covered by the study area in the City of Tampa in 1990.

Figure A 2. %ISA of the 94 tracts covered by the study area in the City of Tampa in 2000.

Figure A 3. %ISA of the 94 tracts covered by the study area in the City of Tampa in 2010.

A6. Abbreviation

DOQQ	Digital Orthophoto Quarter Quads
FLAASH	Fast Line-of-Sight Atmospheric Analysis of Spectral Hypercubes
ISA	Impervious Surface Area
LC	Land Cover
LSMA	Linear Spectral Mixture Analysis
LULC	Land Use and Land Cover
MESMA	Multiple Endmember Spectral Mixture Analysis
NSMA	Normalized Spectral Mixture Analysis
PNMESMA	Pre-screened and Normalized Multiple Endmember
RMSE	Spectral Mixture Analysis
SMA	Spectral Mixture Analysis
Stdev	Standard Deviation
TM	Thematic Mapper
USGS	United States Geological Survey

A7. Location of three high percentage of impervious surface places in the study area

Figure A 4. Location of University Square (A), Downtown (B), and International Airport (C).