An object-based image analysis approach for detecting urban impervious surfaces

Amit Kulkarni
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AN OBJECT-BASED IMAGE ANALYSIS APPROACH FOR DETECTING URBAN IMPERVIOUS SURFACES

A Dissertation

Submitted to the Graduate Faculty of the Louisiana State University and Agricultural and Mechanical College in partial fulfillment of the requirements for the degree of Doctor of Philosophy

in

The Department of Geography and Anthropology

by

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B.E., University of Pune, 1997
M.S., Louisiana State University, and Agricultural and Mechanical College, 2004
December 2012
DEDICATION

This is dedicated to my beloved pilloo. You have taught us a lot, may we all meet in our next life, and put what you have taught us to good use.
ACKNOWLEDGEMENTS

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ABSTRACT

Impervious surfaces are manmade surfaces which are highly resistant to infiltration of water. Previous attempts to classify impervious surfaces from high spatial resolution imagery with pixel-based techniques have proven to be unsuitable for automated classification because of its high spectral variability and complex land covers in urban areas. Accurate and rapid classification of impervious surfaces would help in emergency management after extreme events like flooding, earthquakes, fires, tsunami, and hurricanes, by providing quick estimates and updated maps for emergency response. The objectives of this study were to: (1) compare classification accuracy between pixel-based and OBIA methods, (2) examine whether the object-based image analysis (OBIA) could better detect urban impervious surfaces, and (3) develop an automated, generalized OBIA classification method for impervious surfaces.

This study analyzed urban impervious surfaces using a 1-meter spatial resolution, four band Digital Orthophoto Quarter Quad (DOQQ) aerial imagery of downtown New Orleans, Louisiana taken as part of post Hurricane Katrina and Rita dataset. The study compared the traditional pixel-based classification with four variations of the rule-based OBIA approach for classification accuracy. A four-class classification scheme was used for the analysis, including impervious surfaces, vegetation, shadow, and water. The results show that OBIA accuracy ranges from 85.33% through 91.41% compared with 80.67% classification accuracy from using the pixel-based approach. OBIA rule-based method 4 utilizing a multi-resolution segmentation approach and derived spectral indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and the Spectral Shape Index (SSI) was the best method, yielding a 91.41% classification accuracy. OBIA rule-based method 4 can be automated and generalized for multiple study areas. A test of the segmentation parameters show that parameter values of scale ≤ 20, color/shape ranging from 0.1 - 0.3, and compactness/smoothness ranging from 0.4 - 0.6 yielded the highest classification accuracies. These results show that the developed OBIA method was accurate, generalizable, and capable of automation for the classification of urban impervious surfaces.
CHAPTER 1: INTRODUCTION

1.1 Problem Statement

Urban areas are often exploding centers of growth, and due to their growth and budgetary concerns, GIS along with remote sensing is an effective way for mapping, updating, planning, and management. Urban growth leads to growth in impervious surfaces. Impervious surfaces are all artificial or manmade surfaces which are highly resistant to infiltration of water. Impervious surfaces are a key proxy in assessing the health of urban land use/land cover (LULC) environments because of the myriad ways they affect the urban landscape (Yang et al., 2003). Urban impervious surface detection using remote sensing with high spatial resolution imagery is difficult due to spectral, temporal, and spatial variations of urban areas. Examples of spatial variations are the location of moving objects like vehicles, while temporal variations are the normal seasonal variations in plant growth. Examples of spectral variations are the presence of shadows and the presence of unknown or mixed pixels which are considered as statistical noise. Automated mapping of impervious surfaces with reasonable accuracy in an urban environment is one of the most difficult issues which has still not been addressed completely using remote sensing (Blaschke, 2010). Blaschke (2010) stated that automation in the process of classification is currently achieved in a stepwise manner, with only part of the workflow favorable to automation.

This study investigates possible avenues for automation and assesses the current bottlenecks during processing of imagery using Object-Based Imagery Analysis (OBIA). OBIA incorporates spectral and spatial information in its analysis. OBIA also operates at a better defined level of image objects, which consist of multiple pixels grouped according to a set of pre-defined criteria rather than single pixels used in pixel-based classification. Since most remote sensing land cover detection analysis is inherently an approximation or a snapshot of current reality, if a generic and fast classification with reasonable accuracy is available for impervious surface mapping and its subsequent temporal change detection, it will result in a quicker turnaround analysis of urban environments. Fast and accurate analysis is especially useful in emergency management for natural
hazards like flooding, earthquakes, fires, tsunami, and hurricanes when accurate LULC maps are needed. This study also highlights and summarizes the problems faced in creating frequent and detailed LULC maps of urban impervious surfaces.

New Orleans, Louisiana, was chosen for this study due to its economic importance, and constant threats from the natural hazards of flooding and hurricanes. The city of New Orleans is situated at the mouth of Mississippi delta between Lake Pontchartrain to the north, Lake Borgne to the east, and Lake Cataouatche and Lake Salvador to the south. The Mississippi River travels through the City of New Orleans, and a large area of wetlands to the south/southeast (Source: Google Maps, 2012). Most of the City of New Orleans is below sea level. Having a large percentage of impervious surfaces generally prolongs the peak flow immediately after a major flood event (Hawley & Bledsoe, 2011). Hurricane Katrina devastated New Orleans and caused major damage following its landfall and subsequent levee breakage across the Mississippi River. If a procedure can be used quickly to analyze where the major damage has occurred, after a hurricane impact, based on where the impervious surfaces are situated, it can help guide policy makers to shift resources quickly and minimize detrimental impacts of such events. Federal Emergency Management Agency (FEMA) has a product called Flood Insurance Rate Map (FIRM) which produces a flood map used for calculating the flood insurance for flood-prone areas (Crowell et al., 2007). These FIRMs are used by private insurance companies as well as the US government for insured compensation after flood damage. The need to have good impervious surface estimates is critical because the most important constituents of the regression equations used in the generation of FEMA FIRMs for urban areas are the impervious surface estimates and speed of drainage (United States Geological Survey, 2006). But these maps are updated slowly for large urban areas, which experience such rapid change that automation in this process is truly needed.

1.2 Research Objectives

In general, remote sensing and associated spatial analysis suffers from the Modifiable Area Unit Problem (MAUP), also called the scale problem, due to the inherent nature of the landscape and
that geographic phenomena occur at different scales (Lam & Quattrochi, 1992). So, a multi-scale approach to formation of image objects from the pixels is needed and will be tested by this study. A fully automated and reproducible impervious surface classification for flood vulnerability prediction using high spatial resolution imagery and the object-based approach has not been fully explored in existing literature. Specifically, the objectives of this study are:

1. to compare the classification accuracy and efficiency between the traditional pixel-based classification and OBIA for identifying urban impervious surfaces.
2. to determine whether OBIA in combination with high spatial resolution imagery was effective for the detection of heterogeneous urban impervious surfaces.
3. to investigate the potential for automation and generalization of the OBIA method by deriving the ruleset for classifying impervious surfaces in different urban areas by identifying the prerequisites and parameters needed for achieving it.

1.3 Hypotheses

The hypotheses of this study are:

1. OBIA yields a higher classification accuracy compared to pixel-based maximum likelihood classification using high spatial resolution imagery.
2. OBIA can discriminate with high accuracy among different types of urban land covers from high resolution images: specifically vegetation, impervious surfaces, shadows, and water.
3. A ruleset can be developed in OBIA for automated and generic classification with reasonable accuracy.

1.4 Significance

IKONOS and QuickBird satellites were launched around the year 2000, followed some years later with very high resolution aerial imagery and high resolution LIDAR elevation data. These developments represent a quantum leap in information available for analysis. With the reduction in manual surveying techniques, remote sensing is the only viable alternative for updating GIS
databases. Current urban GIS databases consisting of roads, building footprints, vegetation areas, and other layers need to be updated frequently due to the rapid changes of urbanization. There is an increasing need to derive tangible image objects which can be imported in a GIS-ready form from the many images available for a particular area (Blaschke, 2010). This study will document the problems complicating the automated classification of impervious surfaces in urban areas. The main reason hindering automated classification in urban areas will also be highlighted and explored. The OBIA ruleset developed from this study can be applied to similar imaging sensors, similar applications, and similar elevations at different geographic locations, with reasonable classification accuracy. Extending the proposed methodology by further identification of indices which are useful for automation would also lead to robustness and widespread use for urban monitoring and planning for future development.

Automated detection of impervious surfaces is useful for emergency management after extreme events like flooding, earthquakes, fires, tsunami, and hurricanes, by providing quick estimates and updated maps for emergency response. It is well-known that the amount of runoff in an urban watershed is heavily determined by the percentage of impervious surfaces in urban areas (Brabec et al., 2002; United States Geological Survey, 2006; Erickson & Stefan, 2009; Goldshleger et al., 2009). In some restricted cases of modeling studies, the runoff coefficient can be taken equal to the percentage of the impervious area (Soulis et al., 2009). The total urban impervious surface cover as a percentage of land cover for a country is usually low. But the harmful effects of impervious surfaces on aquatic ecosystems are disproportionate. This dissertation estimates the magnitude, spatial distribution of the impervious surface area and the permeable surface area (vegetation), which are important in a range of issues in global change research (Weng, 2012). This impervious surface data in conjunction with elevation data is useful for approximating the hydrological analysis of the study area. For example, the findings can be used to determine the infiltration capacity of a watershed and the time required to exceed the infiltration capacity of the watershed.
1.5 Dissertation Outline

The current chapter provided an overview of this research including the objectives, hypotheses, and expected significance. Chapter 2 is the literature review of the importance of impervious surfaces, previous studies of urban areas and impervious surfaces using remote sensing, the justification of remote sensing for impervious surface detection, and review of OBIA method. Chapter 3 describes the detailed procedures used to develop a simple and reproducible method for impervious surface detection using the OBIA method. It also lists the procedures followed to cross-check its accuracy with pixel-based classification. Chapter 4 discusses the accuracy assessment results of different classifications and an overall summary of results for each of the four LULC classes. Chapter 5 lists the effects of different segmentation parameters and its influence on the final classification accuracy of imagery. Chapter 6 summarizes the findings of this study, limitations of current approaches and lists some possibilities for further research.
CHAPTER 2: LITERATURE REVIEW

2.1 Importance of Urban Impervious Surfaces

In many parts of the world, economic growth as measured by gross domestic product (GDP) is now concentrated in cities. From a bird’s eye view, most urban growth looks to be composed of impervious surfaces. Impervious surfaces include roads, driveways, sidewalks, buildings, rooftops, parking lots, airport runways, and other artificially constructed surfaces which resist infiltration of water (Small, 2002). Impervious surfaces are usually a thin artificial layer of either concrete or asphalt over natural soils. Figure 2.1 lists some examples of impervious surfaces.

In the early period of the 21st century, combating urban sprawl from inner cities to suburbs is a troubling topic for city planners. Urban sprawl happens because of an increase in suburban population and is usually spread in both the horizontal direction as subdivisions and the vertical direction as skyscrapers. This population increase happens due to the increasing automation of agriculture, causing heavy migration from rural areas for better job opportunities, necessity of acquiring education, better health facilities, and continuous integration into the modern economy (Kaya, 2007). Although the total area occupied by cities and their suburbs is small compared to rural regions, cities house more than half the global population (Small, 2002). A major consequence of suburban sprawl and urbanization for a city is the permanent reduction of its infiltration capacity due to growth in impervious surfaces. The dominant attitude in past urban architecture was to engineer impervious surfaces for achieving economic growth, and de-emphasize natural alternatives of handling runoff (Holman-Dodds et al., 2003).

Impervious surfaces are the most important and dominating LULC type in the urban and suburban environments, and are emerging environmental indicators of its terrestrial and aquatic health (Yang et al., 2003). During a storm, because urban surfaces are mostly impervious and channeled by manmade storm water drains, runoff is increased by a large amount; this excess runoff is usually gathered in big cities in far off detention basins or lagoons for slow infiltration for the watershed (Holman-Dodds et al., 2003; Hogan & Walbridge, 2007; Brodie et al., 2010).
Figure 2.1: Examples of Impervious Surfaces
(Sources: last accessed April 19, 2012)
(a) http://www.techprosecurity.com/security-articles/wp-content/uploads/2010/05/Parking-Lot.jpg
(b) http://images.picturesdepot.com/photo/a/airport_runway_wallpaper-28818.jpg
(c) http://www.highpointpark.org/wp-content/uploads/2010/01/Copy-of-IMG_0286-1024x768.jpg
(d) http://www.goldsmithheckengineers.com/image/cache/IMG_0433.JPG)
Urbanization and impervious surfaces can cause major flooding during rains due to lack of infiltration (Kamini et al., 2006). The excess runoff due to impervious surfaces is often much polluted and contains elevated levels of toxic metals (Fulkerson et al., 2007; Roberts et al., 2009). This is partially because impervious surfaces are not natural soils where helpful bacteria can break down the waste into simpler constituents for eventual absorption into soil. Changes in land use due to impervious surface cover will completely alter the dynamics of organic matter decomposition, which is an important measure of ecosystem function (Chadwick et al., 2006). Due to changes in organic matter content caused by impervious surfaces, there is a change in dissolved organic carbon content, which affects the formation of certain strains of bacteria which help in decomposition and pollution control (Harbott & Grace, 2005).

Impervious surfaces also allow environmental problems to build up and affect other areas. Sometimes due to capacity overload of wastewater treatment plants, this polluted runoff is often left untreated as raw sewage and discharged directly into catchment basins (Passerat et al., 2011). Since this runoff is discharged directly into adjoining water bodies, the pollutants degrade the resulting water quality. It is often found in the increased counts of fecal indicator bacteria: salmonella, and Escherichia coli (E.coli) (Walters et al., 2011). These increased bacteria counts also impact aquatic life negatively due to reduced biochemical oxygen demand (BOD) and ultimately impact human health via fish consumption (Fulkerson et al., 2007; Walters et al., 2011). Runoff due to impervious surfaces can alter physical, chemical, and biological attributes of surrounding stream ecosystems (Morse et al., 2003; Chadwick et al., 2006). With less ground-water available for recharge in urban areas, water flow in urban fed streams often decreases, which causes unforeseen changes in a stream’s natural balance, leading to increasingly severe problems, due to positive feedback (Johnson, 2004). As a result, most urban areas often have urban stream systems which remain dry for most of the year due to absence of natural recharge and ultimately have to depend on sewage for flow. This sewage flow into urban streams is due to intentional discharge of pollutants in natural flow systems. It is imperative to focus on recharge of water table because impervious surfaces reduce the rate of natural hydrological recharge. An inverse relationship exists between the measured percentage of
impervious surfaces and the environmental problems experienced by urban areas (Johnson, 2004). To summarize, the quantity of surface water runoff is increased and the quality of groundwater recharge is decreased by urban impervious surfaces (Erickson & Stefan, 2009).

Another effect of urban development on natural ecosystems is that the expansion of impervious surfaces often comes at the expense of vegetation. When the decrease of vegetation is compared with the percentage of rainfall that becomes runoff, its link to the increased flooding is apparent (Khan, 2005). In combination with blocked drains, such urbanization effects frequently cause flash flooding. The effect is common but is often a poorly understood feature of urban environments. Much of the uncertainty associated with predicting such urban flash flooding events is due to a lack of updated hydrological data. This limits the understanding of the overall health and current status of the watershed under consideration. A combined hydrological model that is based on land cover data derived from remote sensing, as well as watershed and soil properties derived from modeling, can be used to predict the flooding risk from large and sustained peak flows in extreme rainfall events (Foody et al., 2004). Foody et al. (2004) successfully predicted two vulnerable locations within their study area where a large peak discharge could negatively affect those areas. Various models are used for predicting impervious surfaces indirectly by predicting flood parameters such as Water and Energy Transfer between Soil, Plants and Atmosphere (WetSpa), SPAtially Referenced Regressions On Watershed attributes (SPARROW), and Vegetation-Impervious Surface-Soil (V-I-S) (Chormanski et al., 2008; Montzka et al., 2008; Roberts et al., 2009; Weng & Lu, 2009).

A total percentage of impervious surface area of 5-6% is considered to be the critical threshold for stream degradation around urban areas (Morse et al., 2003; Slonecker & Tilley, 2004; Schiff & Benoit, 2007). Erickson & Stefan (2009) found that an increase of 18% in impervious surface area may decrease the surrounding watershed recharge between 20 to 40% of its initial value. Goldshleger et al. (2009) found no major change in runoff for 20% or less impervious surface area, an increase in runoff was found with 20% - 40% impervious surface area, and a guaranteed increase in runoff occurred above 40% impervious surface area. This increased runoff raises flooding vulnerability.
Because impervious surfaces are a good indicator of urban development, imperviousness can be used for investigating socioeconomic factors such as population estimation, population density estimation, flooding, standard of living, and other social conditions (Wu & Murray, 2003; Li & Weng, 2007; Goldshleger et al., 2009). Impervious surfaces, which trap heat during the day and release heat during night, are also useful indicators for urban heat island effects (Yuan & Bauer, 2007). Detection of impervious surfaces is useful in a wide range of urban studies including but not limited to: urban hydrology lifecycle management, urban flooding, watershed management, water quality, urban climate, urban pollution, urban health, urban heat island effects, land use planning, population estimation, urban traffic analysis, and various other resource management indicators (Goetz et al., 2003; Wu & Murray, 2003; Slonecker & Tilley, 2004; Chadwick et al., 2006; Kamini et al., 2006; Toth & Grejner-Brzezinska, 2006; Fulkerson et al., 2007; Schiff & Benoit, 2007; Yuan & Bauer, 2007). Impervious surfaces are not only a critical element in urban sprawl quantification, but also in other natural science applications including forest watershed assessment, marine outflow detection, and other ecological uses (Goetz et al., 2003; Ellis et al., 2006; Xu & Gong, 2007).

The best economical solution to reduce runoff in urban areas and lessen the impact of impervious surfaces is to make use of vegetated green roofs on top of certain flat impervious surfaces such as buildings (Getter & Rowe, 2006). These green roofs efficiently trap, retain, and slowly release storm water compared to conventional roofs (Carter & Rasmussen, 2006). It is also important to design and construct the urban sprawl around existing vegetation instead of cutting down all trees. This allows the soil to “breathe” and slowly recharges the water table. Some of the strategic initiatives available to urban planners are:

1. Design and planting more trees (Volder et al., 2009).
2. Use of permeable concrete, also called green concrete (Volder et al., 2009; Glavind, 2011).
3. Use of aesthetic green roofs for reduced runoff (VanWoert et al., 2005; Schroll et al., 2011).
4. Use of green roofs in urban agriculture (VanWoert et al., 2005; Carter & Rasmussen, 2006).
5. Use of constructed urban wetlands also called “living machines”, for controlling water pollution by phytoremediation (Persson et al., 1999; Harrington & McInnes, 2009).
All or a combination of these strategies should be implemented for reducing the harmful effects of impervious surfaces. Civil engineers are testing the usage of pollution-reducing building materials (Ford, 2010) and developing semi-permeable solutions for impervious surfaces by the National Ready Mixed Concrete Association (Volder et al., 2009; NRMCA, 2012). Figures 2.2, 2.3, 2.4, 2.5, and 2.6 show some strategies useful for reducing the harmful effects of impervious surfaces.

### 2.2 Remote Sensing of Urban Areas

It has been demonstrated that remote sensing is cost effective for urban planning (Yu & Ng, 2007). Even though urban remote sensing is a powerful tool, mapping and change detection in urban areas is difficult because anthropogenic processes operate at widely varying space and time scales (Aplin, 2006). Currently, remote sensing alone cannot replace traditional and manual methods of observation because the temporal sampling interval of the available imagery in a urban planning department is inadequate for fast growing urban areas. Costs for traditional surveying approaches far exceed the total costs of modeling using an integrated remote sensing based approach. Furthermore, for performing frequent updates, cost for the remote sensing approach will drop once this approach is evaluated by policy makers to be cost-effective and enjoys economies of scale pricing. But even if cost alone is not considered, remote sensing-based mapping and change detection analysis is difficult to complete in a timely manner due to other issues: shortage of trained personnel, escalating storage and computing costs to store and analyze remote sensing imagery, correlation of existing dataset with new data, and most importantly lack of reliable automation tools in the work flow to shorten processing times. To illustrate the final issue, a previous LULC analysis may not have been performed, while newer remote sensing imagery has been purchased. A simple update of the urban database between imagery from two different dates may require a significant amount of time because of different projections, quality control issues, disappearance of former features, name changes of roads or other features. These scale, time, space, and logistical issues require proper planning to update LULC information. Innovation is needed to reduce complications arising from these issues and simplify current GIS workflow issues (Aplin, 2006).
Since the launch of IKONOS (derived from the Greek word for image) and QuickBird satellites in the early 2000s, the general trend in remote sensing is toward an increase in the spatial and radiometric resolution of imagery. These modern satellites have image quality which is vastly superior to older-generation satellites. Traditionally, weather-focused satellites had high radiometric resolution, while satellites designed for LULC had high spatial resolution for clear visual interpretation. However, these new-generation satellites have managed to increase both radiometric and spatial resolutions, thus refining their mapping and change detection analyses (Fiete, 2007). An increase in spatial and radiometric resolutions along with increasing commercialization of remote sensing and integration of newer methods from other similar fields like medical image analysis and computer vision has resulted in a flurry of new classification approaches, while also coinciding with the increase in available computing power.

Figure 2.2: Reducing Effects of Impervious Surfaces: Vertical Wall Garden

The high volume and complexity of images requires an automated approach for classification and an increased level of sophistication in image processing (Im et al., 2008). Recent remote sensing
Figure 2.3: Reducing Effects of Impervious Surfaces: Green Roof @ Chicago City Hall

Figure 2.4: Reducing Effects of Impervious Surfaces: Urban Agriculture
Figure 2.5: Reducing Effects of Impervious Surfaces: Urban Wetland in South Los Angeles (Source: http://cdn.archinect.net/images/514x/3z/3zxjt0sq32vu1d8y.jpg, last accessed April 19, 2012)

Figure 2.6: Reducing Effects of Impervious Surfaces: Permeable Concrete at EPA HQ (Source: http://pcj.typepad.com/photos/uncategorized/2007/07/20/dc_epa_permeable_concrete_path.jpg, last accessed April 19, 2012)
literature abounds with new classification methods for approaching automation such as artificial neural networks, knowledge-based or decision trees, rough sets, fuzzy, wavelet, markov random fields, support vector machines, and OBIA (Zhang & Foody, 2001; Im & Jensen, 2005; Leung et al., 2007; Luo et al., 2007; Meher et al., 2007; Hu & Weng, 2009; Weng et al., 2009).

Most of these pixel-based classification methods, with high spatial resolution imagery, have documented problems in urban area classification, and are not true representations of geographical objects due to confusion between LULC categories (Fisher, 1997; Weng & Lu, 2009). This stems from the fact that accurate pixel-to-pixel correlation using geometric rectification is difficult in most medium to low spatial resolutions, due to presence of mixed pixels and lack of discernible GPS tie points, causing errors in hard classification among different LULC classes (Townshend et al., 2000; Weng & Lu, 2009). Errors in classification also arise because a large proportion of information noise is coming from surrounding pixels due to porous transition boundaries, leading to a fairly low signal to noise ratio (Zhou, 2006; Im et al., 2008). Various studies have reported that misclassification is present when utilizing high spatial resolution and a maximum likelihood classifier (MLC) in heterogeneous urban environments (Zhou, 2006). Also, with high spatial resolutions, traditional pixel-based classification techniques may not be as successful as the classification of the previous generation of sensors. This may be either due to high frequency of transitional classes, horizontal stretching caused by off-nadir look angles, and within-class statistical variance (Blaschke & Strobl, 2001; Zhou, 2006; Im et al., 2008). With increasing spatial, spectral, and radiometric resolutions in recent remote sensing images and their increased use in urban studies, urban areas will be recognizable as spectral entities having geometric shape and texture (Addink et al., 2007).

2.3 Remote Sensing of Urban Impervious Surfaces

A number of remote sensing studies have been conducted to assess and report the harmful effects of impervious surfaces on urban ecology all over the world (Yang et al., 2003). Although many urban environmental measures used for urban planning can be measured manually, some are particularly suitable for remote sensing, in part because remote sensing measures reflected light,
which is directly related to the reflectance from urban surface features (Yu & Ng, 2007). Impervious surfaces are so important for environmental planning purposes that these are identified as one of the major land cover components in the National Land Cover database (NLCD) 2000 dataset (Yang et al., 2003; Smith et al., 2010). Urban impervious surface detection is difficult using remote sensing due to the sharp spectral and temporal variations in reflectance of urban areas (Yu & Ng, 2007). In general, urban downtown areas are substantially different from suburban or rural areas in form and density, with higher fragmentation at urban fringes and in newly built subdivisions (Yu & Ng, 2007).

Accurate and automated mapping of urban impervious surfaces is one of the most important issues which have not been addressed adequately using remote sensing. This is because most of the previous studies have used low to medium spatial resolution sensors such as Landsat Multi-spectral scanner (MSS), Landsat Thematic Mapper (TM), and Système Pour l’Observation de la Terre (“System for Earth Observation” or SPOT) for impervious surface extraction (Blaschke & Strobl, 2001; Yuan & Bauer, 2006; Hu & Weng, 2009). Several studies in the mid-late 2000s have focused on using high spatial resolution sensors such as IKONOS, QuickBird, and airborne hyper-spectral data (Blaschke & Strobl, 2001; van der Linden & Hostert, 2009; Weng et al., 2009). Others have examined impervious surfaces at the sub-pixel level using spectral mixture analysis, decision trees, artificial neural networks using self-organizing map or multi-layer perceptron network (Hay et al., 2005; Yuan & Bauer, 2006; Hu & Weng, 2009; Weng et al., 2009). A common theme of most of the impervious surface studies is their reliance mainly on a single type of dataset or a limited region of study (Hay et al., 2005). There is also no agreed definition of an exhaustive list of what constitutes an urban surface or impervious surface between studies (Slonecker & Tilley, 2004; Weng, 2009), and this could certainly affect classification estimates and inhibit straightforward comparison of different studies.

For urban areas, classification accuracy in previously mentioned studies was shown not to be a serious limitation. In general the accuracy estimates were reasonable, exceeding a threshold of 70%. Impervious surface mapping needs high spatial resolution because it is more important
to discriminate and classify compared to higher spectral or radiometric resolutions (Jensen et al., 2005). The requirement of high spatial resolution translates to consideration of texture and context, which is provided by methods such as spectral mixture analysis, object-based and other texture based methods (Jensen et al., 2005).

Also, in order to reveal the complexity of landscape changes due to the increase in impervious surfaces, temporal remote sensing data are needed to capture the baseline as well as subsequent temporal landscape changes (Hay et al., 2001). A remote sensing study also demonstrates that sub-pixel impervious estimation using medium resolution imagery may be a useful alternative over expensive high-resolution mapping for modeling of rainfall vs runoff in a typical watershed (Chormanski et al., 2008). Urban impervious surfaces also suffer from two unique remote sensing phenomena which directly affect accuracy: shadows and obscured objects due to the off-nadir look angle of the remote sensor (van der Linden & Hostert, 2009). The OBIA method is based on sensible pixel grouping which is more representative of real world conditions (Kampouraki et al., 2007).

This study will attempt to explore and highlight the current challenges preventing fully automated classification of impervious surfaces in urban areas. An important question to be asked is: how much does the classification accuracy of a particular method depend on the image scale? Scale is used in two contexts here:

1. Image Resolution: Can the classification method reasonably classify high/medium/low spatial resolution urban imagery?
2. Size of Dataset: Can the same method with no manual interaction, and accounting for all possible variations, be used for large image datasets on a continental scale?

2.4 Object-Based Image Analysis

The object-based approach is easier for extraction of impervious surfaces such as houses, roads, parking lots which lend themselves well to forming image objects (Blaschke & Strobl, 2001). But as yet relatively few studies have incorporated both high spatial resolution and object-based
classification software with a view toward complete automation (Blaschke, 2010). Automation in other texture based techniques suffers from selecting the correct size of ‘moving windows’ used to measure texture patterns (Emerson et al., 2005). It may be possible to take a shadow mask or even classify shadows using image objects in high spatial resolution images. The main difficulty with classifying isolated or non-contiguous impervious surfaces is their random occurrences, variations in size, and complexity (Johnson, 2004). In certain urban landscapes of impervious surfaces, it is probable that many classification approaches would work adequately, but in fragmented urban surfaces, OBIA has the distinct advantage of improved identification of irregular objects. Blaschke (2010) stated that high spatial resolution tends to favor OBIA for classification because the pixels are significantly smaller than the image objects, and the pixels need to be combined for analysis. Blaschke (2010) also stated that for low spatial resolution (i.e., pixels are larger than image objects) sub-pixel techniques are appropriate, while for medium spatial resolution, pixel-based classification techniques are the most appropriate method.

Definiens GmbH introduced an image processing software called eCognition (eCognition is now owned by Trimble Inc.) and popularized object-based image analysis and object-based change detection in the field of remote sensing. Object recognition or segmentation has been used in the fields of computer vision, medical imaging, and general image processing (Chow & Rahman, 2007; Richard et al., 2007; Rivlin et al., 2007; Tremblais et al., 2007; Town, 2007; Unnikrishnan et al., 2007; Blaschke, 2010; Dey et al., 2010). Image segmentation using the so-called “object-based” image classification, and “object-based” change detection has been demonstrated to alleviate some of the glaring problems of per-pixel classification methods (Blaschke & Strobl, 2001; Im et al., 2008). Recently, the object-based image segmentation approach has been widely accepted by the remote sensing and GI Science community and is the focus of this study (Im et al., 2008). Object-based software is an excellent choice for impervious surface automation because it uses contextual information from neighborhood pixels continuously or in a fuzzy way, organizing them at user-specified scales in a hierarchical manner of the expected image objects (Lu & Weng, 2006). This is also called multi-scale image segmentation. In this method, the lowest unit of measure
is not the pixel; rather, it is the image objects, which are formed from relatively contiguous and homogeneous areas in the image (Blaschke & Strobl, 2001). OBIA therefore subsets an image into homogeneous regions based on spectral, geometric, texture, size, intensity, and other parameters, and forms meaningful image objects (or ecological patches) out of them (Yang et al., 2003). The algorithm for forming image objects in eCognition incorporates the self-similarity criterion of fractals and it is based on Fractal Net Evaluation Approach (FNEA) (Dey et al., 2010). Hay et al. (2005) also stated that OBIA is a possible reduction of the MAUP problem in remote sensing. OBIA is defined as a method of partitioning remote sensing imagery into meaningful image objects, and further analyzing through the image objects using classification (Hay & Castilla, 2006 pg 1).

Automatic extraction of impervious surface using remote sensing requires the formulation of procedures with knowledge that encapsulate the entire content of input imagery. Over the last decade the analysis of LULC datasets for analysts has evolved from predominantly per-pixel or sub-pixel based methods to the application of OBIA methods. However, there are several challenges of OBIA, or rather image segmentation that need to be tackled. A big challenge in OBIA is the concept and extraction of scale in an image, and its relative size. When pixels are linked to form image objects, ideally the visual interpretation of image objects and image objects derived from the software must match. This involves two dimensions of scale: (a) absolute scale when segmenting single objects such as individual trees, single house, forest, or water bodies; and (b) relative scale when considering the spatial resolution of different scale data (Blaschke, 2010). The OBIA software has too many parameters which do not produce consistent results across different studies. This per study parameter selection hinders automation and is a big challenge to overcome. To empower end users with these emerging remote sensing technologies, we need a set of conceptual guidelines. Also, remote sensing software needs to be intuitive and easy to use, while requiring little user intervention in method selection and providing results closely matching those found by human interpreters. It is well-known that object recognition is frequently used in the related fields of computer vision, medical imaging, video pattern recognition, and image processing (Dey et al., 2010). In the future, remote sensing will include analysis of moving imagery or full motion video,
since video is a series of still images, any analysis technique should be able to cover both still imagery and moving imagery. Hence, this study uses the original software for OBIA: eCognition.

2.5 Importance of Impervious Surfaces for Modeling Runoff and Water Balance

In general, urban planners employ a strategy of having catchment basins (typically forests) near cities for flood control, while tracking field observations for monitoring water variables in significant water bodies. At a minimum they track discharge, water quality, and indirect soil erosion indicated by muddiness of water and thus sediment transport. These catchment basins or forests hold the excess runoff and allow it to ‘soak’, thus delaying its transport to water bodies. These forests also increase the total evapotranspiration and mitigate flooding. Remote sensing techniques can be employed as part of an integrated study to identify broad-scale forest tree stand and soil surface conditions, which provide information for modeling runoff generation and developing extensive watershed management (Onda et al., 2010). Hydrological modeling of urban watersheds is often adversely affected by a lack of adequate information about specific site conditions (Montzka et al., 2008); because it involves traditional surveying, which is expensive due to manpower costs and is based on expert judgment of average imperviousness for different types of urban land use (Chormanski et al., 2008). Modeling runoff and understanding flow hydraulics of runoff flowing into catchment rivers are important. As human populations in urban areas increase, their water resource utilization increases. Monitoring total water consumption, water quality, and water discharge as water resource management in face of this increased utilization becomes a major problem (Matsushita & Fukushima, 2009). Complete hydrological modeling in urban areas is useful for verification of water growth model outputs, estimation of impervious area, filling in different parameters of various hydrological models, and water resource planning (Jat et al., 2008).

Remote sensing has been widely used for hydrological studies and water resource management (Matsushita & Fukushima, 2009). Remote sensing has been recognized as useful for monitoring the changes in hydrology and for estimating the flood probabilities of a watershed on a near real-time basis (Chen et al., 2008). In that particular study, the authors simulated two rainfall events
against observations from a collection of meteorological base stations of the World Meteorological Organization (Chen et al., 2008). Remote sensing can be and is frequently used for real-time monitoring during extreme rainfall events, by taking samples of water quality and forming polluted runoff estimates of the plume or total flood water extent within a defined interval range (Brodie et al., 2010). There is a necessity of frequent collection of water sample data to serve as a base model in non-flood normal conditions. Remote sensing can also be used for predicting flood vulnerability of newly-built urban areas by constructing a comprehensive vulnerability index. Prediction involves formation of an integrated model which considers maximum runoff/discharge generation, monitoring water quality, current impervious surface estimation, and current estimates of evapotranspiration in urban areas (Matsushita & Fukushima, 2009). Such an integrated model can also quantify the vulnerability based on the percentage of impervious surfaces in urban areas such that exceeding certain percentages of impervious surface area can be predicted to have an increased vulnerability to flooding (Goldshleger et al., 2009). The total amount and intensity of discharge in a watershed is mainly determined by the presence of impervious surfaces (United States Geological Survey, 2006; Chormanski et al., 2008). Chormanski et al. (2008) examined the impact of conventional and remote sensing methods for estimating impervious surfaces cover on the prediction of peak discharges; their study found the presence of impervious surfaces to produce substantially higher estimates of peak runoff with remote sensing method compared to the conventional approaches, which underestimated the peak runoff.

This study will develop a reproducible classification method using OBIA method that will detect and quantify the impervious surfaces in New Orleans, Louisiana. The results from this study should be useful to related hydrological studies in the study area.
CHAPTER 3: DATA AND METHODOLOGY

3.1 Study Area

The study area chosen for this research is downtown New Orleans, Louisiana, and its surrounding area (Figure 3.1), with a particular emphasis on the Mercedes Benz Superdome. It is part of Jefferson, Orleans, and St. Bernard Parishes, Louisiana. The study area is illustrated in Figure 3.2.

Downtown New Orleans, Louisiana, located at the southeast side of the middle image, is mostly composed of high rise commercial buildings, which cause most of the prominent shadows in the image. The Mercedes Benz Superdome sits at the intersection of I-10 and the Pontchartrain Expressway bridge. Also nearby is the New Orleans Union Railway terminus. The northern part of the middle image study area is dominated by the oval shaped Fairgrounds racecourse, and a large vegetation area of the New Orleans Museum of Art, and the New Orleans Botanical Garden on the Northwest portion of the image. Part of Bayou St. John which drains into Lake Pontchartrain is prominent as the water body in the middle of the study area (Source: Google Maps, 2012).

Figure 3.1: Study Area Locations in United States, and Louisiana (Source: (a) Wikipedia New Orleans page and (b) Map created in ArcGIS 10 Desktop from (US Census, 2010) data, last accessed April 19, 2012)
Hurricane Katrina was the costliest and ranks among the five deadliest hurricanes to ever strike the United States, and considering the wide scope of its impacts, it was one of the most devastating natural disasters in United States history (Knabb et al., 2005). There was widespread flooding several miles inland from the Gulf coast, the storm surge due to water level rise of Lake Pontchartrain around New Orleans reached levels between 5 ft and 19 ft (Knabb et al., 2005). The storm surge strained the levee system in the New Orleans area such that several levees were overtopped and/or breached at different times on the day of landfall, resulting in 80% of flooding in New Orleans (Knabb et al., 2005). Most of the City of New Orleans is below sea level. A modern city usually has a large percentage of impervious surfaces, which prolong the peak flow immediately after a major flood event. Due to flooding after Hurricane Katrina, the navigation was difficult due to missing street signs and imperfect landmarks, and the road map became useless. An OBIA analysis of the rapidly changing landscape can prove to be extremely useful in such a disastrous scenario, because of the viable possibility of fast and repeatable LULC analysis generating real time GIS updates.

3.2 Data

In this study, impervious surfaces are detected from high spatial resolution imagery using traditional pixel-based classification and object-based image segmentation (OBIS) techniques. The dataset consists of 1-meter spatial resolution USGS Digital Orthophoto Quarter Quadrangle (DOQQ) of downtown New Orleans, Louisiana, USA. The DOQQ images are part of the Hurricane Gustav archive at the LSU GIS-store, and were all taken on August 29, 2008. The DOQQ images are four band multi-spectral image of the New Orleans area, with red, green, blue and IR4 (near infra red) bands. The LSU GIS-Store has many examples of 1-meter spatial resolution imagery, but few of them have clear cloud-free images and also contain the IR band, which is useful for vegetation analysis. The pixel image data is 8 bits unsigned integer. The images are in UTM Projection Zone 15 North, defined using spheroid of GRS 1980 and datum of NAD83. The study images were subsetted using ERDAS Imagine (ERDAS Imagine, 2009) such that analysis can be conducted on downtown New Orleans with its complicated high rise building shadows and fast spectral transitions.
in urban neighborhoods. The subset image used in majority of this study has dimensions of 4166 x 5680 pixels, giving a study area of approx 4.1 x 5.7 km. The total pixel count was 23,662,880 for this subset which is approximately 24 million pixels for the study area. All the images are cloud free, already pre-processed by geometric orthorectification, and no further geometric or radiometric adjustment was performed. There was no need to orthorectify because the variations in displacement are minimal throughout the study area. The same image of the sub-setted study area was used for ground truth and accuracy assessment of all the classifications.

Table 3.1: Band Statistics for Study Area Subset and LIDAR Image

<table>
<thead>
<tr>
<th>Band #</th>
<th>Min</th>
<th>Max</th>
<th>Mean</th>
<th>Median</th>
<th>Mode</th>
<th>Std. dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>1</td>
<td>255</td>
<td>110.997</td>
<td>111</td>
<td>33</td>
<td>55.893</td>
</tr>
<tr>
<td>2</td>
<td>1</td>
<td>255</td>
<td>115.766</td>
<td>117</td>
<td>121</td>
<td>52.531</td>
</tr>
<tr>
<td>3</td>
<td>1</td>
<td>255</td>
<td>92.541</td>
<td>88</td>
<td>80</td>
<td>45.446</td>
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<td>1</td>
<td>255</td>
<td>110.521</td>
<td>115</td>
<td>142</td>
<td>50.298</td>
</tr>
</tbody>
</table>

LIDAR (meters) -18.7 25.6 0.559 -0.35703 -2.4346 4.15

The LIDAR image in Figure 3.4 is a subset of the layer dataset, collected for the decade-long Louisiana statewide and FEMA initiative to provide a continuous coverage of elevation information for Louisiana. The LIDAR image is of spatial resolution of 5 meters. The LIDAR data were obtained in March 2003 by 3001 Inc. on behalf of U.S. Army Corps of Engineers, St. Louis District. The image is in UTM Projection Zone 15 North, defined using spheroid of GRS 1980 and horizontal datum NAD83. The vertical datum is NAVD88. Table 3.1 shows the band statistics of the sub-setted study area and the Light Detection And Ranging (LIDAR) image.

The Normalized Difference Vegetation Index (NDVI) image in Figure 3.5 is generated by the built-in NDVI functionality in ERDAS Imagine 9.3 using the model ‘VegNDVI.gmd’ and using the Red and IR bands of the image. The NDVI formula is given in Equation (3.1). NDVI ranges from -1 to +1. And the digital numbers (DNs) are scaled by multiplying them by 255, the modified formula which uses NDVI is given in Equation (3.2) (ERDAS Imagine, 2009).
Figure 3.2: Locations of Places in Study Area in Downtown New Orleans (Source: Google Maps)
Figure 3.3: Study Area in High Resolution Natural Color: Bands R, G, B
\[
\text{NDVI} = \left( \frac{\text{IR} - \text{Red}}{\text{IR} + \text{Red}} \right)
\] 

(3.1)

\[
\text{NDVI scaled} = \left( \frac{\text{DN} - \text{GLOBAL MIN(DN)}}{\text{GLOBAL MAX}(\text{DN}) - \text{GLOBAL MIN(DN)}} \right) \times 255
\] 

(3.2)

The formula for Normalized Difference Water Index (NDWI) is given in Equation (3.3) (Ji et al., 2009) and the Spectral Shape Index (SSI) formula is given in Equation (3.4) (Chen et al., 2007). During classification, NDWI index is used to separate water and SSI index is used to separate shadows. These indices do not need human input and are therefore suitable for automation.

\[
\text{NDWI} = \left( \frac{\text{Green} - \text{IR}}{\text{Green} + \text{IR}} \right)
\] 

(3.3)

\[
\text{SSI} = \left| \text{Red} + \text{Blue} - 2 \times \text{Green} \right|
\] 

(3.4)

3.3 Software

The image processing using traditional spectral classification included file manipulation, spectral evaluation, unsupervised and supervised classification, image grouping, signature manipulation, NDVI image generation, and finally the accuracy assessment procedure. These image processing steps were performed using ERDAS Imagine 9.3 image processing software.

The software eCognition Developer version 8.64 was used for OBIA. The 64-bit software was used for the import and manipulation of the subsetted image, multi-resolution segmentation, development of a sample-based/rule-based classification, and sample-based accuracy assessment. eCognition was also used to define the arithmetic expressions to calculate the NDWI and SSI used in the study. These indices are used to differentiate water and shadows respectively.

ArcGIS Desktop Suite 10 and Geomedia Professional 6.1 were used for generating aesthetic maps, and was also used in the study for basic image manipulation.

The machine used for the study was a Sun Workstation Ultra 40, with 2 x Dual Core Opteron 280 CPU and 8 GB of RAM, running on Windows 7 64-bit Enterprise edition.
Figure 3.4: LIDAR Image of Study Area
3.4 Methodology: Pixel-Based Hybrid Classification

The image from LSU GIS-Store was initially subsetted to avoid the southeast or the eastern side which had spurious values in the LIDAR image. The image was also subset with the intention of having a good mix of real world shadows, urban sprawl with both small and tall buildings, water areas, vegetation, bare soil, and impervious surfaces. The image is displayed in Figure 3.3. Histograms of all four bands were checked to verify a multi-modal distribution, which would help in choosing thresholds for the image. Initially, supervised classification was tried, to compare with the similar procedure in OBIA software. But it was difficult to get a reasonably small number of training areas that cover the whole image and also get a reasonably accurate classification. So, an unsupervised classification which is sensitive enough to detect image components, followed by a supervised Maximum Likelihood Classifier (MLC) classification, was deemed to be a superior approach. Because, the unsupervised results could be used as input to a supervised classification combining the advantages of both classifications. The unsupervised classification with 80 classes with a color scheme option of approximate true color with R=1, G=2, B=3 was chosen (natural color).

A “Convergence threshold” of 0.980 (referring to 98% confidence interval) with 100 maximum iterations was chosen. “Skip Factors” was kept at the default 1 for X and Y axis. The unsupervised output and the signature file were saved separately. For ERDAS Imagine, the “Ignore zero in output statistics” option should be chosen wherever possible, or the equivalent “Classify zeros” option was always unchecked.

The unsupervised class assignment process was accelerated by the Grouping Tool in ERDAS Imagine 9.3. The signature file for unsupervised was opened simultaneously while in the Grouping tool, and the unsupervised image was chosen. Clicking on each row of the Grouping tool highlights the corresponding class in the Imagine Viewer in its default Yellow color, which made the class assignment process faster in the Signature Editor. The Signature name column was filled with unique signature names (Veg1, Veg2, Imp1, Imp2 and so on) and all signatures were color coded as per Table 3.2.
Figure 3.5: NDVI Image of Study Area
In this study the focus is on impervious surface classification, so there was no need to generate multiple classes for vegetation. The water and shadows were clustered in only a few classes during unsupervised classification, and were combined in a single landcover class to avoid the difficulty of finding adequate random points during the stratified random sampling for accuracy assessment.

Table 3.2: Scheme for Pixel-based Classification and Accuracy Assessment

<table>
<thead>
<tr>
<th>Land Cover class</th>
<th>Description (Land use)</th>
<th>Recoded value</th>
<th>Assigned Color</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>Roads, rooftops, parking lots</td>
<td>1</td>
<td>Yellow</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Lawn, trees, shrubs</td>
<td>2</td>
<td>Green</td>
</tr>
<tr>
<td>Shadow / Water</td>
<td>Shadowed areas and Water bodies</td>
<td>3</td>
<td>Blue</td>
</tr>
</tbody>
</table>

Afterwards, the pixel count column was copied to the probability column for normalization, and these 80 unsupervised classes which are carefully tagged became the sample input to a supervised classification. Supervised classification was performed by entering the original subset image, the signature file from unsupervised classification, and a new supervised image file. “Fuzzy classification” was unselected, and the default “Non-parametric Rule” selected was “None”. Parametric rule of “Maximum Likelihood” and “Use Probabilities” was also selected. The output of the supervised classification is called hybrid classification, and some processing was required to sharpen its speckled appearance. The hybrid image was fed to the “Recode” function. Recode was chosen with output of “Unsigned 1 bit”, as the output was integer and thematic. All the rows belonging to a class were selected individually and recoded by assigning the appropriate value as given in Table 3.2. The recoded result was then color coded in Imagine Viewer using the Raster Attribute Editor and colored according to Table 3.2. The recoded image was then fed to a “clump” function for clustering related group of pixels, clump was selected with “Connected Neighbors” set to 4 pixels, accepting other defaults. Clump reduces the “salt and pepper” effect and smooths out the original classification. The “eliminate” function was arbitrarily chosen to eliminate pixels less than 15 to further smooth over any isolated pixels which looked to be statistical outliers. Since this is a high resolution image with a single pixel of 1-meter, elimination was done through selection of

31
pixels, and not hectares, acreage, or area in square miles. The post processing procedure described above was achieved easily in OBIA because of image object formation but was accomplished in ERDAS Imagine with considerable logistical difficulties.

3.5 Methodology: Object-Based Image Classification

In general, the OBIA workflow in eCognition Developer 8, 64 bit edition includes performing a image segmentation followed by an image classification procedure. There are other software used for OBIA: ENVI Feature Extraction Module and ERDAS Imagine Objective. For the process of image segmentation there are many segmentation algorithms which are also available in eCognition:

1. chessboard: segments image into equal sized objects,
2. contrast filter: segments image by contrast and gradient to create primitive image objects,
3. contrast split: segments image with a given threshold into bright and dark objects,
4. multi-resolution: segments image and consecutively merge objects at higher scales,
5. multi-threshold: segments image into user specified thresholds,
6. quadtree based: segments image into a quadtree formed by square objects, and
7. spectral difference: merges neighboring image objects from a previously segmented image.

Multi-resolution segmentation is an example of a “bottom up” segmentation which involves assembling neighboring pixels into smaller objects, which in turn are used to create larger objects (eCognition User Guide, 2011). Multi-resolution segmentation is similar to how humans logically form distinct image objects. This study uses the multi-resolution segmentation and the spectral difference segmentation procedures in eCognition. Figure 3.6 shows the image segmentation parameters used in multi-resolution segmentation. Figure 3.7 shows the relationship between the various image segmentation parameters used in multi-resolution segmentation.

3.5.1 Formation and Combination of Image Objects

This section briefly describes the FNEA algorithm used in eCognition, as described in Benz et al. (2004) and Dey et al. (2010). Image segmentation is the process of subdivision of an image into distinct regions and it is realized as an optimization procedure given certain constraints to identify
Figure 3.6: Image Segmentation Parameters for Multi-resolution Segmentation

Figure 3.7: Relation between Image Segmentation Parameters Explained
image object regions with minimum heterogeneity (Benz et al., 2004). Starting with a single pixel as a seed, in multi-resolution segmentation the process of pairwise bottom-up region merging of neighboring pixels occurs to form small image objects. Subsequently, in successive steps, the smaller image objects are merged to form bigger image objects based on a weighted heterogeneity limit \( h \) and a scale parameter \( n \). In every hierarchical merging step, a pair of homogeneous neighboring image objects are merged such that it results in the smallest growth of the defined heterogeneity. If the resulting super image objects exceeds the threshold defined by the scale parameter (which is in reality specifying the maximum size of image object), the object merging process stops. Generally, the size of the generated image objects is bigger for homogeneous land covers and smaller for heterogeneous land covers and is repeatedly reproducible due to the heterogeneity constraints. To obtain an accurate segmentation which is visually reflective of the underlying ecosystem reality, the segmentation should proceed hierarchically using a higher scale parameter. Alternatively, segmentation can be performed at a fine scale and classification can subsequently aggregate the image objects at a coarse scale.

### 3.5.2 Segmentation Parameters in Multi-resolution Segmentation

The multi-resolution segmentation algorithm in OBIA creates image objects based on three input parameters: color/shape, compactness/smoothness, and scale. These three parameters are recommended to be changed in different studies to obtain optimized results. The default values are color/shape = 0.1, compactness/smoothness = 0.5, and scale = 10. Defining the criteria for minimum heterogeneity by specifying segmentation parameter constraints and deciding on the strategy of assembling homogeneous areas leads to a good segmentation result (Benz et al., 2004). The three segmentation parameters are explained here briefly from the literature in Benz et al. (2004), Jensen (2004) and Baatz & Schäpe (2000).

For all the heterogeneity parameters, the higher the weight assigned to an image band, the more importance will be assigned to that particular color band’s pixel information during the segmentation process. To ignore an image band during segmentation, the weight parameter should be set to 0. To emphasize equal weights to all image bands, all bands are set to the same weight value of 1.
The scale parameter has the most effect on size of the image objects, the next segmentation parameter which affects the process is the color/shape segmentation parameter, and the segmentation parameter with the least effect is the compactness/smoothness segmentation parameter.

\[
f = w_{\text{color}} \cdot \Delta h_{\text{color}} + w_{\text{shape}} \cdot \Delta h_{\text{shape}}
\]

where

\[
w_{\text{color}} = \varepsilon [0, 1, ] and w_{\text{color}} + w_{\text{shape}} = 1
\]

\[f\] is the heterogeneity function,

\[w_{\text{color}}, w_{\text{shape}} = \text{weights assigned to color and shape respectively}\]

\[\Delta h_{\text{color}}, \Delta h_{\text{shape}} = \text{heterogeneity criterion for color and shape respectively}\]

As seen from Equation 3.5, the heterogeneity function \(f\) is a product of the individual heterogeneity \(\Delta h_{\text{color}}\) and \(\Delta h_{\text{shape}}\) and the weight parameters \(w_{\text{color}}, w_{\text{shape}}\). The weight parameters adapt the heterogeneity criterion on a per image basis. Both the shape and color heterogeneity criterion range from 0 to 1.

### 3.5.2.1 Color/Shape

The color/shape heterogeneity criterion is a fulcrum of the influence of either color (i.e. spectral value) or texture; the algorithm is based on the Fractal Net Evaluation Approach (FNEA) (Dey et al., 2010). A high value of shape fraction translates to a lower influence of color during the segmentation process but greater emphasis on texture. Similarly, a low value of shape fraction translates to a higher influence of color and lower emphasis on texture during segmentation. For example, a shape weighting of 0.7 results in a color weighting of 0.3 (eCognition User Guide, 2011).

\[
\Delta h_{\text{color}} = \sum_{b} w_{b} \left( n_{\text{merge}} \cdot \sigma_{b, \text{merge}} - \left( n_{\text{obj}_1} \cdot \sigma_{b, \text{obj}_1} + n_{\text{obj}_2} \cdot \sigma_{b, \text{obj}_2} \right) \right)
\]

\[
\Delta h_{\text{shape}} = w_{\text{compact}} \cdot \Delta h_{\text{compact}} + w_{\text{smooth}} \cdot \Delta h_{\text{smooth}}
\]

where

\[w_{b}, w_{\text{compact}}, w_{\text{smooth}} = \text{weights assigned to band b, compactness, and smoothness respectively}\]
\( \Delta h_{\text{compact}}, \Delta h_{\text{smooth}} = \) heterogeneity criterion for compactness, and smoothness respectively

\( n_{\text{merge}} = \) number of pixels within merged object

\( n_{\text{obj}_1}/n_{\text{obj}_2} = \) number of pixels in object 1/object 2 respectively

\( \sigma_b = \) standard deviation within object of band \( b \)

\( \sigma_{\text{obj}_1}/\sigma_{\text{obj}_2} = \) standard deviation within object 1/object 2 respectively

The spectral heterogeneity, \( \Delta h_{\text{color}} \) allows the image analyst to have a best fit segmentation by addition of a weight \( w_b \) and it is defined as given in Equation 3.6. The spectral heterogeneity, or the color criterion, is the second most important segmentation parameter for creating meaningful image objects, because it defines the digital value of color for the image objects (eCognition User Guide, 2011). The spectral heterogeneity is formally defined as the weighted per-band summation of the difference of merged image objects with the sum of adjacent image objects. The image objects are within the standard deviation per band, \( \sigma_b \).

The shape heterogeneity, \( \Delta h_{\text{shape}} \) describes the textural homogeneity of the resulting image objects with regard to the compactness and smoothness of an image object, and it is defined as given in Equation 3.7. The shape heterogeneity, \( \Delta h_{\text{shape}} \) is formally defined as the sum of the weighted compactness heterogeneity and smoothness heterogeneity.

### 3.5.2.2 Compactness/Smoothness

The compactness heterogeneity criterion is also directly correlated with the size of the eventual image objects, and it is a fulcrum between compactness and smoothness. A lower value of compactness equals production of pixel objects that are compact but with jagged edges (less smooth) after the segmentation process. Similarly, a higher value of compactness equals generation of comparatively larger image objects with smooth edges (eCognition User Guide, 2011).

\[
\Delta h_{\text{smooth}} = n_{\text{merge}} \cdot \frac{l_{\text{merge}}}{b_{\text{merge}}} - (n_{\text{obj}_1} \cdot \frac{l_{\text{obj}_1}}{b_{\text{obj}_1}} + n_{\text{obj}_2} \cdot \frac{l_{\text{obj}_2}}{b_{\text{obj}_2}}) \quad (3.8)
\]

\[
\Delta h_{\text{compact}} = n_{\text{merge}} \cdot \frac{l_{\text{merge}}}{\sqrt{n_{\text{merge}}}} - (n_{\text{obj}_1} \cdot \frac{l_{\text{obj}_1}}{\sqrt{n_{\text{obj}_1}}} + n_{\text{obj}_2} \cdot \frac{l_{\text{obj}_2}}{\sqrt{n_{\text{obj}_2}}}) \quad (3.9)
\]
where
\[ n_{\text{merge}} = \text{number of pixels within merged object} \]
\[ l_{\text{merge}} = \text{number of pixels within the perimeter of merged object} \]
\[ b_{\text{merge}} = \text{number of pixels within the bounding box of merged object} \]
\[ n_{\text{obj}_1}/n_{\text{obj}_2} = \text{number of pixels in object 1/object 2 respectively} \]
\[ l_{\text{obj}_1}/l_{\text{obj}_2} = \text{number of pixels within perimeter of object 1/object 2 respectively} \]
\[ b_{\text{obj}_1}/b_{\text{obj}_2} = \text{number of pixels within the bounding box of object 1/object 2 respectively} \]

The smoothness heterogeneity, \( \Delta h_{\text{smooth}} \) optimizes the resulting image objects with regard to smooth borders limited by the shape criterion, and it is defined as given in Equation 3.8. The smoothness heterogeneity, \( \Delta h_{\text{smooth}} \) is formally defined as the difference of merged image objects with the sum of the ratios of the perimeter \( l \) and the bounding box \( b \) of constituent image objects.

The compactness heterogeneity, \( \Delta h_{\text{compact}} \) optimizes the resulting image objects with regard to their overall compactness limited by the shape criterion, and it is defined as given in Equation 3.9. The compactness heterogeneity, \( \Delta h_{\text{compact}} \) is formally defined as the difference of merged image objects with the sum of the ratios of the perimeter \( l \) and the square root of bounding box \( b \) of constituent image objects.

### 3.5.2.3 Scale

The last and most important segmentation parameter for influencing the size of image objects is the scale parameter. The scale parameter can be set to any arbitrary value and is a suggestion to the FNEA algorithm to adjust and limit the output size of the image objects. A scale of 10 would generate smaller image objects in a level called “Level 1”, then in another iteration of the multi-resolution segmentation, a scale of 30 would combine these objects from lower scale to form a new object level “Level 2”.

Scale is a parameter used to control image segmentation process in eCognition. In remote sensing, scale/resolution refers to the spatial resolution or the area covered by a pixel, but hierarchically defined image objects in OBIA also have scale, as scale is used to abstract the cumulative level of
hierarchical aggregation of certain image objects. The scale parameter in eCognition refers to a hard size limit for the formation of image objects, it determines the presence or absence of a certain object class (Benz et al., 2004). Scale is used as a substitute for size in eCognition. An image object appears to be visually different at different scales (or sizes) of interest, and conversely the classification objectives determine the scale (size) for analysis (Benz et al., 2004).

The multi-scale or multi-resolution concept in eCognition for an urban area using a high-resolution sensor is described as follows: at the smallest spatial resolution in remote sensing, the analyst can detect single houses, buildings, roads, trees, and other urban objects. If the viewing distance is enlarged (zoomed out) to take in more area, single structures are aggregated into neighborhoods or subdivisions. At a still larger distance, the entire city is perceived as a single entity with its surrounding natural land covers which might include agricultural areas with water bodies and/or forests. This hypothetical example above described a 3-scale approach:

1. individual land cover structures at a fine scale
2. groups of aggregated land cover structures at a medium scale;
3. cumulative groups of groups from medium scales to form a coarse scale aggregation.

An abstract example of a hierarchical network of image objects which shows simultaneous representation of a 2-scale, 3-scale and 4-scale hierarchy is given in Figure 3.8. There is a hierarchical dependency between the depicted scales for real-world structures. OBIA software map these hierarchical multi-scale image objects to form image segmentations which are visually similar to naturally occurring ecosystem patterns. Different levels of image objects can be segmented using different datasets, upper layers at a coarse scale can be built on GIS layers, while lower layers at a fine scale can be built on remote sensing layers (Benz et al., 2004).

The segmentation in OBIA operates on arbitrary but hierarchical scale levels. Each segmentation of a new scale level is built on top of a lower scale level. To guarantee a definite hierarchy and for repeated reproducibility of image objects the segmentation procedure follows two basic rules (Benz et al., 2004):
1. Object borders at higher scale level strictly follow border of objects on the next lower level.

2. Segmentation at lower scale level is limited by the borders of objects on the next upper level.

Benz et al. (2004) describe the scale parameter as being used as the stop criterion for the region growing process in eCognition. In eCognition, multi-resolution segmentation starts with single pixel as image object, and it also starts with a random location in the image. It is a pair-wise clustering process, with the procedure trying to minimize weighted heterogeneity $n h$ of resulting image objects, where $n$ is the size of an image segment and $h$ is a parameter of heterogeneity. Before merging two adjacent and homogenous objects, the total heterogeneity parameter $f$ in Equation 3.5, is calculated. If the increase in $f$ exceeds a threshold $t$ determined by the scale parameter, then the entire segmentation stops. There is a direct correlation between the input scale and the size of the generated image objects (eCognition User Guide, 2011). The larger is the specified scale parameter, the more number of image objects can be combined, and the resultant image objects are bigger. The segmentation procedure tries to achieve combinations of image objects of similar size and of comparable scale.

### 3.5.3 Exploring and Using eCognition

Initially, the image segmentation heterogeneity parameters of shape = 0.7 (range 0.0 - 0.9) and compactness = 0.4 (range 0.0 - 1.0) were chosen after much trial and error. This part of the process
was time consuming and user unfriendly. A slider for these parameters to see their immediate effects on the study image would be a welcome improvement. The segmentation was performed with 8 hierarchical levels, each on top of another with scale parameter increasing in steps of 10, i.e. 10, 20, 30 until 80. The shape and compactness heterogeneity criterion were also varied. The scale number is an arbitrary number denoting the hierarchical levels of image segmentation. OBIA software displays the initial few multi-resolution segmentation proceeding in multiple consecutive cycles; the last cycle is typically used to compact the image objects. Subsequent multi-resolution segmentation at a higher scale level proceeds in consecutive cycles. It was found that the pixel merging algorithm was incorrectly combining impervious and vegetated areas in places where the vegetated areas dominate. Proceeding with more hierarchical levels was initially not deemed useful as the image objects which are combined to form bigger image objects will most likely be from dissimilar classes. This multi-resolution combination of image objects was not a problem for spectrally clear image objects like a baseball field for example, but in the spectrally confusing area where a dark green tree is mixed with a light shadow it was found to be unacceptable. The multi-resolution segmentation reduced the original 23 million pixels of the study area to less than 10,000 objects. But it also produced improperly combined image objects from the beginning of the segmentation, before classification even started.

After much trial and error, the multi-resolution process was set aside to be explored later, and proceeded with a single scale of 20 for segmentation. Given the size of the DOQQ image of 92 Mb, the initial segmentation process proceeded in multiple cycles ranging from 1 through 10, requiring 10 minutes of dedicated CPU time (25% i.e 1 CPU core maxed out). After a single segmentation, the study image was reduced from the original 23 million pixels to 131,646 objects. Seeking to combine image objects and reduce their total further, the built-in merging algorithm for “Spectral Difference” was used. The Spectral Difference algorithm needs an initial segmentation as input, and cannot operate on a pixel image. Since the DNs range from 0-255 for the 8 bit image, if an image object has a spectral difference of less than 10 with a neighboring image object, they are combined to form a bigger image object in spectral difference merge. This further decreased the count of
unique image objects to 99,288. The multi-resolution segmentation algorithm was experimentally found to be sensitive to changes in the initial color/shape and compactness/smoothness values. It was therefore decided to initially segment the image with priority placed more on color/shape (by choosing color/shape = 0.7), and then classify the images with more priority placed on color for the iteratively developed four methods. Please refer to Appendix 6.3 for a quick guide for exploring and using eCognition.

3.5.4 Sample-based OBIA Classification

Two approaches for classification in OBIA were tested: the nearest neighbor (NN) sample-based classifier and the rule-based classifier. Classification using OBIA is powerful, there are many classification methods which are not explained in this study but can be found in the User Guide (eCognition User Guide, 2011). The first approach, the NN distance classifier, uses spectral information for its samples. An initial image segmentation is needed to produce the image objects. The NN distance classifier in eCognition only operates on image objects to give higher discrimination during classification. The highest segmented hierarchical level is usually used for classification; a level with a scale parameter of 20 was used in this study. Feature space for the NN classifier was chosen to be color and texture. The NN sample-based classification involves selection of samples of all the classes. The classification scheme was implemented with the following classes: impervious, vegetation, water, and shadows. The samples for classification were selected from the image objects. It is important to choose the samples with care to give varied examples of different LULC classes like impervious, vegetation, shadow, water bodies, and also considering the potential for each image object to being assigned to one of the defined LULC classes. The sample editor was useful in determining the samples to select, as selection of a single sample reported its location on the distribution of all possible samples in the image.

Classification was then performed in an iterative and hierarchical fashion, by taking samples of different kinds of impervious surfaces and samples of non-impervious surfaces. Samples which caused misclassification and confusion were removed. It was found after trial and error that the classes were best separated using samples which were chosen right next to each other to aid class
separability and minimize sudden class transition error. The difference between eCognition and ERDAS Imagine for classification was the training image objects (OBIA) versus area of interest (AOI in ERDAS Imagine). In OBIA software, homogenous areas like rooftops or roads could be selected precisely because they are one large object. The same process in ERDAS Imagine involves AOI samples, whose polygons have to be carefully drawn together, a process which is highly prone to error. The classification process in OBIA is thus comparable to supervised classification in ERDAS Imagine. Classification in OBIA also involves taking samples of each landcover class. However, the sample-based OBIA classifier works better than the sample-based classifier in ERDAS Imagine because of its underlying algorithm. Almost all studies which reference OBIA software use the sample-based NN classifier, and few utilize the rule-based approach. In a rule-based classification approach, an image analyst can develop rules and assign pre-determined landcover classes to rules. Based on visual inspection and accuracy assessment, the classification produced by the NN sample classifier was quite good. The sample selection for the NN classifier in eCognition has to be done manually and with considerable care to aid separability. Multiple studies have reported high classification accuracies based on the NN sample classifier (Hay et al., 2001, 2005; Yuan & Bauer, 2006; Im et al., 2008; Zhou & Troy, 2008) and several studies have been summarized in Blaschke (2010). The remote sensing studies which report taking individual samples for each image are not conducive for true automation. So, for these reasons, the rule-based approach to classification was the choice of focus.

3.5.5 Rule-based OBIA Classification

The second approach to classification in OBIA, the rule-based approach, is suitable for automation. This approach proceeds by development of an iterative, hierarchical rule-based and assignment of class values to individual objects based on either of image, object, scene, process, or region features. Such custom built and default algorithms can be tested immediately in the “Feature View” mode. By trial and error it was determined that classification performs best by initially generating rules for landcover classes which cause maximum confusion, and then to generate rules to classify those landcover classes which cause the least amount of confusion. For this study, the shadows and water
LULC classes caused confusion with each other, so they had to be classified first. Many OBIA rules were tried in the “Feature View” window and they are listed in Appendix B.

To illustrate rule-based selection, a short description follows for a “Rectangular Fit” criterion. All image objects should have values between 0.0 to 1.0; an object with a value of 0.95 is highly rectangular, while an object with a value of 0.3 is not rectangular. Figure 3.9, Figure 3.10, and Figure 3.11 show a glimpse of how the interactive “Feature View” works. There was good separability for both length/width ratio (Figure 3.9) and Shape Index Fit (Figure 3.11), i.e. there are dark black areas and bright white areas, and some image objects belonging to a desired class can be classified as dark black or bright white. But there was poor separability for Rectangular Fit (Figure 3.10) because the image appears mostly white as the criterion chosen was 0.3 and all image objects appear to be of similar appearance. If a rule displays good separability in the study image, that particular rule can be possibly used for classification.

3.5.6 Summary of OBIA rule-based Classification Methods

There were four methods developed to test rule-based classification in OBIA.

1. OBIA rule-based method 1 was developed to investigate OBIA classification based on histogram DN thresholds.
2. OBIA rule-based method 2 was developed to perform initial classification using histogram thresholds, subsequently utilize LIDAR as elevation and OBIA specific spatial/texture operators for further refinement of classification accuracy for different LULC in the study area.
3. OBIA rule-based method 3 was developed to utilize band indices like NDVI, NDWI, and SSI for LULC identification while reusing histogram thresholds.
4. OBIA rule-based method 4 was developed to exclusively utilize band indices like NDVI, NDWI, and SSI for LULC identification to aid automation.

In brief, OBIA rule-based method 1 used a manual procedure to classify using the histogram DN thresholds from the best separable image band at a single scale. OBIA rule-based method 2 used the
Figure 3.9: Testing Classification in OBIA: Length/Width Ratio Criterion
Figure 3.10: Testing Classification in OBIA: Rectangular Criterion = 0.3
Figure 3.11: Testing Classification in OBIA: Shape Index Criterion
ERDAS Imagine File Information

File Information:
File Name: subset.img
Last Modified: Mon Oct 31 13:12:59 2011
Number of Layers: 4

Layer Information:
Name: Layer_3
Width: 4166
Height: 5680
Type: Continuous
Block Width: 512
Block Height: 512
Pixel Depth: Unsigned 8-bit
Compression Type: Run-Length Encoding (ESRI)

Histogram:
Bin Function: Linear
Minimum: 0
Maximum: 255
Mean: 92.1873

Figure 3.12: DN Histogram of Layer 3: Blue
same procedure as in OBIA rule-based method 1 in addition to using scene specific LIDAR image as elevation for classifying water, and the length/width ratio for classifying impervious surfaces at a single scale. OBIA rule-based method 3 used histogram DN thresholds as used in OBIA rule-based method 1, but in addition it utilized spectral indices like NDVI, NDWI, and SSI for refining the classification, also used multi-resolution segmentation at various scales. OBIA rule-based method 4 used multi-resolution segmentation at various scales and only used spectral indices of NDVI, NDWI, and SSI for classification of the four LULC classes.

Table 3.3 and Figure 3.13 shows the OBIA classification scheme used during classification and accuracy assessment for all the developed OBIA rule-based methods.

Table 3.3: Scheme for OBIA Classification and Accuracy Assessment

<table>
<thead>
<tr>
<th>Land Cover class</th>
<th>Description (Land use)</th>
<th>Recoded value</th>
<th>Assigned Color</th>
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<tbody>
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<td>Roads, rooftops, parking lots</td>
<td>1</td>
<td>Yellow</td>
</tr>
<tr>
<td>Vegetation</td>
<td>Lawn, trees, shrubs</td>
<td>2</td>
<td>Green</td>
</tr>
<tr>
<td>Shadow</td>
<td>Shadowed areas</td>
<td>3</td>
<td>Pink</td>
</tr>
<tr>
<td>Water</td>
<td>Water bodies</td>
<td>4</td>
<td>Blue</td>
</tr>
</tbody>
</table>

Figure 3.13: Legend for OBIA Classification and Accuracy Assessment
3.5.7 OBIA Rule-based Method 1

Figure 3.14 shows the initial method developed. For reproducible research, a screenshot is provided to easily replicate the procedure. A flowchart is shown in Figure 3.15 to understand the method. In this method, the mean value of image objects for Layer 3 of the original image (which corresponds to the Blue layer) is used. The DNs are chosen based on a threshold value of the histogram, either peaks or valleys (Dare, 2005; Chen et al., 2007; Ji et al., 2009). The DN histogram of each layer was consulted and any sharp peaks as occurred in Figure 3.12 were identified for classifying LULC classes. Simple thresholding is preferred because retrieval of threshold DNs can be obtained programatically from the software. The chosen threshold value of 52 clearly separates water and shadows, so shadows/water were initially classified. Since the dark areas had low DNs below 52, vegetation was classified within a range of DNs between 52 and 100. The impervious surfaces are usually the brightest areas and have DNs above 100. The DN value of 100 was chosen because it signals a transition of land Covers from observing Figure 3.12. In post classification processing, all imagery objects classified as shadows and totally enclosed by impervious surfaces were shifted to the impervious class. Similarly, all shadow objects enclosed by vegetation were reclassified as vegetation. This was accomplished by the “find enclosed by” OBIA algorithm.

3.5.8 OBIA Rule-based Method 2

Figure 3.16 shows the subsequent method developed. The flowchart is provided in Figure 3.17. The initial method was refined and the mean value of image objects for Layer 3 (Blue layer) of the study area was used. The DNs for the histogram DN threshold chosen after looking at Figure 3.12. The post-classification “find enclosed by” was removed and instead vegetation image objects whose ratio of length/width >= 3.5 were substituted and reclassified as impervious. The length/width ratio metric was found to be a statistically good indicator for impervious surfaces in urban areas for this study. Impervious surfaces which were misclassified as vegetation were more likely to be long and narrow, rather than irregular/cloud shaped like most vegetation objects. Misclassified pixels belonging to a combined shadow/water landcover class were correctly classified as water by a OBIA rule of elevation below 10 meters and an image object area greater than 4000 pixels.
Figure 3.14: OBIA Rule-based Method 1
(Layer 1 = Red, Layer 2 = Green, Layer 3 = Blue, Layer 4 = IR)

Figure 3.15: Flowchart for OBIA Rule-based Method 1
Figure 3.16: OBIA Rule-based Method 2
(Layer 1 = Red, Layer 2 = Green, Layer 3 = Blue, Layer 4 = IR)

Figure 3.17: Flowchart for OBIA Rule-based Method 2
3.5.9 OBIA Rule-based Method 3

After evaluating OBIA methods 1 and 2, a combined approach shown in Figure 3.18 and called method 3 was developed. The flowchart is provided in Figure 3.19. In this method, scene specific usage of the LIDAR image was removed as it does not aid automation. Initially, vegetation was classified using NDVI. Then shadow, vegetation, and impervious landcover classes were classified using histogram thresholding with scene specific histogram thresholds. NDWI and SSI were used to further refine the classification by classifying shadows and water body in the image. The equations for NDWI and SSI were defined in customized “Create new Arithmetic feature” in OBIA software. Finally, in post classification processing, all imagery objects which were classified as shadows and are totally enclosed by impervious surfaces are classified and shifted to the impervious landcover class. Similarly, all shadow objects which are enclosed by vegetation are classified as vegetation.

3.5.10 OBIA Rule-based Method 4

Figure 3.20 shows the final method developed, and Figure 3.21 shows the flowchart. In this method, histogram thresholding was removed as it reduces automation in all cases. The bare soil in the NDVI range of -0.05 to +0.01 was classified as impervious surfaces. NDVI is recommended for urban environments with small proportion of barren soil (Yang & Artigas, 2008). The NDVI range from 0.01 to 0.60 was classified as vegetation. NDVI was calculated from DN values in the image itself in the OBIA software, and not from the scaled image generated by ERDAS Imagine. Both NDVI and NDWI were used to classify water. NDWI generates a bright white value for water body. And a low range of SSI from 7 through 21 was used for shadow classification. Care should be taken not to confuse shadow values with impervious surfaces, while selecting the range of acceptable values for SSI. The remaining unclassified image objects were classified as impervious surfaces. Finally, in post classification processing, all imagery objects which were classified as shadows and are totally enclosed by impervious surfaces are classified and shifted to the impervious landcover class. Similarly, all shadow objects which are enclosed by vegetation are classified as vegetation.
Figure 3.18: OBIA Rule-based Method 3

- Multi-Resolution Segmentation (MRS) with shape=0.1, compact=0.5, and scale=10,20,30,40,50

- Form image objects above pixels using spectral diff 5

- Post-MRS region merge

- NDVI used to classify vegetation

- Classify low DN as shadow

- Reclassify midlevel DN’s as veg.

- Classify high DN’s as impervious

- Reclassify water with NDWI, shadow with SSI

- Post-processing LULC classification

Figure 3.19: Flowchart for OBIA Rule-based Method 3
Figure 3.20: OBIA Rule-based Method 4

Figure 3.21: Flowchart for OBIA Rule-based Method 4
3.6 Accuracy Assessment

Accuracy assessment for the pixel-based classification and all OBIA classifications was conducted in ERDAS Imagine. For each defined landcover class, a minimum of 50 samples was selected for accuracy assessment using stratified random sampling (Congalton, 2001). There were four landcover classes: impervious, vegetation, shadow, and water used in the accuracy assessment for the pixel-based and OBIA rule-based methods respectively. For the pixel-based method and for OBIA rule-based method 1, a combined shadow/water class was used as the shadows were combined with water class. For the pixel-based method the image produced from elimination of clumped pixels in the image chain was used for accuracy assessment, whereas in the OBIA rule-based methods the segmented image with highest scale and with optional post-classification refinements was used for accuracy assessment.

Accuracy assessment in eCognition was based on taking samples manually and needed either a separate training and test area (TTA) mask or unique samples for each class. A TTA mask can be reused for the same image. In all OBIA software, the entire process of segmentation, classification, and accuracy assessment is performed on derived image objects, not the pixels. The highest segmented image object level was selected for accuracy assessment. The sample-based error matrix statistics for all landcover classes were exported from eCognition in a .csv format for further manipulation in a spreadsheet software. Accuracy assessment in eCognition Developer version 8.64, 64 bit edition was incorrectly implemented; it lacks an automated stratified random sampling option, which is available in ERDAS Imagine. For both the sample-based NN classifier and the rule-based classification in OBIA, the image analyst must choose samples manually for quantitative verification of the classification. The number of classified pixels for a landcover class for all the OBIA rule-based methods was obtained from eCognition using shapefile export. The area in pixels was exported for each class individually and then summed up externally in a spreadsheet software. This information was unavailable directly in eCognition.

Zhou & Troy (2008) employed a process whereby the OBIA classifications with the highest segmented scale level and all landcover classes selected were exported to .img raster format.
(compatible with ERDAS Imagine), so that the accuracy assessment can be performed in ERDAS Imagine. A quirk of exporting in .img raster format in eCognition is the absence of any associated projection information. Hence the projection was set in ERDAS Imagine by setting the Map Model and specifying the same projection as used for other images in the study. Therefore, accuracy assessment for all the OBIA methods was performed in ERDAS Imagine, based on the process described above (Zhou & Troy, 2008). The thematic image produced in all the classifications used in the study was fed to the accuracy assessment editor in ERDAS Imagine with the default options, the “Number of Points” = 150 (Pixel-based method and OBIA rule-based method 1) or 200 (OBIA rule-based methods 2, 3 and 4) i.e. 50 points for each defined LULC class.

Lillesand & Kiefer (2004) as cited in Kulkarni (2004) describe the accuracy measures used in remote sensing for validation of classification by generating an error matrix (also called confusion matrix or contingency table) and computing the following: producer’s accuracy, user’s accuracy, overall accuracy, and the kappa statistics. Lillesand & Kiefer (2004) state that the classification errors are of either commission (pixels incorrectly assigned to a particular class that actually belong to other classes, indicated by the user’s accuracy) or omission (pixels incorrectly excluded from a particular class, indicated by the producer’s accuracy), and they define the following terms (all terms, except the kappa statistic, are expressed as percentages, to be multiplied by 100):

- “The overall accuracy is defined as the sum of all correctly classified pixels divided by total number of pixels.
- Producer’s accuracy indicates the performance of the analyst in performing the classification of any given land cover type. It is the ratio of correctly classified pixels for each landcover class to the total number of pixels used in the reference dataset.
- User’s accuracy reveals to the user the reliability of the classification procedure. It is defined as the ratio of correctly classified pixels for a given landcover class to the total number of pixels classified in that class.
- Kappa (khat) statistic is defined as a ratio of the measure of the difference of agreement between reference data and classification to the chance agreement between reference and random classification. As kappa approaches 1.0, the classification is accurate, and as it approaches 0, it indicates the classification is not better than the random agreement between the reference and classified pixels.”
CHAPTER 4: CLASSIFICATION ACCURACY ASSESSMENT

This chapter lists the results of the study in the following sequence: accuracy assessment of pixel-based classification, accuracy assessment of OBIA rule-based methods 1, 2, 3, and 4 respectively. In this study, the focus was on impervious surface classification, so there was no need to generate separate and detailed landcover classes for vegetation. All lawns, trees, and shrubs were combined into one vegetation class. For each landcover class, at least 50 samples were selected for accuracy assessment (Congalton, 2001), except for water, which had a low number of objects (OBIA) or pixels (pixel-based classification) in the image. In all classifications, the study area was itself used as a reference image for validation, as it had high enough spatial resolution for verification of classification accuracy.

4.1 Results and Accuracy Assessment for Pixel-based Classification

Figure 4.1 shows the pixel-based classification image and Table 4.1 shows the classification accuracy. The overall classification accuracy for the pixel-based method was 80.67% and the overall kappa statistic was 0.65. The producer’s accuracy for the impervious surfaces was 76.19%, for vegetation it was 87.27%, and for the combined shadow/water class it was 81.82%. The user’s accuracy for the impervious surfaces was 90.14%, for vegetation it was 69.57%, and for the combined shadow/water class it was 90%. The kappa by landcover class was 0.77 for impervious surfaces, 0.52 for vegetation, and 0.89 for the shadow/water class. Table 4.2 shows the percentage of each landcover class in the study area, impervious cover of 48.51%, vegetation cover of 46.62%, and shadow/water has 4.87% coverage. Values in Table 4.2 were obtained from the histogram of ‘Raster Attributes’in Figure 4.1.

The vegetation class, with a user’s accuracy of 69.57% and with a low kappa value of 0.52, was the major reason for the low overall 80.67% pixel-based classification accuracy. A total of 150 points was chosen for accuracy assessment of the three landcover classes using stratified random sampling (Congalton, 2001). With similar area distribution for impervious (48.5%) and vegetation (46.62%) classes, the number of samples chosen automatically for the impervious class was 84,
as compared to 55 for vegetation. This indicates that a sampling problem was present and the minimum number of samples (10 for each class) should be reconsidered. The vegetation in the study area was mostly clustered around the Botanical Gardens, and the sampling tool in ERDAS Imagine chose the more fragmented impervious surfaces for truly random samples. However, there was mixing of shadows with trees and impervious surfaces in the study area, small shadows lesser than 50-100 pixels were being merged with the landcover class causing shadows. The complex process of “recode” $\rightarrow$ “clump” $\rightarrow$ “eliminate” could not completely remove scattered pixels which do not correlate with the ground truth. There was also some confusion for the bare soil class. Some areas like baseball fields were mixed up with impervious due to brightness while grassy bare soil was classed as vegetation. The water and shadows were clustered within similar DNs, and therefore thoroughly confused with each other. The impervious class had the best selection of samples because of their frequent and spectrally unique occurrences. Near the north of the Fairgrounds racecourse area, which had a large rectangular oval shape, shadows are improperly classified as vegetation, leading to the suspicion that there is misclassification of vegetation class which explains the low kappa value for vegetation at 0.52. This confirms the findings of Zhou (2006) which documented high misclassification from the pixel-based maximum likelihood classifier for classifying urban areas using high resolution imagery.

There was a high percentage of impervious surfaces 48.51% for the study area, which covers parts of downtown New Orleans. As expected, most of the impervious surfaces were concentrated near the Mercedes-Benz Superdome area. Vegetation dominated in the northwestern part of the image, which corresponds to the Botanical Gardens. Impervious surfaces like rooftops and roads which were spectrally distinct and close to the ground without causing shadows were easily classified. During the unsupervised classification process, shadows/water were detected in only 3 classes out of a total of 80 used for unsupervised classification. The shadow landcover class was confused with the water of Bayou St. John and was noticeable, but did not give rise to major classification error in the study as water was composed of less than 1% of the total study area. Otherwise, the shadows were classified reliably when caused due to tall trees, tall buildings, or commercial structures.
Figure 4.1: Pixel-based Classification Result
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Dark Blue -> Shadow/Water)
Table 4.1: Pixel-based Hybrid Classification Accuracy

<table>
<thead>
<tr>
<th>Classified</th>
<th>Reference</th>
<th>Vegetation</th>
<th>Impervious</th>
<th>Shadow/Water</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td></td>
<td>48</td>
<td>20</td>
<td>1</td>
<td>69.57%</td>
<td>0.52</td>
</tr>
<tr>
<td>Impervious</td>
<td></td>
<td>6</td>
<td>64</td>
<td>1</td>
<td>90.14%</td>
<td>0.77</td>
</tr>
<tr>
<td>Shadow/Water</td>
<td></td>
<td>1</td>
<td>0</td>
<td>9</td>
<td>90%</td>
<td>0.89</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td></td>
<td>87.27%</td>
<td>76.19%</td>
<td>81.82%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td></td>
<td>80.67%</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Kappa Statistic</td>
<td></td>
<td>0.65</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.2: Number of Classified Pixels in Pixel-based Hybrid Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Pixels</th>
<th>Percentage of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>11,445,871</td>
<td>48.51%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>11,000,807</td>
<td>46.62%</td>
</tr>
<tr>
<td>Shadow/Water</td>
<td>1,149,092</td>
<td>4.87%</td>
</tr>
</tbody>
</table>
4.2 Results and Accuracy Assessment for OBIA Rule-based Method 1

Figure 4.2 shows the classification results of rule-based method 1 in OBIA and Table 4.3 shows the classification accuracy. The overall classification accuracy for method 1 was 85.33% and the overall kappa statistic was 0.77. The producer’s accuracy for the impervious surfaces was 76.39%, for vegetation it was 90.57%, and for the combined shadow/water class it was 100%. The user’s accuracy for the impervious surfaces was 93.22%, for vegetation it was 73.85%, and for the combined shadow/water class it was 96.15%. The kappa by landcover class was 0.87 for impervious surfaces, 0.59 for vegetation, and 0.95 for the shadow/water class. Table 4.4 shows the percentage of landcover class in the study area.

The procedure followed in this classification was to perform a single scale multi-resolution segmentation, a spectral difference segmentation to combine the image objects, and then assign the image objects to different landcover classes based on the class histogram threshold.

The first visual impression after looking at Figure 4.2 was the clarity of the OBIA classification compared to the pixel-based classification. Shadows were better represented and the classification was able to delineate shadows of smaller impervious structures and trees, as compared to merging shadows with vegetation and impervious classes in the pixel-based classification. Shadows were still confused with water bodies in the classification, the confusion was prominent with the water of Bayou St. John, and was a glaring example of misclassification in this image. The vegetation landcover class with a user’s accuracy of 73.85% and the impervious landcover class with a producer’s accuracy of 76.39% explained the overall accuracy of 85.33%.

The vegetation in the study area was clustered around the Botanical Gardens and the Fairgrounds racecourse. The fast transitions in the subdivisions for adjoining vegetation/impervious/shadow classes was better represented in this classification. Large rectangular shaped impervious surfaces were easily classified. In the Botanical Gardens area, the tall trees which caused shadows were not classified as vegetation because of the limitation of the “enclosed by” method, which was not able to completely enclose the shadows and shift them to the vegetation class. Impervious surfaces like roads and rooftops were classified properly, and occurred mostly in the Superdome area.
Figure 4.2: OBIA Rule-based Method 1 Classification Result
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Magenta -> Shadow/Water)
Table 4.3: Classification Accuracy for OBIA Rule-based Method 1

<table>
<thead>
<tr>
<th>Classified</th>
<th>Reference</th>
<th>Impervious</th>
<th>Vegetation</th>
<th>Shadow/Water</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>55</td>
<td>4</td>
<td>0</td>
<td></td>
<td>93.22%</td>
<td>0.87</td>
</tr>
<tr>
<td>Vegetation</td>
<td>17</td>
<td>48</td>
<td>0</td>
<td></td>
<td>73.85%</td>
<td>0.59</td>
</tr>
<tr>
<td>Shadow/Water</td>
<td>0</td>
<td>1</td>
<td>25</td>
<td></td>
<td>96.15%</td>
<td>0.95</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>76.39%</td>
<td>90.57%</td>
<td>100.00%</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>85.33%</td>
<td></td>
</tr>
<tr>
<td>Overall Kappa Statistic</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.77</td>
<td></td>
</tr>
</tbody>
</table>

Table 4.4: Number of Classified Pixels in OBIA Rule-based Method 1 Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Pixels</th>
<th>Percentage of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>9,239,885</td>
<td>39.04%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>10,270,883</td>
<td>43.40%</td>
</tr>
<tr>
<td>Shadow</td>
<td>4,152,112</td>
<td>17.54%</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0%</td>
</tr>
</tbody>
</table>
4.3 Comparison of Pixel-based vs OBIA Rule-based Method 1

Figure 4.3 and Figure 4.4 show the major difference in classification between the traditional pixel-based classification and the classification result for OBIA rule-based method 1. These figures show the Fairgrounds racecourse area, the OBIA method was much more accurate and looks to mimic the real world image more closely. The initial OBIA rule-based method, which was not the best classification method, was chosen for comparison with the pixel-based method to evaluate the differences between the pixel-based and OBIA classification.

There was a noticeable difference in the percentage and absolute number of detected shadows above the racecourse in the warehouse area in the OBIA image of Figure 4.4, when compared with the pixel-based classification. OBIA detects more shadows, possibly because the smaller shadows are not lost by the FNEA algorithm as happened in the clump procedure in ERDAS Imagine. The smaller shadows in OBIA were detected because of the initial segmentation which merges and clusters the shadows. The pixel-based classification also identifies shadows sporadically, in a few places in the subdivision below the Fairgrounds racecourse in Figure 4.3.

The segmentation procedure of OBIA can nicely follow the high frequency transition of classes in high spatial resolution imagery due to the “bottom up” procedure of its region growing method. In the pixel-based classification, only clustered shadow patches are being detected and the smaller sized shadows are merged either into the vegetation or impervious landcover classes. In both classifications, the small patch of water in the Fairgrounds racecourse to the right was confused with shadow because the DNs of shadow and water were spectrally similar. In the OBIA classification, the oval shaped racecourse ground shows a grass lawn which has been recently mowed, and this was faithfully classified as vegetation, as compared to the patchy pixel-based classification. The track for horse racing, along with other impervious structures, was identified clearly in the OBIA classification while it was barely discernible in the pixel-based classification.
Figure 4.3: Pixel-based Hybrid Classification for Fairgrounds Racecourse
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Dark Blue -> Shadow/Water)

Figure 4.4: OBIA Rule-based Method 1 Classification for Fairgrounds Racecourse
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Magenta -> Shadow/Water)
4.4 Results and Accuracy Assessment for OBIA Rule-based Method 2

Figure 4.5 shows the classification results of rule-based method 2 in OBIA and Table 4.5 shows the classification accuracy. The overall classification accuracy for method 2 was 92% and the overall kappa statistic was 0.88. The producer’s accuracy for the impervious surfaces was 93.83%, for vegetation it was 86.49%, for shadow class it was 97.22%, and for water class it was 100.00%. The user’s accuracy for impervious surface class was 91.57%, for vegetation it was 92.75%, for shadow class it was 92.11%, and for the water class it was 90.00%. The kappa by landcover class was 0.86 for impervious surfaces, 0.88 for vegetation, 0.9 for the shadow class, and 0.89 for the water class. Table 4.6 shows the percentage of each landcover class in the study area.

The procedure followed in this classification was to perform a single scale multi-resolution segmentation, a spectral difference segmentation with DN range difference of 10 to combine the image objects, and then to assign the image objects to different landcover classes based on the class histograms. To discriminate water class, LIDAR elevation data was used. Finally, the length/width ratio was used to shift misclassified vegetation into the impervious landcover class.

This method was a refinement to the previous OBIA method with the exception of the last few stages where misclassification of the water landcover class from shadow is corrected. Bayou St. John was now correctly classified as the water class by apriori knowledge that the bayou exists at a lower elevation compared to its surrounding area. The identification of water body in this method was scene specific and unsuitable for automation.

There was little change in the percentage of shadow area between OBIA rule-based method 1 and OBIA rule-based method 2. There was slight change in the percentage of impervious and vegetation classes. The impervious class increased from 39.04% to 45.32% and the vegetation class decreased from 43.4% to 37.06%. This change was due to the usage of the length/width ratio used to shift misclassified vegetation to impervious surfaces; hence some objects which were originally classified as vegetation in OBIA rule-based method 1 were classified as the impervious class for OBIA rule-based method 2.
Figure 4.5: OBIA Rule-based Method 2 Classification Result
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Magenta -> Shadow, Sky Blue -> Water)
Table 4.5: Classification Accuracy for OBIA Rule-based Method 2

<table>
<thead>
<tr>
<th>Classified</th>
<th>Impervious</th>
<th>Vegetation</th>
<th>Shadow</th>
<th>Water</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>76</td>
<td>7</td>
<td>0</td>
<td>0</td>
<td>91.57%</td>
<td>0.86</td>
</tr>
<tr>
<td>Vegetation</td>
<td>5</td>
<td>64</td>
<td>0</td>
<td>0</td>
<td>92.75%</td>
<td>0.88</td>
</tr>
<tr>
<td>Shadow</td>
<td>0</td>
<td>3</td>
<td>35</td>
<td>0</td>
<td>92.11%</td>
<td>0.9</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>9</td>
<td>90.00%</td>
<td>0.89</td>
</tr>
<tr>
<td>Producer’s Accuracy</td>
<td>93.83%</td>
<td>86.49%</td>
<td>97.22%</td>
<td>100.00%</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Accuracy</td>
<td>92%</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Overall Kappa Statistic</td>
<td>0.88</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 4.6: Number of Classified Pixels in OBIA Rule-based Method 2 Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Pixels</th>
<th>Percentage of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>10,725,032</td>
<td>45.32%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>8,771,276</td>
<td>37.06%</td>
</tr>
<tr>
<td>Shadow</td>
<td>3,990,386</td>
<td>16.86%</td>
</tr>
<tr>
<td>Water</td>
<td>176,124</td>
<td>0.74%</td>
</tr>
</tbody>
</table>
4.5 Results and Accuracy Assessment for OBIA Rule-based Method 3

Figure 4.6 shows the classification results of rule-based method 3 in OBIA and Table 4.7 shows the classification accuracy. The overall classification accuracy for method 3 was 89.5% and the overall kappa statistic was 0.84. The producer’s accuracy for the impervious surfaces was 91.03%, for vegetation it was 89.29%, for shadow class it was 82.76%, and for water class it was 100%. The user’s accuracy for the impervious surfaces was 92.21%, for vegetation it was 88.24%, for the shadow class it was 86%, and for the water class it was 90%. The kappa by landcover class was 0.87 for impervious surfaces, 0.8 for vegetation, 0.83 for the shadow class, and 0.89 for the water class. Table 4.8 shows the percentage of each landcover class in the study area.

The procedure followed in this classification was to perform a hierarchical multi-resolution segmentation with default color/shape of 0.1, compactness/smoothness of 0.5, scale parameters of 10, 20, 30, 40, and 50, a spectral difference segmentation with a tighter DN range difference of 5 to combine the image objects, and then assign the image objects to different landcover classes based on the class histograms. NDVI was used to detect vegetation, NDWI was used to detect water, and SSI was used to detect shadows. The overestimate of shadow class has reduced and has been shifted to the other two landcover classes of vegetation and impervious surfaces. This overestimate was corrected by using the “enclosed by” OBIA method to shift any shadow surrounded by a dominant landcover class like vegetation or impervious to vegetation or impervious classes, respectively.

This method correctly classified all the major landcover classes in the study area. The difference between this particular method and the previous two OBIA methods was the addition of using indices like NDVI for vegetation, NDWI for water identification, and SSI for shadow identification. This method used histogram thresholding and indices to obtain its classification.

There was a small decrease in the percentage of shadow area between OBIA rule-based method 2 and OBIA rule-based method 3. There was a higher change in the percentage of impervious and vegetation classes. The impervious class decreased from 45.32% to 41.37% and the vegetation class increased from 37.06% to 46.17%. The change in vegetation was due to part of the shadow landcover class and part of impervious class both being classified as vegetation.
Figure 4.6: OBIA Rule-based Method 3 Classification Result
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Magenta -> Shadow, Sky Blue -> Water)
Table 4.7: Classification Accuracy for OBIA Rule-based Method 3

<table>
<thead>
<tr>
<th>Classified</th>
<th>Impervious</th>
<th>Vegetation</th>
<th>Shadow</th>
<th>Water</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>71</td>
<td>6</td>
<td>0</td>
<td>0</td>
<td>92.21%</td>
<td>0.87</td>
</tr>
<tr>
<td>Vegetation</td>
<td>6</td>
<td>75</td>
<td>4</td>
<td>0</td>
<td>88.24%</td>
<td>0.8</td>
</tr>
<tr>
<td>Shadow</td>
<td>1</td>
<td>3</td>
<td>24</td>
<td>0</td>
<td>86%</td>
<td>0.83</td>
</tr>
<tr>
<td>Water</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>9</td>
<td>90%</td>
<td>0.89</td>
</tr>
</tbody>
</table>

Producer’s Accuracy: 91.03%  89.29%  82.76%  100%

Overall Accuracy: 89.5%
Overall Kappa Statistic: 0.84

Table 4.8: Number of Classified Pixels in OBIA Rule-based Method 3 Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Pixels</th>
<th>Percentage of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>9,789,480</td>
<td>41.37%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>10,925,739</td>
<td>46.17%</td>
</tr>
<tr>
<td>Shadow</td>
<td>2,802,065</td>
<td>11.84%</td>
</tr>
<tr>
<td>Water</td>
<td>145,596</td>
<td>0.62%</td>
</tr>
</tbody>
</table>
4.6 Results and Accuracy Assessment for OBIA Rule-based Method 4

Figure 4.7 shows the classification results of OBIA rule-based method 4 and Table 4.9 shows the classification accuracy. The overall classification accuracy for method 4 was 91.41% and the overall kappa statistic was 0.85. The producer’s accuracy for the impervious surfaces was 92.09%, for vegetation it was 96.34%, for shadow class it was 70.37%, and for water landcover class it was 100%. The user’s accuracy for the impervious surfaces was 96.24%, for vegetation it was 87.78%, for the shadow class it was 82.61%, and for the water class it was 80%. The kappa by landcover class was 0.92 for impervious surfaces, 0.82 for vegetation, 0.8 for the shadow class, and 0.79 for the water class. Table 4.10 shows the percentage of each landcover class in the study area.

The procedure followed in OBIA rule-based method 4 classification was to perform a hierarchical multi-resolution segmentation with default color/shape of 0.1, compactness/smoothness of 0.5, scale parameters of 10, 20, and 50, a spectral difference segmentation with a tight DN range difference of 5 to combine the image objects, and then assign the image objects to landcover classes based on different spectral indices. As in the OBIA rule-based method 3, NDVI was used to detect vegetation, NDWI was used to detect water, and SSI was used to detect shadows. The remaining image objects were classified as impervious surfaces. Finally, the “enclosed by” process from previous OBIA rule-based methods was used, which assigns those shadow objects which are enclosed by either impervious or vegetation objects to impervious or vegetation class, respectively. The overestimate of shadow class was reduced and shifted to the impervious surfaces.

There was a decrease in the percentage of shadow area between OBIA rule-based methods 3 and 4. There was a higher change in the percentage of impervious and vegetation classes. The impervious class increased from 41.37% to 51.29% and the vegetation class decreased from 46.17% to 40.8%. The change in impervious was due to part of the shadow class and part of vegetation class both being classified as impervious. There is known confusion between the bare soil and impervious surfaces when using NDVI and the classification reflects this in the higher percentage of impervious surfaces (Bannari et al., 1996; Leprieur et al., 1996). There was small misclassification for water class with shadow class due to scene specific variation of the SSI.
Figure 4.7: OBIA Rule-based Method 4 Classification Result
(Legend: Yellow -> Impervious, Dark Green -> Vegetation, Magenta -> Shadow, Sky Blue -> Water)
Table 4.9: Classification Accuracy for OBIA Rule-based Method 4

<table>
<thead>
<tr>
<th>Classified</th>
<th>Reference</th>
<th>Impervious</th>
<th>Vegetation</th>
<th>Shadow</th>
<th>Water</th>
<th>User’s Accuracy</th>
<th>Kappa</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>128</td>
<td>2</td>
<td>3</td>
<td>0</td>
<td>96.24%</td>
<td>0.92</td>
<td></td>
</tr>
<tr>
<td>Vegetation</td>
<td>7</td>
<td>79</td>
<td>4</td>
<td>0</td>
<td>87.78%</td>
<td>0.82</td>
<td></td>
</tr>
<tr>
<td>Shadow</td>
<td>3</td>
<td>1</td>
<td>19</td>
<td>0</td>
<td>82.61%</td>
<td>0.8</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>1</td>
<td>0</td>
<td>1</td>
<td>8</td>
<td>80%</td>
<td>0.79</td>
<td></td>
</tr>
</tbody>
</table>

Producer’s Accuracy 92.09% 96.34% 70.37% 100%

Overall Accuracy 91.41%
Overall Kappa Statistic 0.85

Table 4.10: Number of Classified Pixels in OBIA Rule-based Method 4 Classification

<table>
<thead>
<tr>
<th>Class</th>
<th>Pixels</th>
<th>Percentage of total area</th>
</tr>
</thead>
<tbody>
<tr>
<td>Impervious</td>
<td>12,137,944</td>
<td>51.29%</td>
</tr>
<tr>
<td>Vegetation</td>
<td>9,655,219</td>
<td>40.80%</td>
</tr>
<tr>
<td>Shadow</td>
<td>1,637,008</td>
<td>6.92%</td>
</tr>
<tr>
<td>Water</td>
<td>232,709</td>
<td>0.98%</td>
</tr>
</tbody>
</table>
4.7 OBIA Rule-based Method 4 Applied to Various Image Subsets

Table 4.11: Combined Classification Accuracy for Images using OBIA Rule-based Method 4

<table>
<thead>
<tr>
<th>Image Subset</th>
<th>Overall Accuracy</th>
<th>Overall Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Test Study Area 1</td>
<td>80.66%</td>
<td>0.72</td>
</tr>
<tr>
<td>Test Study Area 2</td>
<td>86.43%</td>
<td>0.78</td>
</tr>
<tr>
<td>Test Study Area 3</td>
<td>92.15%</td>
<td>0.88</td>
</tr>
</tbody>
</table>

This section summarizes the results of testing hypothesis 3, which is, investigating the feasibility of automated application of OBIA rule-based method 4 to different study areas. The combined classification accuracies for the all the three test areas is shown in Table 4.11.

Figure 4.8 consists of a typical wetland dominated rural area located on the left side and a subdivision of houses and a baseball field on the right side of the image. The result of the classification was acceptable, with noticeable misclassification of vegetation instead of impervious surfaces (roads) in the image. Water bodies were classified correctly. Part of the baseball field which was bare soil was classified as an impervious surface, while part of the field covered with grass was classified as vegetation. Shadow was not classified in this image at all. The classification accuracy was 80.66% with an overall kappa statistic of 0.72.

Figure 4.9 consists of a Y-shaped small port located approximately in the center and was dominated by impervious surfaces on the left side and by vegetation on the right side of the image. The result of the classification was good, with a small misclassification of water instead of vegetation. Impervious surfaces and vegetation land covers were classified correctly. The classification accuracy was 86.43% with an overall kappa statistic of 0.78.

Figure 4.10 consists of Mississippi River located approximately in the center, barge traffic and storage containers on the left side of the image, and a golf course with dense suburban housing on the right side of the image. The result of the classification was good, with an slight overestimate of vegetation instead of impervious surfaces. All water bodies were classified correctly. The classification accuracy was 92.15% with an overall kappa statistic of 0.88.
Figure 4.8: Test Study Area 1 and Classification Result
Figure 4.9: Test Study Area 2 and Classification Result
Figure 4.10: Test Study Area 3 and Classification Result
4.8 Summary of OBIA Rule-based Methods

The major difference between the results of the pixel-based and OBIA methods was the presence of salt and pepper appearance of the pixel-based classification compared with all OBIA methods. From an automation perspective, pixel-based classification required manual identification of each landcover class in the unsupervised classification procedure. This manual processing stage negatively impacts the time required by pixel-based classification, and supervised classification for high spatial resolution images was found to be time consuming.

OBIA rule-based methods 1, 2, and 3 used histogram DN thresholds which can be accessed programatically through a software development kit (SDK) or application programming interface (API), but was not possible to examine in eCognition because of its unavailability. OBIA rule-based method 2 used LIDAR image for elevation purpose to identify water bodies and used the length/width ratio for impervious surface discrimination. The LIDAR image elevation values are scene specific so using OBIA rule-based method 2 was not conducive for automation. OBIA rule-based method 3 added the use of spectral derived indices like NDVI, NDWI, and SSI but also used histogram DN thresholding. Using histogram DN thresholds was not conducive for automation. OBIA rule-based method 4 only utilized spectral indices derived from the image itself: NDVI, NDWI, and SSI which was demonstrated to be feasible for automation with minimal to no changes required for classification.

Table 4.3, Table 4.5, Table 4.7, and Table 4.9 show the classification statistics for OBIA rule-based methods 1, 2, 3, and 4 respectively. The overall classification accuracies and the percentage area of all landcover classes are summarized in Table 4.12 and Table 4.13, respectively. The overall classification accuracy for OBIA rule-based method 1 is 85.79% and the overall kappa statistic is 0.79. The overall classification accuracy for OBIA rule-based method 2 is 92% and the overall kappa statistic is 0.88. The overall classification accuracy for OBIA rule-based method 3 is 89.5% and the overall kappa statistic is 0.84. The overall classification accuracy for OBIA rule-based method 4 is 91.41% and the overall kappa statistic is 0.85. Table 4.4, Table 4.6, Table 4.8, and Table 4.10 show the number of classified pixels for all the methods.
Initially, the samples for accuracy assessment were chosen manually and the samples per class exceeded the recommended number of 50 samples (Congalton, 2001). The samples were image objects, not individual pixels, and were distributed across the study area in an attempt to be placed randomly. The samples were taken right next to each other, at the edges where they transition into another landcover class. In order to remove operator bias, the accuracy assessment procedure was subsequently performed in ERDAS Imagine, based on a recommended procedure in Zhou & Troy (2008).

For all the OBIA rule-based methods, some operations like “enclosed by”, the “length/width ratio”, and “rectangular fit” are available only in eCognition and offer an advantage when correcting the classification of certain land covers.

### 4.8.1 Summary for Impervious Classification

The percentage of impervious cover for the study area was 39.04% in OBIA rule-based method 1, 45.32% in OBIA rule-based method 2, 41.37% in OBIA rule-based method 3, and 51.29% in OBIA rule-based method 4 respectively.

This percentage was within the high flooding threshold for impervious surfaces as mentioned by Goldshleger et al. (2009). However, New Orleans is unique; the runoff in an extreme flood event would be channeled outside the city and put pressure on the surrounding watershed. New Orleans depends on the levees for flood control and is situated for the most part below sea level; the flooding potential is controlled mostly by the pumping stations which pump the accumulated water into Lake Pontchartrain and other places like Bonnet Carré Spillway. New Orleans is divided into 27 ‘ponding areas’, and each ponding area has multiple pumps with multiple thousand cf/sec capacity of pumping into Lake Pontchartrain (FEMA, 2012; US Army Corps of Engineers, 2012).

In all the OBIA rule-based methods, some dark colored rooftops which should be classified as impervious were being confused with shadows. Most of the impervious surfaces which were easy to classify in OBIA were located in the Mercedes-Benz Superdome area. Impervious surfaces have diverse spectral signatures; specifically the DNs around 100 cause confusion due to influence of vegetation. The impervious class has a wide variation, from a DN of 100 to 200 for a 8-bit image.
Very few impervious objects are bright enough to have high DN values, unusual bright impervious objects are mostly rooftops or pavements painted with artificial colors. Roads have a linear structure and were sometimes confused with shadows and overhanging trees. Whenever there was a “break” in the road due to a bridge or vegetation or shadow, there was sudden class transition, but for the most part all the OBIA methods could correctly classify such broken up impervious objects.

There was a relatively wide percentage range of impervious surfaces for the study area in all OBIA methods, from 39.04% for OBIA rule-based method 1 to 51.29% for OBIA rule-based method 4. The actual percentage after careful deliberation is much closer to the 45.32% mark obtained in OBIA rule-based method 2. The result from the rule-based method 4, at 51.29% is overestimated slightly because slightly negative NDVI values are classified as impervious. This confusion of NDVI with bare soil is a widely known result but this last method offers the fastest processing time because it was quick, and was more suited for generalized automation.

4.8.2 Summary for Vegetation Classification

The percentage of vegetation cover for the study area was 43.4% in OBIA rule-based method 1, 37.06% in OBIA rule-based method 2, 46.17% in OBIA rule-based method 3, and 40.8% in OBIA rule-based method 4 respectively.

There was confusion between the impervious surfaces and vegetation due to sharp transitions in the subdivisions of the study area. Most of the subdivisions are tightly clustered and have a house, a lawn, and a few trees which overlap over a surrounding road or driveways. Vegetation in urban areas has a definite geometrical pattern due to being sculpted. In urban areas, some trees and lawns have rectangular shape, so a nice balance has to be maintained in choosing OBIA processes like “Rectangular Fit” to avoid misclassification. In some places where there is a patch of lawn in the middle of a road and vegetation on both sides of the road, significant parts of the road itself are confused with vegetation. Sometimes, an overhang of trees across an impervious surface like a road results in misclassification as shadow. But overall vegetation of all types (trees, shrubs, and grasses) was detected reliably using NDVI. Vegetation dominates in the northwest corner of the study area with tall trees present in the Botanical Gardens.
There was a relatively narrow percentage range of vegetation for the study area in all OBIA methods, from 37.06% for OBIA rule-based method 2 to 46.17% for OBIA rule-based method 3. The actual percentage after careful deliberation is much closer to the 43.4% mark obtained in OBIA rule-based method 1. The result from the rule-based method 4, at 40.8% is underestimated slightly because bare soil was classified as impervious surfaces.

4.8.3 Summary for Shadow Classification

The percentage of shadow for the study area was 17.54% in OBIA rule-based method 1, 16.86% in OBIA rule-based method 2, 11.84% in OBIA rule-based method 3, and 6.92% in OBIA rule-based method 4 respectively.

Due to the off-nadir look angle in the study area, there was a noticeable variation in light illumination for different sides of tall image objects, causing shadows due to building rooftops and tree canopy. In Landsat TM or other medium resolution imagery these differences are averaged out by the sensor but in a high spatial resolution image they were prominent. Private housing in the subdivisions sometimes have outdoor swimming pools, which are again confused with shadows. Ideally, the percentage of shadows should approach zero as the underlying landcover class was fully classified. So, the classification which decreases the percentage of shadow class and has reasonable classification accuracy was preferred. In some OBIA rule-based methods the “enclosed by” criteria was used to assign shadows to either the impervious or vegetation landcover classes. The SSI index used for shadow classification was found to be dependent on scene specific values, careful attention must be paid such that shadows are not being overestimated or underestimated. Although not explored in this particular study, shadows could be confused with impervious surfaces dependent on the time when study images are captured, due to light/shadow variation.

There was a relatively wide percentage range of shadow for the study area in all OBIA methods, from 6.92% for OBIA rule-based method 4 to 17.54% for OBIA rule-based method 1. The actual percentage which can be reliably classified into either of impervious or vegetation land covers is much closer to the 6.92% mark obtained in OBIA rule-based method 4.
4.8.4 Summary for Water Classification

The percentage of water for the study area was 0% in OBIA rule-based method 1, 0.74% in OBIA rule-based method 2, 0.62% in OBIA rule-based method 3, and 0.98% in OBIA rule-based method 4 respectively.

The major difference between OBIA rule-based methods 1, 2, 3, and 4 was the proper classification of the Bayou St. John water body in the study area. This detection was absent in OBIA rule-based method 1, but it was incorrectly classified by adding LIDAR elevation information in OBIA rule-based method 2, and by using NDWI and NDVI in OBIA rule-based method 3 and method 4 respectively.

Water detection was found to be difficult, but a generic approach of using NDWI and NDVI made it possible and reliable, even with zero a priori knowledge of the study area. This was proved by using OBIA rule-based method 4 on different study area subsets as seen in Figure 4.8, Figure 4.9, and Figure 4.10 respectively.

4.8.5 Concluding Remarks

While working on the development of a simple and generic method for OBIA, considerable time was spent on evaluating texture processing methods but they were considered too unwieldy and time consuming. Simple spectral methods like NDVI, NDWI, SSI, histogram thresholding, or even sample based classification give quite good separability, are relatively fast to process, and were therefore explored in the study. Histogram thresholds are normally used for segmentation but were used for classification in this study, since the subset image used for the study had good distribution of peaks/valleys conducive for separating the four landcover classes of interest.

OBIA rule-based method 4 gave good overall classification accuracy with excellent results for vegetation and water, and acceptable results for shadows; impervious surfaces were detected indirectly. This method was tested on multiple image subsets and is therefore recommended for application to other study areas.

Hypothesis 3, which was “A ruleset can be developed in OBIA for automated and generic classification with reasonable accuracy” has been found to be validated.
eCognition has a few options for manipulation in OBIA but a small variation in multi-resolution segmentation parameters produces varied output which can negatively affect classification accuracy. The parameters were found to be very sensitive and must be changed with care. The segmentation parameters are studied in detail in the following chapter.

Table 4.12: Combined Overall Classification Accuracy for all Methods in Study

<table>
<thead>
<tr>
<th>Method</th>
<th>Overall Accuracy</th>
<th>Overall Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel-based Classification</td>
<td>80.67%</td>
<td>0.65</td>
</tr>
<tr>
<td>OBIA Rule-based Method 1 Classification</td>
<td>85.33%</td>
<td>0.77</td>
</tr>
<tr>
<td>OBIA Rule-based Method 2 Classification</td>
<td>92%</td>
<td>0.88</td>
</tr>
<tr>
<td>OBIA Rule-based Method 3 Classification</td>
<td>89.5%</td>
<td>0.84</td>
</tr>
<tr>
<td>OBIA Rule-based Method 4 Classification</td>
<td>91.41%</td>
<td>0.85</td>
</tr>
</tbody>
</table>

Table 4.13: Combined Percentage Area of all Classes for all Methods in Study

<table>
<thead>
<tr>
<th>Method</th>
<th>Impervious</th>
<th>Vegetation</th>
<th>Shadow</th>
<th>Water</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pixel-based Classification</td>
<td>48.51%</td>
<td>46.62%</td>
<td>4.87%</td>
<td>0.0%</td>
</tr>
<tr>
<td>OBIA Rule-based Method 1 Classification</td>
<td>39.04%</td>
<td>43.40%</td>
<td>17.54%</td>
<td>0.0%</td>
</tr>
<tr>
<td>OBIA Rule-based Method 2 Classification</td>
<td>45.32%</td>
<td>37.06%</td>
<td>16.86%</td>
<td>0.74%</td>
</tr>
<tr>
<td>OBIA Rule-based Method 3 Classification</td>
<td>41.37%</td>
<td>46.17%</td>
<td>11.84%</td>
<td>0.62%</td>
</tr>
<tr>
<td>OBIA Rule-based Method 4 Classification</td>
<td>51.29%</td>
<td>40.8%</td>
<td>6.92%</td>
<td>0.98%</td>
</tr>
</tbody>
</table>
CHAPTER 5: EFFECTS OF SEGMENTATION PARAMETERS ON CLASSIFICATION ACCURACY

5.1 Introduction

This chapter studies the effects observed by changing the various segmentation parameters available for tuning in OBIA: scale, color/shape, and compactness/smoothness. Three images were subsetted for fast image processing and easier visualization of parameter changes. Figure 5.1(a) depicts Bayou St. John with some parking lots and commercial structures. Figure 5.1(b) depicts the Fairgrounds Racecourse surrounded by commercial structures, small water body, and vegetation inter-mixed with impervious structures. Figure 5.1(c) shows a section of the Industrial Canal which connects Lake Pontchartrain with the Mississippi River.

The color/shape and the compactness/smoothness parameters are together known as homogeneity criterion (eCognition Reference Book, 2011). The scale parameter limits the maximum heterogeneity for combining adjoining image objects (eCognition Reference Book, 2011). In a typical OBIA software, segmentation is followed by classification, and then optionally followed by a procedure to check the classification accuracy. To obtain good classification accuracy the segmentation should be reliable and produce consistently good results (Gao et al., 2011). In other words, the quality of segmentation was directly correlated with classification accuracy (Yue et al., 2012). If the resulting classification accuracy was low, then the segmentation has to be repeated with different parameters. Because OBIA software uses parameters like scale, color/shape, compactness/smoothness, and each parameter can have a range of values, different parameter combinations produce a range of differing segmentation results which might be acceptable or unacceptable (Liu et al., 2012). For landslide detection, Martha et al. (2011) found that image segments created using spectral and size criteria are inconsistent for different landslides. In eCognition, without a priori knowledge about the image objects or the scene, it was difficult to obtain reliable segmentation, because of a lack of a clearly defined, automated, and acceptable metric for evaluating the quality of segmentation ( Farmer & Jain, 2005; Dragut et al., 2010). Manual assessment of segmentation quality was performed by noting the discrepancy between polygons and the segmented image segments, this output was used...
Figure 5.1: Study Areas in Segmentation Parameter Study
to guide the analyst to select the optimal combination of segmentation parameter values (Liu et al., 2012).

Images used for urban remote sensing analysis generally have horizontal spatial resolution ranging from 10 cm (high resolution aerial photos) to 30 m (Landsat TM). The images that depict an urban scenario are complex combinations of different reflective surfaces representing natural features like morphology, biology, hydrology, manmade objects like impervious surfaces, and shadows (Sowmya & Trinder, 2000). Unlike medical imagery where the anatomical structures are contextual because they are mostly constrained to relatively fixed positions (Tu & Bai, 2010), remote sensing imagery is free form, consists of multiple scales, and is context unaware. Context and scale in remote sensing have to be inferred from the image itself. In OBIA, the image segmentation procedure aims at maximizing homogeneity within segments and separability between neighbouring segments by obeying Tobler’s first law of Geography within the constraints of the segmentation parameters (Gao et al., 2011). Spatial variation is captured by reflectance, a spatially continuous variable; the spatial variation between reflectance values of any two image objects depends on the lag distance beyond which the image objects are not spatially autocorrelated (Lowe & Guo, 2011).

Lowe & Guo (2011) state, per the Shannon-Nyquist sampling theorem, that image objects should be sampled at half their actual width, such that the spatial resolution of image objects should be half the lag distance. The scale parameter has a maximum effect on the size of generated image objects and is the dominant factor of the multi-resolution segmentation algorithm. Therefore, initial identification of the optimal segmentation scale is very crucial for the success of OBIA for LULC purposes (Dragut et al., 2010; Marpu et al., 2010; Lowe & Guo, 2011; Yue et al., 2012). While adjusting the segmentation parameters of the OBIA software, the image analyst must be aware of the various measures proposed in the scientific literature for checking and validating the problems due to segmentation: its overall quality, over-segmentation, under-segmentation, and overlap between reference polygons and generated segments (Liu et al., 2012). The two most common problems faced by any segmentation algorithm are under-segmentation and over-segmentation. Under-segmentation (or leaking) refers to inclusion of unwanted artifacts during segmentation,
while over-segmentation was defined as formation of multiple image objects instead of a single image object (also known as over-cutting), resulting in an incomplete segmentation (Liu et al., 2006). A right mix of the segmentation parameters can be achieved by first choosing the correct scale, and then choosing the other parameters. Following this procedure reduces the negative effects by improving the resultant segmentation and enhances the final classification accuracy.

5.2 Methodology

Multiple sections of the various input images of 1-meter spatial resolution, 4 band USGS DOQQ surrounding downtown New Orleans, Louisiana, were subsetted in ERDAS Imagine such that different land covers such as vegetation, impervious surfaces, water, and shadows were visible in the three images selected. Image subsets capable of display with high fidelity were studied. A output screen shot was exported for display for each increment of segmentation parameters. Not all of the images were displayed due to space constraints. Number of image objects was recorded from the status bar. No attempt was made to calculate the percentage of each landcover class.

For testing the range of optimal scale parameter, the scale parameter was chosen as an arbitrary number 10, 20, 30 till 80 creating distinct image object levels. The image object levels at higher scales were not built hierarchically by assembling previous lower scales of image objects, because the classification accuracy was decided by the lowest initial scale parameter used, irrespective of whether it was a single scale or a multi-scale segmentation. For testing the range of optimal heterogeneity criterion of compactness/smoothness and color/shape parameters, they were increased sequentially in small steps of 0.1. In all the three cases, while varying one segmentation parameter, the other two segmentation parameters were kept constant. For easier visual inspection, a red polygon was used to flag an error for incorrect combination of different landcover classes due to combination of segmentation parameters. Images were classified by applying OBIA rule-based Method 4 for all combinations of segmentation parameters. Classification images were not shown, only segmentation images were shown. The images were exported for checking classification accuracy, the procedure follows those described in section 3.6.
5.3 Results and Discussion

5.3.1 Effects of the Scale Segmentation Parameter

Table 5.1 shows the number of generated image objects for the change in scale segmentation parameter, while Figure 5.2 shows the decrease in the number of segmented image objects plotted as scale parameter increases. Figure 5.3(a) through 5.3(f) and Figure 5.4(a) through 5.4(h) depict the visual results of changing the scale segmentation parameter with a constant color/shape value of 0.1 and a compactness/smoothness value of 0.5. Table 5.2 and Table 5.3 show the scale variation and its effects on classification accuracies. Figure 5.5 shows the classification accuracy, plotted against scale parameter. Figure 5.3 does not show the results with higher scale parameters since they are quite similar to the image with scale parameter value of 60.

The highest classification accuracy exceeding 90% was observed for the scale parameters of 10 and 20 respectively. This was tested with images for Bayou St. John and Fairgrounds Racecourse. For a single value of scale parameter, the classification accuracy decreased linearly with increase in scale parameter. Although not shown, there is no effect on hierarchical multi-scale classification accuracy, the final accuracy remains the same as the accuracy for the initial scale parameter.

Figure 5.3(a), Figure 5.3(b), Figure 5.4(a), Figure 5.4(b), Table 5.2, and Table 5.3 clearly show that the number of generated image objects was quite high for low values of scale. Table 5.1 demonstrates an inverse, non-linear relationship between the scale segmentation parameter and the number of generated objects. For low values of scale parameter, there was high incidence of generated image objects, and for high values of scale segmentation parameter, there was lower incidence of generated image objects. Figure 5.2 shows graphically that the number of image objects initially decrease exponentially for small increases in scale parameter, and then the decrease in image objects was very small, approaching saturation.

The segmentation appears accurate for higher scale parameters in Figure 5.3 and Figure 5.4, but this was misleading, as Figure 5.3(d) through 5.3(f) show that the high scale parameter forces incorrect combination of vegetation and impervious surface (rooftop). Figure 5.4(d) through 5.4(h) also show erroneous combinations of impervious surface (road) with vegetation (grassy area).
Table 5.1: Scale Effects on Number of Image Objects

<table>
<thead>
<tr>
<th>Scale Parameter</th>
<th>Image Objects</th>
<th>Image Objects</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Industrial Canal (7,797,800 pixels)</td>
<td>New Orleans Subset (23,662,880 pixels)</td>
</tr>
<tr>
<td>1</td>
<td>6,043,724</td>
<td>21,711,396</td>
</tr>
<tr>
<td>2</td>
<td>3,150,431</td>
<td>14,786,723</td>
</tr>
<tr>
<td>3</td>
<td>1,642,231</td>
<td>9,287,340</td>
</tr>
<tr>
<td>4</td>
<td>920,604</td>
<td>5,856,859</td>
</tr>
<tr>
<td>5</td>
<td>582,333</td>
<td>3,819,377</td>
</tr>
<tr>
<td>6</td>
<td>400,169</td>
<td>2,609,038</td>
</tr>
<tr>
<td>7</td>
<td>293,659</td>
<td>1,869,245</td>
</tr>
<tr>
<td>8</td>
<td>224,170</td>
<td>1,402,423</td>
</tr>
<tr>
<td>9</td>
<td>176,377</td>
<td>1,094,061</td>
</tr>
<tr>
<td>10</td>
<td>126,092</td>
<td>829,186</td>
</tr>
<tr>
<td>15</td>
<td>36,669</td>
<td>330,600</td>
</tr>
<tr>
<td>20</td>
<td>20,300</td>
<td>202,268</td>
</tr>
<tr>
<td>30</td>
<td>6,981</td>
<td>92,830</td>
</tr>
<tr>
<td>40</td>
<td>4,071</td>
<td>57,426</td>
</tr>
<tr>
<td>50</td>
<td>2,738</td>
<td>39,367</td>
</tr>
</tbody>
</table>

Figure 5.2: Count of Image Objects vs Scale
Figure 5.3: Effect of Scale Change for Bayou St. John
Figure 5.4: Effect of Scale Change for Fairgrounds Racecourse
Table 5.2: Scale Testing on Image Objects for Bayou St. John (Color/Shape = 0.1, Compactness/Smoothness = 0.5)

<table>
<thead>
<tr>
<th>Scale Parameter</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>6,355</td>
<td>93.16%</td>
<td>0.87</td>
</tr>
<tr>
<td>20</td>
<td>1,939</td>
<td>91.53%</td>
<td>0.86</td>
</tr>
<tr>
<td>30</td>
<td>950</td>
<td>89.17%</td>
<td>0.85</td>
</tr>
<tr>
<td>40</td>
<td>496</td>
<td>86.62%</td>
<td>0.82</td>
</tr>
<tr>
<td>50</td>
<td>320</td>
<td>82.52%</td>
<td>0.77</td>
</tr>
<tr>
<td>60</td>
<td>226</td>
<td>76.77%</td>
<td>0.71</td>
</tr>
</tbody>
</table>

Table 5.3: Scale Testing on Image Objects for Fairgrounds Racecourse (Color/Shape = 0.1, Compactness/Smoothness = 0.5)

<table>
<thead>
<tr>
<th>Scale Parameter</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>10</td>
<td>15,277</td>
<td>94.91%</td>
<td>0.91</td>
</tr>
<tr>
<td>20</td>
<td>4,537</td>
<td>92.19%</td>
<td>0.88</td>
</tr>
<tr>
<td>30</td>
<td>2,257</td>
<td>88.81%</td>
<td>0.85</td>
</tr>
<tr>
<td>40</td>
<td>1,373</td>
<td>87.03%</td>
<td>0.8</td>
</tr>
<tr>
<td>50</td>
<td>953</td>
<td>81.32%</td>
<td>0.76</td>
</tr>
<tr>
<td>60</td>
<td>678</td>
<td>77.41%</td>
<td>0.72</td>
</tr>
<tr>
<td>70</td>
<td>529</td>
<td>73.28%</td>
<td>0.66</td>
</tr>
<tr>
<td>80</td>
<td>403</td>
<td>67.13%</td>
<td>0.62</td>
</tr>
</tbody>
</table>

Figure 5.5: Classification Accuracy vs Scale Parameter
5.3.2 Effects of the Color/Shape Segmentation Parameter

Figure 5.6(a) through 5.6(f), Figure 5.7(a) through 5.7(f), and Figure 5.8(a) through 5.8(f) depict the visual results of testing for the color/shape segmentation parameter for scale values of 10, 40, and 50 with a compactness/smoothness value of 0.5. Table 5.4, Table 5.5, and Table 5.6 show the number of image objects for change in color/shape parameter, and the accuracy statistics. Figure 5.9 shows the change in segmented image objects plotted against the color/shape variation. Figure 5.10 shows the classification accuracy plotted against color/shape parameter.

The classification accuracy ranged from a low of 65.61% to 94.15%. Low values of image objects in Table 5.5 and Table 5.6, not exceeding 1000 image objects caused initial concern about the reliability of classification. Because for each landcover class, at least 50 samples are needed for accuracy assessment (Congalton, 2001). As it was impossible to fulfill that rule when the number of segmented water objects was less than the minimum number of 10, the requirement was ignored. The highest classification accuracy occurred for low values of color/shape segmentation parameter, 0.1, 0.2, 0.3. From Figure 5.10 the classification accuracy decreases linearly with increase in the color/shape segmentation parameter, this was verified for scale values of 10, 40, and 50 respectively.

Table 5.4, Table 5.5, and Table 5.6 show that the number of image objects increase with increasing color/shape segmentation parameter. The increase was fairly linear as seen from Figure 5.9 for different values of scale parameter (scale = 10 and 40). Testing the color/shape parameter with scale parameter = 50 shows similar results i.e, low overall number of generated image objects, with small increase directly proportional to increase in color/shape parameter.

Figure 5.6 does not visually show any major influence of color/shape as all images appear over-segmented and split into multiple image objects. Figure 5.7(a) and Figure 5.7(b) show an incorrect combination of shadow with impervious surface (rooftop) indicated by red polygon. The segmentation forces incorrect combination of vegetation and impervious surface (rooftop or parking lots) in Figure 5.8(e) and Figure 5.8(f), but they are explained as caused due to the high scale parameter of 50, rather than due to high color/shape combination.
Figure 5.6: Effect of Changing Color/Shape for Bayou St. John (Scale = 10)
Figure 5.7: Effect of Changing Color/Shape for Bayou St. John (Scale = 40)
Figure 5.8: Effect of Changing Color/Shape for Bayou St. John (Scale = 50)
Table 5.4: Color/Shape Testing on Image Objects with Scale = 10 for Bayou St. John
(Compactness/Smoothness = 0.5)

<table>
<thead>
<tr>
<th>Color/Shape</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>6,355</td>
<td>94.15%</td>
<td>0.91</td>
</tr>
<tr>
<td>0.2</td>
<td>7,027</td>
<td>92.67%</td>
<td>0.89</td>
</tr>
<tr>
<td>0.3</td>
<td>7,398</td>
<td>90.23%</td>
<td>0.87</td>
</tr>
<tr>
<td>0.4</td>
<td>7,720</td>
<td>86.19%</td>
<td>0.84</td>
</tr>
<tr>
<td>0.5</td>
<td>8,009</td>
<td>86.38%</td>
<td>0.81</td>
</tr>
<tr>
<td>0.6</td>
<td>8,265</td>
<td>84.27%</td>
<td>0.81</td>
</tr>
<tr>
<td>0.7</td>
<td>8,506</td>
<td>82.43%</td>
<td>0.78</td>
</tr>
<tr>
<td>0.8</td>
<td>8,725</td>
<td>80.57%</td>
<td>0.76</td>
</tr>
<tr>
<td>0.9</td>
<td>8,914</td>
<td>78.92%</td>
<td>0.76</td>
</tr>
</tbody>
</table>

Table 5.5: Color/Shape Testing on Image Objects with Scale = 40 for Bayou St. John
(Compactness/Smoothness = 0.5)

<table>
<thead>
<tr>
<th>Color/Shape</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>382</td>
<td>86.91%</td>
<td>0.82</td>
</tr>
<tr>
<td>0.2</td>
<td>489</td>
<td>84.44%</td>
<td>0.79</td>
</tr>
<tr>
<td>0.3</td>
<td>534</td>
<td>80.82%</td>
<td>0.77</td>
</tr>
<tr>
<td>0.4</td>
<td>591</td>
<td>79.53%</td>
<td>0.72</td>
</tr>
<tr>
<td>0.5</td>
<td>628</td>
<td>77.02%</td>
<td>0.74</td>
</tr>
<tr>
<td>0.6</td>
<td>654</td>
<td>74.06%</td>
<td>0.71</td>
</tr>
<tr>
<td>0.7</td>
<td>680</td>
<td>72.32%</td>
<td>0.69</td>
</tr>
<tr>
<td>0.8</td>
<td>707</td>
<td>69.79%</td>
<td>0.67</td>
</tr>
<tr>
<td>0.9</td>
<td>727</td>
<td>68.12%</td>
<td>0.63</td>
</tr>
</tbody>
</table>

Table 5.6: Color/Shape Testing on Image Objects with Scale = 50 for Bayou St. John
(Compactness/Smoothness = 0.5)

<table>
<thead>
<tr>
<th>Color/Shape</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>244</td>
<td>82%</td>
<td>0.79</td>
</tr>
<tr>
<td>0.2</td>
<td>315</td>
<td>78.77%</td>
<td>0.73</td>
</tr>
<tr>
<td>0.3</td>
<td>348</td>
<td>78.23%</td>
<td>0.75</td>
</tr>
<tr>
<td>0.4</td>
<td>380</td>
<td>75.54%</td>
<td>0.72</td>
</tr>
<tr>
<td>0.5</td>
<td>405</td>
<td>74.09%</td>
<td>0.72</td>
</tr>
<tr>
<td>0.6</td>
<td>418</td>
<td>72.43%</td>
<td>0.69</td>
</tr>
<tr>
<td>0.7</td>
<td>431</td>
<td>69.56%</td>
<td>0.65</td>
</tr>
<tr>
<td>0.8</td>
<td>448</td>
<td>68.23%</td>
<td>0.65</td>
</tr>
<tr>
<td>0.9</td>
<td>473</td>
<td>65.61%</td>
<td>0.6</td>
</tr>
</tbody>
</table>
Figure 5.9: Count of Image Objects vs Color/Shape for Bayou St. John

Figure 5.10: Classification Accuracy vs Color/Shape for Bayou St. John
5.3.3 Effects of the Compactness/Smoothness Segmentation Parameter

The results of the previous segmentation parameters was used to choose the default values of scale = 20 and color/shape value of 0.1 for testing the compactness/smoothness parameter. Figure 5.11(a) through 5.11(f) and Figure 5.12(a) through 5.12(h) visually depict the results of testing the compactness/smoothness segmentation parameter. Table 5.7 and Table 5.8 show the number of generated image objects and the classification accuracy statistics as the compactness/smoothness parameter changes. Figure 5.13 plots the count of image objects vs the change of compactness/smoothness segmentation parameter. Figure 5.14 shows the classification accuracy plotted against the compactness/smoothness parameter.

Table 5.7 and Table 5.8 show that the classification accuracy ranges from a low of 77.91% through 93.86%. From Figure 5.14, the classification accuracy curve is bell shaped with the highest accuracies occurring between the range of 0.4 - 0.6 values of the compactness/smoothness segmentation parameter. Table 5.7 and Table 5.8 also show that the number of generated image objects increases linearly with increasing values of compactness/smoothness parameter. Not all figures of compactness/smoothness were shown in Figure 5.11 and Figure 5.12, only the most relevant images were shown due to space constraints.

Figure 5.11(a) and Figure 5.11(b) show an incorrect combination (indicated by red polygon) of vegetation with impervious surfaces (rooftops and roads) for compactness/smoothness values of 0.2 and 0.4, respectively. Figure 5.12(a) through 5.12(h) show minor errors for all selected compactness/smoothness values due to incorrect combinations of impervious surface (road) and vegetation. Other land cover types were correctly segmented.

5.4 Conclusion

The change in scale parameter had the most dramatic effect on final segmentation, as the highest classification accuracies were obtained with low values of the scale parameter. Low values of scale allow an optimal segmentation and do not allow incorrect combination of dissimilar land cover features, scale values 10 through 20, are therefore recommended, because any resulting
Figure 5.11: Effect of Changing Compactness/Smoothness for Bayou St. John
Figure 5.12: Effect of Changing Compactness/Smoothness for Fairgrounds Racecourse
Table 5.7: Compactness/Smoothness Testing on Image Objects for Bayou St. John (Color/Shape = 0.1 and Scale = 20)

<table>
<thead>
<tr>
<th>Compactness/Smoothness</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>1,521</td>
<td>78.32%</td>
<td>0.75</td>
</tr>
<tr>
<td>0.2</td>
<td>1,715</td>
<td>82.52%</td>
<td>0.78</td>
</tr>
<tr>
<td>0.3</td>
<td>1,770</td>
<td>84.43%</td>
<td>0.8</td>
</tr>
<tr>
<td>0.4</td>
<td>1,866</td>
<td>91.72%</td>
<td>0.87</td>
</tr>
<tr>
<td>0.5</td>
<td>1,931</td>
<td>93.03%</td>
<td>0.91</td>
</tr>
<tr>
<td>0.6</td>
<td>1,998</td>
<td>90.37%</td>
<td>0.85</td>
</tr>
<tr>
<td>0.7</td>
<td>2,067</td>
<td>83.29%</td>
<td>0.79</td>
</tr>
<tr>
<td>0.8</td>
<td>2,128</td>
<td>80.83%</td>
<td>0.76</td>
</tr>
<tr>
<td>0.9</td>
<td>2,202</td>
<td>77.91%</td>
<td>0.72</td>
</tr>
</tbody>
</table>

Table 5.8: Compactness/Smoothness Testing on Image Objects for Fairgrounds Racecourse (Color/Shape = 0.1 and Scale = 20)

<table>
<thead>
<tr>
<th>Compactness/Smoothness</th>
<th>Image Objects</th>
<th>Classification Accuracy</th>
<th>Kappa Statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.1</td>
<td>3,171</td>
<td>80.23%</td>
<td>0.76</td>
</tr>
<tr>
<td>0.2</td>
<td>3,696</td>
<td>83.83%</td>
<td>0.79</td>
</tr>
<tr>
<td>0.3</td>
<td>3,969</td>
<td>86.25%</td>
<td>0.83</td>
</tr>
<tr>
<td>0.4</td>
<td>4,201</td>
<td>92.47%</td>
<td>0.88</td>
</tr>
<tr>
<td>0.5</td>
<td>4,437</td>
<td>93.86%</td>
<td>0.88</td>
</tr>
<tr>
<td>0.6</td>
<td>4,597</td>
<td>91.84%</td>
<td>0.86</td>
</tr>
<tr>
<td>0.7</td>
<td>4,785</td>
<td>86.16%</td>
<td>0.82</td>
</tr>
<tr>
<td>0.8</td>
<td>5,031</td>
<td>82.19%</td>
<td>0.77</td>
</tr>
<tr>
<td>0.9</td>
<td>5,273</td>
<td>79.28%</td>
<td>0.73</td>
</tr>
</tbody>
</table>
Figure 5.13: Count of Image Objects vs Compactness/Smoothness (Scale = 20)

Figure 5.14: Classification Accuracy vs Compactness/Smoothness (Scale = 20)
Figure 5.15: Slivers Produced in Segmentation
over-segmentation (forming fine or extremely small image objects) can be corrected in subsequent hierarchical multi-resolution segmentation at the next higher level. The recommended scale parameter values, 10 through 20, leads to less chance of incorrect combination of image objects. High values of scale parameter are not recommended for initial segmentation because they lead to under-segmentation (forming coarse or giant image objects) and spectrally heterogeneous image objects were being combined. This under-segmentation subsequently results in poor classification accuracies. Using very low values of scale, lower than 10, lead to an exponential rise in processing time and memory required to complete the segmentation. As a result the image objects formed were too small and highly over-segmented, the image objects formed were equal in size or slightly larger than individual pixels. Although not shown, there is a minuscule difference in classification accuracy in single digit scale values and a scale value of 10. Choosing very low values of scale parameters yield little benefit as the over-segmented image objects need to be combined at a hierarchical higher scale level, the end result is a similar segmentation and classification accuracy. Hence, the classification accuracy was chosen to be performed in steps of 10 for scale parameter for testing of all segmentation parameters. The results also showed that the size and number of generated image objects was constrained principally by the scale parameter and as the scale parameter was increased, the size of generated image objects increased.

The next parameter which significantly affected the classification accuracy was the color/shape parameter. In general, high values of color/shape cause under-segmentation or incorrect combinations of land covers. The recommendation for optimal range of values for the color/shape segmentation parameter was 0.1 through 0.3. Higher values of color/shape parameter, such as 0.6 through 0.9, lead to increased emphasis on texture and conversely lower emphasis on pixel color during segmentation. Not all images can benefit from having an increased emphasis on texture during segmentation. At the recommended lower scale parameters (10 through 20) and within the recommended color/shape range of 0.1 through 0.3 the resulting segmentation tends to the ideal segmentation and has less incidence of over-segmentation. The results also showed that as the color/shape parameter was increased, the size and number of image objects increased linearly.
The study found there was little influence of the compactness/smoothness segmentation parameter on the final classification accuracy. There are noticeable problems for highly urban areas for low values of compactness/smoothness parameter, ranging 0.1 through 0.4 as seen in Figure 5.11(a) and 5.11(b). The recommendation for compactness/smoothness was a range of 0.4 through 0.6, the default value of 0.5 was found to be acceptable. The results also showed that as the compactness/smoothness parameter was increased, the size and number of image objects increased linearly.

Scale parameter affects classification accuracy to a large extent by dominating over changes in the color/shape and the compactness/smoothness segmentation parameters. The segmentation procedure produces image objects which are constrained by the scale and homogeneity criterion. Even if there was confirmation of continuous spectral homogeneity between adjoining pixels, due to the limit of a scale parameter, image objects are constrained from growing. Practically speaking, the segmentation procedure always over-segments the image at a low scale parameter value, because of the formation of small image objects which can be actually combined to form larger ones. This over-segmentation is then rectified partially by subsequent segmentation using higher scale value in a multi-resolution hierarchical manner. Also, it was important to realize that because of the sampling theorem and its relation to image object size, different parts of an urban area will have different requirements of scale parameter (large range of image object sizes) compared to a land cover covered with vegetation (generally uniform). This would make the segmentation more accurate and remove a source of analyst error, if the analyst forgets to perform another hierarchical multi-resolution segmentation by providing a higher scale parameter. There was no one appropriate scale for an image as the ideal segmentation would form distinct image objects, independent of its size. OBIA proves that a remote sensing image simultaneously contains multiple sizes/scales of image objects.

The segmentation in eCognition produces slivers - long thin lines of image objects as seen in Figure 5.15(a) and Figure 5.15(b) respectively. To conclude, we need an automated procedure for multi-scale segmentation and for deriving image objects, which ideally does not require the
tuning of parameters like shape, color, and texture (Tzotsos et al., 2011). Based on this analysis, the segmentation parameters that yielded the highest classification accuracy are scale \( \leq 20 \), color/shape between 0.1 - 0.3, and compactness/smoothness between 0.4 - 0.6. Hence, the default segmentation parameters in eCognition of scale = 10, color/shape = 0.1, and compactness/smoothness = 0.5 were found to be reasonable and give a high classification accuracy for the selected four land cover classes: vegetation, impervious surfaces, water, and shadows.
CHAPTER 6: CONCLUSION

Automated detection of urban impervious surfaces remains one of the most challenging problems in remote sensing. This dissertation studied how urban area impervious surfaces with high spatial resolution imagery can be classified efficiently with several methods. Urban impervious surfaces are indicators of many anthropological activities, and are a direct link to increased flood vulnerability. Quick classification of impervious surfaces is necessary post-disasters for timely flood estimation and property damage assessment. This research examined the use of OBIA and explored the problems hindering automated classification.

6.1 Summary of Findings

The objectives of this study were:

1. to compare the classification accuracy and efficiency between the traditional pixed-based classification and the object-based classification for identifying urban impervious surfaces.
2. to determine whether OBIA in combination with high spatial resolution imagery was effective for the detection of heterogeneous urban impervious surfaces.
3. to investigate the potential for automation and generalization of the OBIA method by deriving the ruleset for classifying impervious surfaces in different urban areas by identifying the prerequisites and parameters needed for achieving it.

The hypotheses of this study were:

1. OBIA yields a higher classification accuracy compared to pixel-based maximum likelihood classification using high spatial resolution imagery.
2. OBIA can discriminate with high accuracy among different types of urban land covers from high resolution images: specifically vegetation, impervious surfaces, shadows, and water.
3. A ruleset can be developed in OBIA for automated and generic classification with reasonable accuracy.
Regarding the results of the hypotheses:

1) All the four developed OBIA classification methods were found to have higher classification accuracies compared to the pixel-based classification for our study area. Since OBIA rule-based methods 2, 3, and 4 used spectral information not used in the pixel-based method, a direct comparison was deemed scientifically valid only between OBIA rule-based method 1 and the pixel-based method. It was found that the factors which negatively affect the classification accuracy in pixel-based classification in urban areas are due to shadows being confused with water bodies and vegetation being confused with impervious surfaces. The classification result for the pixel-based classification has speckle effects and isolated pixel clusters which remain after post-processing. The failure to follow sharp variations was noted in all the classes including shadow, impervious, and vegetation classes in the pixel-based classification. The visual appearance of the OBIA classification was excellent compared to the pixel-based classification. For OBIA rule-based method 1, which used histogram DN thresholds, shadows were also confused with water bodies, as in the pixel-based classification. But the OBIA method was able to detect a greater amount of the shadow class. For impervious surface classification, the OBIA rule-based method 1 was much superior as it was better able to follow the sharp transitions occurring in subdivisions between vegetation, impervious and shadows. In the OBIA method, rectangular shaped impervious surfaces were easily classified, impervious surfaces with spectrally confusing signatures were classified with partial success but the classification was better than the pixel-based method.

2) OBIA rule-based methods 1, 2, and 3 used histogram DN thresholds which proved useful to discriminate amongst urban land covers in this study. While OBIA rule-based methods 3 and 4 used spectral indices like NDVI, NDWI, and SSI for land cover detection. The impervious surface components which were classified the best were the rectangular structures like buildings, rooftops, and parking lots with strong defined visual signatures. The segmentation procedure of the OBIA could nicely follow the high frequency transition of classes for high spatial resolution urban areas, especially in subdivisions. The classification accuracy achieved was excellent, in excess of 85% for all the OBIA rule-based methods.
3) OBIA rule-based method 4 was used successfully for a guided automated classification with an acceptable overall accuracy in the 80% - 92% range over multiple image subsets. It was not possible yet for OBIA to completely automate the classification process because of scene specific variation in derived NDWI and SSI and the need for an operator to select the right values for the spectral indices for automation in this study. The best set of rules was formed when one combined spectral indices like NDVI for vegetation, NDWI for water, and SSI for shadow identification of land covers, in an urban area, as used in OBIA rule-based method 4. eCognition has proven to be a useful software for deriving a detailed impervious surface classification, the process was much faster when using eCognition than the equivalent process using pixel-based classification. The OBIA approach truly raises the possibility of automation.

Hypotheses 1 and 2, about higher classification accuracy and better discrimination between land covers have been confirmed. While Hypothesis 3, about full automation, was found to be partially confirmed.

To conclude, the analysis of segmentation parameters shows that the best combination of multi-scale image objects was formed when the parameters of scale \( \leq 20 \), color/shape between 0.1 - 0.3, and compactness/smoothness between 0.4 - 0.6 were used. OBIA rule-based method 4 was tested on multiple images and found to give acceptable classification accuracy for impervious surfaces, similar to the method used by Aytekin et al. (2012), who utilized NDVI for impervious surface derivation.

### 6.2 Limitations of Current OBIA Remote Sensing Approaches

In eCognition, the samples for accuracy assessment are not generated randomly, which is a serious oversight in the software where samples have to be chosen manually. To have confidence in classification we need to have confidence in accuracy assessment, and this needs to be addressed in future versions of eCognition. For small study areas, an OBIA classification produces low number of image objects, this study found image objects ranging in the 200-400 range. In that case, a better classification scheme is needed to quantitatively validate classification accuracy.
Initially, the 32 bit eCognition Developer 7.0 version was used, but limitation of image size and inability to process imagery in excess of 3000 x 3000 pixels proved to be serious. The newer 64-bit versions of eCognition software reduced the memory processing problems. But in general, eCognition tries to process the initial segmentation in-memory and consequently uses a lot of memory. Processing the imagery in a streaming window manner was an enhancement which needs to be utilized for fast processing of large mosaicked imagery (Agarwal et al., 2006; Isenburg et al., 2006). This author tested with a mosaic of 16,000 by 11,000 pixels and the software could scale; the current limitation to processing large size imagery remains the physical memory (RAM) of the machine, and dependence on a single CPU for processing of imagery. Parallel processing using multiple threads, such that all cores of the CPU and/or GPU are utilized for processing, needs to be implemented in future versions of eCognition.

Various steps of the remote sensing process have been automated: geometric registration, image mosaicking, but not classification. Other studies on OBIA have come to a similar conclusion regarding automation (Blaschke, 2010), that is, the classification can only be semi-automated. It was possible in eCognition to analyze the scale of imagery, and suggest a good range of segmentation parameters. The segmentation parameters were selected through a trial-and-error approach which was the main bottleneck in OBIA analysis. Too much time was being spent on selecting image segmentation parameters. Genetic algorithms, which produce only few survivors of the best segmentation parameters, could be used in aiding automated segmentations.

It was possible to use the same spectral approach as used in OBIA rule-based method 4 for the pixel-based classification. That is, use additional layers such as NDVI, SSI, and NDWI to derive the impervious surfaces. But the output produced by the OBIA process was superior to the pixel-based process, and it was more conducive to automation. There are only two ways classification can be automated using OBIA: sample-based NN classification or rule-based classification. Currently, image pattern matching using sample based raster datasets is increasingly popular. With widespread use of Oracle GeoRaster and Postgis WKT Raster databases, it is hoped rule-based approach can be useful in the next decade. This study contributed to the rule-based approach using OBIA.
6.3 Suggestions for Future Research

Sample-based object classification was not explored in this study (Blaschke, 2010). But since the widespread availability of raster databases, there is the possibility of automated sampling and data mining of imagery by usage of graphical matching of certain geometric patterns on deformable image models (Lafarge et al., 2010). There should be an easily available method to export image object samples from OBIA software into an external raster database and have the image objects classified with deformable models using GPU’s for efficient computation as suggested by Lafarge et al. (2010). Different strategies for classification could be used on individual parts of image by use of ensemble methods or multiple classification systems based on bagging and boosting (Briem et al., 2002; Tzeng et al., 2009). The need for ensemble methods arises because it is difficult for one classification method to be used for classifying all types of LULC accurately. Polygons for impervious surfaces areas could be extracted and exported to a shape file. The polygons can be used in a future study with high resolution point-cloud LIDAR data for predicting the flooding potential and hotspots in downtown New Orleans.
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APPENDIX A: USING RULESETS IN ECOCGNITION

eCognition is not a full suite of image processing software; it is exclusively focused on
image classification by using several different segmentation approaches. For pre-processing and
post-processing of the dataset, a separate image processing software like ERDAS Imagine or ENVI
needs to be used. The software can handle limited image formats; we choose to use .img format for
this study. The ruleset was developed iteratively in the “Rule Set” mode; the “Quick Map” mode
of eCognition was not considered in this study. Once the development of the desired rulesets is
complete, then it is feasible to use them in the “Quick Map” mode.

In File ⇒ “Load Image File”, load a pre-processed image to be used for classification. In
File ⇒ “Modify Open Project”, edit the names for layer alias. This makes it easier to refer to
the different layers when building a custom ruleset based on layer names. It is easier to call a
layer “Red” rather than “Layer 1”. Add any derived layers like NDVI, LIDAR etc. and edit the
names in the layer alias. Click Process ⇒ “Process Tree” and select “Insert child” for creation
of a new rule. Simply click ok in the resulting “Edit Process” dialog. This places a blank node at
the top labeled “…do” under which all resulting process actions would be hierarchically executed.
Next click “Insert Child” and then click drop down “Algorithm” and choose the desired algorithm
“multi-resolution segmentation”. Set the segmentation parameters: shape, compactness, and scale.
Name the output level of the multi-resolution segmentation, so that it is different from the default
name of “New Level”. Experiment with adding more nodes in a hierarchical manner by “Append
New” and then ok, ⇒ “Insert Child” and add desired algorithm. There are many different methods
to choose from to improve the classification: assign class, find enclosed by class, spectral difference
segmentation etc. To test a rule in eCognition, first segment the image and then double click on a
particular rule. If a rule needs any parameters, fill them (most rules do not need any extra input),
and watch the variation in rule output on the image. This variation is tested by hovering with a
mouse over an image object, and noting the numerical value. The separability effect of using the
rule on the overall image should also be observed.
APPENDIX B: ALGORITHMS EXPLORED IN ECOCOGNITION

- In Feature View $\Rightarrow$ Object Features $\Rightarrow$ Layer Values $\Rightarrow$ Mean: mean value of objects for Brightness, R, G, B, IR layers.

- In Feature View $\Rightarrow$ Object Features $\Rightarrow$ Layer Values $\Rightarrow$ Pixel-based: Ratio, minimum and maximum pixel values, mean of inner or outer borders, contrast to neighbor pixels.

- In Feature View $\Rightarrow$ Object Features $\Rightarrow$ Layer Values $\Rightarrow$ To neighbors: mean difference to neighbors/brighter/darker objects, number of brighter or darker objects.

- In Feature View $\Rightarrow$ Object Features $\Rightarrow$ Geometry $\Rightarrow$ Extent: Number of pixels present in Area, Border length, Length, Thickness, Volume, and Width. Also, the ratios of Length/Thickness and Length/Width.

- In Feature View $\Rightarrow$ Object Features $\Rightarrow$ Geometry $\Rightarrow$ Shape: Shape Index, Roundness, Rectangular Fit, Compactness, Border Index etc.
VITA

Amit Kulkarni was born and raised in Thane, India. He earned a Diploma in Electronics from St. Xavier’s Technical Institute, Mumbai and a Bachelor degree of Engineering in Electronics and Telecommunication from the College of Engineering, Pune. He has developed a lifelong interest in Geography and Environmental Science, and will be forever grateful for the opportunity to pursue a PhD in Geography in LSU which has so many facilities. He would like to remind people again about this quote from Louis L’Amour: “No one can get an education, for of necessity education is a continuing process.”