Identifying Land Use/Land Cover (LULC) Using National Agriculture Imagery Program (NAIP) Data as a Hydrologic Model Input for Local Flood Plain Management

by

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Dedication

This paper is dedication to my best friend, soul mate, and spouse. Without her support, I would not have mustered the courage or energy to climb the humble heights of accomplishment that I have summited thus far. Her support (in this endeavor and all others in my life) has proven priceless and is valued only behind her love and companionship in the ranking of my most prized “possessions”.

Acknowledgements

I cannot complete this paper without paying homage to those that have assisted me throughout the process and during the life experiences that have led me to the process. First and foremost, I must thank my family. My parents, sister, and grandparents have been an unwavering support group and fan club throughout my life. Nothing that I have (or will) accomplished cannot be credited, at least in some part, to them. As one of the more blessed people in this world, I have an amazing group of friends and relatives that make up my extended family. Their support has also been a valued and cherished resource. A nod must also be given to the brain trust of philosophical, technological, and applied knowledge that formed my research committee. Without their insight, this paper would have made an even more humble contribution to the planning community than it does in its present state. Finally, I must thank the faculty and staff in the Public Administration, Political Science, and Geography Departments at Texas State. If I ever am fortunate enough to return to San Marcos, let it be known that I owe a lot of favors to a lot of people.

About the Author

W. Gabe Powell was born and raised in Cookeville, TN. His love for nature, technology and helping others has continually guided his professional and academic experiences. In 2001, Gabe graduated from Tennessee Technological University with a B.S. in Environmental Agriscience. Upon graduation, he was hired as a research assistant at Mississippi State University. Thanks to funding from a NASA grant, Gabe was able to complete an M.S. in Weed Science while working to apply hyperspectral remote sensing techniques to soil conservation applications in agriculture. After graduating from Mississippi State, Gabe made two important and life changing decisions: 1) he married his lovely wife, Stefanie and 2) he enlisted in the United States Army. After several years as a paratrooper/satellite communications specialist in the 82nd Airborne Division, Sergeant Powell was selected to return to college to earn a Masters of Public Administration and a commission as a second lieutenant. Identifying Texas State University's Public Administration and Geography departments as two of the nation's best, the happy couple made the long journey from Fort Bragg, NC to San Marcos, TX. At Texas State, Gabe was able to combine the best of both departments and earned a Master of Public Administration with a heavy emphasis on emergency response and geospatial technologies. This ARP is the culmination of an intensive, challenging, and rewarding experience at Texas State. With degree in hand and a gold bar on his chest, Gabe will return to the operational Army and apply his newfound skills as a Military Intelligence Officer. He looks forward to many years of public service and contribution to our national security. Eventually, the author and his wife plan to return to the hills of Tennessee and wile away their golden years in a secluded woodland retreat.

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Abstract

The purpose of this study was to explore the utility of remotely sensed data acquired for agricultural applications to assist urban planners in land use and land cover (LULC) classifications. The National Agriculture Imagery Program (NAIP) offers local planners a high resolution (i.e. one-meter), multispectral (4 bands: red, blue, green and near infrared) dataset at little (or no) cost. NAIP imagery was selected because of its low cost and potential for small scale land use and land cover classifications similar to the success Landsat (30 meter, multispectral: 4 band) imagery has achieved with large scale classifications. The study was conducted using a subdivision in South-central Texas (i.e. El Camino Real) and the surrounding (rural) property. Supervised (parametric and non-parametric) classification procedures were conducted on the El Camino Real subset using ERDAS Imagine 9.3®. Stratified random sample points were generated for accuracy assessment via a ground based visual assessment of each point's LULC class. By using a 7 class LULC schema, a supervised classification of the NAIP imagery resulted in classification accuracy of 86%. When the schema was reduced to two broad classes (i.e. impervious and pervious cover), the classification accuracy climbed to 95%. These results suggest the need for a continued exploration of NAIP data utility for local planning purposes.

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Chapter 1. Introduction

Scenario[1]

After many years as a quiet river town, the heartbeat of Anytown, Texas is racing like that of a thoroughbred on the last leg of the Kentucky Derby. City planner Norman Ware, an aging public servant whose years of military service are hidden well by his expanding beltline and thinning grey hair, is overrun with applications for new developments within his city limits. Norm's office is bombarded with requests for new subdivisions, shopping centers, and numerous other commercial development ventures. The request sitting on top of Norm's inbox, as the sun rises on what threatens to be an unusually hot Hill Country morning, is for the approval of construction on the third phase of a local subdivision, Deerfield Estates. Deerfield Estates, before it became the bustling home of over 250 Anytown families, was much like its surrounding area today: a patchwork of various agricultural enterprises.

The subdivision was once home to many heads of cattle and acre upon acre of corn, cotton, and hay fields. The soft earth and grass of the area that once soak up the rain water like a dry sponge in a tea cup has since been replaced by houses, sidewalks, streets, and patios that are as accepting of rainwater as Norm's elderly father is of loud music and mohawk haircuts. As a steward of his beloved Anytown, Norm must consider all consequences of the new construction before he can allow the developers to break ground on Deerfield Estates: Phase Three. His main concern with the application at hand is that each new phase of construction has brought the subdivision closer to a nearby floodplain as identified by the Flood Rate Insurance Map (FIRM) spread across his desk.

[1] For examples of illustrative scenarios in academic papers see Este (2007) and O'Neill (2008).

The Federal Emergency management Agency (FEMA) created this specific FIRM in 2004 making the information contained within to be more than slightly outdated for his current needs. The FIRM was an excellent source of information when construction began on Deerfield Estates: Phase One in 2004. Norm's years of experience in the planning field had taught him that a little change can go a long way when new developments are situated near floodplains. Feeling somewhat helpless, Norm wondered how in the heck he was going to identify the new boundaries of the floodplain perched at the southwest corner of the already constructed Deerfield Estates: Phases One and Two. It sure wasn't with the five year old FIRM that he had already relegated to a coaster for the overfull mug of Folgers® that was, until now, sloshing on his desk. As he carefully sipped his morning brew, Norm thought "Now what?"

Research Problem

Issues regarding floodplains are especially pertinent to those in charge of the cities and communities in which we live. Floodplain utilization and management issues affect the majority of the United States population. Therefore, today's city planners need an accurate and efficient means to update existing floodplain maps/models for planning and development purposes. Numerous factors (e.g. natural disasters, infill and urbanization) can alter the land use and land cover[2] (LULC) and, therefore, hydrologic characteristics of a floodplain (Burby and French 1985; Johnston 1992; Maidment 2002). Such change will alter the flood risk in affected areas. In rapidly developing

[2] Land use relates to human activities conducted on a parcel or property that are directly related to the land itself [e.g. cropland (agriculture), forest land (forestry), urban areas (densely populated), or transportation (roadways)] (Anderson 1976; Clawson and Stewart 1965). The category of land cover actually describes the constituents (natural and manmade) on the surface of a parcel or property (e.g. trees, shrubs, grass, crops, roads, or buildings) (Anderson 1976; Burley, 1961). In many cases the land use and land cover for an area is closely related (e.g. forestry uses are covered with trees and urban areas are covered with buildings and roads) (Anderson 1976).

communities, the current floodplain is unlikely to be the same floodplain mapped two years ago. Today's city planners lack the information necessary to better understand their flood risks based on current land use and land cover conditions. The intent of this study is to explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP[3] data) to identify current land use and land cover conditions.

Water and Our Attraction

Water, because of its immense intrinsic value, is a population and industrial magnet. Due to the value presented by water's numerous uses (e.g. manufacturing, transportation, agriculture and recreation), over half of our national population lives near a large body of water (U.S. Commission on Ocean Policy 2004). By selecting locations in the vicinity of vast amounts of water, residents and businesses place themselves in (or near) floodplains (i.e. land of relatively low elevation, usually adjacent to a body of water, which is "shaped by and continually subject to inundation") (Johnston 1992, 4). The proximity of citizens to floodplains has made flooding the most prevalent natural disaster in the United States and the world (Shim et al. 2002; Lins and Slack 1999). Fortunately, by understanding the inherent risks and developing strategies for proper mitigation, flooding is also the most preventable natural disaster (Romano and Vaccaro 2005).

[3] The National Agriculture Imagery Program (NAIP) was created by the U.S. Department of Agriculture to provide agricultural producers throughout the nation with free (or low cost), high resolution, natural color and color infrared imagery acquired during the growing season (USDA 2007).

Floodplain Management

The authority for floodplain management resides at the state and local level. Local authorities rely on three distinct approaches to mitigate flood hazards: (1) guiding development away from flood hazards; (2) implementation of specialized floodplain construction standards and; (3) construction of flood control structures (Burby and French 1985). Flood control structures (e.g. levees, channels and detention basins) often only postpone inevitable inundation and ensure catastrophic damages when their engineering limitations are exceeded. Because of their physical limitations, “there will never be enough funds available to solve flood problems by structural means” (Burby and French 1985, 153). Implementing land use regulations to guide new developments away from flood hazard areas is the most certain way to ensure decreased flood damage because it eliminates (or greatly reduces) the potential for loss (Peterson, Helfrich and Smith 1999).

The adoption of strict building codes for new or significantly improved structures in floodplains has also helped to lessen the consequences of flooding (Wetmore 2006). While not developing areas in or around floodplains will virtually eliminate all losses from flooding, it may also significantly inhibit economic growth and income for a city. The loss of tax revenue and economic input from excessively stringent land development regulations can severely decrease the monetary funds for a community. Unrestricted floodplain development, however, threatens the lives and property of individuals and businesses located in flood hazard areas. Reducing mitigation strategies to the lowest level (that still provides significant hazard reduction) protects community resources while promoting safe development and economic growth.

Flood Hazard Mapping

Communities rely on flood hazard maps to effectively manage flood plain development and mitigate the inherent hazards. Such maps may be created by modeling surface water conveyance and catchment regions for a watershed (Hoggan 1997). Property use and ground cover (i.e. LULC) data and digital elevation models are the two types of data sets required to model surface water conveyance for a watershed (Maidment 2002). Unfortunately for city managers, watershed (and floodplain) conditions can change rapidly and drastically. Dynamic natural events (e.g. floods and hurricanes) have the ability to drastically alter the use and topographic characteristics of a floodplain in a matter of days, if not hours (Mannion 2002). Widespread destruction of homes and businesses, coupled with topographic changes caused by the immense forces of nature, (e.g. flood sediment and coastal erosion) will drastically alter the characteristics of a floodplain warranting immediate assessment to understand newfound risks. Subsequent recovery efforts will also alter the floodplain. Often post-disaster reconstruction proceeds unregulated and undocumented for many months after the initial disaster. Such unimpeded and often haphazard development has an increased potential of negatively altering/utilizing a floodplain and exposing citizens to unnecessary risk.

For many communities, especially smaller cities and the suburban fringe of larger cities, the resources are not available to conduct watershed modeling procedures in-house; therefore, local governments have traditionally relied on external agencies to develop land use and land cover data for management purposes (Johnston 1992). This outsourcing has been required due to the complexity of land use and land cover analysis. Traditional methods required extensive fieldwork and the labor intensive process of ground-truthing the classification (Singh, et al. 2001). Unfortunately, relying on external agencies to deliver the data is a costly (if outsourced to private corporations) and slow (especially with federal assets) method for acquiring land use and land cover data. The obstacles of traditional land use and land cover classification methods have created a chasm between the land use and land cover information available to a city for a particular watershed and the actual land use and land cover conditions for that watershed (USGS 2007; USGS 2006). Planners need a quick, low cost and accurate method for assessing land use and land cover conditions in our rapidly developing communities.

National Flood Insurance Program

Currently, the National Flood Insurance Program (NFIP) is attempting to meet community flood hazard mapping needs (Wetmore 2006). The NFIP has developed flood hazard maps [i.e. Flood Insurance Rate Maps (FIRMs)] for the entire nation. Unfortunately, the development and approval process for a FIRM is lengthy and, therefore, makes maintaining current flood hazard maps in our rapidly urbanizing society difficult. Even with the Map Modernization Program that began in 2003, most available FIRMs are created outside of the two year relevance window that is required for accurate floodplain assessment (FEMA 2007; Group 1999; Lovell, et al. 1999).

Using current procedures, flood hazard maps and FIRMs cannot be updated at the same rate as the changes caused by population growth and the accompanying watershed urbanization. These changes in population size and density result in altered watershed characteristics (Mannion 2002). The U.S. population has grown from 226 million in 1980 to 296 million in 2003 (Crossett et al. 2004). Projections place the 2015 national population around 322 million (Crossett et al. 2004).

Research Purpose

The Issues

These two issues, slow generation of FIRMs and widespread floodplain/watershed alterations, necessitate the development of a new method for generating flood hazard maps for city planning purposes. The new method must utilize timely data that is readily available at a low cost and a high resolution (less than 2 meters). It must also facilitate the production of flood hazard maps by city or county agents with minimal analysis resources and expertise. The purpose of this study is to explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP data) to identify current LULC conditions.

The Solution

While the National Agriculture Imagery Program was implemented to serve the agriculture industry, the information it provides has potential for aiding urban and suburban areas at little or no cost to the community. National Agriculture Imagery Program data has potential for fulfilling current land use and land cover classification needs for community flood mapping purposes. It provides information similar to the time-tested remote sensing platforms (i.e. Landsat Thematic Mapper and Enhanced Thematic Mapper) currently used for land use and land cover classification. Where the National Agriculture Imagery Program data displays the greatest promise is in its ability to provide the required information at a small scale[4] that allows much greater detail and it does so at no (or a minute) cost to the end user (e.g. city, town, community).

[4] NAIP Imagery is captured at a resolution that is 225 to 900 times greater than Landsat imagery (Lillesand and Kiefer 1994; USDA 2008).

The Application

Once generated, the critical information (i.e. land use and land cover data derived from NAIP imagery) can be applied to hydrologic models (along with topographic data) to enable communities to manage their flood risk based on actual conditions. National Agriculture Imagery program data possess great potential to satisfy the present need for an accurate and efficient means to identify local land use and land cover conditions. Such knowledge will assist planners when updating existing floodplain/flood hazard maps, as well as, allow communities to understand their actual flood risk based on current conditions. By implementing straight forward analysis techniques on modest data sets, communities may generate new maps to better understand their current flood hazard risks. The newfound ability to model current situations and not rely on outdated, inaccurate (i.e. low resolution), and/or costly information will provide planners and managers the ability to develop precise strategies to mitigate flood risks in their current state.

Scenario – Deerfield Estates, Anytown, TX

Deerfield Estates is your classic middle-class, tract housing development. Small lot sizes (less than .5 acres) allow for a great deal of development to occur in a small area. Norm knows dense developments (even those that are not dense by Bigcity, Texas standards) result in significant increases in impervious cover. By cramming a house, driveway, sidewalk, and a patio into a third of an acre and then repeating the process on the adjoin lots creates enormous potential to drastically affect the characteristics of the neighboring floodplain(s).

Study Area

The study utilizes a local (i.e. within San Marcos) subdivision (and its surrounding area) as a case study to explore the utility of National Agriculture Imagery Program data to identify land use land cover conditions on a small scale (i.e. 1 meter resolution). The El Camino Real subdivision (Figures 1.1 and 1.2) is a medium density residential community that offers numerous types of land use and land cover within a small area. The area immediately surrounding the community, currently consists of active and abandoned agricultural land, several small wooded areas and a few small areas that permanently contain water. The varied land use and land cover conditions in and around El Camino Real and the distinct transition from one class to the next (e.g. rooftop to lawn to concrete sidewalk to asphalt road to corn field) will facilitate a comprehensive analysis of the utility of NAIP data to accurately identify each land use and land cover type.

Figure 1.1 2005 NAIP True Color Image of the Southwest Portion of San Marcos, Texas (Image courtesy of TNRIS: http://www.tnris.state.tx.us/)

Figure 1.2 2005 NAIP True Color Image of the El Camino Real Subdivision in San Marcos, Texas (Image courtesy of TNRIS: http://www.tnris.state.tx.us)

Predicted Outcomes

1) Communities will possess a playbook (i.e. this ARP) detailing how to extract critical information (i.e. current LULC conditions form NAIP data) for planning purposes.

2) By applying current LULC data[5] generated from NAIP data (through procedures identified in this paper) to hydrologic models, community planners/managers will have the ability to develop flood hazard maps to fill in between federally issued maps allowing them to make zoning and development decisions based on real time flood hazards.

3) During the initial recovery phase of a natural disaster, communities can assess normally undocumented LULC conditions of a recovering area (using NAIP technology and supplemental, post-disaster data collections) in order to make informed decisions regarding recovery and redevelopment.

4) The development of a means (through use of NAIP data) for expediting, supplementing, and eventually substituting the FEMA Map Modernization Program by improving the ability for flood plain management at the local level.

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[5] For more information on other uses of land use and land cover data see Gillfillan (2008), Schacheri (2008), and Ellis (2006).

Chapter Summaries

Chapter 2 reviews literature concerning the problems with contemporary floodplain management and land use land cover classification procedures and the inadequacies of the technologies currently applied to the processes. It also identifies National Agriculture Imager Program data as a potential solution to the current problems. One working hypothesis (two sub-hypotheses) is developed to explore the utility of the NAIP data for land use and land cover classification. Chapter 3 provides a description of the study area (i.e. El Camino Real Subdivision in San Marcos, TX) and the dataset with which the land use land cover classification was attempted. Chapter 4 details, in a step by step "playbook", the supervised image classification process. The results of the land use land cover classification attempt are presented and analyzed in Chapter 5. Chapter 6 highlights of the findings of the research and provides recommendations for future research.

Chapter 2. Literature Review

Chapter Purpose

The notion of sustainability and community resilience is increasing in popularity as the most prevalent trend in contemporary urban planning (Manyena 2006). Sustainable, resilient communities have the ability to withstand and recover quickly from natural disasters. The need for resilient communities is undeniable. The planning and practices necessary for achieving resilient communities, however, are still in need of greater refinement, further development, and increased implementation. One of the most prolific contemporary hazards facing communities is the increasing potential for inundation (i.e. flooding). In order to prevent, or significantly reduce, the impacts of floods and other disasters, communities must understand their current risk based on an assessment of their existing community conditions. The understanding of current conditions (land use/land cover and terrain relief) is essential for identifying at risk areas. To maintain resiliency (i.e. achieve sustainability), communities must be able to monitor changes caused by continued development/urbanization. They must also understand the effects of those changes on potentially flood prone areas. The ability to monitor and understand change will allow communities to regulate new development and reduce flood risks.

Realizing the currently unmet need for an affordable and efficient means of assessing current conditions, the purpose of this chapter is to review and examine the scholarly literature on the effects of land use and land cover change and the need to assess and quantify those changes. This chapter shows that with accurate and timely information identifying local land use and land cover changes, community planners can increase resiliency to flood hazards.

The chapter begins with a discussion of the increasing trend towards development of sustainable, resilient communities. It then discusses the importance sustainable floodplain management. Following a discussion of floodplains, the impact of land use and land cover on hydrologic systems[6] and the importance of quantifying land use and land cover change (in order to model the behavior of such systems) is addressed. For proper assessment of hydrologic systems, terrain relief must be represented by digital elevation models (DEMs). With this in mind, a brief literary assessment of available sources of DEMs is included. Then, the shortcomings of current floodplain management and LULC assessment techniques are identified along with a call for further research in this area. Finally, a working hypothesis is developed and conceptualized as the foundation of this research. The working hypothesis was created to explore the applicability of NAIP data for land use and land cover classification using a subdivision (and the surrounding area) in San Marcos, TX.

Community Resiliency

An International Issue

Ideally, all community planners desire sustainable and resilient communities. They seek to foster development that can survive and recover rapidly from extreme geophysical events (Tobin 1999). Since the introduction of the paradigm of sustainability in 1987, there is an undeniable international trend promoting sustainable development.

[6] Hydrologic systems encompass surface runoff and ground-water flow, as well as, their interactions with atmospheric water (i.e. precipitation and evapotranspiration) (Winter 2001).

The 1990s were designated by the United Nations as the International Decade for Natural Disaster Reduction[7] (IDNDR) with the intent to incorporate science and technology to prevent disaster losses (United Nations 2000). As the decade ended, a new body was created to continue the promotion of sustainable development. The International Strategy for Disaster Reduction (ISDR) was created in 1999 with the goal of "building disaster resilient communities by promoting increased awareness of the importance of disaster reduction as an integral component of sustainable development, with the goal of reducing human, social, economic and environmental losses due to natural hazards" (Stanganelli 2008, 95; United Nations 2002). In 2005, the ISDR adopted the Hyogo (Japan) Framework for Action to integrate risk assessment and sustainability strategies into international development policies, planning and programming (United Nations 2007).

Figure 2.1 illustrates the comprehensive framework created by all of the various activities required for effective risk management. The importance of this framework is that it connects all phases (i.e. assessment, prevention, mitigation, monitoring, early warning and preparedness) and demonstrates that maintaining community resiliency (i.e. achieving sustainability) is a dynamic process that requires feedback between all phases. In the United States, the Federal Emergency Management Agency (FEMA) has adopted a strategy promoting the enhancement of state and local mitigation based on natural hazard risk assessment and knowledgeable spatial planning (Stanganelli 2008). The functionality of this strategy relies heavily on risk assessment, mitigation and monitoring at the local level (Stanganelli 2008).

[7] The International Decade for Disaster Reduction also became the title for the UN task force chartered to reduce "the loss of life, property damage, and social and economic disruption caused by natural disasters" (Munasinghe and Clarke 1994, ii).

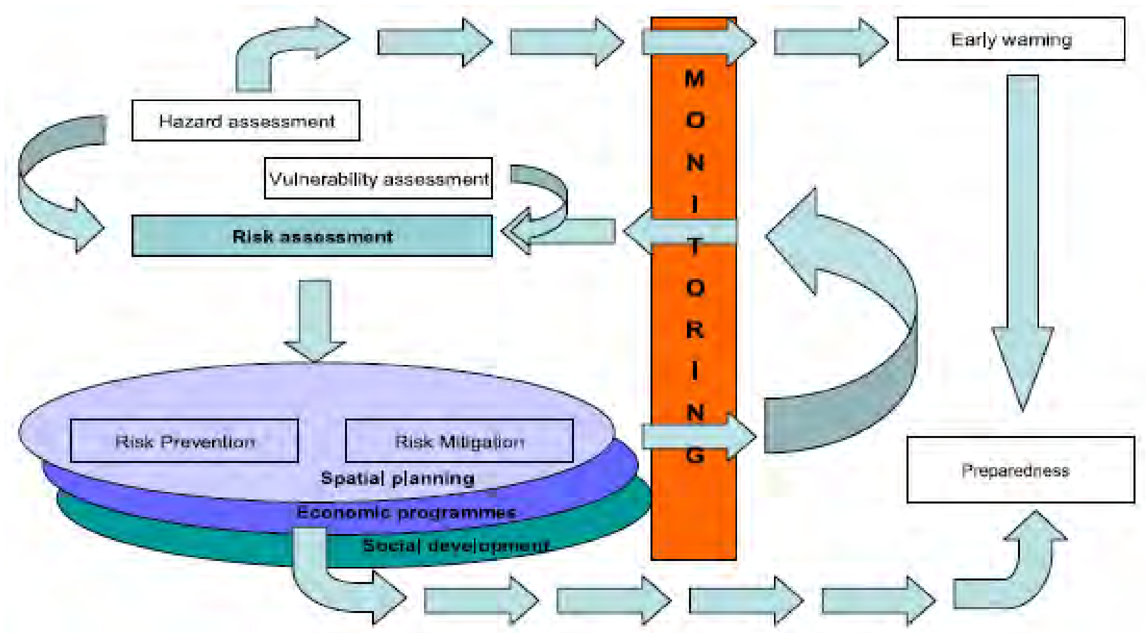

Figure 2.1: The Hyogo Framework for Action Risk Management Process
(Stanganelli 2008, 93)

Hazards, Disasters, and Risk

An extreme event, such as flooding, only poses a hazard when it exposes humans (directly or indirectly) to danger (Cross 2001). Disasters occur when the danger is realized by an actual event that causes widespread and intense damage in proportion to the total population (Cross 2001). If a community is unable to "anticipate, cope with, resist and recover from the impact of a natural hazard" it is considered vulnerable (Cross 2001). Three strategies (i.e. options) are available for communities to reduce the risks that accompany natural hazards: 1) choosing change, 2) reducing losses and 3) accepting losses (Klein et al. 2003). Traditionally, communities have chosen to decrease losses by reducing the existence of a hazard through the implementation of warning systems, defense works and resistant infrastructures (Klein et al. 2003). In the US it is also common to accept losses by sharing the cost of the loss over a large portion of the population through mechanisms such as federally funded flood insurance. The most promising strategy for reducing losses and promoting resiliency is choosing change (i.e. accepting the hazard and adapting land uses to prevent exposure to the hazard) (Klein et al. 2003).

Regardless of which strategy is chosen, comprehensive knowledge (by community planners/managers) of the current community conditions is necessary to follow the risk reduction phases set forth by the Hyogo Framework of Action (i.e. risk assessment, risk management and emergency preparedness) (Stanganelli 2008). It is impossible to foster resiliency and prepare for a potential disaster without comprehensive knowledge of a community's current conditions as they apply to that hazard (e.g. current land use/land cover and its effects on flooding). The need of local planners and emergency managers for accurate and detailed information of current community conditions (e.g. land use and land cover) is especially important for the prevention of flooding and attaining sustainable floodplain management.

Water: Our Attraction and Its Perils

Attraction

Water, because of its immense intrinsic value, is a population and industrial magnet. Due to the value presented by water's numerous uses (e.g. manufacturing, transportation, agriculture and recreation), the global population is drawn to locations near bodies of water. By 2015, 33 cities in the world will have more than eight million inhabitants each (Klein et al. 2003). Of the 33 predicted megacities, 17 are located in coastal areas with the potential for flooding. As the world's population increases (9.3 billion people by 2050) so will the number of people dwelling in floodplains (Klein et al.

2003). In the United States, currently over half of our national population lives near a large body of water (U.S. Commission on Ocean Policy 2004).

Perils

By selecting locations in the vicinity of vast amounts of water, residents and businesses place themselves in (or near) floodplains (i.e. land of relatively low elevation, usually adjacent to a body of water, which is "shaped by and continually subject to inundation") (Johnston 1992, 1-4). The proximity of citizens to floodplains has made flooding the world's most prevalent natural disaster and the leading cause of economic loss and death (Ramlal and Baban 2008). The European Union considers flooding the most important natural disaster facing all of Europe (Stanganelli 2008). Of the twenty greatest natural disasters in history, twelve are related to some type of inundation (Stanganelli 2008). When the top twenty disasters are selected based on total financial losses, the number rises to seventeen disasters that were in some way affected by inundation (Stanganelli 2008). The greatest of the disasters is also the most recent. Hurricane Katrina and the accompanying storm surge struck the United States in 2005 leaving a wake of destruction and economic losses in excess of $142 billion (Burton and Hicks 2005[8]).

Moths to a Flame

Our attraction to locations near water seems to outweigh our perception of the inherent risks of floodplains. In 1993 flooding of the Upper Mississippi River Basin

[8] Burton and Hicks (2005) estimated that Hurricane Katrina and the accompanying storm surge caused damages exceeding: $21 billion to commercial structures, $36 billion to commercial equipment, $75 billion to residential homes and their contents, $231 million to electric utilities, $3 billion to highways, $1.2 billion to sewer systems, and $4.6 in lost commercial revenues. Damages not estimated included those to the water system and environment, as well as, costs of lost lives.

resulted in damages exceeding $12 billion. Despite federal recommendations to curb development in the affected areas, new development has poured into the flood-affected zones (Hipple et al. 2005). Based on comparison of 1990 and 2000 US Census data for the Upper Mississippi River Basin, a 17% population growth has occurred in the 500 year floodplain (Hipple et al. 2005). Over the same 10 year period, an 18% growth in population has occurred in the flood-affected zones accounting for a 28% increase in developed land area (Hipple et al. 2005).

Sustainable Floodplain Management

With our global population's seemingly unquenchable thirst to inhabit land areas prone to inundation, floodplain utilization and management issues have gained unprecedented attention by the majority of the world population. Although flooding is the world's most prevalent natural disaster, by understanding the risks associated with floodplains and developing strategies for proper risk mitigation, it is also the most preventable (Romano and Vaccaro 2005). The ability to prevent flood losses through proper application of relevant mitigation strategies make issues regarding sustainable floodplain management especially pertinent to those in charge of the cities and communities in which we live.

The Goal

At its best, sustainable floodplain management maintains the ability of the floodplain to adapt, adjust and absorb a disturbance in order to preserve its original functions and structure (Colding 2007). Because of the changing internal and external processes, the goal of all community managers must be preservation of a floodplain's ability to continue providing valuable social and ecological functions (e.g. flood control, sediment and nutrient retention, recreation opportunities and wildlife habitat). According to Pickett et al. (2004, 373) the emphasis of sustainable floodplain management should not be “on reaching or maintaining a certain endpoint or terminal condition, but on staying in the game”.

The Authority

The authority for floodplain management resides at the state and local level. Local authorities rely on three distinct approaches to mitigate flood hazards: (1) guiding development away from flood hazards, (2) implementing specialized floodplain construction standards and (3) constructing flood control structures (Burby and French 1985). Since Mother Nature possess the ability to build storms that surpass our engineering and financial resources, flood control structures (e.g. levees, channels and detention basins) often only postpone inevitable inundation and ensure catastrophic damages when their engineering limitations are exceeded. Because of their physical limitations, “there will never be enough funds available to solve flood problems by structural means” (Burby and French 1985, 153). Implementing land use regulations to guide new developments away from flood hazard areas is the most certain way to ensure decreased flood damage because it eliminates (or greatly reduces) the potential for loss (Peterson et al. 1999). The adoption of strict building codes for new or significantly improved structures in floodplains also helps to lessen the consequences of flooding (Wetmore 2006).

The Compromise

While not developing areas in or around floodplains will virtually eliminate all losses from flooding, it may also significantly inhibit economic growth and income for a city. The loss of tax revenue and economic input from excessively stringent land development regulations can severely decrease the money available to a community. Unrestricted floodplain development, however, threatens the lives and property of individuals and businesses located in flood hazard areas. Reducing mitigation measures to the lowest level (that still provides significant hazard reduction) protects community resources while promoting safe development and economic growth.

Hydrologic Modeling for Floodplain Management

More than a Floodplain

Since watersheds incorporate the diverse processes of subterranean and overland hydrologic transport[9] into floodplains, the practice of sustainable floodplain management must be expanded to include the corresponding watershed(s) (Hipple et al. 2005). In a flood hazard mitigation context, the goal of watershed management should be a comprehensive knowledge of the results of the hydrologic processes (as they affect floodplains) and identification of at risk areas. Therefore, proper watershed management requires a thorough knowledge of current watershed conditions and the ability to perform real-time assessments of those conditions after dynamic events.

Monitoring a Dynamic Hazard

Communities rely on flood hazard maps (National Flood Insurance Program Flood Insurance Rate Maps) to manage floodplain development and mitigate the inherent hazards. Such maps are created by modeling surface water conveyance and catchment regions for a watershed (FEMA 2007; Hoggan 1997). Property use and ground cover

[9] Overland hydrologic transport consists of the movement of water and any substances it carries across the land surface. Overland hydrologic transport does not include sub-surface water or movement within stream and river banks (Zhang and Cundy 1989).

(i.e. land use and land cover) data and digital elevation models are the two types of data sets (besides actual water inputs) required to model surface water conveyance for a watershed (Maidment 2002). There is a need for data sets to be current and up-to-date because, watershed (and floodplain) conditions can change rapidly and drastically. Dynamic natural events (e.g. floods and hurricanes) have the ability to drastically alter the use and topographic characteristics of a floodplain in a matter of days, if not hours (Mannion 2002). Topographic changes and widespread destruction of homes and businesses caused by the immense forces of nature, (e.g. flood sediment and coastal erosion) can drastically alter the characteristics of a floodplain. Such drastic topographic changes warrant immediate assessment to understand and determine the presence of newfound risks. Subsequent recovery efforts can also alter the floodplain. Often post-disaster reconstructions proceed unregulated and undocumented for many months after the initial disaster. Such unimpeded and often haphazard development has an increased potential of negatively altering/utilizing a floodplain and exposing citizens to unnecessary risk.

Limited Resources

For many communities, especially smaller cities and the suburban fringe of larger cities, the resources are not available to conduct accurate in-house watershed modeling procedures. As a result, local governments have traditionally relied on external agencies to develop land use and land cover data for their management purposes (Johnston 1992). This outsourcing has been required due to the complexity of LULC analysis. Traditional methods required extensive fieldwork and the labor intensive process of ground-truthing[10] the classification (Singh et al. 2001). Unfortunately, relying on external agencies to deliver the data is a costly (if outsourced to private corporations) and slow (especially with federal assets) method for acquiring land use and land cover data. The obstacles of traditional land use and land cover classification methods have created a chasm between the land use and land cover information available to a city for a particular watershed and the actual land use and land cover conditions for that watershed (USGS 2007; USGS 2006). Planners need a quick, low cost, and accurate method for assessing land use and land cover conditions in rapidly developing communities.

Scenario – Norm's Dilemma

Like the majority of planners for small to medium sized cities, Norm does not have a plethora of resources at his disposal. The only resource for which he does not have to grovel and plead is his time, but after years of hard work, his time is the resource Norm values most. Perplexed by his current dilemma, Norm allows himself an uncharacteristic moment of mental repose, kicks back in his threadbare office chair and lets his mind wander. His thoughts careen haphazardly until they transport him to 1999, where a much younger Norman Ware was attending a national planning conference at the Gaylord Opryland Resort Hotel and Convention Center. It was here, in the heartland of country music and the former home of many great Texans, that Norm had endured (half awake/half asleep) a lifeless presentation discussing the success of satellite images to assess changes in land use and land cover. Norm's brain began firing a little faster. Another portion of the presentation came to mind, although no more clear than the first.

[10] Ground-truthing is a term commonly used in the remote sensing field to refer to the process of collecting reference data in an attempt to approximate actual ground conditions and verify interpretations of remotely sensed data. Ground-truthing may be conducted by visiting the area of interest (remotely sensed area) or by analyzing other images or photographs of the area (Lillesand and Kiefer 1994).

If he remembered correctly, the land use and land cover data had been used to model runoff and… BINGO, FLOODPLAINS! Suddenly, Norm jerked to total consciousness and allowed the elation of his recent recollection to overshadow the painful memory of the monotone lecture. Norm's celebration quickly subsided as he tried to remember the specifics provided by the sedated speaker a decade ago.

He immediately turned to his computer and hit up his old pal GOOGLE™ for the answer. As his screen filled with the first of 298,000 results for "satellite imagery land use land cover classification," Norm wondered how he ever accomplished anything in the days before the internet. A cursory survey of the search results revealed imagery from the Landsat satellites as the foremost data set for land use and land cover classification. It wasn't until a more in depth study that Norm determined the Landsat data was just not right for his situation. With single pixels that cover 900 square meters, assessing the area proposed for Deerfield Estates: Phase Three with Landsat data would be about as effective as trying to recreate the Mona Lisa with a paint roller.

Norm didn't want to make broad classification strokes; he needed something that could handle the intricate details of a masterpiece. His thoughts were interpreted by a not so distant growl. Norm looked at the clock… 11:30. It was the second Friday of the month. That made it his cousin's (an agent with the local USDA office) turn to buy lunch. Norm's settling physique implied that he never missed a meal, much less a free one. "Deerfield Estates would have to wait," Norm thought as he strolled down the hall and across the street to the USDA office. It was lunch time.

Remote Sensing

The most promising means of assessing land use and land cover conditions is through the use of remote sensing technologies. In its purest sense, remote sensing is the science (or art) of gathering information about an object or area without coming into contact with the object or area under investigation (Lillesand and Kiefer 1994). By gazing at a distant object, one is employing remote sensing techniques using one's eyes as the sensors to gather information without contact. Modern technology has elevated the art of remote sensing to a science through development of numerous sensors that incorporate a wide variety of techniques. Modern sensors are commonly designed (especially for LULC assessment) to measure the reflectance properties of a target. The characteristics of a target may be derived from the incident energy reflected by the object. When this energy is measured as a function of wavelength, it is termed spectral reflectance. The combination of spectral reflectance of the wavelengths captured by a sensor is the spectral reflectance curve, or spectral signature for that specific target (Lillesand and Kiefer 1994).

In theory, by sensing the proper combination of wavelengths two, or more, targets may be differentiated by differences in their spectral signatures. The process may be likened to the use of social security numbers to identify all United States citizens. By viewing the unique 9-digit combination, it is possible to differentiate one citizen from another. In the same manner, a spectral signature (utilizing the appropriate wavelengths) may be used to identify a target for all other types of targets within an area of interest.

For land use and land cover assessment purposes, the goal is to identify a sensor (device for electronic/digital data capture) that focuses on the specific wavelengths necessary to accurately differentiate various land use and land cover classes and is contained in a readily available and affordable platform. Many attempts have been made and small successes achieved in the search for the ideal land use and land cover remote sensing system. Yet, the need still exists for a remote sensing system that incorporates all of the desired attributes: a high level of accuracy (less than two meter resolution) capable of assessing land use and land cover at the sub-watershed level, a high level of flexibility facilitating repeated acquisitions as necessary to assess change, and a total cost that is not prohibitive to mid- and small-sized cities and municipalities.

Landsat MSS, TM and ETM+

Perhaps the most common platform for remotely acquiring land use and land cover data is the moderate-resolution, multi-spectral Landsat system (for examples of Landsat satellites see Figure 2.2). The Landsat program was initiated by the National Aeronautical and Space Administration (NASA) in 1967 and the first satellite for this purpose was launched in 1972 (Lillesand and Kiefer 1994). Since 1972 six Landsat systems have reached orbit and remain in an operational state. The most commonly used Landsat sensors for land use and land cover assessment are the Thematic Mapper (TM) systems (found on Landsat 4 and 5) and the Enhanced Thematic Mapper + (ETM+) system (found on Landsat-7). The Landsat 5 TM and Landsat 7 ETM+ have become the most commonly used remote sensing systems for land use and land cover classification. Table 2.1 illustrates some of the principal applications for each band of the TM and ETM+ systems. The table also identifies the wavelengths that define each band. For the more visual learner, Figure 2.3 illustrates the seven Landsat spectral bands and their corresponding wavelengths. Bands 1 through 4[11] (i.e. blue, green, red and near infrared) are of utmost interest for land use and land cover classification (see Table 2.1 "Principal Applications").

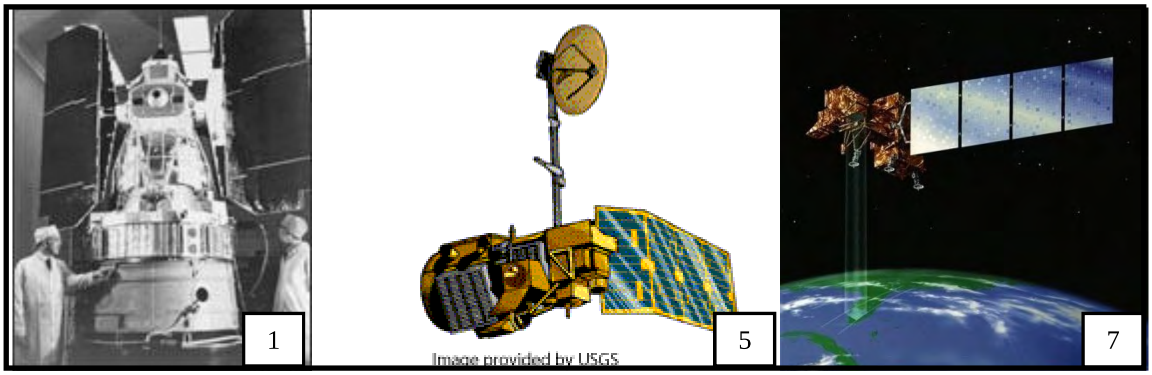

Figure 2.2 Landsat 1 (MSS)[a], Landsat 5 (TM)[b], and Landsat 7 (ETM+)[c]

[a]http://www.csc.noaa.gov/crs/rs_apps/sensors/images/landsat_sensor.gif
[b]http://landsat.gsfc.nasa.gov/about/
[c]http://www.satimagingcorp.com/media/images/landsat_orbiting_earth.jpg

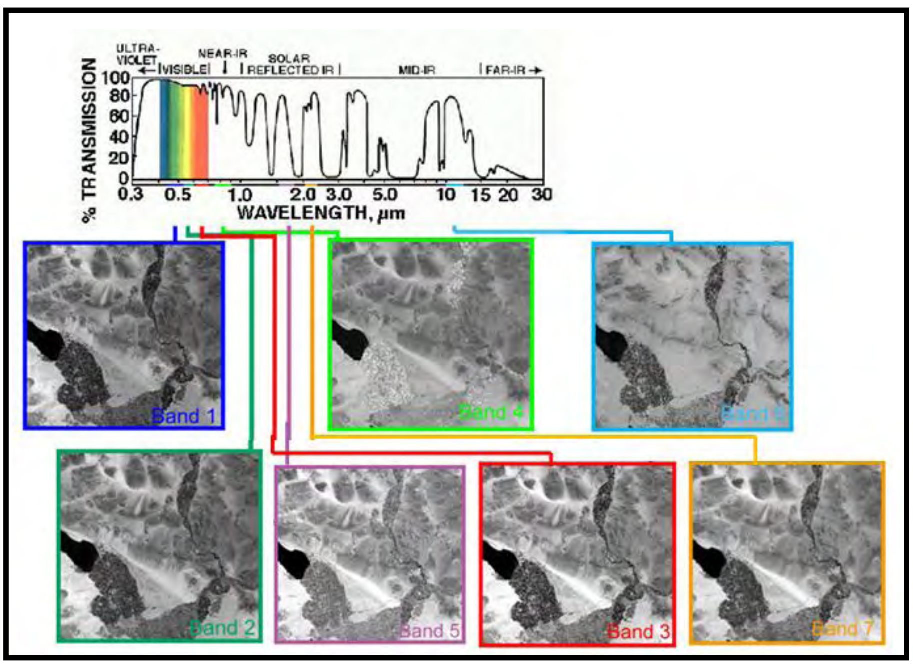

Figure 2.3 Landsat TM and ETM+ Spectral bands (Figure courtesy of NASA: http://landsat.gsfc.nasa.gov/education/compositor/)

[11] As discussed later in this chapter, bands 1 through 4 are the Landsat bands that most closely resemble the four bands (i.e. blue, green, red, and near infrared) available in National Agriculture Imagery Program data.

Landsat TM is a highly advanced sensor that incorporates several improvements over the original Multispectral Scanner Systems (MSS) of the earlier Landsat sensors systems (Lillesand and Kiefer 1994). Beginning with Landsat 4, the TM and ETM+ systems were placed in a lower orbit allowing for an improved resolution of 30 m and reduced repeat coverage cycle of 16 days. (MSS had a 57 m resolution and an 18 day repeat cycle.) TM also incorporated three additional spectral bands for a total of seven (see Table 2.1). Having learned a great deal from the earlier Landsat missions, NASA selected the TM bands to maximize differentiation of features on the Earth's surface (see Table 2.1).

Landsat 7 ETM+ incorporates increased spectral sampling by adding a panchromatic band and a higher resolution (60 m) thermal infrared band (see Table 2.1). With the unprecedented spectral range and earth observation capabilities, it is easy to understand why the TM and ETM+ have had such success in land use and land cover assessment. The following section contains a brief review of a sample of the more recent accomplishments in LULC classification utilizing the various Landsat systems.

Table 2.1 Landsat Thematic Mapper (TM) and Enhanced Thematic Mapper[a] (ETM+) Spectral Bands

Band	Wavelength (μm)	Nominal Spectral Location	Principal Applications
1	0.45-0.52	Blue	Designed for water body penetration, making it useful for costal mapping. Also useful for soil/vegetation discrimination, forest type mapping, and cultural feature identification.
2	0.52-0.60	Green	Designed to measure green reflectance peak of vegetation for vegetation discrimination and vigor assessment. Also useful for cultural/feature identification.
3	0.63-0.69	Red	Designed to sense in a chlorophyll absorption region aiding in plant species differentiation. Also useful for cultural feature identification.
4	0.76-0.90	Near infrared	Useful for determining vegetation types, vigor, and biomass content, for delineating water bodies, and for soil moisture discrimination.
5	1.55-1.75	Mid-infrared	Indicative of vegetation moisture content and soil moisture. Also useful for differentiation of snow from clouds.
6[b]	10.4-12.5	Thermal infrared	Useful in vegetation stress analysis, soil moisture discrimination, and thermal mapping applications.
7[b]	2.08-2.35	Mid-infrared	Useful for discrimination of mineral and rock types. Also sensitive to vegetation moisture content.

[a]ETM+ contains and additional panchromatic band not available on the TM.
[b]Bands 6 and 7 are out of wavelength sequence because band 7 was added to the TM late in the system design process.
(Lillesand and Kiefer 1994, 468 and 484)

Landsat and LULC Classification

The numerous successes with land use and land cover classifications utilizing Landsat data warrant continued research with the spectral bands sensed by Landsat TM and Landsat ETM+. While multi-spectral remote sensing is promising for continued progress regarding economical sensor data and efficient classification techniques, the medium-resolution (30 m) data captured by Landsat sensors inhibits detailed assessments of land use and land cover. The following reviewed sources suggest that land use and land cover classifications are limited to a maximum of 9 categories (i.e. classes). As far back as 1976, Anderson et al. (14-15) identified ninety-two potential classes of land use and land cover. With current classification attempts only utilizing ten percent of the possible land use and land cover classes, there is a multitude of LULC information that is not being incorporated into urban planning. This lack of information contributes to one of the greatest obstacles to accurate hydrologic modeling of surface water conveyance (and therefore floodplain behavior): the inability to accurately quantify the surface characteristics (LULC) necessary for developing model inputs (e.g. hydraulic roughness) over a large spatial extent (Vieux 2001). The ability to accurately identify a greater number of land use and land cover classes should provide decision makers valuable information for understanding and managing their communities.

The proven spectral bands of Landsat TM and ETM+ and the unmet need to precisely classify a greater number of land use and land cover categories, warrants the identification of a high-resolution sensor that incorporates Landsat's comprehensive spectral capture. The next subsections provide a review of a mere sample of the immense literature available discussing the strengths (i.e. comprehensive spectral capture, especially bands 1-4) of land use and land cover classification with Landsat data. Following the literature Landsat research review, this chapter offers a promising solution[12] for the Achilles heel of the almighty Landsat data (i.e. low resolution).

California

Rogan et al. (2008) utilized Landsat-5 TM (Landsat MSS and ETM+ Images of San Jose, CA are show in Figures 2.4 and 2.5) to map land cover modifications over large areas in northern and southern California. Four Landsat-5 TM images from 1990 to 1996 were classified. Rogan et al. (2008) chose a supervised classification method incorporating machine learning algorithms (MLA), fuzzy neural network algorithms, and

[12] High resolution (1 m) data acquired for the United States Department of Agriculture (USDA) National Agriculture Imagery Program (NAIP) has the potential replace Landsat data as the premier LULC dataset.

classification trees (CT) in ERDAS Imagine®[13] to classify the TM data into 9 land cover classes (i.e. shrub, hardwood, conifer, mixed, urban, herbaceous, barren, water and agriculture). The resulting classifications averaged an overall accuracy of approximately 84% and can be considered indicative of the potential for TM data in land cover assessment over a diverse area.

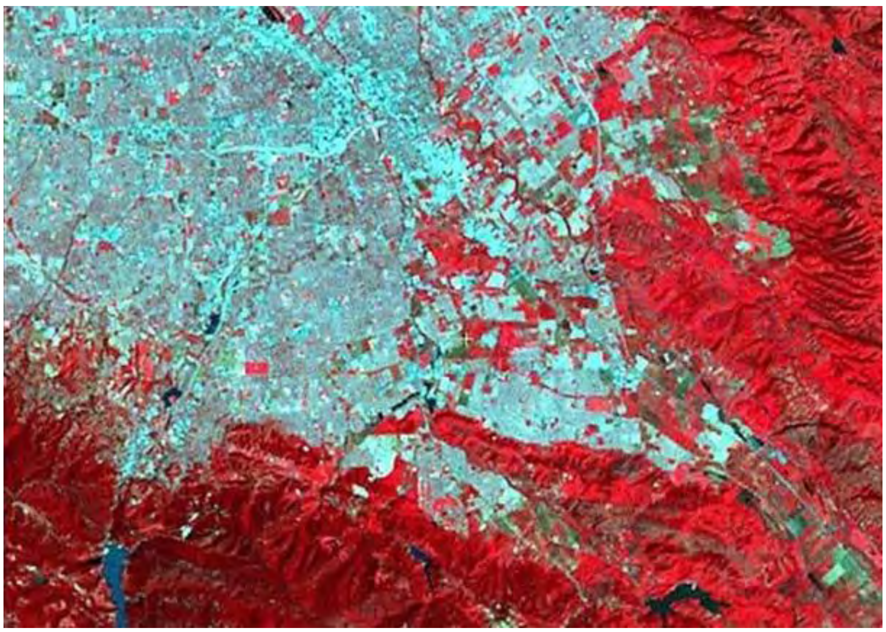

Figure 2.4 1973 Landsat MSS Image of San Jose, CA (Image courtesy of www.fas.org/irp/imint/docs/rst/Sect4/Sect4_1.html)

[13] ERDAS Imagine® is an image processing software created by Leica Geosystems GIS & Mapping, LLC (Leica Geosystems GIS and Mapping, LLC 2008)

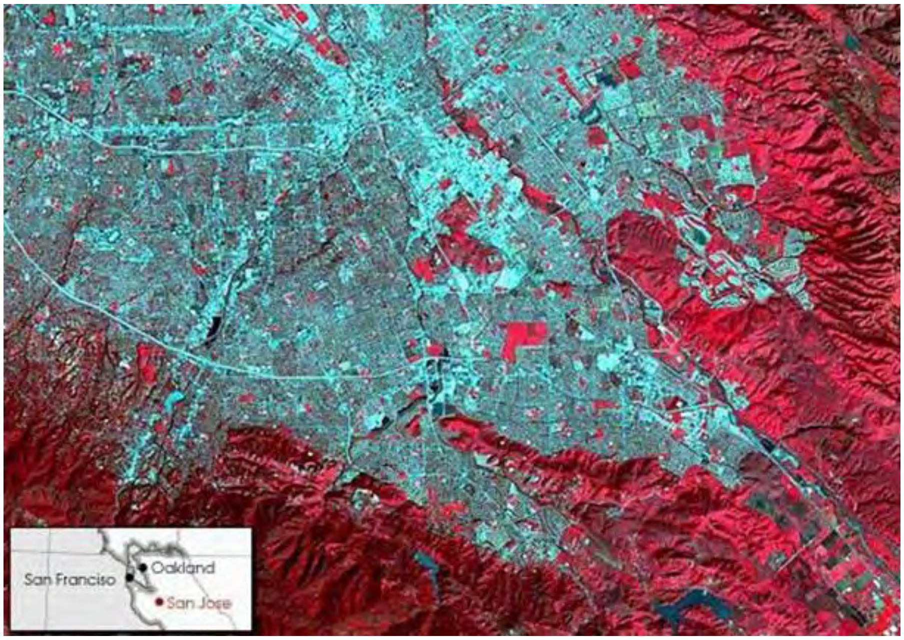

Figure 2.5 1999 Landsat ETM+ Image of San Jose, CA (Image courtesy of www.fas.org/irp/imint/docs/rst/Sect4/Sect4_1.html)

Twin Cities

In the Twin Cities (Minnesota) Metropolitan Area, Yuan et al. (2005) was able to achieve high overall land cover classification accuracies (94%) by analyzing TM and ETM+ data (classification outputs would have been similar to the land use map in Figure 2.6). Yuan et al. chose 7 land cover classes based on an Anderson et al. (1976) classification schema. The 7 classes (i.e. agriculture, grass, extraction, forest, urban, water and wetland), when identified from Landsat data through hybrid (supervised/unsupervised) image analysis (ERDAS Imagine 8.5 ®) proved to be an accurate and economical means for identifying land cover change.

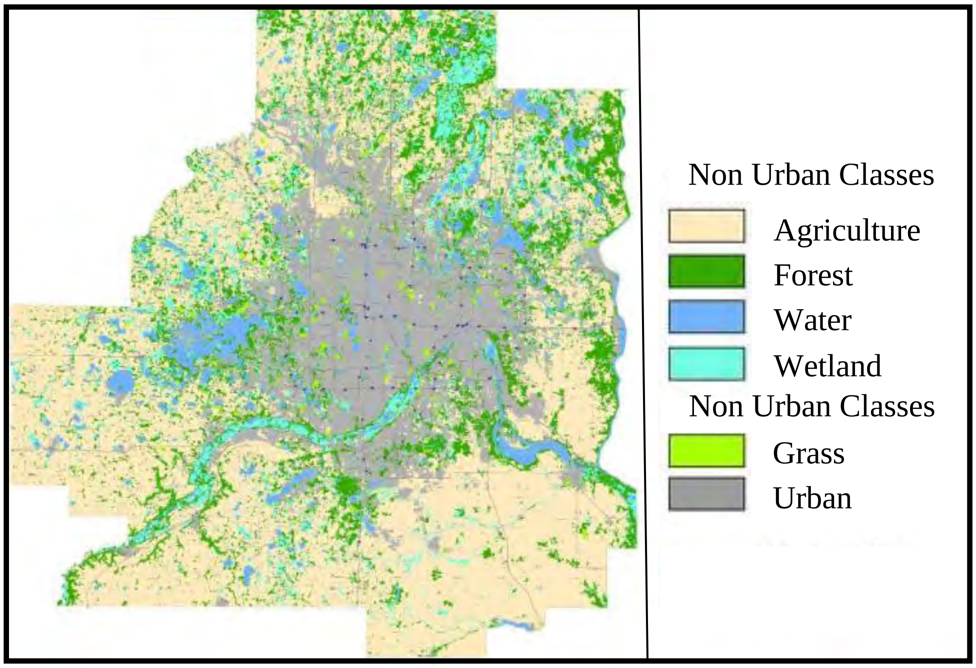

Figure 2.6 Land Use Classification of Landsat Image for the Twin Cities Minnesota Area (Map courtesy of the University Of Minnesota: http://land.umn.edu/ quickview_data/index.html)

Kenya

Landsat data has also been used successfully in identifying forestland cover change in Kenya (Ouma et al. 2008). TM and ETM+ bands 3, 4 and 5 were chosen for unsupervised classification attempts in PCI Geomatica 9.1®[14]. The 1986 (TM) and 2001 (ETM+) images were classified into 4 classes [i.e. non-forest, deforested, forest-unchanged (broadleaf) and afforestation (pine)] with an 88.4% overall classification accuracy. The high classification accuracies derived from unsupervised classification techniques are an indication of the potential for Landsat data in land cover classifications without *a priori* knowledge of land cover classes.

Brazil

[14] PCI Geomatica 9.1 is an imagery analysis software package created by PCI Geomatics (PCI Geomatics 2009)

Land use change in the Brazilian Savanna was assessed via TM (1986) and ETM+ (2002) imagery similar to that shown in Figure 2.7 (Brannstrom et al. 2003). Unsupervised classifications were performed on the imagery (including the ETM+ panchromatic 0.52-0.90 µm band). Five initial land use and land cover classes were later grouped into 3 classes [i.e. savanna, cropland/pasture and dark objects (water bodies and burned areas)] and identified with classification accuracies ranging from 72-84%. Low classification accuracies were attributed to misinterpretation of panchromatic data rather than misclassification of the other spectral bands.

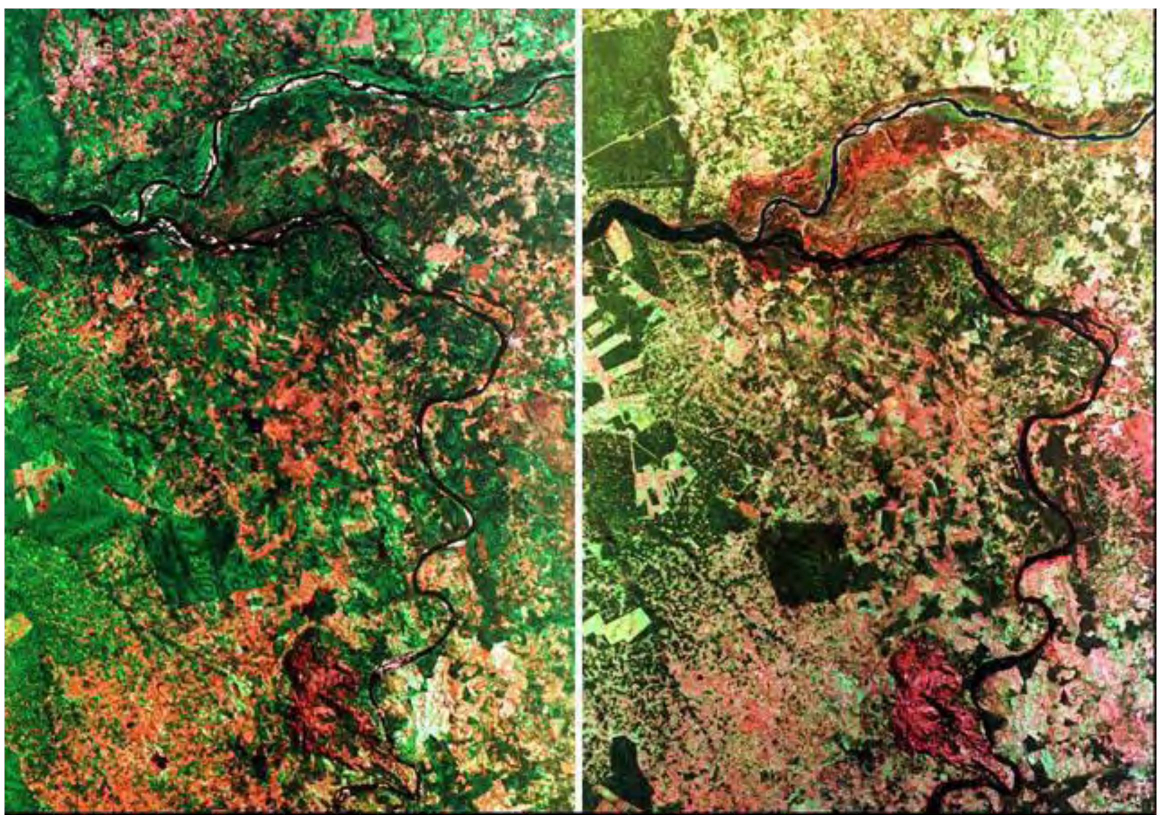

Figure 2.7 Landsat 5 TM Images Depicting Urbanization of Amazon Rainforest in Brazil Occurring Between August 1995 and May 1997 (Imagery courtesy of NASA Goodard Space Flight Center, http://www.nasa.gov/centers/goddard/news/topstory/2004/0301landsat5.html)

Northern China

In north China, Xiao et al. (2006) evaluated urban expansion and land use change with 1987 TM and 2001 ETM+ data. A 9-class supervised classification of the data resulted in successful identification of urban, residential, crop-field, vegetable-field, forest/trees, orchard, grass, water body and barren/sandy land cover classes with an 87% overall accuracy (results would have been similar to the land cover classification in Figure 2.8). Successful land use and land cover classification allowed Xiao et al. to identify a relationship between land use and land cover change and urban expansion.

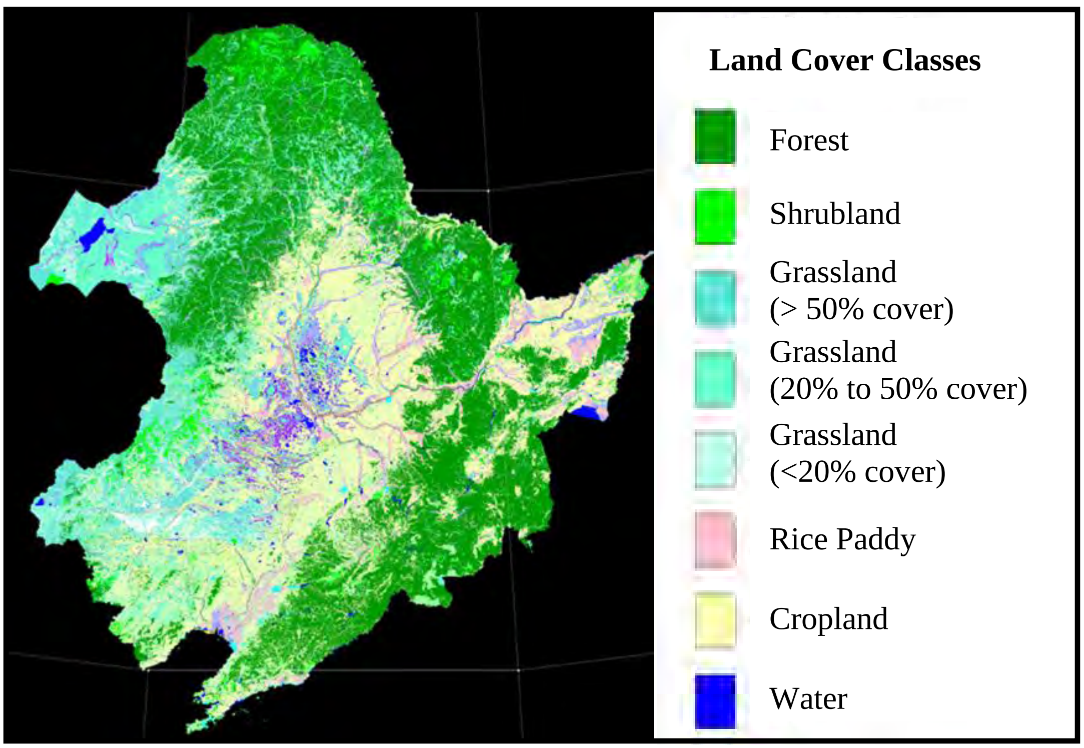

Figure 2.8 Land Cover Classification of Landsat ETM+ Image for North East China (Map courtesy of the University of Maryland: lcluc.umd.edu/products/pdfs/ 2003AnPrgRp/AnPrgRp_SunG_2003_images.ppt)

In 2006, Ji et al. conducted a study to determine trend and patterns of urban land changes. To identify the progression of land use and land cover change over time Landsat data from 1972 (MSS), 1979 (MSS), 1985 (TM), 1992 (TM), 1999 (ETM+) and

2001 (ETM+) were analyzed. Supervised classification attempts were conducted in ERDAS Imagine to identify 4 land cover classes (built up areas, forestland, non-forest vegetation, and water bodies). Resulting classification accuracies ranged from 85.5% to 89.5% with the lowest accuracies corresponding to MSS and highest accuracies to ETM+ data. Increased classification accuracies for the more recent data may be attributed to the improvements made during the development of the newer Landsat systems.

Egypt

In the northwestern coastal zone of Egypt, 7 land use and land cover classes (i.e. salt marshes, salt-flats, cropland, grassland, bare land urban and areas with exposed soil surface layers) were identified for classification by remote sensing and GIS techniques (Shalaby and Tateishi 2007). Supervised classification techniques were applied to all TM (1987) and ETM+ (2001) bands and the results were manipulated for improved accuracy based on visual interpretation of images created with bands 2, 3 and 4. Visual interpretation and manipulation of the supervised classifications increased overall classification accuracy by 10% to approximately 91%. The ability to achieve significant improvement of land use and land cover classification accuracies through visual interpretation and manipulation indicates the potential for continued progress in classification of remotely sensed data and the need for data that facilitates more detailed, precise land use and land cover classes.

In an attempt to predict locations sensitive to flash flooding in an arid environment (Egypt's Eastern Desert), Foody et al. (2004) performed a supervised classification on TM bands 3, 5 and 7. Five land cover classes were identified for the study: basement rocks, desert pavement, unconsolidated wadi bed deposits, consolidated wadi bed deposits and sedimentary rocks. The resulting 89.5% overall classification accuracy demonstrated the applicability of TM data for land cover classification.

Scenario – An Agricultural Solution for an Urban Problem?

The lunch break had had yielded more than a free meal. Norm, never one to let his troubles collect dust, had voiced his dilemma to his dining associates. The response from one of the USDA extension agents left Norm so excited that he nearly offered to pick up the tab in his zealous state. "Luckily," he thought, "I didn't let the good news go to my head." The "good news" was that the local Anytown USDA field office had access to imagery that was modeled after Landsat data. Actually, the "good news" was that the USDA imagery ("nape imagery" they called it) was collected at a 1 meter resolution. Norm did the arithmetic, "That's 900 times more detailed than Landsat data." "That's certainly not a paint roller," Norm thought, "but is it good enough for da Vinci?"

National Agriculture Imagery Program (NAIP)[15]

Apples to Apples

The numerous successes of land use and land cover classifications with Landsat data prove that a few select spectral bands can provide the information necessary for the LULC classification process. These successes suggest that the bands utilized by National Agriculture Imagery Program data will result in similar classification successes. Current NAIP acquisition contracts specify sensing of color and color infrared bands resulting in the acquisition of four spectral bands (blue, green, red, and near infrared) similar to Landsat bands 1-4 (see Table 2.2) (Lillesand and Kiefer 1994; USDA 2008). By sensing similar wavelengths (i.e. bands), the NAIP data produces an image very

[15] National Agriculture Imagery Program imagery is captured with a Leica Geosystems ADS40 airborne digital sensor (USDA 2007).

similar to Landsat data. A visual comparison of Landsat and NAIP images of Salt Lake City Utah (see Figure 2.9), demonstrates the parallels in colors and textures for the two types of images.

Table 2.2 Similarity of Spectral Bands for National Agriculture Imagery Program Data and Landsat ETM+ Data

Band	NAIP	Landsat
1 Blue	Yes	Yes
2 Green	Yes	Yes
3 Red	Yes	Yes
4 Near Infrared	Yes	Yes
5 Mid-Infrared	No	Yes
6 Thermal Infrared	No	Yes
7 Mid-Infrared	No	Yes

(Lillesand and Kiefer 1994; USDA 2008)

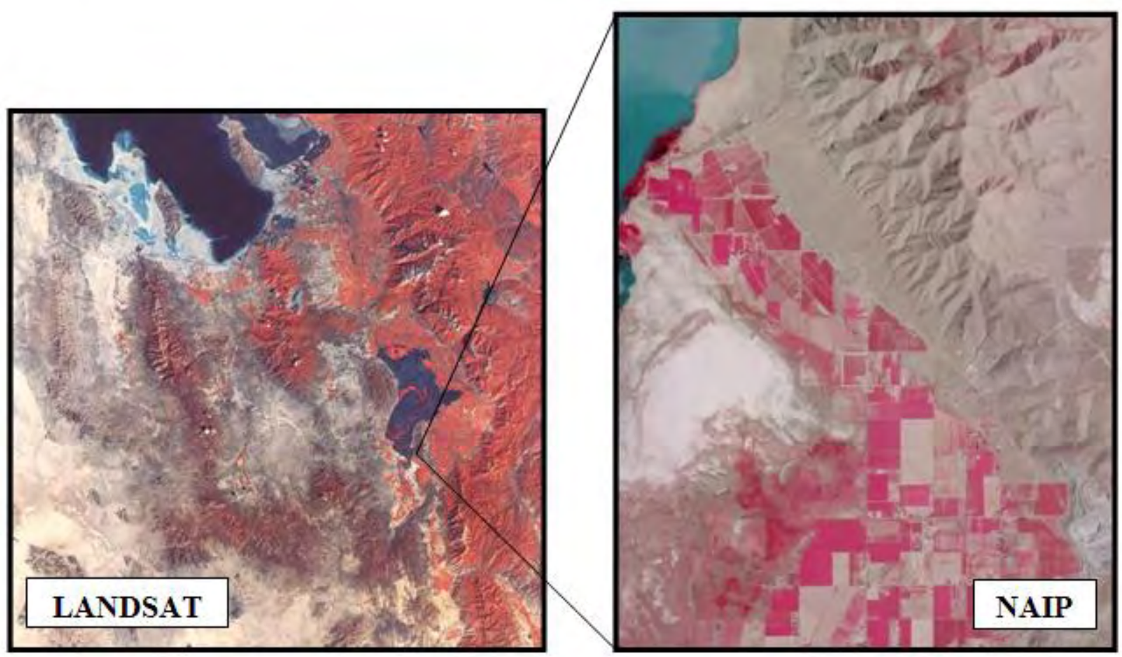

Figure 2.9 A NAIP Color Infrared (Green, Red, and Near Infrared Bands 2, 3, and 4) Image of a Portion of Salt Lake City, Utah Shown as a Subset of A Landsat TM Color Infrared (Green, Red, and Near Infrared Bands) Image of Salt Lake City, Utah and a Portion of the Great Salt Lake (Images courtesy of NASA: history.nasa.gov/SP-4312/ch5.htm and the USDA APFO: http://gis.utah.gov/naip2006)

NAIP v. Landsat: a Scalpel v. a Chainsaw

What the Landsat platforms lack is the ability to capture data at a high enough resolution to facilitate the small scale land use and land cover classifications required for local community planning. NAIP data is acquired at a scale that provides information at a detail of 225 (2 m resolution) to 900 (1 m resolution) times greater than the 30 m resolution Landsat data. Similar to the manner in which a digital camera takes a "picture," when a remote sensor captures data, it complies (i.e. averages) all of the information within each "pixel" (1 m for NAIP data and 30 m for Landsat data). The compiled (averaged) data is used to generate one value (or set of values) for the individual "pixel" area sensed. Similar to the "mega pixel" ratings for digital cameras, the greater the number of "pixels" within an image, the better the "picture". Figure 2.10 illustrates the superiority of NAIP sensors over Landsat sensors for data collection. As seen in Figure 2.10, one "pixel" of NAIP data will represent 1 square meter on the ground. One square meter is generally a high enough resolution to capture only part of most targets (e.g. roads, cars, trees, sidewalks, buildings, etc.) on the ground. In contrast, the 30 m "pixel" size of Landsat images has the potential to capture several targets within one "pixel" (see Figure 2.10). By capturing data in such superior detail, NAIP data presents a great deal of potential to provide local planners with an accurate data set for small scale land use and land cover classification.

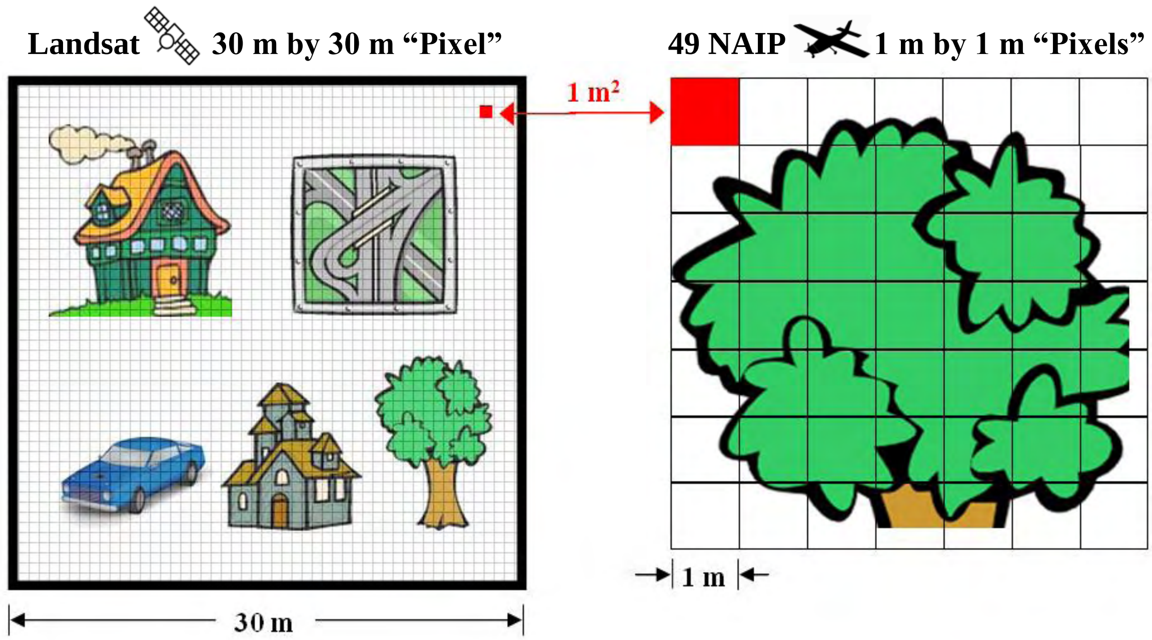

Figure 2.10 Amount of Data Captured within a Single 30 Meter by 30 Meter Landsat "Pixel" Compared to the Amount of Data Captured within a 1 Meter by 1 Meter NAIP Image "Pixel" (Each square within the 30 m Landsat "pixel" represents one NAIP "pixel")

<u>NAIP: It's Not all About the Resolution</u>

An increased imaging resolution is not the only catalyst behind the assessment of National Agriculture Imagery Program data's potential for land use and land cover classification. Three other factors: its acquisition methods, availability, and low cost; make NAIP data an even more promising solution the LULC classification problems that plague local planners.

Although NAIP contracting criteria will allow data from spaced-based sensors (i.e. satellites), all NAIP data, thus far, has been acquired from aerial platforms (i.e. airplane mounted sensors). The use of airplanes over satellites as sensor platforms significantly reduces the cost of image acquisition[16]. Use of aerial sensor platforms also allows for increased flexibility when capturing data. In our modern society, small aircraft

[16] Satellite launches can cost between $90 million and $120 million (Hassan et al. 2005). The cost of a small airplane is approximately $300,000 (Lyons 2007).

flights are coordinated and launched with relative ease. The spaced-based Landsat platforms have a 16 to 18 day repeat cycle requiring a lapse of more than two weeks before they can collect data from the same location (Lillesand and Kiefer 1994).

Because NAIP imagery is designed to assist agricultural producers, contract specifications mandate annual to triennial[17] data acquisition during the peak agricultural growing season (USAD 2007). Although intended for crop assessment, the resulting "leaf on" imagery will facilitate delineation of vegetative from impervious cover for land use and land cover purposes (Lillesand and Kiefer 1994). NAIP data collection criteria also requires that images are acquired by commercial providers at a high resolution (1-2 m), resulting in the use of imaging platforms are representative of the most current commercial and public remote sensing trends (USDA 2007). Therefore, successes with NAIP data classification will suggest potential in similar, modern-day platforms.

Finally, one of NAIP data's most appealing characteristics to local planners is its low (often free) cost. County mosaics of NAIP imagery are available for free download through the data gateway on the Natural Resource Conservation Service (NRCS) website: (http://datagateway.nrcs.usda.gov/gatewayhome.html). Compressed County Mosaics (CCM) and Quarter Quad (QQ) digital imagery is available at a relatively low cost (approximately $20 per CCM and $2 per QQ) through the USDA Aerial Photography Field Office (APFO).

Image Classification

With National Agriculture Imagery Program data displaying such promise for accurate, high definition LULC classification, the next step is to determine the best

[17] Since the inception of the NAIP, Texas has benefited from three comprehensive image acquisitions (2004, 2005, 2008).

method(s) for image classification. A review of several sources[18] suggests the use of two broad LULC classification techniques based on remotely sensed images. They are supervised and unsupervised classification. Neither method appeared superior to the other. Regardless of the method used, the objective of image classification is to enable the user to iteratively create and refine signatures and classify remotely sensed data to arrive at a desired final classification (Smith and Brown 1997). To do this, statistics are derived from the spectral characteristics of all pixels in an image. The pixels are then sorted based on mathematical criteria. Classification is divided into two portions: training and classifying. Training is the process of defining the criteria by which the spectral patterns are recognized for the image being assessed (Hord 1982). Classification takes place when the pixels of the image are assigned to discrete categories based on statistical analysis of each pixel's spectral signature.

Opening the Lock

Figure 2.11 illustrates the differences in spectral signatures for three different targets: an actively growing corn plant, corn residue (i.e. dead plant material left after harvest), and a common Mississippi soil (i.e. Dundee sandy loam). The figure allows one to visualize the specific wavelengths at which the reflectance values were recorded. For classification purposes, the reflectance values are used to create a unique number combination that could only identify each specific target. The number combination works in a similar manner to a combination used to open a padlock. For demonstration purposes, a "padlock combination" has been created from the spectral signatures for each

[18] See Rogan et al. 2008, Yuan et al. 2005, Ouma et al. 2oo8, Brannstrom et al. 2003, Xiao et al. 2006, Ji et al. 2006, and Shalaby and Tateishi 2007.

of the three targets. For a three number "padlock combination," reflectance values at wavelengths of 800 nm, 1300 nm, and 1750 nm are utilized. The combination for the living corn plant is .47 - .45 - .31. The combinations for the corn residue and soil are .34 - .60 - .62 and .30 - .39 - .46 respectively. The creation of these "padlock combinations" represents the training process of image classification. During the actual classification process, the "padlock combinations" (i.e. spectral signatures) of other unknown targets are compared to the "padlock combinations" of the known targets (i.e. training data) and labeled as the type of target with the most similar combination. Where the combination is created within the classification process determines if the classification is a supervised or unsupervised process.

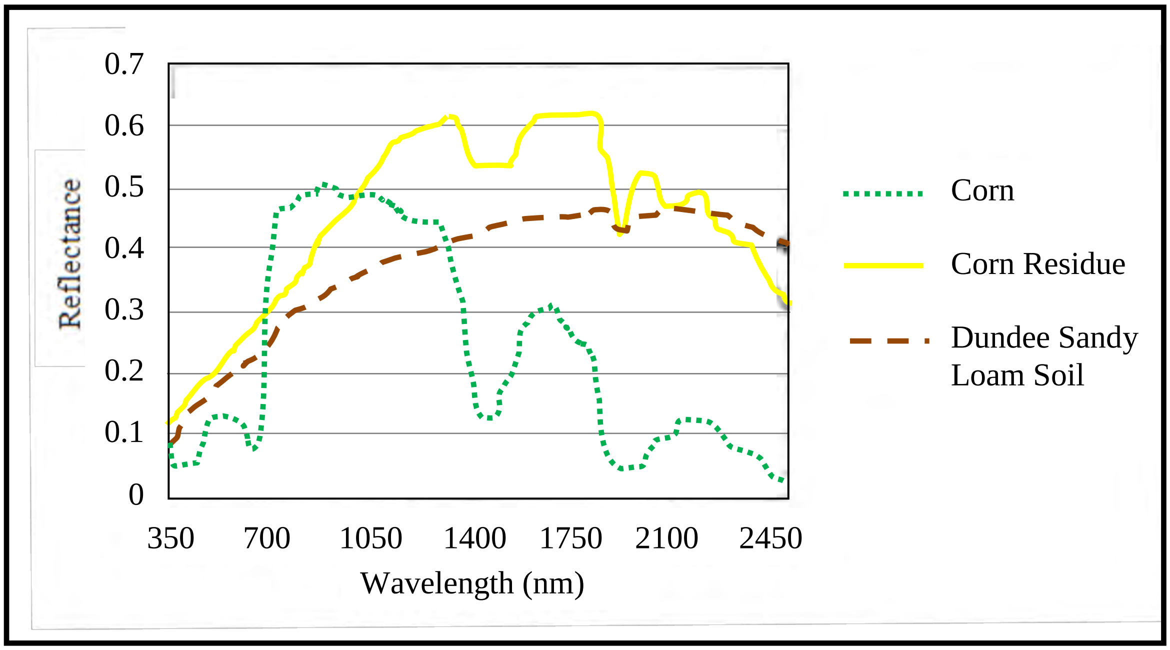

Figure 2.11 Spectral Signatures of Corn, Corn Residue, and Dundee Sandy Loam Soil (Powell 2003, 17).

<u>Supervised Classification</u>

For supervised classification, the "padlock combinations" are defined for specific target categories before unknown targets are assessed. Supervised classification requires more control and attention from the analyst. For supervised training, the user selects pixels or groups of pixels that represent land cover features, or other areas of interest, that they recognize. For example, prior to image classification, the user may already know (*a priori* knowledge) the location of several forests (area of interest) within an image and draw a boundary around the pixels within one forest (training area) to provide a representative sample for classification of other forests within the image. Areas of interest can be determined from many different sources of ancillary information (e.g. aerial photos, ground truthing, *a priori* knowledge, etc.). Using these areas of interest, the user can train the computer system to identify pixels with similar spectral characteristics. Providing that the training is accurate, the resulting classes should represent all of the data that falls within the categories already identified. Supervised classification is best when the user wants to identify relatively few classes, when the training sites can be verified with ground-truthed data, and/or when the user can identify distinct, homogeneous regions that represent each desired class (Lillesand and Kiefer 1994).

Unsupervised Classification

For unsupervised classification, the "padlock combinations" are not associated with a specific type of target. Instead all targets remain undefined and are simply grouped with those that possess similar combinations. Unsupervised classification is a more computer-automated process. With unsupervised classification the user sets parameters that the computer uses to uncover statistical patterns that are inherent in the data. The determined patterns do not necessarily correspond to readily recognizable categories such as in supervised classification. They are simply clusters of pixels with similar spectral characteristics. For this type of classification, the data itself provides the definition for the classes. Unsupervised training is best when there is little or no *a priori* knowledge of the data set being evaluated and if the resulting classes can be appropriately interpreted (Lillesand and Kiefer 1994). Regardless of what type of classification strategy is used, the training sets result in a series of signatures that define the training sample. Each signature corresponds to a different class and is used with a decision rule (e.g. statistical limits or spectral signature definitions) to assign the pixels in the image to a class, or category.

Comparison of Classification Techniques

Continuing with the previous example in Figure 2.11, Figures 2.12, 2.13, and 2.14 provide a visual depiction of simulated supervised and unsupervised classifications[19] of a corn field that has been partially harvested. The field contains actively growing corn plants, bare soil, and corn residue (i.e. dead plant material left on the ground after harvest). The two classification techniques delivered nearly identical outputs. The only difference is that the output for the supervised classification (Figure 2.13) identifies the areas classified by the target names (e.g. bare soil) identified in the training process. Since the process of unsupervised classification does not include the identification of training areas prior to image classification, the output in Figure 2.14 has only grouped similar spectral signatures into one of three categories[20]. After classification, the resulting categories in Figure 2.14 must be linked to specific targets in order to complete the unsupervised classification process. Therefore, when the user possesses *a priori*

[19] Classification outputs in Figures 2.13 and 2.14 were manufactured by the author for illustration purposes.
[20] The number of classification categories is a user defined input for the unsupervised classification process.

knowledge of the classification area, supervised classification is generally the more efficient (and preferred) method for image classification.

Figure 2.12 Aerial Photo of Unharvested Corn Field (with bare soil between rows) and Harvested Corn Field (Photo courtesy of www.procorbis.com)

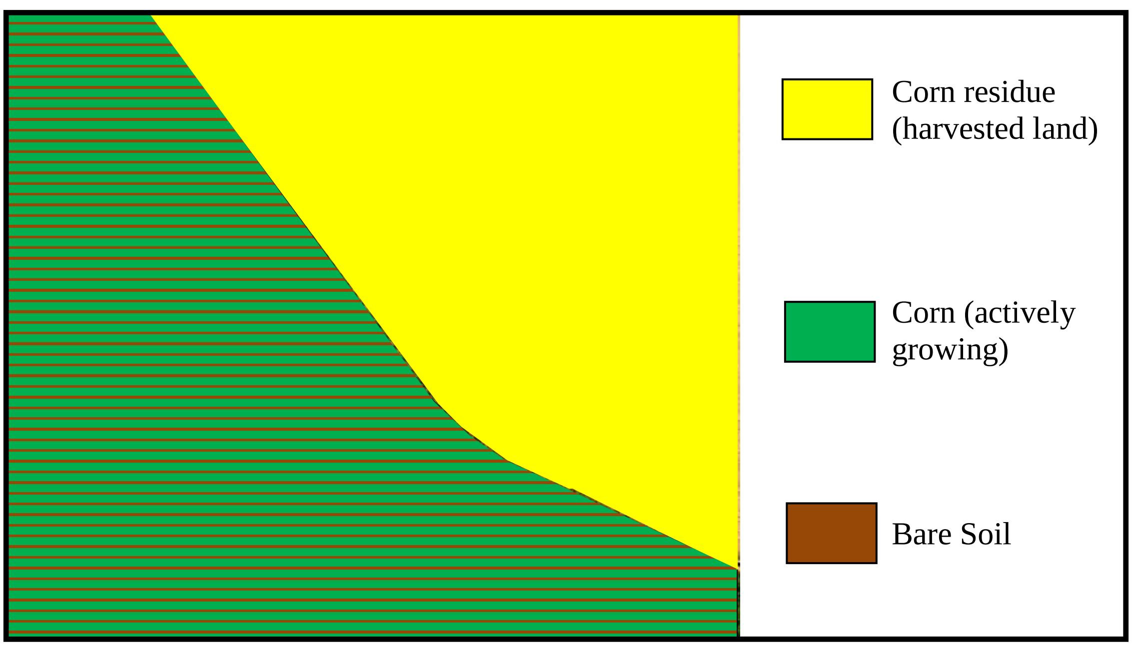

Figure 2.13 Simulated Supervised Image Classification of Corn Fields in Figure 2.12 Using Three Defined Training Areas (Classification output manufactured by author)

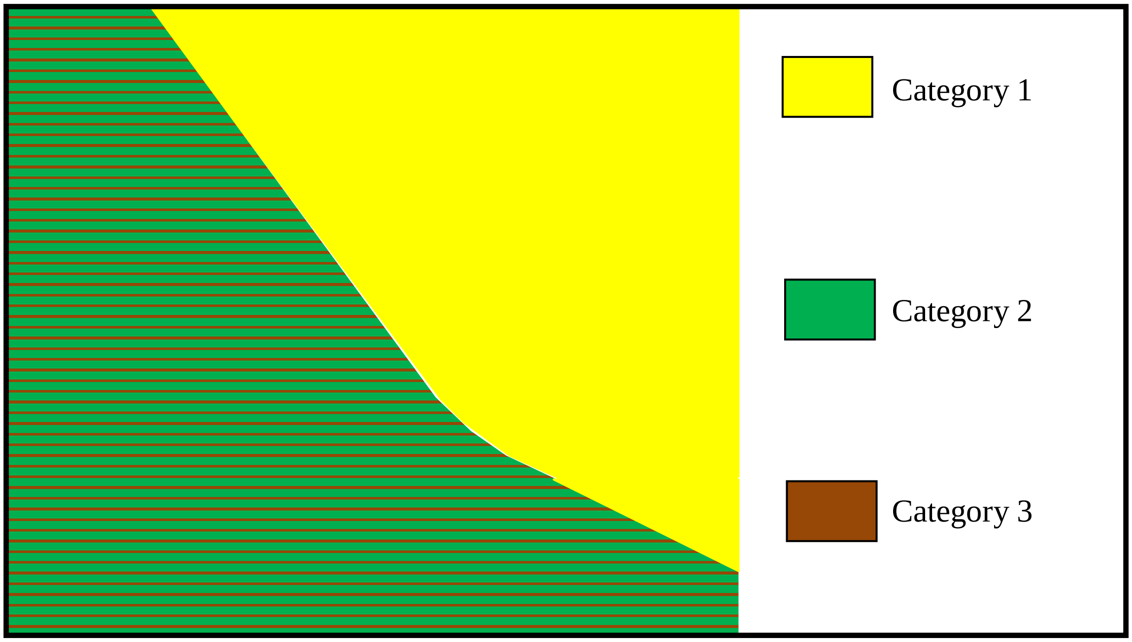

Figure 2.14 Simulated Unsupervised Classification of Corn Fields in Figure 2.12 Using Three Classification Categories (Classification output manufactured by author)

Digital Elevation Models

Digital elevation models (DEMs) are the predominant means of quantifying geographical elevation variations in a watershed (Maidment 2002). A national DEM data set is currently available at a resolution of 30 meters (USGS 2007). DEMs of higher resolution are beginning to be generated for some areas. With construction codes requiring that homes are built only 1 foot above 100 year flood elevations, coarse resolution DEMs (e.g. 30 m) do not possess the detail necessary to manage a floodplain at the local level (Guoan et al. 2001). Small changes in floodplain characteristics can easily encroach on such a small (i.e. 1 foot) margin of safety. Several methods have already been proven for developing high resolution (1-2 m) DEMS using remotely sensed data (e.g. photogrammetry, LIDAR and IFSAR) (Allen and Birk 2000). These high resolution DEMs are becoming increasingly available to city managers through commercial and public channels and are highly beneficial for use in floodplain management. The incorporation of DEMs and land use and land cover classifications derived from high resolution data sets should facilitate accurate hydrologic modeling for floodplain management.

Working Hypothesis

As demonstrated by the previous review of literature, National Agriculture Imagery Program data displays great potential for small scale land use and land cover classifications. The aforementioned potential has led to the development of a working hypothesis:

> **WH_1**: Current land use and land cover conditions can be measured[21] by temporally and financially efficient methods derived from low-cost, high resolution, multi-spectral, remotely sensed imagery (i.e. NAIP data).

To facilitate a comprehensive exploration of the working hypothesis, it is divided into two sub-hypotheses. Table 2.3 illustrates the conceptualization of the working hypothesis[22], its division into two sub-hypotheses, and the scholarly support that led to their development.

[21] A classification accuracy greater than or equal to 95% is the acceptable accuracy level for mapping purposes as suggested by the National Standard for Spatial Data Accuracy (Allen and Birk 2000).
[22] For more information on formulation of working hypotheses see Shields (1998) and Shields and Tajalli (2006). For examples of working hypotheses and sub-hypotheses see Johnson (2008) and Prentice (2006).

Table 2.3 Summary of Conceptual Framework Linked to the Literature

Research Purpose: To explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP data) to accurately identify land use and land cover (LULC) conditions.	
Working Hypotheses	*Scholarly Support*
WH: Current LULC conditions can be measured by temporally and financially efficient methods derived from low-cost, high resolution, multi spectral, remotely sensed imagery (i.e. NAIP data). WH_a: The application of supervised image classification procedures to NAIP imagery will result in LULC classification accuracies at, or above, the 95% accuracy threshold. WH_b: The application of supervised image classification procedures to NAIP imagery will result in the discrimination of impervious from pervious cover with classification accuracies at, or above, the 95% accuracy threshold.	Allen and Birk 2000, Anderson et al. 1976, Burby and French 1985, Colding 2007, Cross 2001, Crossett et al. 2004 , FEMA 2007, Foody et al. 2004, Group 1999, Guoan et al. 2001, Hipple et al. 2005, Hoggan 1997, Hord 1982 , Johnston 1992, Klein et al. 2003, Lillesand and Kiefer 1994, Lovell et al. 1999, Maidment 2002, Mannion 2002, Oumaet al. 2008, Peterson et al. 1999, Pickett et al. 2004, Ramlal and Baban 2008, Rogan et al. 2008, Romano and Vaccaro 2005 , Singh et al. 2001, Smith and Brown 1997, Stanganelli 2008, Tobin 1999, U.S. Commission on Ocean Policy 2004, US Department of Agriculture 2007, US Department of Agriculture 2006, USGS 2007, USGS 2006, Vieux 2001, Wetmore 2006, Yuan et al. 2005

Scenario – Landsat in HD

After a spending little time with the USDA gentlemen, Norm was convinced the NAIP imagery (pronounced "nape", but not spelled that way Norm learned) was just what he needed to assess the current land use and land cover conditions in and around Deerfield Estates: Phases One, Two, and Three. Since the information captured was so similar to that from the Landsat data (but at a much higher resolution), it only made sense that the tried and true classification techniques used for Landsat images would also work for his NAIP imagery. Armed with some "light" reading on Landsat image classification procedures, Norm read the energy conservation sticker on the cover plate for the tenthousandth time, flipped the light switch in his office to the "off" position, and headed home for the weekend. He needed the break; Monday would bring the challenge of classifying the NAIP imagery and applying the resulting land use and land cover data to the creation of an accurate floodplain map. "If this works," Norm said aloud, "my job just got a lot easier."

Conclusion

Today's local planners are at a loss when attempting to determine the current land use and land cover conditions within their communities. Although proven for large scale land use and land cover classification purposes, Landsat data does not provide planners the detail necessary to assess their situation (i.e. LULC conditions) on a level applicable for community decision making. The detailed LULC information is critical for planners when assessing alterations to local watersheds and determining the corresponding changes to their flood risks. To date, a source of highly detailed information that possesses the ability to address the LULC classification needs of local planners has not been identified. The following chapters demonstrate how a low cost, relatively current dataset (i.e. NAIP imagery) can fulfill those needs.

Chapter 3. Setting

Introduction

This paper explores the potential of multi-spectral, high resolution remotely data to identify land use and land cover conditions at the local (e.g. city, town, or neighborhood) level. This chapter first discusses the characteristics of the El Camino Real Subdivision located in San Marcos, TX. El Camino Real served as the area of interest utilized for testing the working hypothesis described in the previous chapter (Chapter 2). Then this chapter discusses the experimental unit for this study. Aerial imagery acquired for the National Agriculture Imagery Program was the experimental unit for this study to which the treatment was applied. The treatment (image classification via pattern recognition algorithms) and the software utilized for its application (i.e. ERDAS Imagine 9.3®) are discussed as part of the methodology in Chapter 4.

Study Area

The El Camino Real subdivision in San Marcos, Texas (Figures 3.1 and 3.2) is a medium density residential community in South-central Texas that offers numerous types of land use and land cover within a small area. Construction began in 2004, with the most intense construction occurring in 2008 as the subdivision reached 100% occupancy. The community is built on agricultural land that once consisted of pastures for grazing livestock and hay production. The area immediately surrounding the 200+ home community currently consists of active and abandoned agricultural land, several small wooded areas and a few small areas that permanently contain water. Directly to the south of the subdivision (as defined by a 2005 Flood Insurance Rate Map[23]) lies a 100-year floodplain. Continued construction since 2005 has certainly increased the amount of impervious cover for the area and has likely affected the characteristics of the floodplain. The varied land use and land cover conditions in and around El Camino Real and the distinct transition from one class to the next (e.g. rooftop to lawn to concrete sidewalk to asphalt road to corn field) should facilitate a comprehensive analysis of the utility of NAIP data to accurately identify each land use and land cover type. The land use and land cover data can then be input into a hydrologic model (along with elevation/terrain information) to determine if the floodplain at the subdivision's southern border has encroached upon the subdivision due to land cover changes since 2005 (the most recent FIRM).

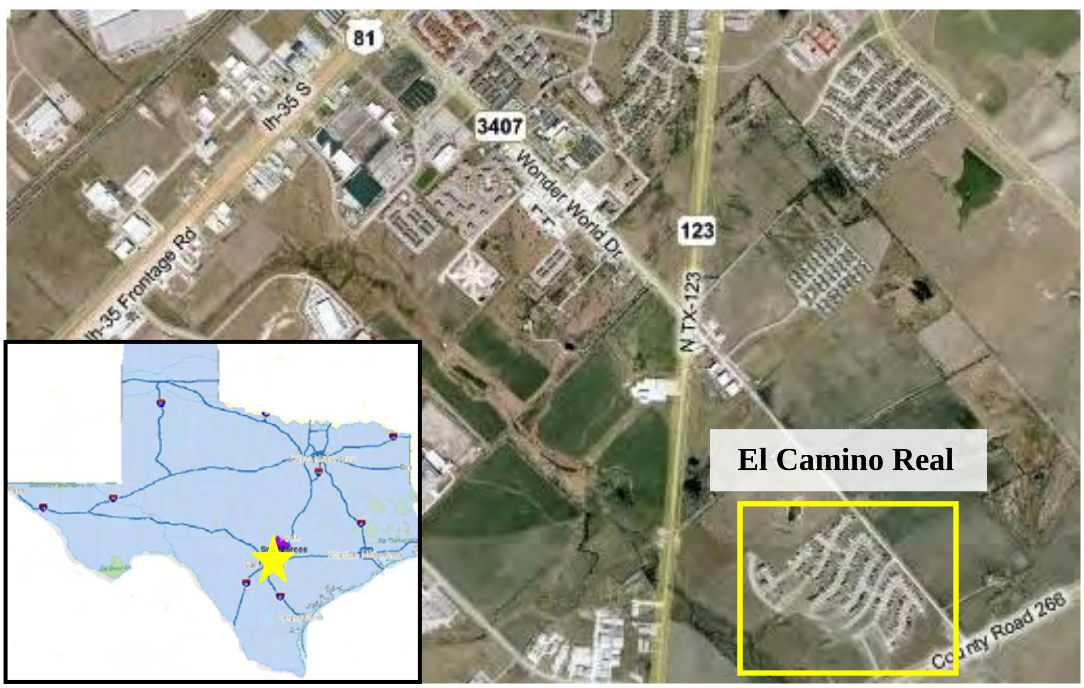

Figure 3.1 2005 NAIP True Color Image of the Southwest Portion of San Marcos, Texas (Image courtesy of TNRIS: http://www.tnris.state.tx.us/; Texas inset from Gillfillan 2008)

[23] The Flood Insurance Rate Map for the El Camino Real subdivision may be found at http://msc.fema.gov/webapp/wcs/stores/servlet/MapSearchResult?storeId=10001&catalogId=10001&langId=-1&userType=G&panelIDs=48209C0388F&Type=pbp&nonprinted=&unmapped=

Figure 3.2 2005 NAIP True Color Image of the El Camino Real Subdivision in San Marcos, Texas (Image courtesy of TNRIS: http://www.tnris.state.tx.us)

Dataset

NAIP imagery, captured with a Leica Geosystems ADS40 airborne digital sensor, was used for all land use and land cover classifications. NAIP imagery is a relatively current (2008) and readily available, high resolution, multispectral dataset. NAIP imagery is acquired during the peak growing season (i.e. "leaf on" imagery) at a 1 meter ground sample distance (GSD) with a horizontal accuracy that matches within 5 meters of referenced ortho imagery. The "leaf on" acquisition period of NAIP imagery will facilitate delineation of vegetative from impervious cover for land use and land cover purposes. One meter compressed county mosaic, 4-band images files[24] of NAIP imagery are available for free download through the data gateway on the Natural Resource Conservation Service (NRCS) website (http://datagateway.nrcs.usda.gov/

[24] Current NAIP data capture red, blue, green, and near infrared bands (i.e. wavelengths) and are available in JPEG2000 format (USDA 2008).

gatewayhome.html). The available resolution (1 m) is representative of present commercial and public remote sensing trends and should facilitate future duplication of study procedures using other, similar datasets.

Chapter 4. Methodology

Scenario – The Land Use and Land Cover Classification Process

Mondays are not Norm's favorite day of the week. They're not even in his top five. Yet, this Monday he finds himself in an extraordinary hurry to start the work week. Armed with a bucket of his choice brew and two massive ERDAS Imagine® Field Guides, Norm fidgets impatiently outside the office for the City of Anytown's GIS department. Finally, someone arrives and Norm enters the office, heads to a nearby computer, and finds a home for his liquid life support (and the 900+ pages of manuals he is toting). Quickly the computer is humming and Norm is off on a high tech quest to solve a classic planning problem: will the future residents of Deerfield Estates: Phase Three be safe from the long arm of Mother Nature, well at least, the arm of Old Man Flood? After several hours of nightstand research, Norm knows the first step towards finding the answer is to determine the current land use and land cover conditions for the area.

Introduction

This chapter explains the methods utilized to explore the utility of National Agriculture Imagery Program data to assess land use and land cover conditions for the El Camino Real subdivision in San Marcos, TX. The data analyzed was captured during the summer months of 2008 and compared to actual ground conditions in late March 2009. All imagery analysis and initial accuracy assessment procedures were performed in ERDAS Imagine 9.3®. Statistical computations for accuracy assessment were conducted in Microsoft Excel 2007©. This chapter is intended to provide an overview of the basic steps necessary for land use land cover assessment in ERDAS Imagine 9.3®. For a more in depth discussion of additional software capabilities visit the "Knowledge Database" at the ERDAS website (http://gi.leica-geosystems.com/LGISub2x443x0.aspx) or reference the ERDAS Field Guides that accompany every Imagine® license. Before the stepwise image analysis overview, this chapter discusses how the working hypothesis (and sub hypotheses) was operationalized.

Operationalization of the Working Hypothesis

The exploration of the utility of National Imagery Program data to measure land use and land cover conditions was approached at the neighborhood scale. All data and research procedures listed in Table 4.1 were utilized in the operationalization of both sub hypotheses. The sub-hypotheses (see Table 4.1) rely on supervised classification techniques of a subset of 2008 NAIP data for Hays County. Classification was conducted by further dividing the El Camino Real subset into two representative subsets (i.e. one training subset and one classification subset). A modified Anderson land use/land cover classification schema was further modified to address the LULC classification needs of the subset (i.e. the El Camino Real subdivision). Due to preprocessing required by the Texas Natural Resource Information System (TNRIS) NAIP imagery acquisition contracts, the imagery contained coordinates that allowed pixels within imagery to be correlated to specific (within 1 meter) locations on the ground. This prior georeferencing aided accuracy assessment by ensuring classified pixels were compared to the actual, ground-based targets. Chapter 5 presents the results of the image classification; and Chapter 6 provides recommendations and conclusions based upon the data presented in Chapter 5.

Table 4.1 Operationalization of the Conceptual Framework: Linking the Research Methods to the Working Hypothesis

Research Purpose: To explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP data) to accurately identify land use and land cover (LULC) conditions.		
Working Hypothesis	*Data*	*Research Procedures*
WH: **Current LULC conditions can be measured by temporally and financially efficient methods derived from low-cost, high resolution, multi spectral, remotely sensed imagery (i.e. NAIP data).** WH_a: The application of supervised image classification procedures to NAIP imagery will result in LULC classification accuracies at, or above, the 95% accuracy threshold. WH_b: The application of supervised image classification procedures to NAIP imagery will result in the discrimination of impervious from pervious cover with classification accuracies at, or above, the 95% accuracy threshold.	WH: **-2008 *NAIP imagery (Leica Geosystems ADS40 airborne digital sensor)*** ***-Latitude and longitude for study area, LULC class boundaries, training areas and sample points*** ***-Modified Anderson LULC classification schema*** ***-Output of supervised image classification***	WH: **-Identify El Camino Real subdivision and surrounding area on 2008 NAIP image** **-Divide study area (½ training, ½ testing)** **-Supervised classification in ERDAS Imagine 9.3®** **-Accuracy assessment (stratified random sample points)** **-Ground-based visual accuracy assessment (related to conditions during image acquisition)** **-Develop "playbook" outlining methodology for image classification**

Step 1: Import the Imagery into ERDAS Imagine 9.3®

To begin any imagery analysis the user must first open the software and import the necessary imagery. For this study, the Classic Viewer (see Figure 4.1) in ERDAS Imagine 9.3® was selected because of the similarity of the interface with that of previous versions of ERDAS Imagine®. The Classic Viewer allows access to all necessary software functions for this study and (based upon the author's personal experience) is the most commonly used ERDAS Imagine® user interface. The Hays County NAIP data[25] was added to the Viewer as a raster[26] layer (see Figure 4.2). The imported raster data contained four bands, but software limitations only allow the viewing of three bands at once (see Figure 4.3). The Hays County NAIP data was defaulted to open as a color infrared image where Bands 4 (near infrared), 3 (red), and 2 (green) were represented by the colors red, green, and blue respectively (see Viewer ID in Figure 4.4). Once the image was opened, the classification process could begin.

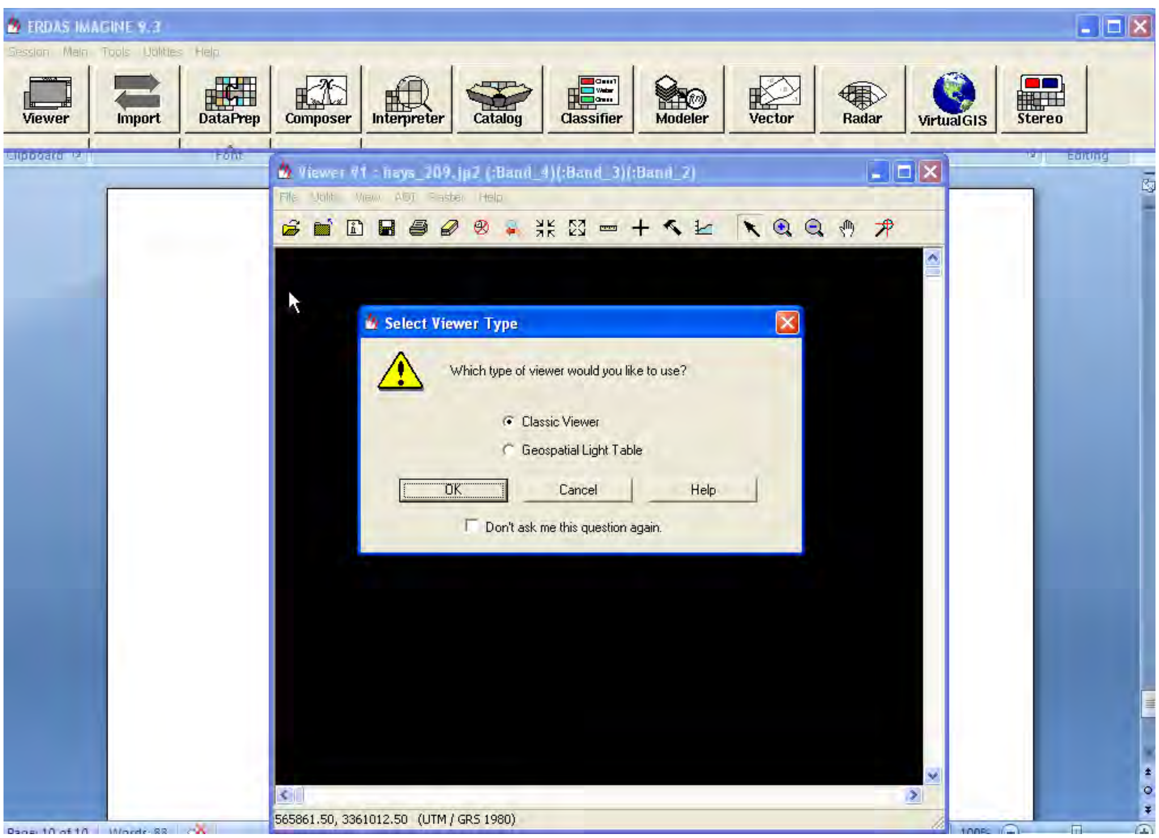

Figure 4.1 Opening a Viewer in ERDAS Imagine 9.3®

[25] The 2008 Hays County imagery was delivered as a county mosaic 4-band image file in JPEG2000 format.
[26] "Raster image data are laid out in a grid similar to the squares on a checkerboard. Each cell of the grid is represented by a pixel, also known as a grid cell" (Leica Geosystems GIS & Mapping 2008, I-1)

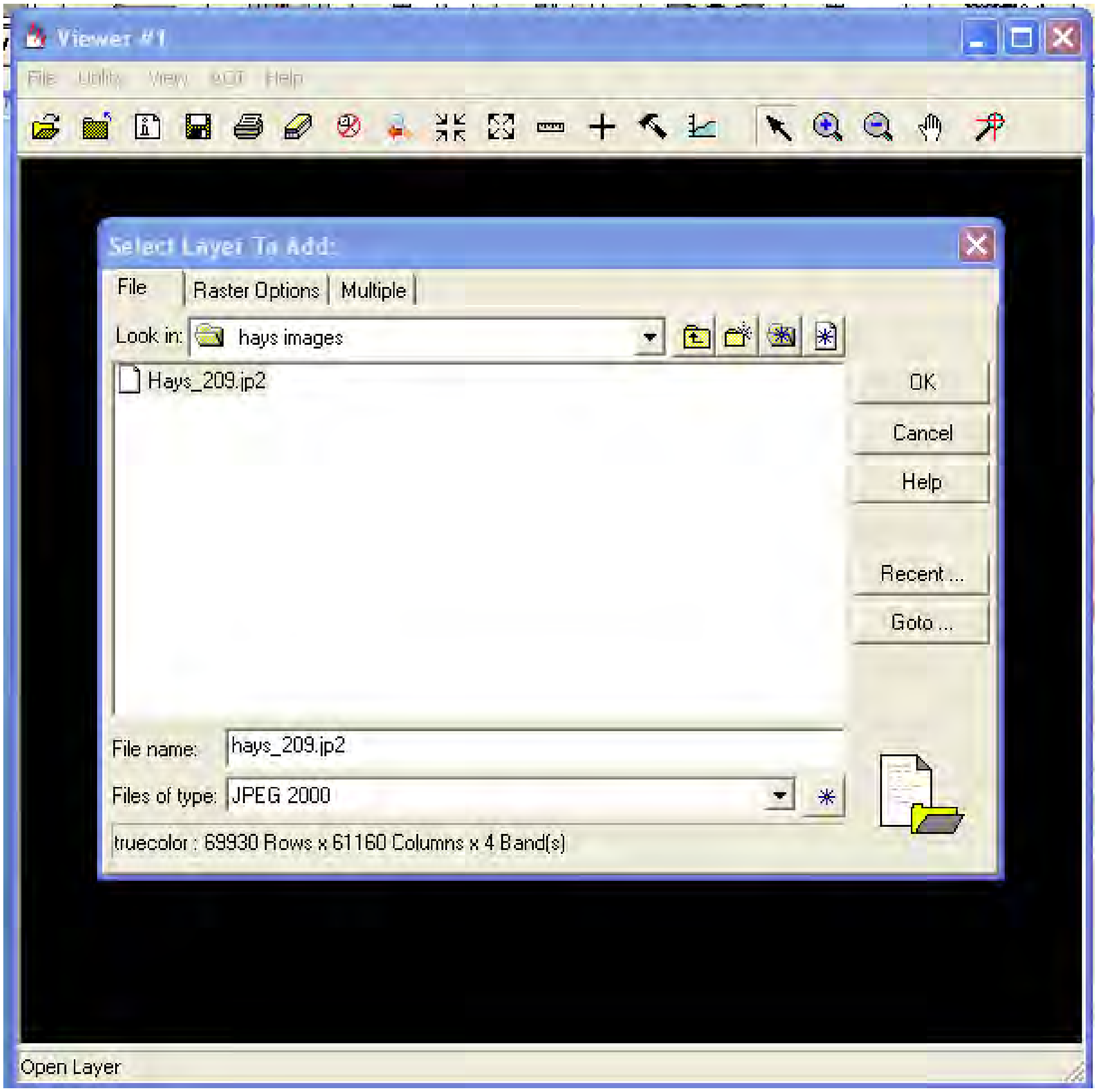

Figure 4.2 Opening Hays County NAIP Imagery in ERDAS Imagine 9.3®

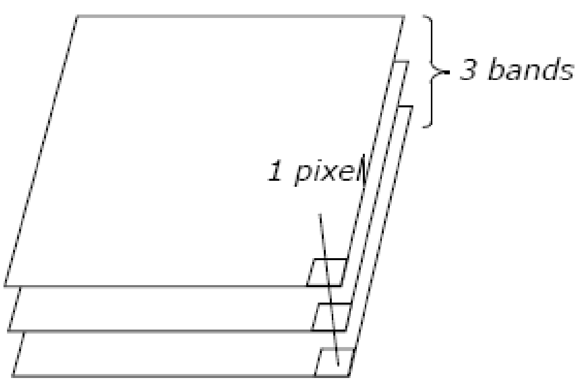

Figure 4.3: Bands Viewable within a Raster Image (Leica Geosystems GIS & Mapping 2008, I-2)

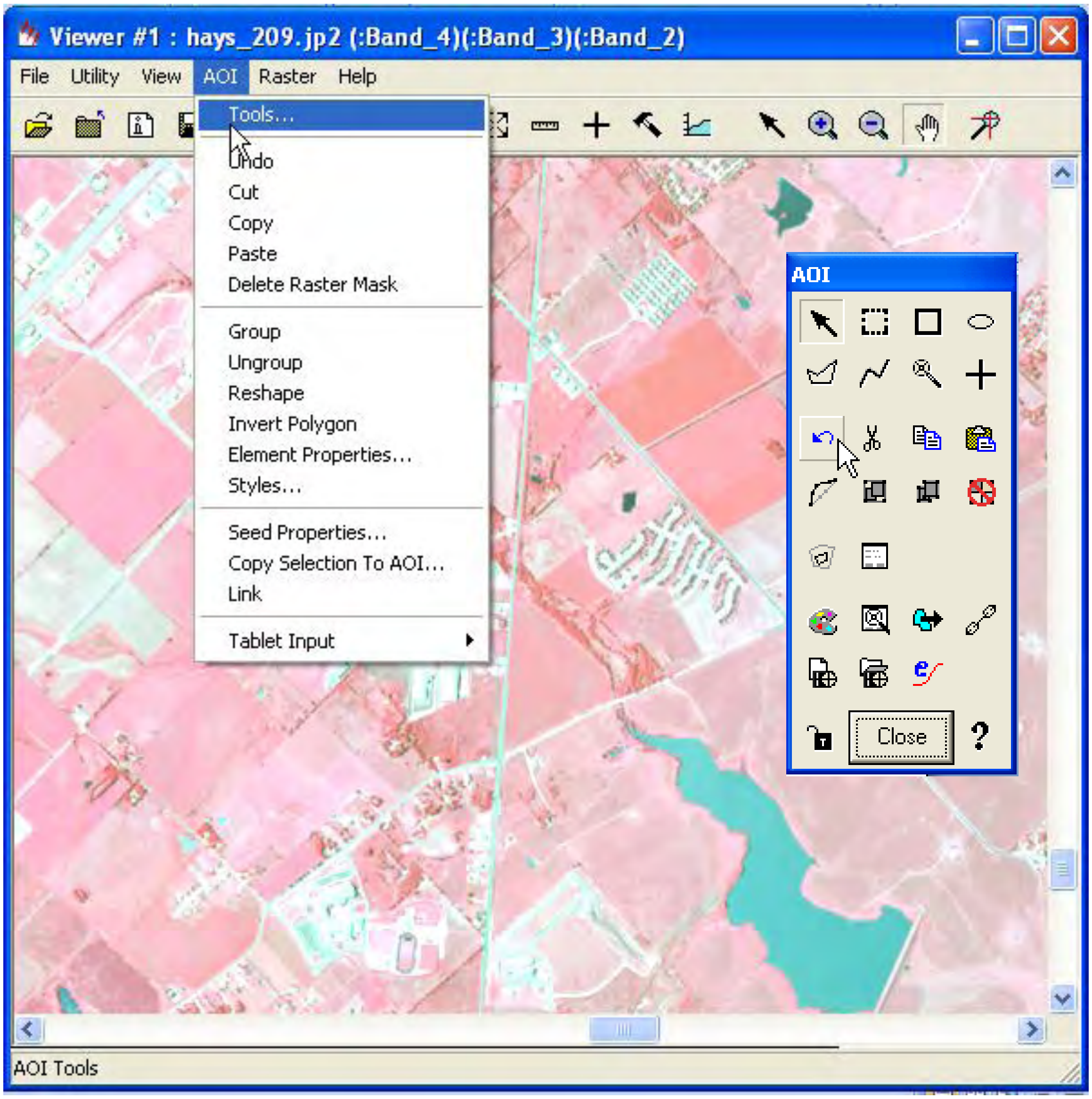

Figure 4.4 Selection of the Main Area of Interest in ERDAS Imagine 9.3®

Step 2: Sub Setting the Image: Definition of the Main Area of Interest

Since county sized data sets of 1 meter resolution are quite large[27], the processing time for image analysis can be reduced by selecting only the particular area of interest for a specific project. The area of interest (AOI) for this study was the El Camino Real subdivision and the adjacent properties; therefore, a subset of the Hays County image was

[27] The Hays County mosaic file was 1.03 GB.

created to remove all data extraneous to this study (see Figures 4.4, 4.5, 4.6, and 4.7). The initial AOI selection process began by opening the “AOI > Tools” menu and drawing a polygon around the land selected for the study (see Figures 4.4 and 4.5).

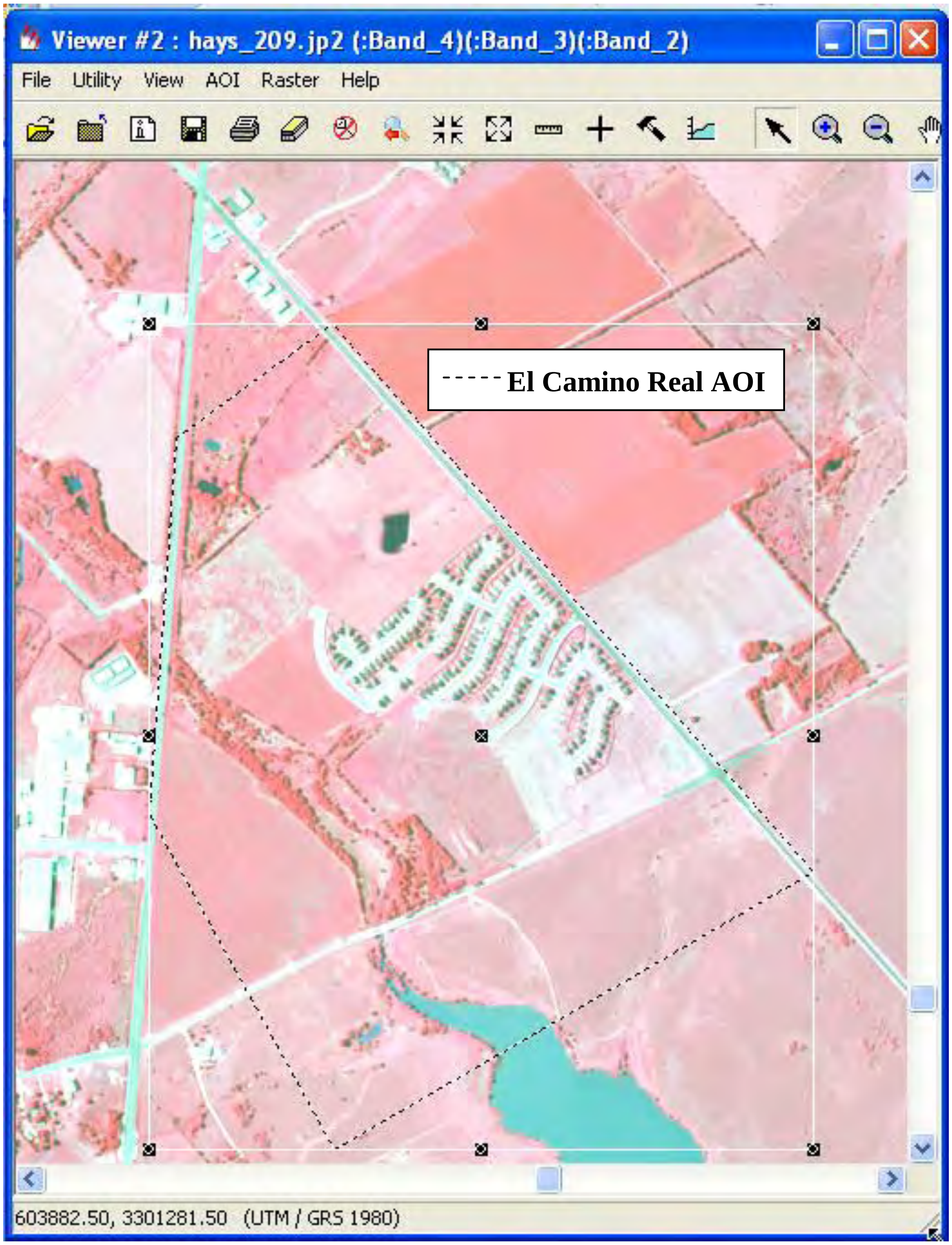

Figure 4.5 Area of Interest – Polygon Defining the El Camino Real Subdivision and Surrounding Lands

Next, the "Data Prep" menu was accessed in order to subset the Hays County image based on the previously created AOI (see Figure 4.6). The resulting, reduced size[28] image file (see Figure 4.7) became the primary dataset for the remaining image classification procedures. Before the actual classification procedures could begin, two more subsets had to be created (i.e. one training subset and one classification subset.) In order to facilitate division of the El Camino Real subdivision into two additional subsets, a site specific land use and land cover classification schema was developed (Step 3) for the study area.

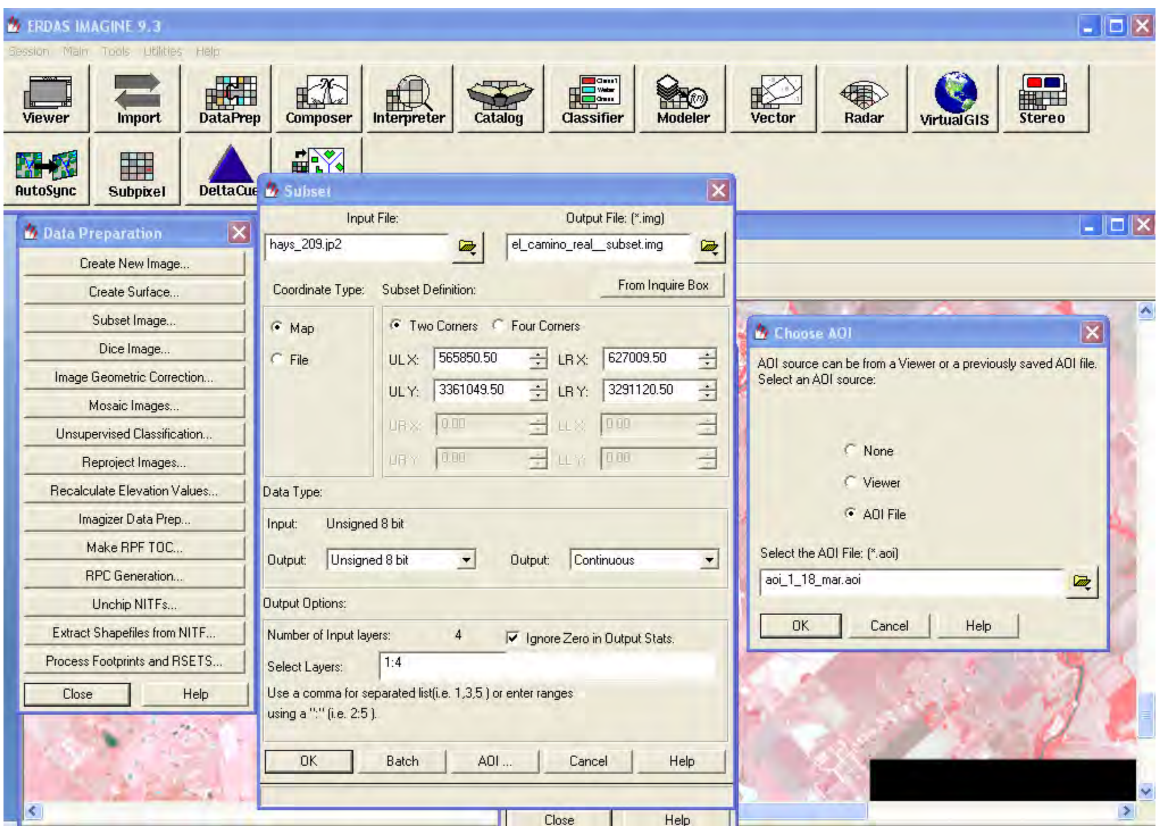

Figure 4.6 Creation of the El Camino Real Subset in ERDAS Imagine 9.3®

[28] The resulting El Camino Real subset file was only 7.24 MB compared to the 1.03 GB Hays County file.

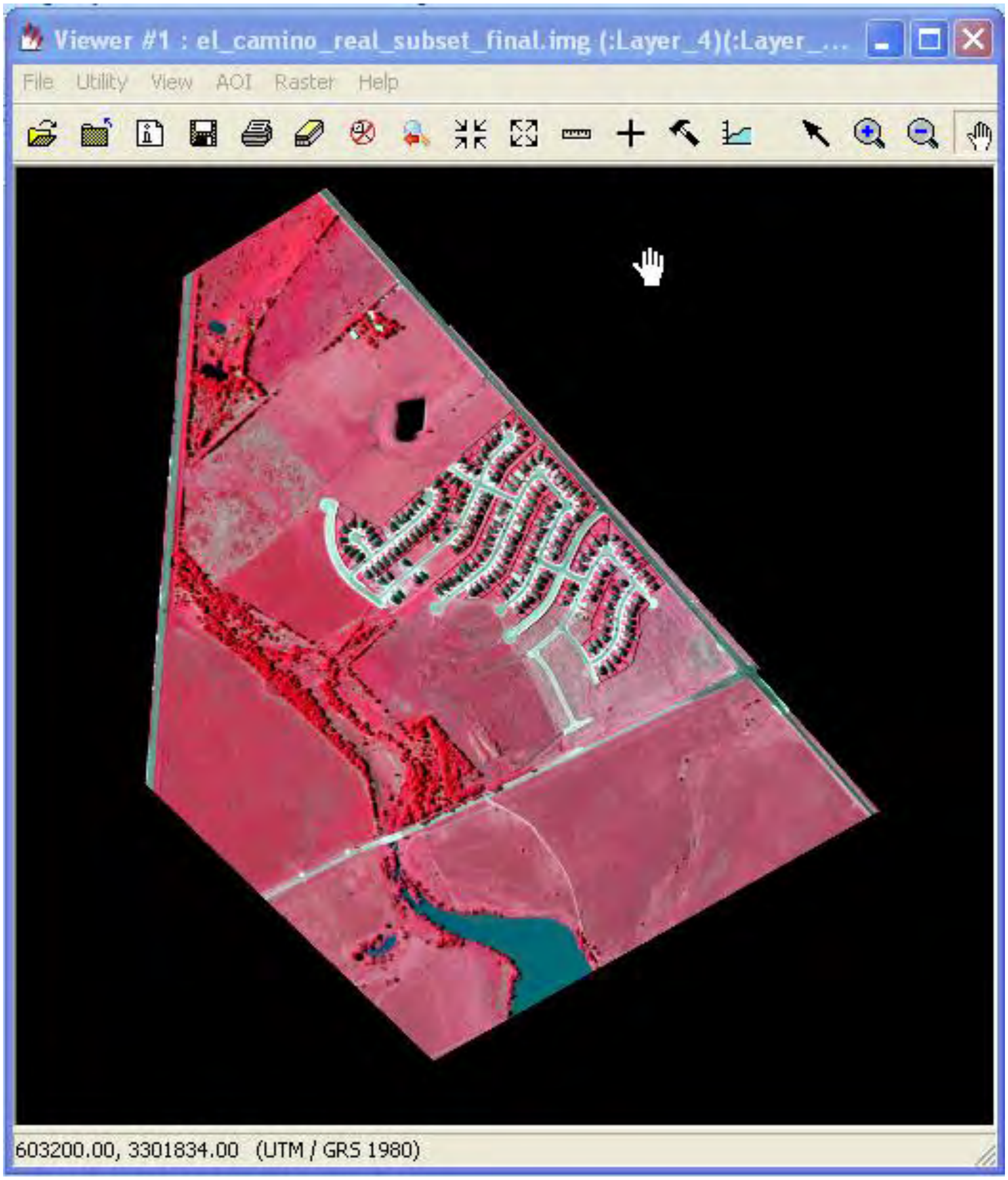

Figure 4.7 The El Camino Real Subset of the Hays County NAIP Image

Step 3: Adaptation of a Modified Anderson Classification Schema to the El Camino Real Subset

To ensure the study area was divided into two equally representative samples, an Anderson LULC classification schema[29] modified by the Texas Commission on Environmental Quality (2001) was further adapted to fit the specific needs of this study. The initial modification to Anderson et al.'s (1976) schema was conducted for a land use and land cover assessment of the Arroyo Colorado and the Brazos Colorado Coastal watersheds located in southwest Texas (Texas Commission on Environmental Quality 2001). Since the Arroyo/Brazos schema (see Appendix B) was intended for LULC classification of a different area of Texas using data with a 30 meter resolution, it was further modified to accommodate the higher resolution of the NAIP imagery and the LULC present in the El Camino Real subdivision. Identification of distinct land use and land cover subclasses is important because each subclass functions as a unique "hydro response unit" (Maidment 2002, 119). Each subclass possesses distinct characteristics that affect surface water conveyance (i.e. runoff) (see Table 4.3). By identifying (and measuring the area of) each LULC class planners will have more accurate and detailed information for hydrologic modeling of their communities.

The resulting El Camino Real schema contained 15 specific LULC subclasses. The 15 subclasses were grouped into 4 main LULC cover classes (i.e. water, developed areas, bare areas, and vegetated areas). A detail description of the each class and its subclasses is presented in Appendix A. Of the 15 subclasses, 11 represented LULC conditions that were promising for interpretation through spectral image classification techniques. Those 11 subclasses would be used for training signature generation (see

[29] In 1976, James Anderson et al. developed a comprehensive outline for land use/ land cover classifications that are adapted for remotely sensed data.

Table 4.2). The remaining 5 subclasses (e.g. transitional bare) represented LULC conditions that would require post-classification interpretation for accurate classification results.

Table 4.2 The 11 Land Use and Land Cover Classification Definitions Used for Training Signature Generation in the El Camino Real Subdivision: A Twice Modified Anderson Classification Schema (Texas Commission on Environmental Quality 2001)

LULC Subclass	**Abbreviated Subclass Definition**
Open water	open water with less than 25% vegetative or developed cover
Asphalt shingles	residential housing units roofed with asphalt shingles
Metal roof	commercial buildings roofed with metal
Asphalt roads and surfaces	asphalt surfaces utilized for transportation or vehicle storage
Concrete/gravel roads and surfaces	concrete and gravel surfaces utilized for transportation or vehicle storage
Bare soil	areas in a relatively static state that contain less than 25% vegetative cover
Forested	land where trees form at least 25% of the canopy cover
Shrub land	areas where trees have less than 25% canopy cover and the existing vegetation is dominated by plants that have persistent woody stems, a relatively low growth habit, and which generally produce several basal shoots instead of a single shoot
Natural herbaceous	areas dominated by native or naturalized grasses, forbs, ferns and weeds
Pasture/hay	areas of cultivated perennial grasses and/or legumes (e.g., alfalfa) used for grazing livestock and seed or hay production
Lawn/turf	areas of cultivated perennial grasses maintained at a height of less than 8 centimeters for lawn use or turf grass production

Table 4.3 Examples of Land Use and Land Cover Class Effects on Surface Water Conveyance for Floodplain Modeling (Renard et al. 1996)

LULC Subclass	Effect(s) on Surface Water Conveyance
Open water	-collection point for surface water -occurs near areas of potential flooding
Asphalt shingles	-impervious cover with generally steep slope - rapidly conveys surface water to adjacent areas
Metal roof	-impervious cover with generally steep slope - rapidly conveys surface water to adjacent areas
Asphalt roads and surfaces	- impervious cover of varying slope - generally (depending on topography) conveys surface water to adjacent areas
Concrete/gravel roads and surfaces	-impervious or nearly-impervious cover of varying slope - generally (depending on topography) conveys surface water to adjacent areas
Bare soil	-pervious or semi-pervious cover of varying slope -generally possesses minimal surface roughness to slow surface water movement, but may allow groundwater recharge/evaporation for areas with minimal slopes
Forested	-pervious cover -generally possesses high surface roughness and facilitates groundwater recharge (i.e. reduces runoff)
Shrub land	-pervious cover -generally possesses high surface roughness and facilitates groundwater recharge
Natural herbaceous	-pervious cover -generally possesses high surface roughness and facilitates groundwater recharge
Pasture/hay	-pervious cover -generally possesses moderate to high surface roughness and facilitates groundwater recharge (i.e. except in areas with steep slopes)
Lawn/turf	-pervious cover -generally possesses moderate surface roughness and facilitates groundwater recharge (except in areas with steep slopes)

Step 4: Creation of the Training and Classification Areas of Interest

Since a supervised classification method[30] was chosen for this study, the study area was divided into two portions: a training area of interest and a classification area of interest. The two AOIs were created in the same manner as the El Camino Real subset AOI without the actual subset generation executed from the "Data Prep" menu. The El Camino real subset was divided into two similar areas of interest along a Southwest to Northeast axis created by the main entrance to the subdivision. Division of the study area along this axis created a slightly smaller training area of interest (see Figure 4.8) that contained all sample of every land use and land cover class found in the classification area of interest. With a training area created, the next step was to define the spectral signatures for each land use and land cover class within the training area.

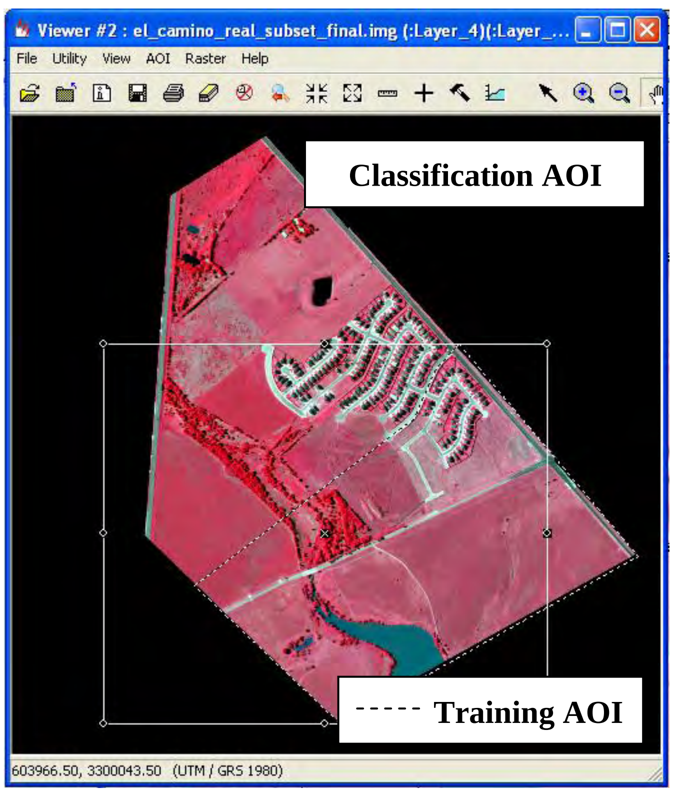

Figure 4.8 El Camino Real Supervised Classification Training Area of Interest

[30] For more information on supervised classification procedures, see Step 5: Creation of Land Use and Land Cover Class Spectral Signatures.

Step 5: Creation of Land Use Land Cover Class Spectral Signatures

The science of computer based image classification is simply a process of pattern recognition. The ERDAS Imagine® software package allows for the use of spectral and/or spatial pattern recognition techniques (Leica Geosystems GIS & Mapping 2005). Since the intent of this study is to assess the potential of the NAIP imagery for land use and land cover classification, all classification attempts focused on spectral pattern recognition. Our brains perform spectral pattern recognitions all the time. Our assessment of the color(s) of objects around us is a continuous exercise in spectral pattern recognition. By determining that the grass is green or the sky is blue, we have subconsciously identified spectral patterns within the visible wavelengths of the targets (i.e. grass and sky).

> In a computer system, spectral pattern recognition can be more scientific. Statistics are derived from the spectral characteristics of all pixels in an image. Then, the pixels are sorted based on mathematical criteria. The classification process breaks down into two parts: training and classifying (using a decision rule). (Leica Geosystems GIS & Mapping 2005, 243)

Of the two parts, the training process is conducted first. The supervised classification training process allows the software to recognize each land use and land cover class based upon user defined training signatures (Hord 1982). Supervised classification techniques were selected because they incorporate the use of *a priori* knowledge that local planners should possess for their communities. It is the capitalization on local planners' knowledge of their communities (i.e. *a priori*) that makes supervised[31]

[31] The process of creating training signatures for supervised classifications is conducted by the analyst. For supervised classifications, the analyst selects groups of pixels that represent patterns (i.e. land use and/or land cover classes) identified from personal knowledge of the area or use of additional sources (e.g. aerial photos) (Leica Geosystems GIS & Mapping 2005).

classification a more efficient method than unsupervised classification[32] for local land use and land cover determinations.

Training signatures are identified through the creation of specific AOIs representative of each land use and/or land cover class. Training signature AOIs are created in the same manner as the El Camino Real AOI (without the "Data Prep" subset procedures) in Step 2 (see Figure 4.9). Once each training signature AOI was created, it was input to the Signature Editor via the "Classifier > Signature Editor" menu (see Figure 4.9). Once an AOI and signature was created for each of the subset's 11 applicable land use and land cover classes the collection of signatures was saved as signature file (see Figure 4.10) to be used in the supervised classification attempt.

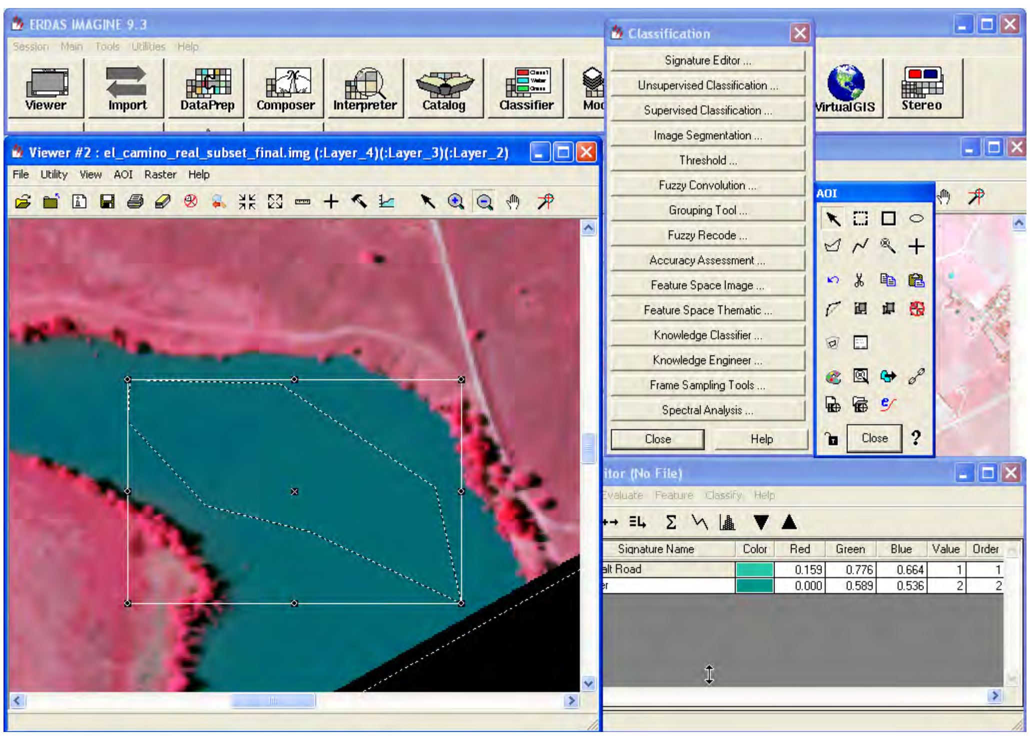

Figure 4.9 Creation of Target Signatures within Training AOI in ERDAS Imagine 9.3®

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[32] Unsupervised training relies on the information contained within the imagery to allow the software to identify and define the classes. It then becomes the analyst's responsibility to correlate the computer generated classes with the actual land use and land cover classes; therefore, unsupervised classification attempts are usually reserved for situations where little is known about the data prior to classification (Jensen 1996).

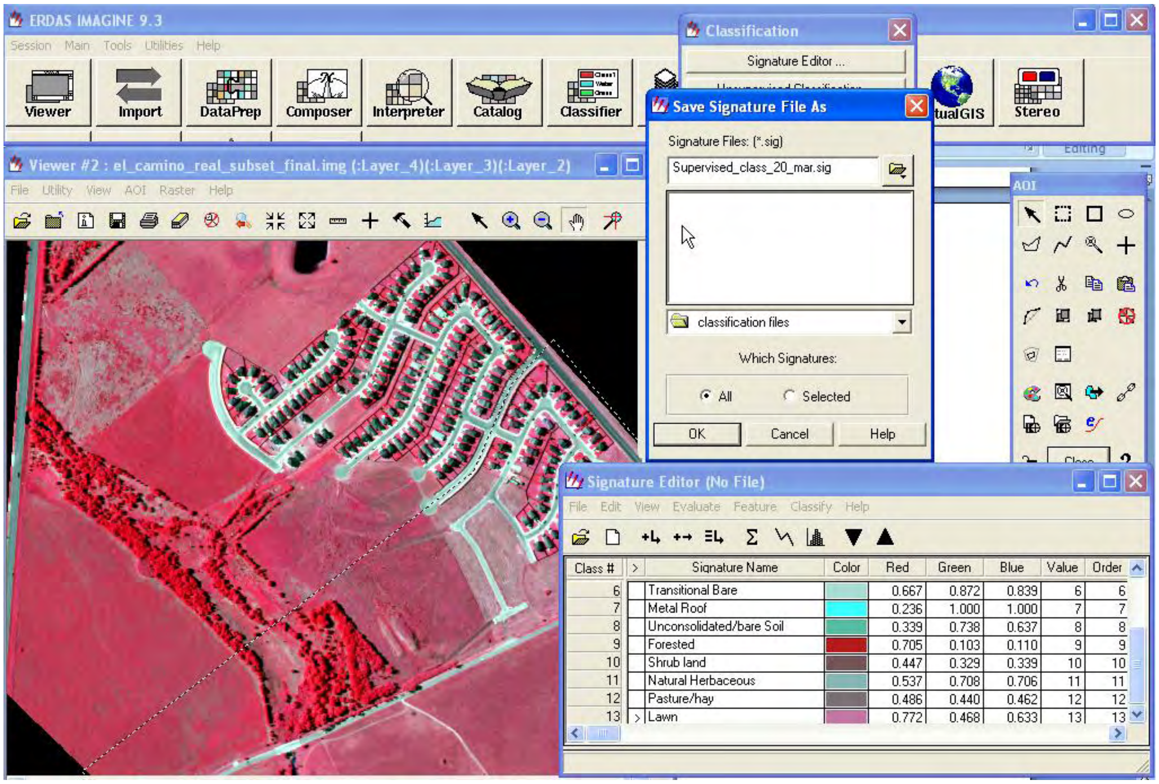

Figure 4.10 Creation of a Signature File in ERDAS Imagine 9.3®

Step 6: Supervised Classification

Supervised classification was conducted via the "Classifier > Supervised Classification" menu. The previously created (see Step 4) classification AOI was input from a viewer (see Figure 4.11). Two types of decision rules (i.e. non-parametric and parametric[33]) were set for the classification process (see Figure 4.11).

[33] Non-parametric decision rules are not based on statistical parameters, but on user defined polygons (i.e. AOIs) in a feature space image. Parametric decision rules are based on statistical parameters set by the analyst (Leica Geosystems GIS & Mapping 2005).

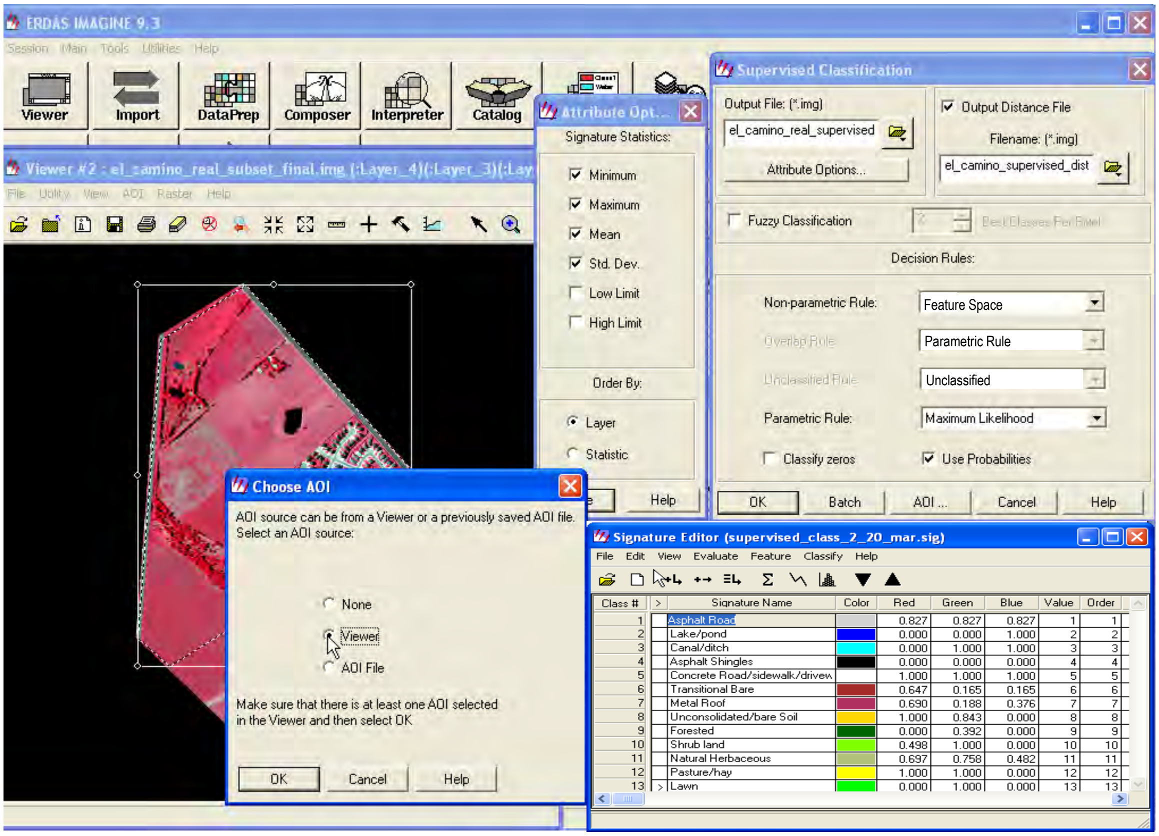

Figure 4.11 Supervised Classification in ERDAS Imagine 9.3®

Non-parametric Decision Rule

The "Feature Space" option with a secondary parametric classification for unclassified cells and for overlapping regions was selected as the non-parametric decision rule (see Figure 4.11). The feature space decision rule compares pixels to the training signatures (i.e. signature file created in Step 5) created from the training AOIs. This non-parametric decision rule was selected because it works well when classifying an area that contains both urban and rural land use and land cover classes (Leica Geosystems GIS & Mapping 2005). The main disadvantages to the feature space decision rule can be overcome by incorporating a parametric decision rule into the classification process (Leica Geosystems GIS & Mapping 2005). Table 4.4 illustrates the major advantages and disadvantages of the feature space decision rule. The incorporation of a parametric decision rule will ensure overlapping and unclassified pixels will be placed into a single class.

Table 4.4 Feature Space Decision Rule Advantages and Disadvantages (Leica Geosystems GIS & Mapping 2005, 275)

Advantages	**Disadvantages**
Often useful for a first-pass, broad classification.	Allows overlap and unclassified pixels.
Provides an accurate way to classify a class with a nonnormal distribution (e.g. residential and urban).	Classified image may be difficult to interpret.
Certain features may be more visually identifiable, which can help discriminate between classes that are spectrally similar and hard to differentiate with parametric information.	
Fast processing.	

Parametric Decision Rule

A parametric, maximum likelihood decision rule using probabilities was selected for the classification process to overcome the shortfalls of the non-parametric (i.e. feature space) rule (see Figure 4.11). As one would infer, the maximum likelihood decision rule[34] assesses the probability (i.e. likelihood) of a pixel falling within a particular land use or land cover class. The maximum likelihood decision rule was chosen because it is the most accurate of the decision rules available within the ERDAS Imagine® software package (for more advantages and disadvantages see Table 4.5) (Leica Geosystems GIS & Mapping 2005). Preceding the maximum likelihood decision rule with the feature space decision rule (designating training signatures for each LULC class) should greatly reduce the impact of the shortcomings of the maximum likelihood parametric rule (i.e.

[34] For a mathematical explanation of the maximum likelihood decision rule, see Appendix B.

dependence on normal distribution of within spectral bands and the tendency to over classify pixels) and provide the greatest possible classification success (Kloer 1994).

Table 4.5 Maximum Likelihood Decision Rule Advantages and Disadvantages (Leica Geosystems GIS & Mapping 2005, 275)

Advantages	**Disadvantages**
The most accurate of the classifiers in the ERDAS IMAGINE® system (if the input samples/clusters have a normal distribution), because it takes the most variables into consideration.	An extensive equation that takes a long time to compute. The computation time increases with the number of input bands.
Takes the variability of classes into account by using the covariance matrix.	Maximum likelihood is parametric, meaning that it relies heavily on a normal distribution of the data in each input band.
	Tends to over classify signatures with relatively large values in the covariance matrix. If there is a large dispersion of the pixels in a cluster or training sample, then the covariance matrix of that signature contains large values.

Classification Workflow

Figure 4.12 illustrates the classification process as determined by the decision rules selected for this study. Pixels were first assessed by the non-parametric feature space rule. Pixels that did not fit into any of the AOI generated training signatures or pixels that might have fit into more than one signature were then assessed by the maximum likelihood decision rule. All pixels were forced into one of the 11 land use and land cover classes selected for the classification process. Once the classification process was complete (see Figure 4.13 for an example of a supervised classification output), it was necessary to assess the accuracy of the resulting classified image.

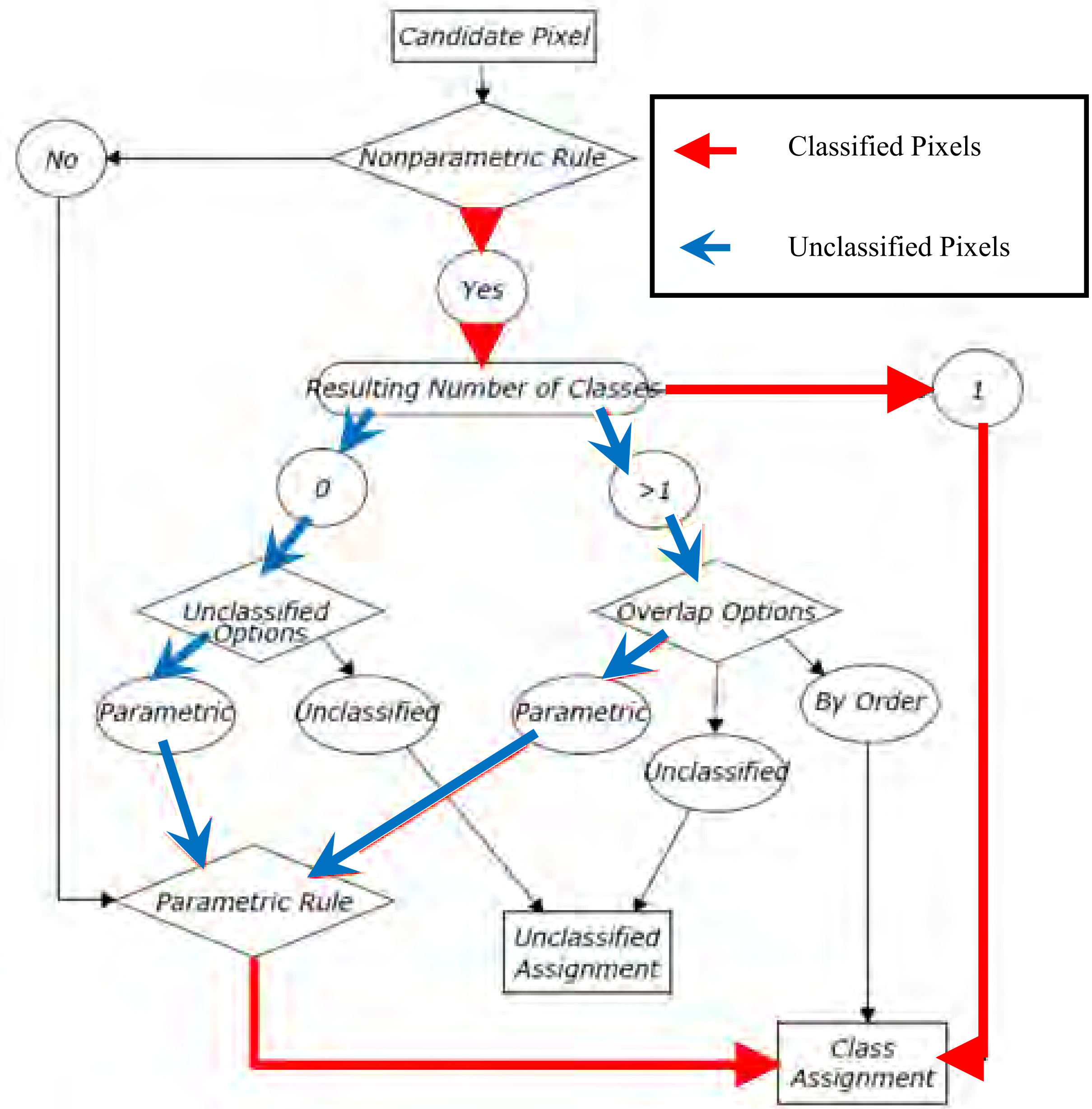

Figure 4.12 ERDAS Imagine® Classification Flow Diagram (Leica Geosystems GIS & Mapping 2005, 271)

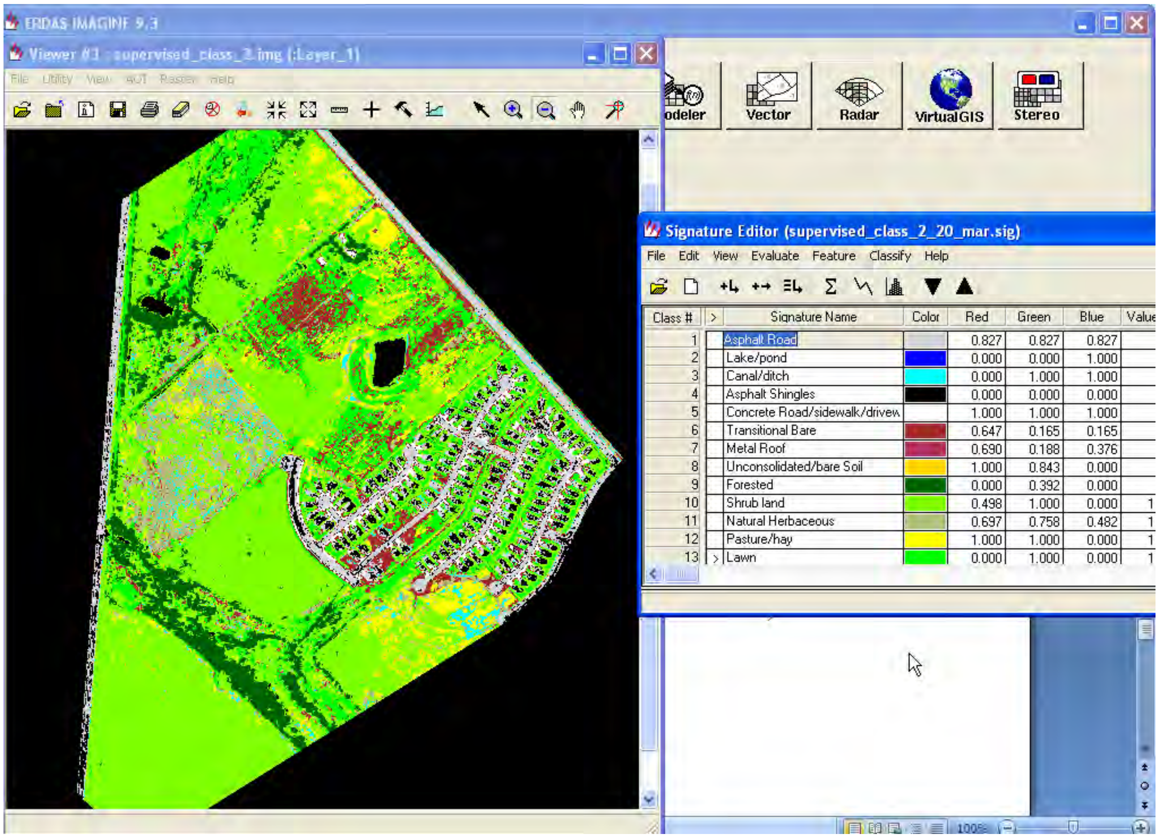

Figure 4.13 Supervised Classification Results (Maximum Likelihood)

Step 7: Accuracy Assessment

Accuracy for the supervised classification was assessed using 101 stratified random sample points. Each sample point corresponded to an individual pixel within the image and the ground based location represented by that pixel. Sample point generation was accomplished through the "Classifier > Accuracy Assessment" menu (see Figure 4.14). Attempts were made to generate more than 101 sample points with at least 10 points in each class as identified by the supervised classification output. Due to the small size of the classification AOI, the software was only able to generate a total of 101 sample points. The sample point saved and opened in a Viewer containing the unclassified El Camino Real subset image (see Figure 4.15). The sample points were then "ground truthed" by a visual assessment of the original El Camino Real (NAIP) subset. If the land use and land cover class for a sample point could not be determined from the image, the point's actual location on the ground was assessed. Actual ground assessments were conducted via the embedded coordinates within the NAIP data and a Trimble GeoXT™ hand held GPS unit. The Trimble GeoXT™ is capable of sub meter accuracy ensuring the determination of sample points with a level of accuracy that places them within the pixel being assessed (Trimble Navigation Limited 2008). Once all 101 sample points were correlated to land use and land cover conditions (via visual image assessment or actual ground truthing), the land use and land cover class was determined for each sample point on the classified image (see Figures 4.16 and 4.17 for a visual comparison of sample point 39 on each image). Percent accuracy assessments were calculated in Microsoft Excel 2007©. Each correctly classified sample point was assigned a value of 0.9909. The values for all correctly classified points were summed to determine the percent classification accuracy. Chapter 5 presents the results of the image classification as determined by the accuracy assessment.

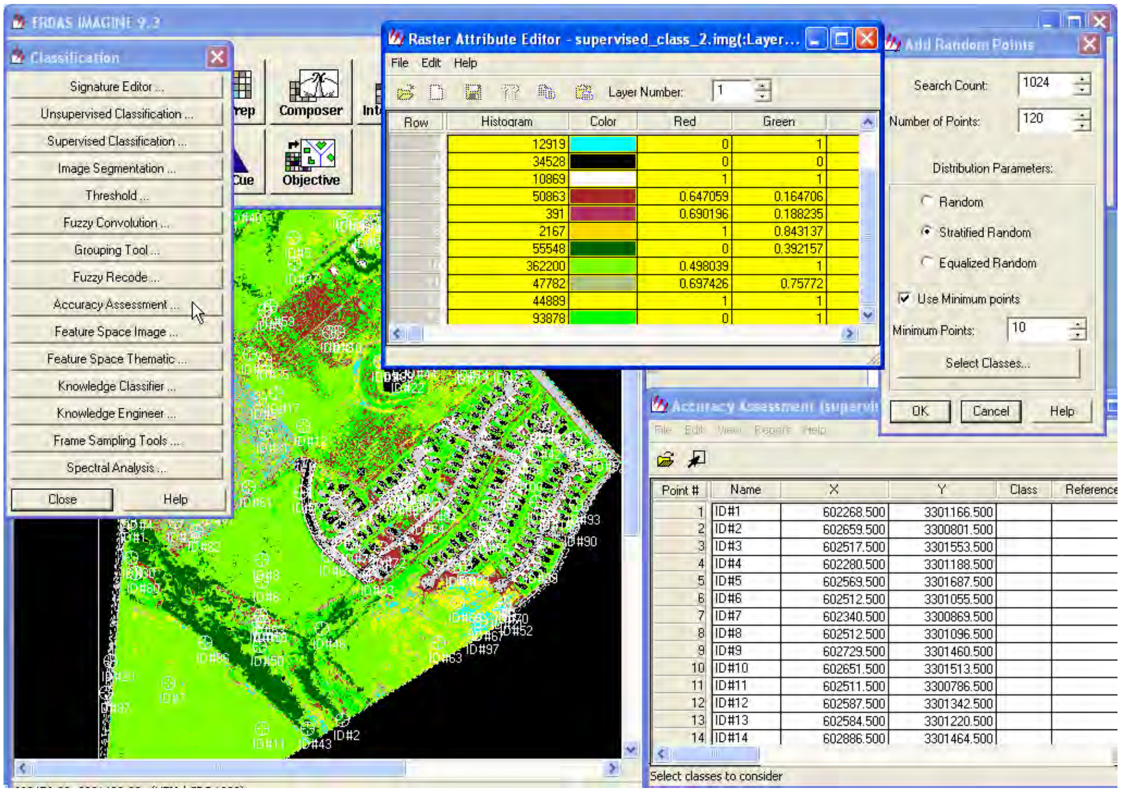

Figure 4.14 Accuracy Assessment – Stratified Random Sample Point Generation in ERDAS Imagine 9.3®

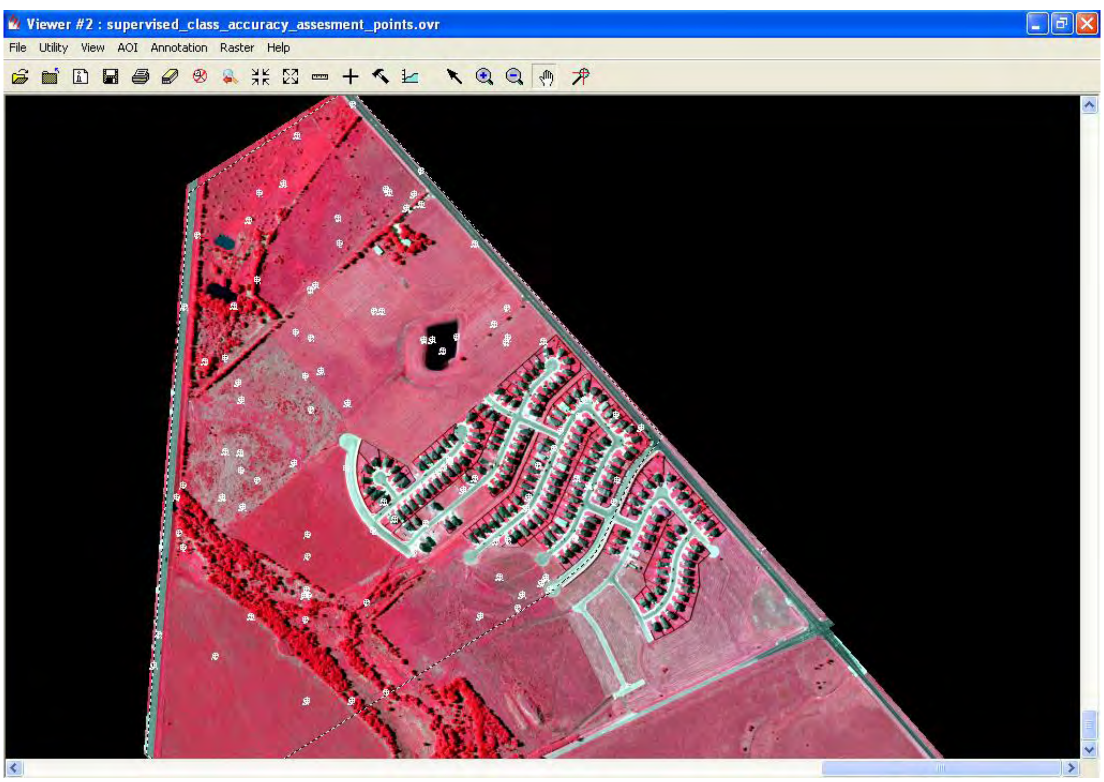

Figure 4.15 Accuracy Assessment Points on El Camino Real Subset (NAIP) Image

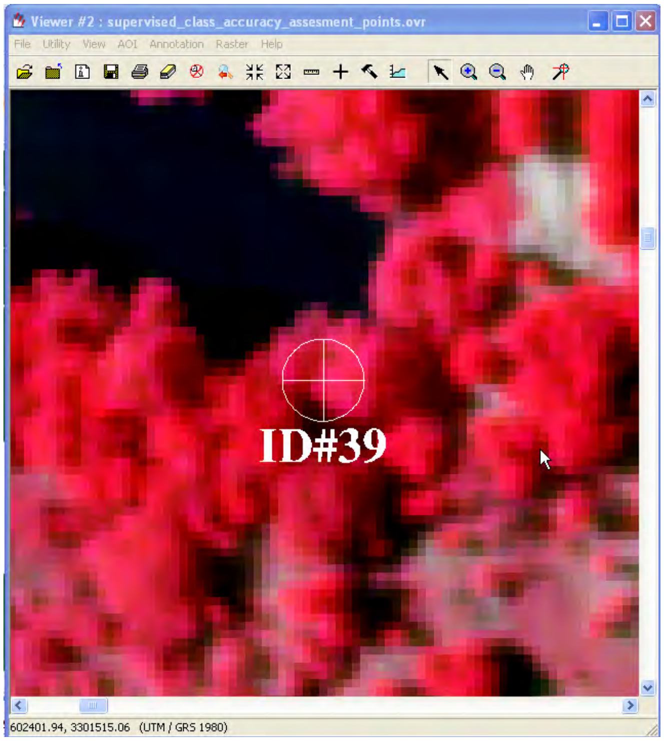

Figure 4.16 Accuracy Assessment of Point 39 on the El Camino Real (NAIP) Subset

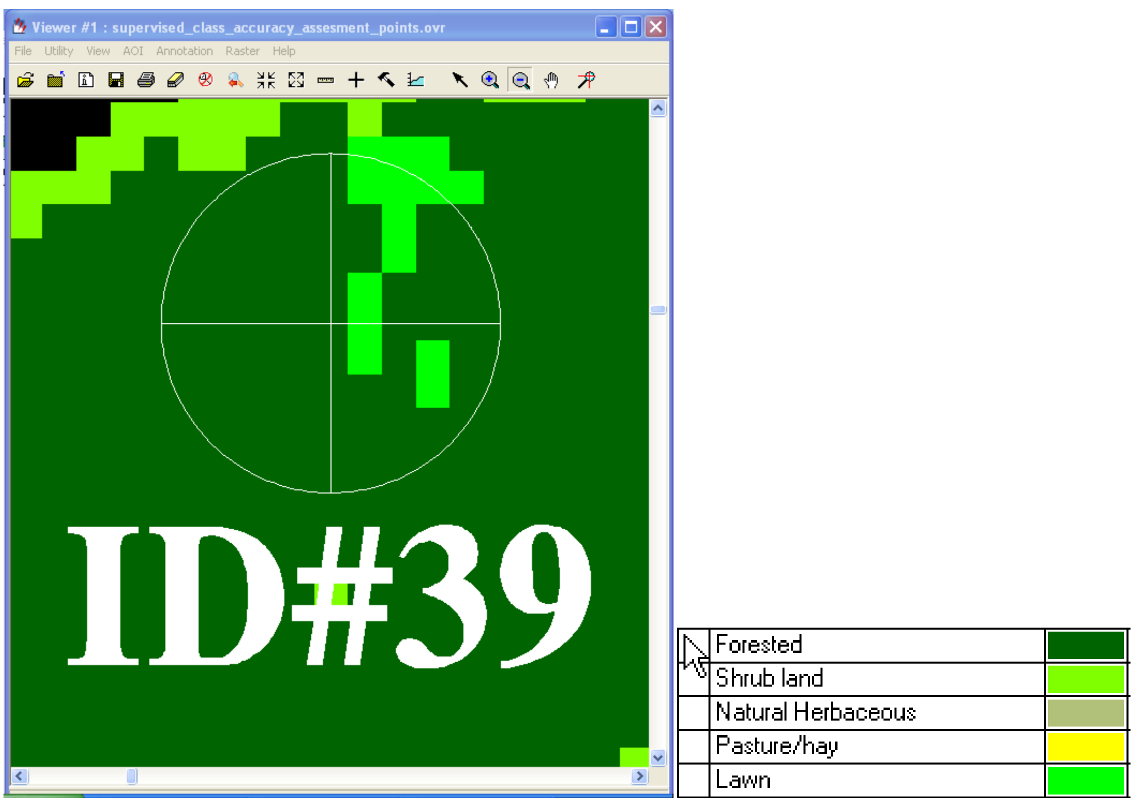

Figure 4.17 Accuracy Assessment of Point 39 on the Classification Output

Scenario – Classification Complete!?

"Wow," thought Norm. Despite the slight shaking of his extremities due to over-caffeination, he felt pretty good about what he had accomplished today. Norm collected the massive manuals, his thrice emptied coffee bucket, and the fruits of his labor now neatly arranged in orderly rows of ones and zeros on his thumb drive. "Tomorrow, we'll find out just how good I really am," Norm exclaimed as he fidgeted his way to his car.

Chapter 5. Results

Scenario - Victory

After spending several minutes entering the data from yesterday's image classification into a spreadsheet, Norm's mental drum roll was abruptly interrupted by the subpar percent classification accuracy that filled the cell before him. "I see now why everything I read called them classification 'attempts'," sighed Norm under his breath. After a few seconds of self-pity, the quintessential phrase of every great infomercial popped into Norm's head… "But wait, there's more!" "There must be more," Norm thought. Then the brainstorming began. "What if I used fewer classes, or I could even just look at current levels of impervious and pervious cover. After all, that's the big question when it comes to development planning and floodplain management." When the numbers were crunched for that final question and the result was in black and white before him, Norm knew he had won a victory for planners everywhere.

Introduction

The purpose of this study was to explore the utility of National Agriculture Imagery Program data to identify land use and land cover conditions using an imagery subset of the El Camino Real subdivision in San Marcos, Texas. Previous chapters detailed the thought process (i.e. literature review and development of a working hypothesis) behind the study and the steps taken to test the hypothesis (i.e. methodology). In this chapter the results of the study[35] are revealed along with possible explanations for the successes and failures. The results and accompanying discussions are divided into two sections based on the relevant sub-hypothesis. The ability of NAIP data to identify

[35] For a detailed list of all 101 sample points and classification accuracy assessments see Appendix D.

local land use and land cover conditions is discussed first, followed by a discussion of the same data's ability to differentiate impervious from previous cover.

WH_{1a}: The application of supervised image classification procedures to NAIP imagery will result in LULC classification accuracies at, or above, the 95% threshold.

The basis of working sub-hypothesis A was to determine the potential for NAIP imagery to identify LULC conditions at the local level. Table 5.1 provides an overview of the data and basic procedures utilized to explore NAIP imagery's potential for precise LULC classification. Classification accuracy for sub-hypothesis A was calculated by conducting an individual assessment of 101 random pixels within the image based on four different classification methods (see Table 5.2). The evidence failed to support WH_{1a}. The poor classification accuracies (42% to 86%) would not facilitate precise area calculations for each cover class and, therefore, would inhibit accurate hydrologic modeling.

Table 5.1 Operationalization of the Conceptual Framework: WH_{1a}

Research Purpose: To explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP data) to accurately identify land use and land cover (LULC) conditions.		
Working Hypothesis	*Data*	*Research Procedures*
WH_a: The application of supervised image classification procedures to NAIP imagery will result in LULC classification accuracies at, or above, the 95% accuracy threshold.	WH_a: **-2008 *NAIP imagery (Leica Geosystems ADS40 airborne digital sensor)*** ***-Latitude and longitude for study area, LULC class boundaries, training areas and sample points*** ***-Modified Anderson LULC classification schema*** ***-Output of supervised image classification***	WH_a: **-Identify El Camino Real subdivision and surrounding area on 2008 NAIP image** **-Divide study area (½ training, ½ testing)** **-Supervised classification in ERDAS Imagine 9.3®** **-Accuracy assessment (stratified random sample points)** **-Ground-based visual accuracy assessment (related to conditions during image acquisition)**

Table 5.2 Classification Accuracies for 101 Sample Points

Accuracy Assessment Procedure	Classification Accuracy (%)
Strict LULC Interpretation	42%
Pixel-Based Assessment (PBA)	50%
PBA with a Combined Class for Asphalt Shingles and Asphalt Roads	53%
PBA with Asphalt Class + a Combined Class for Pasture, Lawn, Natural Herbaceous, and Shrubland	86%

Strict LULC Interpretation

The first method used to assess the classified image (see Figure 5.1) was a strict interpretation of land use and land cover classes based upon the area in which the sample pixel assessed was located. Basing the land use land cover class of a sample pixel used for accuracy assessment is not a "fair" assessment of the capabilities of the NAIP data. Since the NAIP imagery is captured at a one-meter resolution, the variability of LULC from one pixel to the next can be quite high. For example, a forest, as defined by the Modified Anderson classification schema (see Appendix A) must have more than 25% canopy cover. When sampling at intervals smaller than the canopy area of one tree (e.g. one meter), it is possible to have a pixel fall completely within a forest, but on an area that has no canopy cover. That leaves the possibility for 74% of the pixels within a forest to be void of trees. Due to such limitations, less than half of the sample pixels were correctly classified when assessed using a strict LULC interpretation (see Table 5.2).

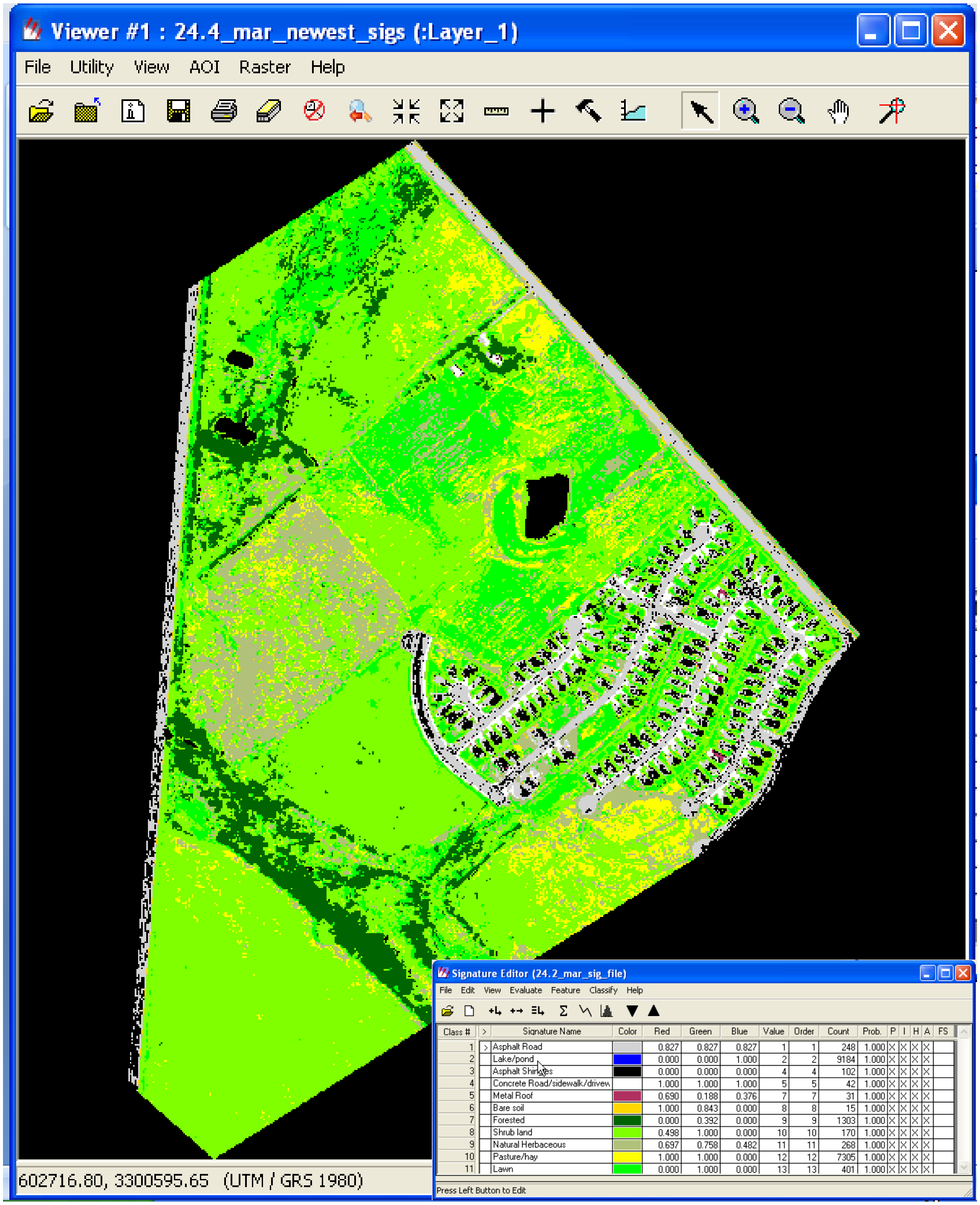

Figure 5.1 Supervised Classification of El Camino Real Subset using 11 LULC Classes

Pixel-Based LULC Classification Assessment

A slightly more "fair" method of assessment than the strict interpretation was the pixel-based accuracy assessment. For the pixel-based assessment, only the actual LULC class for the individual sample pixel being assessed was utilized for comparison to the classified image. This method improved the classification accuracy as compared to the strict interpretation because it addressed the issue of pixel variability that accompanies high resolution (e.g. one-meter) imagery. Continuing with the example from the previous section, with the pixel-based assessment method, if a sample pixel fell within the forest area, but not on a tree, it was assessed as the target within the actual sample pixel and not as the LULC class of the surrounding area. Unfortunately, the pixel-based accuracy assessment only resulted in exactly half of the sample pixels being accurately classified.

A probable cause for the poor classification accuracy is this study's ambitious division of LULC classes. Previous attempts at classifying Landsat data have done no better than 87% classification accuracy when using two fewer (9) LULC classes than this study (see Table 5.3). Also, the Landsat based classification attempts covered diverse areas at large scales (e.g. state, national, and global). By conducting classification attempts over large areas with coarse imagery (e.g. 30 meter resolution), researchers using Landsat data were more readily capable of identifying broad LULC classes with distinct characteristics separating each class. Attempting LULC classifications within a small area using NAIP data (i.e. high resolution imagery) forced the classification software to differentiate patterns that were much more similar than those created by the Landsat (i.e. low resolution) generated signatures. With these limitations in mind, it is understandable that, though improved, the pixel-based assessment using 11 LULC classes only resulted in 50% classification accuracy.

Table 5.3 Classification Accuracies for Landsat based LULC Classification Attempts

Number of Classes	Classification Accuracy	Classification Method	Source
9	87%	Supervised	Xiao et al. 2006
9	84%	Supervised	Rogan et al. 2008
7	94%	Supervised/Unsupervised	Yuan et al. 2005
7	10-91%	Supervised	Shalaby and Tateishi
5	89.5%	Supervised	Foody et al.
4	85.5-89.5%	Supervised	Ji et al. 2006
4	88.4%	Unsupervised	Ouma et al. 2008
3	72-84%	Unsupervised	Brannstrom et al. 2003

Combined LULC Classes Accuracy Assessment

After performing a visual assessment of the NAIP image (see Figure 5.2) and the ground based conditions of the study area, similarities were discovered among several LULC classes. Based upon this discovery it was determined that the 11 LULC classes could be further reduced to 7 classes by combining the asphalt road and asphalt shingle classes and by grouping the pasture/hay, lawn, natural herbaceous, and shrubland classes. With the new LULC class combinations (see Figure 5.3), classification accuracy soared to a level (86%) on par with the reviewed Landsat classifications (see Table 5.3). Even with such substantial improvement, classification accuracy was still below the threshold (95%) suggested as the National Standard for Spatial Data Accuracy (Allen and Birk 2000). Despite the relative success of the 7-class assessment, the accuracies were still below the suggested 95% threshold and did not support WH_{1a}. Following the near miss by WH_{1a}, an accuracy assessment (see working sub-hypothesis B) was conducted at the most elementary level necessary to still supply the vital information required for floodplain management.

Figure 5.2 El Camino Real Subset (Unclassified) of NAIP Image

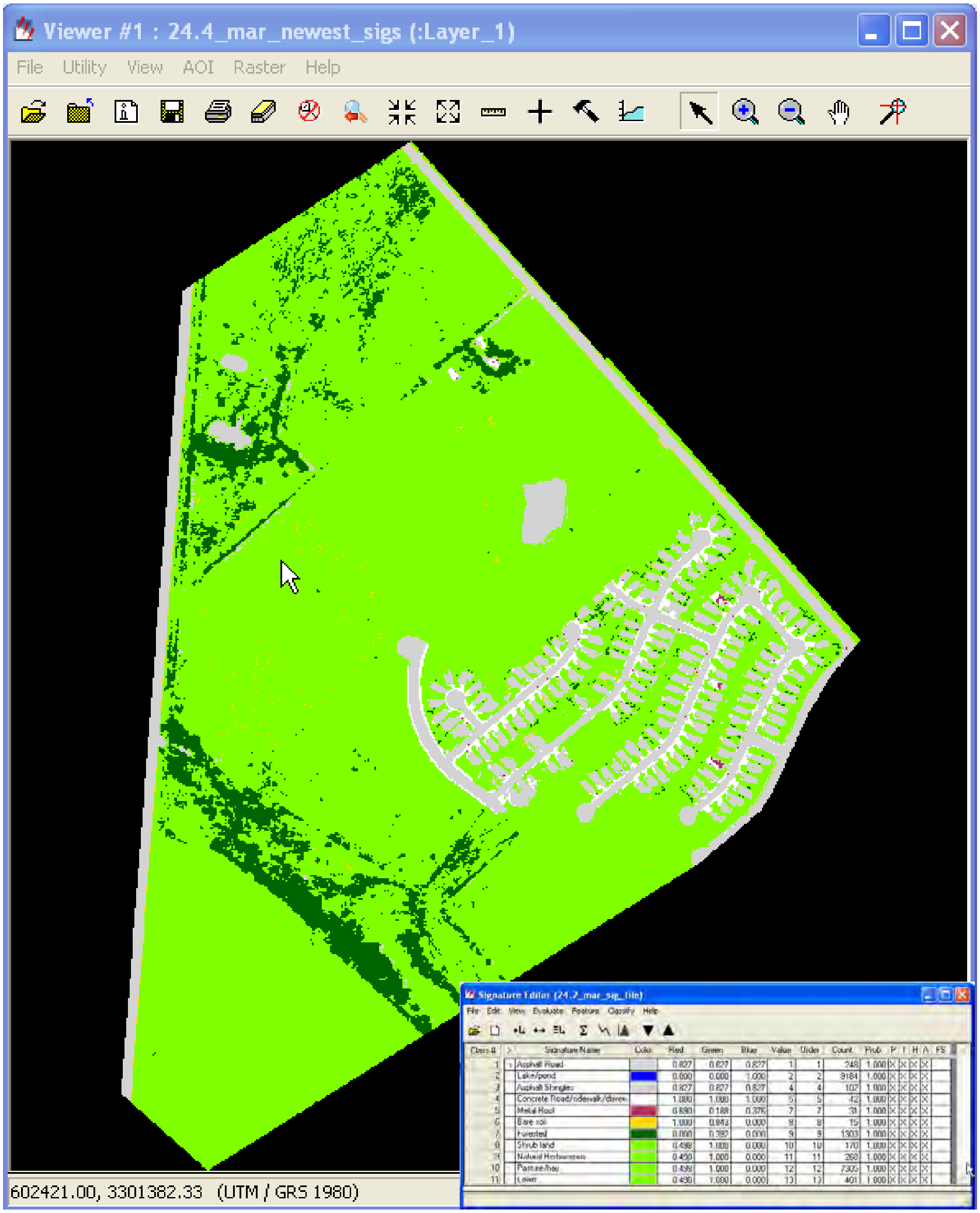

Figure 5.3 Supervised Classification of El Camino Real Subset with Combined (Pasture/Hay + Lawn + Natural Herbaceous + Shrubland and Asphalt Shingles + Asphalt Road) LULC Classes

WH_{1b}: The application of supervised image classification procedures to NAIP imagery will result in the discrimination of impervious from pervious cover with classification accuracies at, or above, the 95% accuracy threshold.

WH_{1b} incorporated the same data and procedures as the first sub-hypothesis (see Table 5.4), however, it sought to answer one basic question: can NAIP imagery be used to differentiate pervious from impervious cover in a combined urban and rural environment? While classification of specific LULC classes would provide local planners with much useful information about their communities, the basic determination of impervious and pervious cover is essential for proper floodplain management.[36] To assess the NAIP imagery's ability to differentiate the two cover types, the signatures for the 11 LULC classes were relabeled as either pervious or impervious cover. Table 5.5 illustrates the LULC class combinations that led to the two cover classes. By combining the classes into two distinct classes, a much greater degree of separation was created between the definitions (i.e. spectral signatures) of the two new cover classes (i.e. impervious and pervious). Figure 5.4 displays the supervised classification output for impervious and pervious cover discrimination. When differentiating impervious from pervious cover, classification accuracy (95%) equivalent to the National Standard for Spatial Data Accuracy was achieved (see Table 5.6). The 95% accuracy achieved supported WH_{1b}. With the accuracy of the pervious v. impervious cover classification (see Figure 5.4) was above 95%, local planners may then confidently calculate the total area for each LULC class and input that information to a hydrological model to facilitate mapping of the current flood hazards for the area.

[36] For more information on the uses of impervious and pervious cover data for land use planning purposes see Gillfillan (2008).

Table 5.4 Operationalization of the Conceptual Framework: WH_{1b}

Research Purpose: To explore the utility of readily available, high resolution, multi-spectral, remotely sensed data (i.e. NAIP data) to accurately identify land use and land cover (LULC) conditions.		
Working Hypothesis	*Data*	*Research Procedures*
WH_b: The application of supervised image classification procedures to NAIP imagery will result in the discrimination of impervious from pervious cover with classification accuracies at, or above, the 95% accuracy threshold.	WH_b: -**2008** ***NAIP imagery (Leica Geosystems ADS40 airborne digital sensor)*** -***Latitude and longitude for study area, LULC class boundaries, training areas and sample points*** -***Modified Anderson LULC classification schema*** -***Output of supervised image classification***	WH_b: **-Identify El Camino Real subdivision and surrounding area on 2008 NAIP image** **-Divide study area (½ training, ½ testing)** **-Supervised classification in ERDAS Imagine 9.3®** **-Accuracy assessment (stratified random sample points)** **-Ground-based visual accuracy assessment (related to conditions during image acquisition)**

Table 5.5 LULC Class Combinations for Differentiation of Impervious and Pervious Cover

Impervious Cover	**Pervious Cover**
Asphalt Shingles + Asphalt Roads/Surfaces + Concrete Roads/Surfaces + Metal Roofs	Pasture/Hay + Lawn + Natural Herbaceous + Shrubland + Forest + Bare Soil + Open Water

Table 5.6 Classification Accuracy for Differentiation of Impervious and Pervious Cover

Accuracy Assessment Procedure	**Classification Accuracy (%)**
Impervious v. Pervious Cover	95%

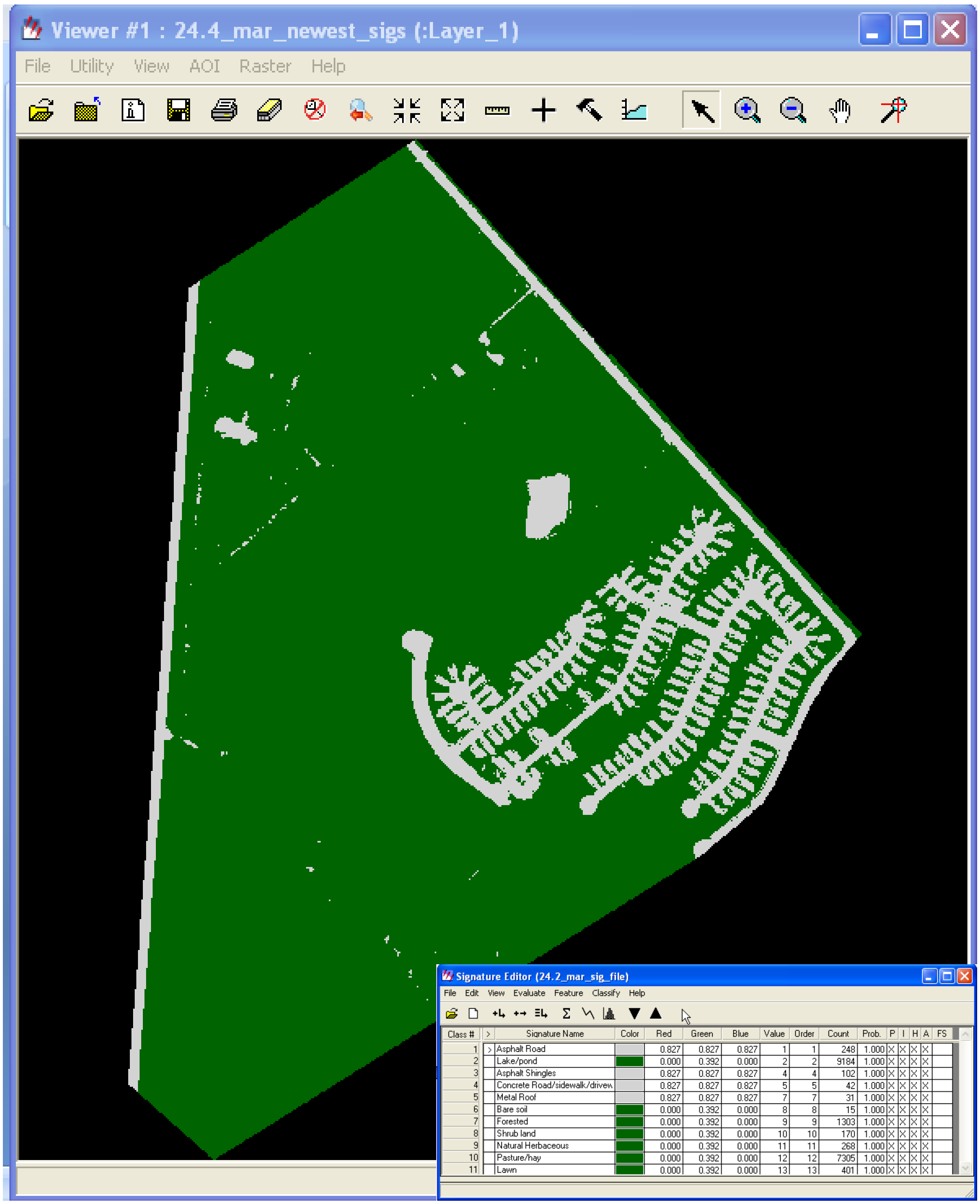

Figure 5.4 Supervised Classification Output for Differentiation of Impervious and Pervious Cover

Chapter 6. Conclusions and Recommendations

Scenario – The Next Step

Norms' success at classifying impervious and pervious cover within Deerfield Estates promised to take much of the guesswork out of land use and land cover classifications for planners throughout the nation. Once the two types of cover (i.e. pervious and impervious) were accurately classified, the area they covered could be quantified. Through simple calculations available for most GIS and imagery analysis software, the square footage (or acreage, square meters, or square kilometers) of each cover class could be determined and input into a hydrologic model (e.g. ArcHydro created by David Maidment at the University of Texas at Austin). The cover data coupled with terrain information (i.e. digital elevation models) would allow planners to create maps of their community's flood risks that were as current as the input data. Since NAIP imagery was issued 2 to 5 times as often as FEMA's maps, Norm (and planners throughout the United States) would have a better grasp of the conditions affecting their communities. Norm's thoughts led him to realize his work was not complete. At the moment, knowledge of the utility of NAIP data for local planners was his and his alone. For him to truly help "planners everywhere," he would have to let them know about his success. Unfortunately, Norm did not fancy himself as a writer or a public speaker, finding pleasure in neither task. After a quick search of the web, he discovered that the American Planning association was accepting papers for their next convention in Palm Beach. "A spoon full of sugar," Norm said aloud. "A little dose of sun and sand will certainly ease the pain of public speaking," Norm thought as he began composing his thoughts for the first draft of his presentation.

Conclusions

National Agriculture Imagery Program data possesses immense potential for accurately classifying land use and land cover classes through the use of pattern recognition software such as ERDAS Imagine 9.3®. For this study, classification accuracies ranged from 42-95% (see Table 6.1). By a rudimentary application of supervised image classification procedures to the NAIP image of the El Camino Real subdivision, impervious cover was discriminated from pervious cover with a high degree of certainty (95%) (see Table 6.1). Even when assessing 7 land use and land cover classes, the level of accuracy was comparable to classification accuracies achieved with Landsat data using similar techniques (see table 6.2). Based on the research findings, the first working sub-hypothesis (A) was not supported because the level of accuracy achieved was below the 95% threshold (see Table 6.3). Still, the findings suggest a great deal of potential for reaching the 95% accuracy threshold when classifying NAIP data. Working sub-hypothesis B was completely supported by the research findings (see table 6.3) and offers a valuable new tool to community planners.

Table 6.1 Classification Accuracies for 101 Sample Points

Accuracy Assessment Procedure	**Classification Accuracy (%)**
Strict LULC Interpretation	42%
Pixel-Based Assessment (PBA)	50%
PBA with a Combined Class for Asphalt Shingles and Asphalt Roads	53%
PBA with Asphalt Class + a Combined Class for Pasture, Lawn, Natural Herbaceous, and Shrubland	86%
Impervious v. Pervious Cover	95%

Table 6.2 Classification Accuracies for Landsat based LULC Classification Attempts

Number of Classes	Classification Accuracy	Classification Method	Source
9	87%	Supervised	Xiao et al. 2006
9	84%	Supervised	Rogan et al. 2008
7	94%	Supervised/Unsupervised	Yuan et al. 2005
7	10-91%	Supervised	Shalaby and Tateishi
5	89.5%	Supervised	Foody et al.
4	85.5-89.5%	Supervised	Ji et al. 2006
4	88.4%	Unsupervised	Ouma et al. 2008
3	72-84%	Unsupervised	Brannstrom et al. 2003

Table 6.3 Summary of Results for the Working Hypothesis

Working Sub-Hypothesis	Accuracy	Supported
WH_a: The application of supervised image classification procedures to NAIP imagery will result in LULC classification accuracies at, or above, the 95% accuracy threshold.	**42-86%**	**No**
WH_b: The application of supervised image classification procedures to NAIP imagery will result in the discrimination of impervious from pervious cover with classification accuracies at, or above, the 95% accuracy threshold.	**95%**	**Yes**

Recommendations for Future Research and Implementation

Because of the near success with a multi class LULC classification, future research efforts should focus on increasing the level of accuracy for classifications with multiple classes (see Table 6.4). Manipulation of the image classification (pattern recognition) procedures used in ERDAS Imagine® should be attempted in order to achieve the highest possible accuracy. Yuan et al. (2005) achieved an acceptable level of accuracy (94%) by applying supervised and unsupervised classification procedures to Landsat data. Application of Yuan et al.'s (2005) methodology to NAIP data should be the next step in LULC classification attempts using NAIP data.

Once communities possess the ability to achieve accurate land use and land cover classifications, two final hurdles will remain. First, future research will need to identify a means to allow local planners to conduct the procedures without prior training or experience. One possible solution is the development of a graphical user interface (GUI) that allows planners to outline the local area of interest and then conduct the classification using previously set parameters and training data. Second, no matter how easily LULC data (or the resulting floodplain maps) are generated, their effectiveness will be limited unless they are afforded some degree of legal standing. With the vast amounts of money involved in new developments, planners will need backing by their local, state, and federal governments to enforce decisions based upon LULC data derived from remotely sensed data.

Table 6.4 Recommendations for Future Research and Implementation

Recommendation	**Operationalization**
Continue exploring supervised classification techniques	- Apply other parametric decision rules - Attempt fuzzy classification techniques[37]
Combine supervised and unsupervised classification techniques	- See Yuan et al. 2005
Make the technology and procedures more readily available/understood at the local level	- Create a graphical user interface (GUI) to aid local planners in applying classification techniques
Implement classification results (i.e. LULC maps) as part of local regulatory policy	- Develop rules and regulations to provide legal standing for classification results (e.g. levy environmental impact fees based on information derived from LULC classifications)

[37] Fuzzy classification methods help to account for pixels with mixed targets (i.e. pixels that contain different LULC classes) (Leica Geosystems GIS & Mapping 2005).

Bibliography

Allen, J, and R Birk. 2000. "Flood mapping specifications: Technology-centric vs application-centric." *ASPRS Conference Proceedings.* Wasington D.C.: ASPRS.

Anderson, James R., Ernest Hardy, John T Roach, and Richard E Witmer. 1976. "A land use and land cover classification system for use with remote sensor data." *Geological Survey Professional Paper - U.S. Geologic Survey Circular 671.* Washington, DC: United States Government Printing Office.

Burby, Raymond, and Steven French. 1985. *Floodplain land use management a national assessment.* Boulder, CO: Westview Press.

Burley, Terence M. 1961. "Land use or land utilization?" *Professional Geographer*, 13 (6): 18-20.

Burton, Mark L. and Michael J. Hicks. 2005. "Hurricane Katrina: Preliminary estimates of commercial and public sector damages." Hunting ton, WV: Marshal University Center for Business and Economic Research. www.marshall.edu/cber/research/katrina/Katrina-Estimates.pdf *(*Accessed March 3, 2009)

Clawson, Marion and Charles L. Stewart. 1965. *Land use information. A critical survey of U.S. statistics including possibilities for greater uniformity*. Baltimore, MD: The Johns Hopkins Press for Resources for the Future, Inc.

Colding, Johan. 2007. "'Ecological land-use complementation' for building resilience in urban ecosystems." *Landscape and Urban Planning*: 46-55.

Cross, John A. 2001. "Megacities and small towns: different perspectives on hazard vulnerability." *Environmental Hazards*: 63-80.

Crossett, K. M., T. J. Culliton, P. C. Wiley, and T. R. Goodspeed. 2004. "Population Trends along the coastal United States." *NOAA National Ocean Service.* September 2004. www.oceanservice.noaa.gov/programs/mb/pdfs/coastal_pop_trends_complete.pdf (accessed September 29, 2007).

Ellis, Ronald L. 2006. "Residential land use policy and conservation development in the Blanco River basin". Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/110/ (accessed January 3, 2009).

Este, Stephen. 2007. "The challenges of accountability in the human services: performance management in the Adult Protective Services Program of Texas." Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/250 (accessed March 4, 2009)

FEMA. 2007. *Map Modernization.* October 4. http://www.fema.gov/plan/prevent/fhm/mm_main.shtm (accessed January 9, 2008).

Foody, Giles M., Eman M. Ghoneim, and Nigel W. Arnell. 2004. "Predicting locations sensitive to flash flooding in an arid environment." *Journal of Hydrology*: 48-58.

Gillifillan, Abigail. 2008. "Using geographic information systems to develop and analyze land-use policies." Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/273/ (accessed October 14, 2008).

Group, Interagency LULC Working. 1999. "Texas land classification system." *Texas Geographic Information Council.* October. http://www.dir.state.tx.us/tgic/pubs/lulc-report.pdf (accessed December 7, 2007).

Guoan, T, L Yongmei, L Wangging, C Zhengjiang, and Z Mudan. 2001. "The impact of resolution on the accuracy of hydrologic data derived from DEMs." *International Cartographic Conference Proceedings.* Beijing, China: International Cartographic Conference.

Hassan, R., R. de Neufville, O. de Weck, D. Hastings, and D. McKinnon. 2005. "Value-at-risk analysis for real options in complex engineered systems." IEEE Conference Proceedings on Large-Scale Infrastructures, Hawaii.

Hipple, James D., Barry Drazkowski, and Patrick M Thorsell. 2005. "Development in the Upper Mississippi Basin 10 years after the Great Flood of 1993." *Landscape and Urban Planning*: 313-323.

Hoggan, Daniel. 1997. *Computer-assisted floodplain hydrology and hydraulics 2nd Ed.* New York, NY: McGraw-Hill.

Hord, R. Michael. 1982. *Digital image processing of remotely sensed data*. New York: Academic Press.

Jensen, J. R. 1996. *Introductory Digital Image Processing: A Remote Sensing Perspective*. 2d Ed. Englewood Cliffs, New Jersey: Prentice-Hall.

Johnson, Timothy L. 2008. "The downtown Austin planning process as a community of inquiry: an exploratory study." Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/276/ (accessed February 23, 2008).

Johnston, L.R. (Associates). 1992. *Floodplain management in the United States.* Assessment Report, Prepared for the Federal Interagency Floodplain Management Task Force.

Klein, Richard J.T., Robert J Nicholls, and Frank Thomalla. 2003. "Resilience to natural hazards: How useful is this concept?" *Environmental Hazards*: 35-45.

Kloer, B. R. 1994. “Hybrid Parametric/Non-Parametric Image Classification.” Paper. Reno, Nevada: CSM-ASPRS Annual Convention.

Leica Geosystems GIS & Mapping, LLC. 2008. ERDAS Field Guide, Volume 1. Norcross, GA: Leica Geosystems Geospatial Imaging, LLC.

Leica Geosystems GIS & Mapping, LLC. 2005. ERDAS Field Guide. Norcross, GA: Leica Geosystems Geospatial Imaging, LLC.

Lillesand, Thomas M., and Ralph W Kiefer. 1994. *Remote sensing and image interpretation.* New York, NY: John Wiley and Sons, Inc.

Lins, Harry F. and James R. Slack. 1999. “Streamflow trends in the United States.” *Geophysical research letters*, 26 (2): 227-230.

Lovell, Troy, Emilia Salcido, and Michael Moya. 1999. "Upgrading FEMA maps with master drainage plans." *Planning Ahead Reducing Flood Losses in the 21st Century.* Portland, OR: Assoc. of State Floodplain Managers. 155-159.

Lyons, Holly M. 2007. “Issue review*:* Iowa State Patrol’s general fund budget, vehicle depreciation and fuel expenses.” Report. Des Moines, IA: Iowa Legislative Services Agency Fiscal Services Department.

Maidment, David R. ed. 2002. *Arc Hydro GIS for water resources.* Redlands, CA: ESRI.

Mannion, A. M. 2002. *Dynamic world land-cover and land-use change.* New York, NY: Oxford University Press.

Manyena, Siambabala Bernard. 2006. “The concept of resilience revisited.” *Disasters*, 30 (4): 434-450. Somerset, NJ: Blackwell Publishing.

Munasinghe, Mohan and Caroline Clarke. 1995. *Disaster prevention for sustainable devlopment:economic and policy issues.* A report from the Yokohama World Conference on Natural Disaster Reduction. Washington, D.C.: International Bank for Reconstruction and Development

O'Neill, Brian. 2008. "A model assessment tool for the incident command system: a case study of the San Antonio Fire Department." Applied Research Project: Texas State University – San Marcos.http://ecommons.txstate.edu/arp/270 (accessed February 15, 2009).

Ouma, Yashon O., S.S. Josaphat, and Ryutaro Tateishi. 2008. "Multiscale remote sensing data segmentation and post-segmentation change detection based on logical modeling: Theoretical exposition and experimental results for forestland cover change analysis." *Computer and Geosciences*: 715-737.

PCI Geomatics 2009. “PCI Geomatics unveils latest version of geo-imaging software”. Press Release. Ontario, Canada: PCI Geomatics. http://www.pcigeomatics.com/pressnews/2009_PCI_geomatica.html (Accessed March 3 2009).

Peterson, Gary, Thomas Helfrich, and Leo Smith. 1999. "Reducing flood losses through floodprone land acquisition." *Planning Ahead Reducing Flood Losses in the 21st Century.* Portland, OR: Assoc. of State Floodplain Managers: 12-16.

Pickett, S.T.A., M.L. Cadenasso, and J.M. Grove. 2004. "Reslient cities: meaning, models, and metaphor for integrating the ecological, socio-economic, and planning realms." *Landscape and Urban Planning*: 369-384.

Powell, William G. 2003. “Discrimination and measurement of crop residues on soil surfaces using hyperspectral remote sensing techniques.” Thesis: Mississippi State University.

Prentice, Tina Forward. 2006. "Case study research: exploring the most commonly used grantmaking criteria within public and private foundations in Austin, Texas and other foundations funding Austin, Texas public health initiatives.” Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/184 (accessed March 3, 2009).

Ramlal, Bheshem, and Serwan M.J. Baban. 2008. "Developing a GIS based integrated approach to flood management in Trinidad, West Indies." *Journal of Environmental Management*: in press.

Renard, K.G., G.R. Foster, G.A. Weesies, D.K. McCool, and D.C. Yoder. 1996. “Predicting soil erosion by water: a guide to conservation planning with the Revised Universal Soil Loss Equation (RUSLE).” U.S. Department of Agriculture, Agriculture Handbook No. 703.

Rogan, John, Janet Franklin, Doug Stow, Jennifer Miller, Curtis Woodcock, and Dar Roberts. 2008. "Mapping land-cover modifications over large areas: A comparison of machine learning algorithms." *Remote Sensing of Environment*: 2272-2283.

Romano, Greg, and Chris Vaccaro. 2005. "NOAA flood forecasting helps save lives and property." *NOAA Magazine Online.* (March 31) http://www.magazine.noaa.gov/stories/mag166.htm (accessed December 28, 2007).

Schacheri, Bradley A. 2008. “Assessing smart growth in San Antonio, Texas.” Applied Research Project: Texas State University – San Marcos. http://ecommons.txstate.edu/arp/279/ (accessed March 2, 2008)

Shalaby, Adel and Ryutaro Tateishi. 2007. “Remote sensing and GIS for mapping and monitoring land cover and land-use changes in the northwestern coastal zone of Egypt.” *Applied Geography*: 28-41.

Shim, Kyu-Cheoul Shim, Darrell G. Fontane, and John W. Labadie. 2002. “Spatial decision support system for integrated river basin flood control.” *Journal of Water Resources Planning And Management*, May/June: 190

Singh, R.B., Jefferson Fox, and Yukio Himiyama eds. 2001. *Land use and cover change.* Enfield, NH: Science Publishers, Inc.

Shields, Patricia M. 1998. Pragmatism as philosophy of science: A tool for public administration. *Research in Public Administration* 4: 195-225. http://ecommons.txstate.edu/polsfacp/33/

Shields, P. and H. Tajalli 2006. Intermediate theory: The missing link in successful student scholarship" *Journal of Public Affairs Education* 12 (3): 313-334. http://ecommons.txstate.edu/polsfacp/39/

Smith, C. and N. Brown. 1997. *ERDAS Field Guide*. Fourth Edition. Atlanta, Georgia: ERDAS Inc.

Stanganelli, Marialuce. 2008. "A new patern of risk management: The Hyogo Framework for action and Italian practise." *Socio-Economic Planning Sciences*: 92-11.

Texas Commission on Environmental Quality. 2001. “Arroyo-Colorado Watershed: 30-Meter Land Use Land Cover: A Geospatial Data Presentation.” Austin, TX: TCEQ.

Tobin, Graham A. 1999. "Sustainability and community resilience: the holy grail of hazard planning?" *Environmental Hazards*: 13-25.

Trimble Navigation Limited. 2009. “GeoXT Handheld [PN 022501-164B (01/09)] Datasheet.” http://www.trimble.com/geoxt_ds.asp (accessed March 5, 2009).

United Nations. 2000. *International Decade for Natural Disaster Reduction: successor arrangements.* UN Resolution A/Res/54/219. 3 February 2000.

United Nations. 2002. *International Strategy for Disaster Reduction*. UN Resolution A/Res/56/195. 21 January 2002.

United Nations. 2007. *Hyogo Framework for Action 2005-2015: Building the resilience of nations and communities to disasters*. Extract from the final report of the World Conference on Disaster Reduction. Geneva: UN/ISDR.

U.S. Commission on Ocean Policy. 2004. "U.S. ocean action policy." *NOAA.* (September 20) http://ecosystems.noaa.gov/docs/US_Ocean_Action_Plan.pdf (accessed December 19, 2007).

US Department of Agriculture Aerial Photography Field Office. 2008. "Four band digital imagery information sheet." *APFO Support Documents - NAIP Imagery.* (July) www.fsa.usda.gov/Internet/FSA_File/fourband_info_sheet_2008.doc *(*accessed March 3 2009).

US Department of Agriculture Aerial Photography Field Office. 2007. "National Agriculture Imagery Program (NAIP) information sheet." *APFO Support Documents - NAIP Imagery.* (December 10) (accessed January 22, 2008).

US Department of Agriculture Aerial Photograpy Field Office. 2006. *APFO imagery programs – NAIP imagery.* (September 16) http://www.fsa.usda.gov/ FSA/apfoapp?area=home&subject=prog&topic=nai (accessed January 17, 2008).

USGS. 2007. *Geographic data download data set information.* (October 10) http://edc2.usgs.gov/geodata/index.php (accessed December 2, 2007).

USGS. 2007. *Land Cover Institute.* (March) http://landcover.usgs.gov/ landcovertrends.php (accessed January 10, 2008).

USGS. 2006. *Multi resolution land use characteristics 2001.* (August 22) http://eros.usgs.gov/products/satellite/mrlc2001.html (accessed January 4, 2008).

Vieux, Baxter E. 2001. *Distributed hydrologic hodeling using GIS.* Dordrecht, Netherlands: Kluwer Academic Publishers.

Wetmore, French ed. 2006. "National Flood Insurance Program final report." *FEMA.* (October) http://www.fema.gov/library/viewRecord.do?id=2573 (accessed October 5, 2007).

Winter, Thomas C. 2001. “The concept of hydrologic landscapes.” *Journal of the American Water Resources Association*. 37 (2): 335-349.

Yuan, Fei, Kali E Sawaya, Brian C Loeffelholz, and Marvin E Bauer. 2005. "Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing." *Remote Sensing of Environment*: 317-328.

Zhang, w. and T.W. Cundy. 1989. “Modeling of two-dimensional overland flow.” *Water Resources Research WRERAQ*. (September): 2019-2035, September 1989.

Appendix A

Land Use and Land Cover Classification Definitions for the El Camino Real Subdivision: A Modified Anderson Classification Schema (Texas Commission on Environmental Quality 2001, 3-6)

1.0 WATER - area covered by water, snow, or ice with less than 25% vegetated or developed cover, unless specifically included in another category

1.1 Open water - all areas of open water with less than 25% vegetative or developed cover

1.11 Stream/river/canal/ditch - a natural body of flowing water or a man-made open waterway constructed to transport water, to irrigate or drain land, to connect two or more bodies of water, or to serve as a waterway for water craft. Includes streams and rivers that have been channelized in order to control flooding or erosion or to maintain flow for navigation. No software classification of this use class will occur. Class assignment will be made by operator interpretation.

1.12 Lake/pond - a non-flowing, naturally-existing, body of water. Includes water impounded by natural occurrences and artificially regulated natural lakes. The delineation of a lake is based on the areal extent of water at the time the imagery was acquired. No software classification of this use class will occur. Class assignment will be made by operator interpretation.

2.0 DEVELOPED - areas of the earth which have been improved by man. Includes all "built up" and urban areas of the landscape. Does NOT include mining lands, crop lands, or waste-disposal areas (dumps). This land use category takes precedence over a land cover category when the criteria for more than one category are met.

2.1 Residential - lands containing structures used for human habitation

2.11 Single-family residential - lands used for housing residents in single-family dwelling units. Only pertains to land directly under housing unit. Includes mobile homes.

2.111 Asphalt shingles – residential housing units roofed with asphalt shingles.

2.112 Driveway – concrete and asphalt vehicle entrances adjacent to residential units. Will be classified as 2.261 or 2.262 by classification software and interpreted by operator.

2.113 Patio/stone landscaping – stone, gravel, or concrete surfaces adjacent to residential housing units. Will be classified as 2.262 by classification software and interpreted by operator.

2.2 Non-residential Developed - any "developed" area or feature which is used for a purpose other than habitation.

2.21 Metal roof – commercial buildings roofed with metal.

2.22 Transportation - roads, railroads, and airports. Roads and railroads do not include the right-of-way, interchanges, and median strips. Category includes railroad stations, railroad yards, bus stations, highway maintenance yards, school bus parking and service yards, and park-and-ride lots.

2.221 Asphalt roads and surfaces – all asphalt surfaces utilized for transportation or vehicle storage. Includes roads, streets, highways, paved pedestrian and bike paths, and parking areas.

2.222 Concrete/gravel roads and surfaces – all concrete and gravel surfaces utilized for transportation or vehicle storage. Includes roads, streets, highways, pedestrian and bike paths, and parking areas.

2.3 Mixed urban - developed areas which have such a mixture of residential and non-residential features where no single feature meets the minimum mapping unit specification. This category is used when more than one-third of the features in an area do not fit into a single category. Often applicable in the central, urban-core area of cities. No software classification of this use class will occur. Class assignment will be made by operator interpretation.

3.0 BARE - undeveloped areas of the earth not covered by water which exhibit less than 25% vegetative cover or less than 5% vegetative cover if in an arid area. The earth's surface may be composed of bare soil, rock, sand, gravel, salt deposits, or mud.

3.1 Transitional bare - areas dynamically changing from one land cover/land use to another, often because of land use activities. Includes all construction areas, areas transitioning between forest and agricultural land, and urban renewal areas which are in a state of transition. No software classification of this use class will occur. Class assignment will be made by operator interpretation.

3.2 Bare soil – areas in a relatively static state that contain less than 25% vegetative cover

4.0 VEGETATED - areas having generally 25% or more of the land or water with vegetation. Arid or semi-arid areas may have as little as 5% vegetation cover.

4.1 Woody Vegetation - land with at least 25% tree and (or) shrub canopy cover

4.11 Forested - land where trees form at least 25% of the canopy cover

4.12 Shrub land - areas where trees have less than 25% canopy cover and the existing vegetation is dominated by plants that have persistent woody stems, a relatively low growth habit, and which generally produce several basal shoots instead of a single shoot. Includes true shrubs, trees that are small or stunted because of environmental conditions, desert scrub, and chaparral. In the eastern US, include former cropland or pasture lands which are now covered by brush to the extent that they are no longer identifiable or usable as cropland or pasture. Clear-cut areas will exhibit a stage of shrub cover during the regrowth cycle. Some common species which would be classified as shrub land are mountain mahogany, sagebrush, and scrub oaks.

4.2 Herbaceous Vegetation - areas dominated by non-woody plants such as grasses, forbs, ferns and weeds, either native, naturalized, or planted. Trees must account for less than 25% canopy cover while herbaceous plants dominate all existing vegetation.

4.21 Natural Herbaceous - areas dominated by native or naturalized grasses, forbs, ferns and weeds. It can be managed, maintained, or improved for ecological purposes such as weed/brush control or soil erosion. Includes vegetated vacant lots and areas where it cannot be determined whether the vegetation was planted or cultivated such as in areas of dispersed grazing by feral or domesticated animals. Includes landscapes dominated by grass-like plants such as bunch grasses, palouse grass, palmetto prairie areas, and tundra vegetation, as well as true prairie grasses.

4.22 Planted/Cultivated Herbaceous - areas of herbaceous vegetation planted and/or cultivated by humans for agronomic purposes in developed settings. The majority of vegetation in these areas is planted and/or maintained for the production of food, feed, fiber, pasture, or seed. Temporarily flooded are included in this category. Do not include harvested areas of naturally occurring plants such as wild rice and cattails.

4.221 Cultivated grasses - areas of herbaceous vegetation, including perennial grasses, legumes, or grass-legume mixtures that are planted by humans and used for erosion control, for seed or hay crops, for grazing animals, or for landscaping purposes

4.2211 Pasture/Hay - areas of cultivated perennial grasses and/or legumes (e.g., alfalfa) used for grazing livestock or for seed or hay crops. Pasture lands can have a wide range of cultivation levels. It can be managed by seeding, fertilizing, application of herbicides, plowing, mowing, or baling. Pasture land has often been cleared of trees and shrubs, is generally on steeper slopes than cropland, is intended to graze animals at a higher density than open rangeland, and is often fenced and divided into smaller parcels than rangeland or cropland. Hay fields may be more mottled than small grain fields as they are not plowed annually and may be harvested and baled two or three times a year in some locations. This category also contains turf farms and maintained lawn grasses.

4.2212 Lawn/turf - areas of cultivated perennial grasses maintained at a height of less than 8 centimeters for lawn use or turf grass production

Appendix B

Land Use and Land Cover Classification Definitions for the Arroyo Colorado Watershed Project and the Brazos Colorado Coastal Watershed Project: A Modified Anderson Classification Schema (Texas Commission on Environmental Quality 2001, 3-6)

1.0 WATER - area covered by water, snow, or ice with less than 25% vegetated or developed cover, unless specifically included in another category

1.1 Open Water - all areas of open water with less than 25% vegetative or developed cover

1.11 Stream/river - a natural body of flowing water. Includes streams and rivers that have been channelized in order to control flooding or erosion or to maintain flow for navigation.

1.12 Canal/ditch - a man-made open waterway constructed to transport water, to irrigate or drain land, to connect two or more bodies of water, or to serve as a waterway for water craft

1.13 Lake/pond - a non-flowing, naturally-existing, body of water. Includes water impounded by natural occurrences and artificially regulated natural lakes. The delineation of a lake is based on the areal extent of water at the time the imagery was acquired.

1.14 Reservoir - any artificial body of water, unless specifically included in another category. It can lie in a natural basin or a man-constructed basin. The delineation of a reservoir is based on the areal extent of water at the time the imagery was acquired. (The water control structures are classified as Communications/Utilities)

1.15 Bay/estuary - the inlets or arms of the sea that extend inland

1.16 Sea/ocean - an area of the great body of salt water that covers much of the earth

1.2 Perennial Ice/Snow - areas covered year-round with snow and ice

1.21 Snowfield - permanent snow not underlain by a glacier

1.22 Glacier - a body of ice and snow, showing evidence of past or present flow

2.0 DEVELOPED - Areas of the earth which have been improved by man. Includes all "built up" and urban areas of the landscape. Does NOT include mining lands, crop lands, or waste-disposal areas (dumps). This land use category takes precedence over a land cover category when the criteria for more than one category are met.

2.1 Residential - lands containing structures used for human habitation

2.11 Single-family Residential - Lands used for housing residents in single-family dwelling units. Includes trailer parks, mobile home parks, and entire "farmsteads" when where is a home in the complex. (If no home is in the complex, it should be classified as Agricultural Business.) Single-family residential buildings located within another category, such as military family housing, should be identified in this category.

2.12 Multi-family Residential - All lands devoted to housing more than one family on a permanent or semi-permanent basis, group living situations, and their associated grounds. Includes apartments, apartment complexes, duplexes, triplexes, attached row houses, condominiums, retirement homes, nursing homes, and residential hotels. Residential building located within another category such as barracks and dormitories, should be identified in this category when possible.

2.2 Non-residential Developed - Any "developed" area or feature which is used for a purpose other than habitation.

2.21 Commercial/Light Industry - structures and associated grounds used for the sale of products and services, for business, or for light industrial activities. Includes all retail and wholesale operations. Include "industrial parks" and other features which cannot be clearly classified as either a retail service or light industry, such as heavy equipment yards, machinery repair, and junkyards.

2.22 Heavy Industry - structures and their associated grounds used for heavy fabrication, manufacturing and assembling parts which are, in themselves, large and heavy; or for processing raw materials such as iron ore, timber, and animal products. Accumulated raw materials are subject to treatment by mechanical, chemical, or heat processing to render them suitable for further processing, or to produce materials from which finished products are created. Heavy industries generally require large amounts of energy and raw materials and produce a significant amount of waste products. Indicators of heavy industry may be stock piles of raw materials, energy producing sources and fuels, waste disposal areas and ponds, transportation facilities capable of handling heavy materials, smokestacks, furnaces, tanks, and extremely large buildings which are complex in outline and roof structure. Include associated waste piles and waste ponds. Heavy industry is usually located away from residential areas. Includes steel mills, paper mills, lumber mills, chemical plants, cement and brick plants, smelters, rock crushing machinery, and ore-processing facilities associated with mining.

2.23 Communications and Utilities - structures or facilities and associated grounds used for the generation and transfer of power and communications, the treatment or storage of drinking water, waste management, flood control, or the distribution and storage of gas and oil not associated with a unique feature. Includes pumping stations (oil, gas, or water), tank farms, power plants, electric substations, sewage treatment facilities and ponds, garbage collection facilities (not the final dumping ground - these are included in Bare), dams, levees, and spillways of appropriate dimensions, filtration plants, and heavy concentrations of antennas or satellite dishes; along with the related operational buildings.

2.24 Institutional - specialized government or private features which meet the educational, religious, medical, governmental, protective, and correctional needs of the public. Parking lots and associated grounds are included with these features. Includes public and private schools (not day care), cemeteries, state capitols, city halls, courthouses, libraries, churches, convents, monasteries, hospitals and training hospitals, post offices, police and fire departments, prisons, and military bases. Only the military-business areas of a military base are classified here; residential, airport, athletic fields, and vegetated areas are classified in the appropriate category. 2.25 Agricultural Business - structures and all associated grounds used for raising plants or animals for food or fiber. Includes fish farms and hatcheries, feedlots, poultry farms, dairy farms, temporary shipping and holding pens, animal breeding or training facilities, and greenhouses. (Farmsteads including a dwelling are classified as Residential, not Agricultural Business.)

2.26 Transportation - Roads, railroads, airports, port facilities, and their associated lands. Roads and railroads include the right-of-way, interchanges, and median strips. Category includes railroad stations, railroad yards, bus stations, highway maintenance yards, school bus parking and service yards, and park-and-ride lots. Port facilities include loading and unloading facilities, docks, locks and, temporary storage areas. Associated warehousing and transfer stations for truck or rail are included only if they appear to be an integral part of the airport or port facility. Nearby but separate warehouses will be classified as light industry.

2.27 Entertainment and Recreational - areas and structures used predominantly for athletic or artistic events, or for leisure activities, and all associated lands and developed parking areas. Includes outdoor amphitheaters, drive-in theaters, campgrounds, zoos, sports arenas (including indoor arenas), developed parks and playgrounds, community recreation centers, museums, amusement parks, public swimming pools, fairgrounds, and ski complexes (not the ski slopes). Marinas with over 25% of water surface covered by docks and boats are included here.

2.3 Mixed Urban - developed areas which have such a mixture of residential and non-residential features where no single feature meets the minimum mapping unit specification. This category is used when more than one-third of the features in an area do not fit into a single category. Often applicable in the central, urban-core area of cities.

3.0 BARE - undeveloped areas of the earth not covered by water which exhibit less than 25% vegetative cover or less than 5% vegetative cover if in an arid area. The earth's surface may be composed of bare soil, rock, sand, gravel, salt deposits, or mud.

3.1 Transitional Bare - areas dynamically changing from one land cover/land use to another, often because of land use activities. Includes all construction areas, areas transitioning between forest and agricultural land, and urban renewal areas which are in a state of transition.

3.2 Quarries/Strip Mines/Gravel Pits - areas of extractive mining activities with significant surface disturbance. Vegetative cover and overburden are removed for the extraction of deposits such as coal, iron ore, limestone, copper, sand and gravel, or building and decorative stone. Current mining activity does not need to be identifiable. Inactive or unreclaimed mines and pits are included in this category until another land cover or land use has been established. Includes strip mines, open-pit mines, quarries, borrow pits, oil and gas drilling sites, and gravel pits with their associated structures, waste dumps, and stockpiles.

3.3 Bare Rock/Sand - includes bare bedrock, natural sand beaches, sand bars, deserts, desert pavement, scarps, talus, slides, lava, and glacial debris.

3.4 Flats - A level landform composed of unconsolidated sediments of mud, sand, gravel, or salt deposits. Includes coastal tidal flats and interior desert basin flats and playas.

3.5 Disposal - designated areas where refuse is dumped or exists, such as landfills, trash dumps, or hazardous-waste disposal sites. Reclaimed disposal areas or those covered with vegetation do not qualify.

4.0 VEGETATED - areas having generally 25% or more of the land or water with vegetation. Arid or semi-arid areas may have as little as 5% vegetation cover.

4.1 Woody Vegetation - land with at least 25% tree and (or) shrub canopy cover

4.11 Forested - land where trees form at least 25% of the canopy cover

4.12 Shrub land - areas where trees have less than 25% canopy cover and the existing vegetation is dominated by plants that have persistent woody stems, a relatively low growth habit, and which generally produce several basal shoots instead of a single shoot. Includes true shrubs, trees that are small or stunted because of environmental conditions, desert scrub, and chaparral. In the eastern US, include former cropland or pasture lands which are now covered by brush to the extent that they are no longer identifiable or usable as cropland or pasture. Clear-cut areas will exhibit a stage of shrub cover during the regrowth cycle. Some common species which would be classified as shrub land are mountain mahogany, sagebrush, and scrub oaks.

4.13 Planted/Cultivated Woody (Orchards/Vineyards/Groves) - areas containing plantings of evenly spaced trees, shrubs, bushes, or other cultivated climbing plants usually supported and arranged evenly in rows. Includes orchards, groves, vineyards, cranberry bogs, berry vines, and hops. Includes tree plantations planted for the production of fruit, nuts, Christmas tree farms, and commercial tree nurseries. Exclude pine plantations and other lumber or pulp wood plantings which will be classified as Forest.

4.132 Citrus - trees or shrubs cultivated in orchards or groves that bear edible fruit such as orange, lemon, lime, grapefruit, and pineapple.

4.133 Non-managed Citrus - orchards or groves containing fruit bearing trees or shrubs which are no longer maintained or harvested by humans. Evidence of non-managed citrus includes the growth of non citrus shrubs, trees, and grasses within a orchard or grove.

4.2 Herbaceous Vegetation - areas dominated by non-woody plants such as grasses, forbs, ferns and weeds, either native, naturalized, or planted. Trees must account for less than 25% canopy cover while herbaceous plants dominate all existing vegetation.

4.21 Natural Herbaceous - areas dominated by native or naturalized grasses, forbs, ferns and weeds. It can be managed, maintained, or improved for ecological purposes such as weed/brush control or soil erosion. Includes vegetated vacant lots and areas where it cannot be determined whether the vegetation was planted or cultivated such as in areas of dispersed grazing by deral or domesticated animals. Includes landscapes dominated by grass-like plants such as bunch grasses, palouse grass, palmetto prairie areas, and tundra vegetation, as well as true prairie grasses.

4.22 Planted/Cultivated Herbaceous - areas of herbaceous vegetation planted and/or cultivated by humans for agronomic purposes in developed settings. The majority of vegetation in these areas is planted and/or maintained for the production of food, feed, fiber, pasture, or seed. Temporarily flooded are included in this category. Do not include harvested areas of naturally occurring plants such as wild rice and cattails.

4.223 Row Crops - areas used for the production of crops or plants such as corn, soybeans, vegetables, tobacco, flowers and cotton. Fields which exhibit characteristics similar to row crops, but that do not have any other distinguishing features for a more specific category may be included.

4.2232 Sugar Cane - a very tall tropical grass up to 15 feet high with thick tough stems that is cultivated as the main source of sugar. It can be found in tropical and sub-tropical areas of the United States such as Louisiana, Florida, Hawaii, and Texas.

4.224 Cultivated grasses - areas of herbaceous vegetation, including perennial grasses, legumes, or grass-legume mixtures that are planted by humans and used for erosion control, for seed or hay crops, for grazing animals, or for landscaping purposes

4.2241 Pasture/Hay - areas of cultivated perennial grasses and/or legumes (e.g., alfalfa) used for grazing livestock or for seed or hay crops. Pasture lands can have a wide range of cultivation levels. It can be managed by seeding, fertilizing, application of herbicides, plowing, mowing, or baling. Pasture land has often been cleared of trees and shrubs, is generally on steeper slopes than cropland, is intended to graze animals at a higher density than open rangeland, and is often fenced and divided into smaller parcels than rangeland or cropland. Hay fields may be more mottled than small grain fields as they are not plowed annually and may be harvested and baled two or three times a year in some locations. On the Arroyo Colorado Project, this category also contains turf farms and maintained lawn grasses.

4.3 Vegetated Wetland - areas where the water table is at, near, or above the land surface for a significant part of most years and vegetation indicative of this covers more than 25% of the land surface. Wetlands can include marshes, swamps situated on the shallow margins of bays, lakes, ponds, streams, or reservoirs; wet meadows or perched bogs in high mountain valleys, or seasonally wet or flooded low spots or basins. Do not include agricultural land which is flooded for cultivation purposes.

4.31 Woody Wetland - areas dominated by woody vegetation. Includes seasonally flooded bottom land, mangrove swamps, shrub swamps, and wooded swamps including those around bogs. Wooded swamps and southern flood plains contain primarily cypress, tupelo, oaks, and red maple. Central and northern flood plains are dominated by cottonwoods, ash, alder, and willow. Flood plains of the Southwest may be dominated by mesquite, saltcedar, seepwillow, and arrowweed. Northern bogs typically contain tamarack or larch, black spruce, and heath shrubs. Shrub swamp vegetation includes alder, willow, and buttonbush.

4.32 Emergent Herbaceous Wetlands - areas dominated by wetland herbaceous vegetation which is present for most of the growing season. Includes fresh-water, brackish-water, and salt-water marshes, tidal marshes, mountain meadows, wet prairies, and open bogs.

Appendix C
Equation for the ERDAS Imagine® Maximum Likelihood Classifier (Decision Rule)

The equation for the maximum likelihood classifier is as follows:

$D = \ln(a_c) - [0.5 \ln(|Cov_c|)] - [0.5 (X-M_c)T (Cov_{c-1}) (X-M_c)]$

Where:

D = weighted distance (likelihood)

c = a particular class

X = the measurement vector of the candidate pixel

M_c = the mean vector of the sample of class c

a_c = percent probability that any candidate pixel is a member of class c (defaults to 1.0, or is entered from *a priori* knowledge)

Cov_c = the covariance matrix of the pixels in the sample of class c

$|Cov_c|$ = determinant of Cov_c (matrix algebra)

Cov_{c-1} = inverse of Cov_c (matrix algebra)

ln = natural logarithm function

T = transposition function (matrix algebra)

The inverse and determinant of a matrix, along with the difference and transposition of vectors, would be explained in a textbook of matrix algebra. The pixel is assigned to the class, c, for which D is the lowest (Leica 2005, 279).

Appendix D

Accuracy Assessment of Classified Image by 101 "Ground Truthed" Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

Sample Point	Actual LULC	Classified LULC	Strict LULC Interpretation	Based on Actual Pixel Not LULC Class of Surrounding Area	+ Grouping of Asphalt Shingles and Asphalt Road	+ Grouping of Pasture, Lawn, Natural Herbaceous, and Shrubland	Impervious v. Pervious
1	Forest	Forest	.9909	.9909	.9909	.9909	.9909
2	Forest	Forest	.9909	.9909	.9909	.9909	.9909
3	Shrubland	Shrubland	.9909	.9909	.9909	.9909	.9909
4	Forest (Pixel contains partial shadow)	Shrubland	0	0	0	0	.9909
5	Shrubland	Shrubland	.9909	.9909	.9909	.9909	.9909
6	Pasture/Hay	Shrubland	0	0	0	.9909	.9909
7	Natural Herbaceous	Shrubland	0	0	0	.9909	.9909
8	Pasture/Hay	Shrubland	0	0	0	.9909	.9909
9	Pasture/Hay (Bare ground/depression below dam)	Natural Herbaceous	0	0	0	.9909	.9909
10	Pasture/Hay	Natural Herbaceous	0	0	0	.9909	.9909
11	Natural Herbaceous	Shrubland	0	0	0	.9909	.9909
12	Pasture/Hay	Shrubland	0	0	0	.9909	.9909
13	Concrete Sidewalk	Concrete	.9909	.9909	.9909	.9909	.9909
14	Pasture/Hay	Pasture/Hay	.9909	.9909	.9909	.9909	.9909

Accuracy Assessment of Classified Image by 101 “Ground Truthed” Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

15	Natural Herbaceous (Mowed portion of state road right of way less than 8 cm tall)	Lawn	0	.9909	.9909	.9909	.9909
16	Shrubland	Shrubland	.9909	.9909	.9909	.9909	.9909
17	Pasture/hay	Shrubland	0	0	0	.9909	.9909
18	Lawn	Shrubland	0	0	0	.9909	.9909
19	Pasture/Hay	Natural Herbaceous	0	0	0	.9909	.9909
20	Shrubland (Natural herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909
21	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
22	Lake/pond	Asphalt Shingles	0	0	0	0	0
23	Asphalt Shingles	Asphalt Road	0	0	.9909	.9909	.9909
24	Shrubland (Tree/forest pixel)	Forest	0	.9909	.9909	.9909	.9909
25	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909
26	Lawn (Very rough lawn looks like pasture but less than 8 cm tall)	Pasture/Hay	0	0	0	.9909	.9909
27	Shrubland	Lawn	0	0	0	.9909	.9909
28	Forest	Forest	.9909	.9909	.9909	.9909	.9909
29	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909

Accuracy Assessment of Classified Image by 101 "Ground Truthed" Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

30	Forest	Forest	.9909	.9909	.9909	.9909	.9909
31	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909
32	Shrubland (Borders forest and contains partial shadow)	Forest	0	0	0	0	.9909
33	Forest	Forest	.9909	.9909	.9909	.9909	.9909
34	Pasture/Hay	Shrubland	0	0	0	.9909	.9909
35	Pasture/Hay	Lawn	0	0	0	.9909	.9909
36	Natural Herbaceous	Pasture/Hay	0	0	0	.9909	.9909
37	Asphalt Shingles (Shadow in pixel)	Asphalt Shingles	.9909	.9909	.9909	.9909	.9909
38	Lawn	Lawn	.9909	.9909	.9909	.9909	.9909
39	Forest	Forest	.9909	.9909	.9909	.9909	.9909
40	Shrubland	Forest	0	0	0	0	.9909
41	Shrubland	Natural Herbaceous	0	0	0	.9909	.9909
42	Asphalt Road (Mixed pixel with concrete curb)	Asphalt Shingles	0	0	.9909	.9909	.9909
43	Forest (Pixel borders natural herbaceous)	Shrubland	0	0	0	0	.9909
44	Pond/Lake	Asphalt Shingles	0	0	0	0	0
45	Shrubland	Natural Herbaceous	0	0	0	.9909	.9909

Accuracy Assessment of Classified Image by 101 "Ground Truthed" Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

46	Forest (Shadow in pixel)	Forest	.9909	.9909	.9909	.9909	.9909
47	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909
48	Pasture/Hay	Lawn	0	0	0	.9909	.9909
49	Shrubland	Lawn	0	0	0	.9909	.9909
50	Forest (Natural herbaceous pixel)	Lawn	0	0	0	0	.9909
51	Asphalt Road	Asphalt Shingles	0	0	.9909	.9909	.9909
52	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909
53	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
54	Asphalt Road (Mixed pixel with bare road shoulder)	Bare Soil	0	0	0	0	0
55	Shrubland	Natural Herbaceous	0	0	0	.9909	.9909
56	Natural Herbaceous	Lawn	0	0	0	.9909	.9909
57	Natural Herbaceous (Bare portion of Redwood Road right of way)	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
58	Asphalt Shingles	Asphalt Road	0	0	.9909	.9909	.9909
59	Shrubland	Shrubland	.9909	.9909	.9909	.9909	.9909

Accuracy Assessment of Classified Image by 101 “Ground Truthed” Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

60	Forest (Mixed pixel with natural herbaceous)	Lawn	0	0	0	0	.9909
61	Shrubland	Pasture/Hay	0	0	0	.9909	.9909
62	Pasture/Hay	Lawn	0	0	0	.9909	.9909
63	Natural Herbaceous	Shrubland	0	0	0	.9909	.9909
64	Natural Herbaceous	Pasture/Hay	0	0	0	.9909	.9909
65	Natural Herbaceous	Pasture/Hay	0	0	0	.9909	.9909
66	Natural Herbaceous	Pasture/Hay	0	0	0	.9909	.9909
67	Natural Herbaceous	Pasture/Hay	0	0	0	.9909	.9909
68	Lawn (Full shadow in pixel)	Shrubland	0	0	0	.9909	.9909
69	Concrete Sidewalk	Concrete	.9909	.9909	.9909	.9909	.9909
70	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
71	Lawn (Borders natural herbaceous)	Natural Herbaceous	0	0	0	.9909	.9909
72	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
73	Pasture/Hay	Lawn	.9909	.9909	.9909	.9909	.9909
74	Shrubland	Shrubland				.9909	.9909
75	Shrubland (Natural herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909
76	Shrubland (Natural herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909

Accuracy Assessment of Classified Image by 101 "Ground Truthed" Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

77	Pasture/Hay	Pasture/Hay	.9909	.9909	.9909	.9909	.9909
78	Asphalt Shingles	Asphalt Shingles	.9909	.9909	.9909	.9909	.9909
79	Lawn (Mixed pixel with concrete patio)	Shrubland	0	0	0	.9909	.9909
80	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
81	Shrubland (Natural Herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909
82	Shrubland (Natural Herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909
83	Concrete Sidewalk	Concrete	.9909	.9909	.9909	.9909	.9909
84	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
85	Concrete Driveway	Concrete	.9909	.9909	.9909	.9909	.9909
86	Natural Herbaceous (Located in depression)	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
87	Asphalt Road	Asphalt Road	.9909	.9909	.9909	.9909	.9909
88	Shrubland (Natural herbaceous pixel)	Natural Herbaceous	0	.9909	.9909	.9909	.9909
89	Pond/Lake	Asphalt Shingles	0	0	0	0	0
90	Lawn(Mixed Pixel with lawn, concrete, and shadow)	Shrubland	0	0	0	.9909	.9909

Accuracy Assessment of Classified Image by 101 “Ground Truthed” Sample Points (Correct Classification = .9909, Incorrect Classification = 0)

91	Asphalt Shingles	Asphalt Shingles	.9909	.9909	.9909	.9909	.9909
92	Concrete Sidewalk (Mixed pixel with asphalt road)	Asphalt Shingles	0	0	0	0	.9909
93	Lawn (Full shadow in pixel)	Asphalt Shingles	0	0	0	0	0
94	Concrete Driveway	Concrete	.9909	.9909	.9909	.9909	.9909
95	Shrubland	Shrubland	.9909	.9909	.9909	.9909	.9909
96	Concrete Sidewalk	Concrete	.9909	.9909	.9909	.9909	.9909
97	Natural Herbaceous	Natural Herbaceous	.9909	.9909	.9909	.9909	.9909
98	Concrete Sidewalk	Concrete	.9909	.9909	.9909	.9909	.9909
99	Concrete Driveway	Concrete	.9909	.9909	.9909	.9909	.9909
100	Concrete Driveway	Asphalt Road	0	0	0	0	.9909
101	Natural Herbaceous	Bare Soil	0	0	0	0	.9909
Sample Point	Actual LULC	Classified LULC	Strict LULC Interpretation	Based on Actual Pixel Not LULC Class of Surrounding Area	+ Grouping of Asphalt Shingles and Asphalt Road	+ Grouping of Pasture, Lawn, Natural Herbaceous, and Shrubland	Impervious v. Pervious
Overall Classification Accuracies (%)			**41.5842**	**49.5050**	**53.4654**	**86.1386**	**95.0495**