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**A Comparison of Two Common Classification Procedures for Economical
Urban Land Cover Mapping using NAIP Imagery**

by

Kent Lowell Simons

A thesis submitted to the faculty of

Brigham Young University

in partial fulfillment of the requirements for the degree of

Master of Science

Department of Geography

Brigham Young University

March 2009

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BRIGHAM YOUNG UNIVERSITY

GRADUATE COMMITTEE APPROVAL

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This thesis has been read by each member of the following graduate committee and by majority vote has been found to be satisfactory.

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ABSTRACT

A Comparison of Two Common Classification Procedures for Economical Urban Land Cover Mapping using NAIP Imagery

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Department of Geography

Master of Science

Detailed urban land cover maps are increasingly useful and important applications of remote sensing. Municipal agencies and others use land cover maps and data for numerous critical local planning and monitoring functions and for urban geographical research studies. Because of this, there is a demand for accurate urban land cover maps that can be produced quickly and economically. The availability of very high resolution multispectral imagery is an important factor in enabling such production, as the judicious selection of source imagery has a large impact on the resulting map products. Likewise, the implementation of appropriate digital image processing methods is crucial for deriving urban land cover maps of acceptable accuracy and cost. This study compared two common image classification algorithms using 2006 NAIP 1-meter GSD CIR images of Orem and Provo, Utah. The two classification procedures – conventional per-pixel supervised classification coupled with post-classification filtering, and object-based feature extraction – were compared for resulting accuracy and, in general terms, for their cost-effectiveness. Results demonstrated that object-based feature extraction has the

potential to produce maps with better accuracy, but at a somewhat higher cost than per-pixel supervised classification. Classification errors and their probable causes are discussed; also a number of options for improving the classification accuracy are presented together with considerations of the potential costs involved. Although the ultimate goal of economical production of accurate urban land cover maps was not fully realized, this study nevertheless has established a cost containment baseline upon which methodological improvements can be built.

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A Comparison of Two Common Classification Procedures for Economical Urban Land Cover Mapping using NAIP Imagery

INTRODUCTION

Municipal government agencies are primary users of urban land cover data and maps. These agencies have responsibility and purview over local concerns that typically include urban planning and development, local environmental monitoring and management, transportation planning, utilities and services, recreation and parks, environmental justice, public health, emergency planning and management, urban forestry, and so forth. Accurate and timely maps of urban land cover can be important sources of information useful to municipal agencies and others for analysis and decision support in all these application areas and perhaps more.

However, acquisition of useful land cover maps can be problematic for municipal governments. Practical issues such as budget constraints and inadequate in-house technical capabilities may limit the ability of agencies to produce or otherwise obtain the type of land cover map products they need. Ideally, maps of urban land cover should be affordable and relatively easy to produce or acquire, while providing acceptable accuracy in their thematic content. Whether map products are created in-house by the agency itself or are acquired through a procurement process from a geospatial mapping services provider, the end goal is the same: high quality, temporally relevant, cost-effective maps that meet the agency's needs.

Historically, the production of detailed land cover data for urban areas has been a labor- and time-intensive endeavor (Fitzpatrick-Lins, 1981; Mathieu, Aryal, & Chong, 2007). It required skilled personnel to perform visual interpretation of aerial photographs and/or obtain extensive *in situ* field data measurements. With the goal of drastically reducing human labor costs, researchers

during the past 20 years have developed digital processing algorithms that harness computer power to semi-automatically create GIS-ready map layers from remotely sensed data. Nevertheless, it is interesting to contemplate whether or not the objective has actually been realized. Indeed, the question may be asked: Are high quality, cost-effective maps of urban land cover being routinely produced on an operational basis for use by municipal agencies today? Evidence supporting an affirmative answer to this question seems to be lacking.

Two critical factors – source imagery and processing methods – are at the nexus of the decision process for producing usable urban land cover maps. Other factors will also exert influence, but these two key elements must be selected and executed effectively for there to be a reasonable prospect of achieving the goal. The recent proliferation of options for source imagery and processing algorithms makes this decision process non-trivial and possibly confusing for municipal agencies and others who desire to move forward with programs that require current land cover maps.

Numerous methods have been developed to create accurate urban land cover maps from remotely sensed data. However, many of these methods utilize relatively complex and/or experimental algorithms and computationally-intensive processing steps, or require extensive and detailed preparation of knowledge bases, expert rules, etc. A large percentage of research studies reported in the literature were exclusively focused on accuracy as their core concern; most of these virtually ignored issues of cost and operational viability. Similarly, a variety of remotely sensed imagery are available that have potential for use in creating urban land cover maps. Some studies noted in the literature used source imagery that is either costly and/or difficult to acquire, or not of appropriate resolution for detailed urban applications. Unfortunately, the issue of careful selection of source imagery and processing methods for creating urban land cover maps has often been dealt with only superficially in the research literature.

In the specific context of this study it was necessary to narrow the problem to a manageable scope. It was not feasible to test every existing type of source imagery, nor was it possible to test

every type of processing method mentioned in the literature. Fortunately, comprehensive, exhaustive tests were not necessary: information available in the literature has helped to focus and refine realistic choices for imagery and methods. Some researchers have addressed imagery characteristics including spatial resolution, spectral resolution and band selection, temporal concerns, pre-processing, and even cost issues, that are germane to selection of imagery for urban applications (e.g., Aplin, 2003; Herold, Gardner, Hadley, & Roberts, 2002; Walker & Blaschke, 2008). Likewise, many researchers have tackled processing methods and results with respect to their relevancy for detailed urban studies and applications (e.g., Thomas, Hendrix, & Congalton, 2003; Yuan & Bauer, 2006).

Based on such prior work, this study selected source imagery and processing methods that are considered to be viable candidates for economical production of accurate urban land cover maps. The source images selected are US National Agricultural Imagery Program (NAIP) 1-meter GSD CIR scenes of Orem and Provo, Utah. Two competing processing methods have been selected: 1) per-pixel supervised classification coupled with post-classification filtering; and 2) object-based feature extraction.

Research Questions and Hypotheses

The research questions addressed in this study are:

1. Is NAIP 1-meter CIR imagery a useful and appropriate selection of source data for urban land cover mapping?
2. Can conventional per-pixel supervised classification produce urban land cover maps of usable accuracy, and can application of post-classification filters improve the accuracy?
3. Can object-based feature extraction result in better accuracy than supervised classification, and if so what are the additional costs in analyst time and computer processing time?

To address these questions, this research has two related hypotheses:

1. Object-based feature extraction will create a more accurate urban land cover map than per-pixel supervised classification, using the same NAIP CIR imagery as source data for both methods.
2. The object-based feature extraction procedure will require more investment in analyst/operator time and computer processing time than the supervised classification procedure.

In this study, the first hypothesis was tested using standard accuracy assessment methods and metrics including error/confusion matrices, overall accuracy, and the Kappa statistic (Foody, 2002). The second hypothesis was tested by recording and reporting the elapsed times required by the analyst and the computer to perform each step of the candidate procedures. The time measurements served as proxies for cost metrics and were used to inform a general discussion of the cost-effectiveness of the two methods.

Significance of this Research

The purpose of this study was not to develop any new technology or advance new theory. Rather, an applied research approach was adopted in an effort to further the practical application of remote sensing to help solve local urban geographical issues. There is an apparent gap between achievements in research laboratory settings and what actually becomes operational in real-world problem-solving situations (Steering Committee on Space Applications and Commercialization, 2001). Efforts are needed to help transition research results into the development of viable applications that can deliver tangible benefits to communities and their residents.

LITERATURE REVIEW

Because land cover classification and mapping has been one of the foremost areas of remote sensing research for at least 30 years, the research literature in this area is plentiful. However, studies involving detailed urban applications of land cover have mostly come about only in the past 8-10 years, which generally corresponds to the advent of very high resolution satellite data. The following subsections review and discuss concepts found in the literature that are particularly relevant to the research questions of this study.

Development of Remote Sensing for Urban Land Cover Mapping

The first known overhead remotely sensed image was a crude aerial photograph taken from a hot air balloon over the city of Paris in 1858 (J. R. Jensen, 2007, p. 67). It was therefore also the first case of urban remote sensing. However, automated derivation of detailed urban thematic maps from remotely sensed imagery is very much a contemporary science. The demand for detailed urban geographical studies has intensified in the past two decades or so, due to worldwide trends in rapid urbanization and accompanying concerns about environmental impacts and sustainable growth (Andersson, 2006; Maktav, Erbek, & Jurgens, 2005). This increase in demand has, in turn, driven much research in urban geography and especially development of remote sensing capabilities aimed at providing the detailed data and information needed to better manage urban growth and its accompanying concerns (Longley, 2002). Simultaneously, dramatic improvements in computer processing power including both hardware capabilities and image processing software algorithms have occurred in recent years. Also, just in the last 8-10 years, very high spatial resolution (4 meter and finer) commercial satellite imagery has become available (Stoney, 2007). This convergence of information demand, computer processing power, and high resolution imagery in the past decade has fueled dramatic developments in detailed urban land cover and land use research and applications.

Before further consideration of recent developments, a brief look back is needed. Aerial reconnaissance of military targets, beginning in World War I and progressing throughout the 20th century, laid the basic groundwork for later civilian applications of urban remote sensing (J. R. Jensen, 2007, pp. 74-80). Analog aerial photography dominated non-military remote sensing before the launch of the first Landsat satellite in 1972 (then known as Earth Resource Technology Satellite). Visual photo interpretation was practically the only viable processing methodology prior to development of effective computer-based processing. Techniques to quantify and map land cover usually employed sampling and statistical methods, and oftentimes manual drafting or digitizing of thematic boundaries (Fitzpatrick-Lins, 1981; Nowak et al., 1996). These techniques were labor/cost-intensive, non-synoptic, and reliant on human interpretations, thus highly variable and not able to be standardized.

The series of Landsat satellites launched by NASA starting in 1972 were the first orbital platforms put into operation with capability of providing global-coverage imagery for civilian research and applications. The first three Landsat satellites were equipped with the Multispectral Scanner (MSS) instrument which produced digital images in five spectral bands with 79-meter spatial resolution. Landsat 4 (launched 1982) and 5 (launched 1984) carried the Thematic Mapper (TM) sensor which imaged the earth surface at 30-meter spatial resolution in 7 spectral bands. After failure of the Landsat 6 mission, Landsat 7 was launched in 1999 with the Enhanced Thematic Mapper Plus (ETM+) sensor on board, which provides 7-band multispectral imagery at 30-meter spatial resolution and adds a panchromatic band at 15-meter resolution (J. R. Jensen, 2007, pp. 198-211; Stoney, 2007). The Landsat program has continued to provide earth imagery long past its expected lifespan.

The Landsat program has had immeasurable influence on the science of thematic mapping in general and land cover mapping in particular. It was designed and primarily used for medium-scale observations of the earth's surface for environmental studies, and has been used for uncounted regional studies and applications (e.g., Vogelmann, Sohl, Campbell, & Shaw, 1998).

The availability of the satellite data spurred many avenues of research into image processing and made possible numerous applications of earth imagery. The US Geological Survey (USGS) sponsored the first proposed standard for land use/land cover classification systems, spurred by the increase in interest and research in this area (Anderson, Hardy, Roach, & Witmer, 1976). Despite the relatively poor (by today's standards) spatial resolution, some researchers even began to apply MSS and TM data to urban geographical problems (e.g., J. R. Jensen, 1979). The MSS and TM data could not resolve details of urban scenes; nevertheless it was the best satellite data available and researchers developed methods such as Spectral Mixture Analysis (SMA) in efforts to understand sub-pixel level details of land cover in urban areas. The majority of useful digital image processing techniques for land cover classification were initially developed and tested during the era of Landsat TM data. Even now, Landsat data continues to be used in applications such as urban change detection/analysis (e.g., Xian & Crane, 2005), as the archival imagery is the most consistent multi-date data source available.

In the meantime, aerial imagery capabilities and usage also progressed, although somewhat in the shadow of interest in satellite-based remote sensing. In the period of the 1980's and 1990's, aerial imagery moved into the digital era. Photographic film gradually was superseded by digital sensors. These became more precise and were coupled with airborne inertial navigation systems and then GPS capabilities. Aerial imagery was able to provide very high spatial resolution data well-suited for detailed urban studies long before any satellite systems could do so. For example, a landmark study of urban ecology and human-environmental systems was performed in Salt Lake City, Utah, in the early-mid 1990's using high resolution color-infrared aerial imagery (Ridd, 1995).

Another important development occurred in the 1990's with the introduction of imaging spectrometry or hyperspectral systems (J. R. Jensen, 2007, p. 241). These sensors, such as NASA's Airborne Visible Infrared Imaging Spectrometer (AVIRIS), provided very high spectral resolution data, sometimes with over 200 very narrow bands. Researchers began using

hyperspectral imagery for urban research and applications because of its ability to make fine distinctions between similar urban land cover materials (Herold, Gardner, Hadley, & Roberts, 2002; Roessner, Segl, Heiden, & Kaufmann, 2001). The spatial resolution of hyperspectral data sometimes is not as fine as multispectral aerial imagery, which can be a limitation for some applications; nevertheless hyperspectral imagery will continue to be an important and valuable data source for urban studies into the future (Gamba & Dell'Acqua, 2007).

The launch and operation of new higher-resolution satellites starting in late 1999 with IKONOS-2 signaled another milestone in urban mapping development. The IKONOS instrument provides multispectral imagery with 4-meter spatial resolution and a 1-meter panchromatic band. Then in 2001 the QuickBird satellite became operational and began delivering imagery with sub-meter panchromatic resolution, and multispectral bands with nominal 2.44-meter resolution (Stoney, 2007). Even before the IKONOS launch, in anticipation of these very high resolution satellite data becoming available, some researchers performed simulation experiments to evaluate the performance of this type of imagery for urban land cover mapping purposes (Aplin, Atkinson, & Curran, 1999). A marked increase in research and development of urban remote sensing applications can be linked directly to availability of very high spatial resolution satellite imagery beginning less than 10 years ago.

The confluence of technological developments with the demand for better urban geographical studies in just the past 10 years is remarkable. Geographical tools and systems we now take (almost) for granted have not been around for very long: high resolution imagery, sophisticated digital image processing systems, un-restricted GPS signals and devices, modern integrated GIS software and geospatial databases, and computer processing power – these have all gained significant maturity and integration in less than a decade. They are all being applied to help solve problems of rapid urban growth and sprawl, urban environmental and ecological issues, and other urban quality-of-life and sustainability concerns.

Principal Uses of Urban Land Cover Maps

The following subsections review several categories of applications of urban land cover maps that are noted in the research literature.

Change Detection/Analysis

Detailed land cover maps are commonly used to perform post-classification change detection, analysis, and/or modeling. Urban growth and sprawl is a significant concern for many communities throughout the world, and using multi-temporal land cover data is a valuable device for detecting and thus better understanding its extent and effects on an urbanizing area. As mentioned by textbook authors (e.g., J. R. Jensen, 2005, p. 482), post-classification analysis is often the preferred change detection procedure, and requires as input two (or more) accurately classified maps. For example, a study in the Puget Sound area of Washington used medium-resolution Landsat ETM+ imagery from 1991 and 1999 to create two classified land cover maps used to perform a change comparison and analysis (Alberti, Weeks, & Coe, 2004). In another wide-ranging study, areas in the city of Baltimore, Maryland, and several medium-sized towns in China were analyzed to determine urban ecological changes over time (Ellis et al., 2006); a combination of source imagery was used to first map land cover using a very detailed ecotope-based classification system, then a change analysis revealed fine-scale landscape ecotope changes. Another study examined urbanization in the Tampa Bay, Florida, watershed and used land cover data derived from 1991 and 2001 imagery as input to a cellular automata growth model to predict future urban growth patterns (Xian & Crane, 2005). A recent study used the Baltimore, Maryland, metropolitan area as a test-bed for examining object-based land cover classified maps as input to an object-based change analysis procedure (W. Zhou, Troy, & Grove, 2008). In a broadly-based position paper, Aspinall (2002) discussed and proposed a comprehensive data & analytical infrastructure in which land cover data and maps are central to the envisioned change analysis and modeling processes. These examples, among others, highlight

the importance of accurate land cover maps in performing detailed post-classification change analysis for urban areas.

Urban Planning

In a related vein, accurate and timely maps of urban land cover are useful to help inform urban planning activities, and to support sustainable development policies and practices. Urban planners fundamentally need to know what is “on the ground” now, before they can make rational decisions about future development options and plans. As an example, researchers at the University of Connecticut reported sharing research results (including land cover maps) with local municipal officials as an aid in land use planning decisions (Civco, Hurd, Wilson, Arnold, & Prisløe, 2002); the provided land cover data included information on impervious surface measurements, forest fragmentation, and urban growth/sprawl. Another research study, performed in Korea, reported performing analyses of land cover changes for the express purpose of informing regional sustainable development planning and policy (X. Chen, 2002). In a positional article, Maktav, Erbeck, & Jurgens (2005) called for increased use of remote sensing-derived maps in areas experiencing rapid urbanization (especially in developing countries) as a means to support and inform better urban planning and sustainable development. A recent study in China used ASTER imagery and an object-based methodology to map land cover for the city of Beijing (Y. Chen, Shi, Fung, Wang, & Li, 2007). Transportation system origins and destinations have been analyzed for travel distances and accessibility based on land cover types mapped from remote sensing imagery (Wang & Trauth, 2006). Finally, the report of a workshop entitled “Earth Observation for Urban Planning and Management” discussed then-current state of the art and made a number of recommendations for enhanced application of remote sensing for urban planning purposes; included are specific ideas for increased usage of accurate, detailed urban land cover maps (Nichol et al., 2007).

Urban Ecological Studies

Awareness and study of urban environmental and ecological concerns has increased greatly in recent decades, paralleling the global urban growth trend. Accurate and timely maps of urban land cover can play an important role in assessing and monitoring urban ecological health. A recent article on urban ecology discussed the use of “spatially explicit data” integrated with socio-economic data layers, to help assess urban ecology and ecological services (Andersson, 2006). In his landmark study, Ridd (1995) put forward the V-I-S (vegetation-impervious-soil) model (a form of land cover map) as an approach to the study of human ecosystems, urban biophysical systems, and urban morphology. Several other studies have emphasized the role of vegetation in urban environments and so focused their remote sensing classification work to extract and highlight urban vegetation cover and its distribution (Buyantuyev, Wu, & Gries, 2007; Conway & Hackworth, 2007; Hashiba, Tanaka, & Sugimura, 2006; Myint, 2006; Nichol & Lee, 2005; Small, 2001). Creation and use of a detailed urban land cover map for biodiversity assessment and modeling was at the center of another study (Mathieu, Aryal, & Chong, 2007), and a recent study in Minnesota created detailed land cover maps to analyze urban change and to model impacts on the local environment (Yuan, 2008). In another paper that is focused on urban ecosystems, the authors devise and advance a hierarchical classification system that is intended to facilitate interdisciplinary research in human-natural heterogeneous systems (Cadenasso, Pickett, & Schwarz, 2007).

Irrigation Assessment

Growing cities located in more arid climatic regions are challenged to supply irrigation water for residences, parks, golf courses, commercial enterprises, etc. Land cover maps (sometimes supplemented with land use data) have been used to quantify the areal extent of irrigated vegetation within a city’s scope of responsibility as a means to address current and future water needs (Stow et al., 2003).

Urban Forestry

Urban forests are an important sub-set of urban vegetation and have often been treated independently due to the special environmental properties of city trees. Accordingly, the measurement and assessment of urban forests is an important use of detailed land cover maps derived from remote sensing. Early articles (Nowak et al., 1996; Sacamano, McPherson, Myhre, Stankovich, & Weih, 1995) reported on methods for measuring the urban forest that relied on visual interpretation of aerial photographs or videography and statistical sampling methods. An updated study discussed the use of AVHRR and Landsat TM data, but still used statistical methods to estimate urban forest cover as a substitute for creating land cover maps (Nowak, Noble, Sisinni, & Dwyer, 2001). Another study, performed in Germany, used high resolution aerial CIR imagery coupled with an experimental texture detection algorithm to extract and map trees in Berlin, Germany, but this approach ignored other types of land cover (Zhang, 2001). More recently, in a Baltimore, Maryland, study that analyzed distributions of urban trees, the researchers employed manual heads-up digitizing of high resolution IKONOS multispectral data to derive land cover map fragments of selected sample neighborhoods (Grove et al., 2006). Another study, done in Phoenix, Arizona, used true color aerial digital imagery and an object-based automated classification procedure to map the urban forest (Walker & Briggs, 2007). From these examples one can infer the value of a high quality urban land cover map that would provide detailed data about the urban forest (along with all other classes of land cover).

Impervious Surfaces

Impervious surfaces are another important class of land cover that has been the focus of study by a number of researchers. These surfaces (i.e., pavements, building roofs, etc.) are indicative of human settlements and altered natural land cover regimes, and they affect changes in storm water runoff, groundwater resources, water quality, etc. In one study the researchers used a variety of high resolution imagery and a combination of processing methods to derive maps of

imperviousness, from which several municipal uses were discussed including calculating storm water runoff per parcel (J. R. Jensen, Hodgson, Tullis, & Raber, 2005). Another study done for the city of Scottsdale, Arizona, mapped impervious surfaces to model storm water runoff and potential flood impact areas (Thomas, Hendrix, & Congalton, 2003). The effects on water quality from runoff pollution sources have been discussed as important uses of land cover maps that detail impervious surfaces (Hester, Cakir, Nelson, & Khorram, 2008; Park & Stenstrom, 2008; Sawaya, Olmanson, Heinert, Brezonik, & Bauer, 2003; Yuan & Bauer, 2006). Furthermore, engineering work to design storm water drainage systems requires the determination of an areal runoff coefficient value, which can be calculated based on impervious surface map data (Thanapura et al., 2007).

Urban Heat Island

The land cover of an urban area, particularly the balance between vegetation and impervious surfaces, has been shown to be correlated to the urban heat island effect. Remotely sensed imagery has been used to create land cover data needed for various analytical approaches to measuring and monitoring the urban heat island (Akbari, Rose, & Taha, 2003; Gluch, Quattrochi, & Luvall, 2006; Myint, Mesev, & Lam, 2006; Weng & Lu, 2008).

Population Estimation

There is often a need to estimate current population for a given area in the interim period between censuses. Toward this end, a recent study examined the statistical relationship between housing unit density and land cover types based on land cover metrics derived from a classification of remotely sensed imagery (Hardin, Jackson, & Jensen, 2008).

Input for Additional Analysis

As mentioned or implied already, sometimes an urban land cover map is not an end-product in itself but can be valuable input for further analyses and integration with other datasets. An important example is the case where a land use map is to be derived from a land cover map

(Aplin, 2003; Barr & Barnsley, 2000; Herold, Scepan, Muller, & Gunther, 2002) (also, see discussion below on the distinction between land use and land cover). Another example is where multi-temporal land cover maps are a key data source used to build dynamic urban growth models (Aspinall, 2002; Civco et al., 2002; Hardin, Jackson, & Otterstrom, 2007; Xian & Crane, 2005). Several studies have integrated land cover maps with socio-economic data to study quality of life (R. R. Jensen, Gatrell, Boulton, & Harper, 2004; G. Li & Weng, 2007), environmental justice (R. R. Jensen, Gatrell, Boulton, & Harper, 2005), and relationships between human and natural features in urban environments (Grove et al., 2006; Mennis, 2006).

Clearly, detailed maps of urban land cover can be used for a variety of valuable applications. It is interesting to observe that in many of the examples cited in the literature, researchers were first obliged to create one or more land cover maps as a prelude to their ultimate study objectives. If such a thing as standardized, timely, and accurate land cover maps already existed for a given urban study area, advanced research work could simply leverage them as a trusted data source rather than needing to create such 'from scratch' from source remote sensor data.

Land Cover, Land Use, and Classification Schemes

The terms land cover and land use are related but not synonymous. Several definitions have been offered for these terms (Briassoulis, 2000; J. R. Jensen, 2005, p. 340). Land cover is more fundamental: it refers to structural elements/features/materials on or very near the surface of the earth with no regard for how human beings use them. On the other hand, land use is the way that land cover types have functional meaning for human usage. For example, a land cover class may be 'grass', but a land use definition might be interpreted to be 'residential lawn', 'golf course', or 'city park'. Similarly, 'building' or 'roof' is a land cover class, but when a structure is identified as 'single-family home', 'apartment building', or 'commercial building', then those are land use labels. An important distinction is that land cover can be directly classified from remote sensing imagery, but land use usually cannot. Land use must be interpreted or inferred using land cover,

neighborhood contextual clues, and human *a priori* knowledge (Aplin, 2003; Briassoulis, 2000; Mesev, 2003).

Unfortunately, land use and land cover have not always been clearly distinguished from each other in classification research reported in the literature. A number of studies used classification schemes with mixed land cover and land use classes (Aitkenhead & Dyer, 2007; X. Chen, 2002; Choi & Usery, 2004; Herold, Liu, & Clarke, 2003; Myint, Wentz, & Purkis, 2007; Park & Stenstrom, 2008; Platt & Goetz, 2004; Platt & Rapoza, 2008; Pozzi & Small, 2005; Wentz, Stefanov, Gries, & Hope, 2006; Xu & Gong, 2007). On the other hand, clear distinctions between land cover and land use have been made by many researchers, and several have emphasized the inferential nature of deriving the latter from the former (Aplin, 2003; Barr & Barnsley, 2000; Cadenasso et al., 2007; Herold, Scepan et al., 2002; Mesev, 2003).

Land cover classification schemes are devised to help transform remote sensor data into useful thematic information. As outlined by J Jensen (2005, p. 341), a successful classification system should be mutually exclusive (no taxonomic overlap of classes, i.e., each class is distinct), exhaustive (nothing omitted, no resulting unclassified areas), and hierarchical (multi-level structure that defines sub-classes and super-classes). The set of classes selected for use in a classification scheme become the labels used on the legend of the resulting thematic map.

A number of land classification schemes have been designed and promulgated as standards (Anderson et al., 1976; Cadenasso et al., 2007; J. R. Jensen, 2005, pp. 340-349). One of the first widely implemented standard schemes was Anderson et al (1976) under the auspices of the US Geological Survey. The Anderson or USGS classification system is hierarchical and combines both land use and land cover classes. Levels I and II were designed for use with low to medium resolution data (such as Landsat MSS or TM) at regional and continental scales, not for highly detailed urban studies. The National Land Cover Dataset 2001 (Homer et al., 2007) employs this classification scheme. Levels III and IV of the Anderson scheme can be useful at local/urban scales.

The landmark study by Ridd (1995) introduced the vegetation-impervious-soil or V-I-S model. While Ridd's paper was not explicitly about mapping urban land cover, it nevertheless has influenced thinking on urban land cover classification systems. The simplicity of the V-I-S model enhances its utility, and it has been used as a base for other urban classification schemes (e.g., Phinn, Stanford, Scarth, Murray, & Shyy, 2002).

Some research has employed vegetation indices in various forms, the most common of which are the Normalized Differential Vegetation Index (NDVI) and Leaf Area Index (LAI). NDVI or LAI have sometimes been used as a substitute for land cover classification. In studies that have used vegetation indices, actual land cover classes are often inferred from and/or statistically correlated with index values (Conway & Hackworth, 2007; R. R. Jensen et al., 2004; Thanapura et al., 2007).

Detailed classification of urban areas requires a classification system that matches the fine-scale heterogeneity of city features. In their paper, Cadenasso, Pickett, & Schwartz (2007) propose a new classification scheme named High Ecological Resolution Classification for Urban Landscapes and Environmental Systems (HERCULES) that is designed specifically for detailed urban land cover applications. This is a simple, flexible, hierarchical system that explicitly separates structure (land cover) from function (land use). A few recent urban land cover studies have used HERCULES or a variant/extension of it (Grove et al., 2006; W. Zhou et al., 2008).

The number of classes used in a classification scheme seems to be inversely related to the resulting accuracy of a classified map: using fewer general classes tends to higher accuracies, while using many detailed classes can be a factor in lower accuracies (Jain & Jain, 2006). Specialized classified maps, such as for urban forest or imperviousness mapping, typically divide the feature space into just two classes and thus can achieve fairly high accuracy (Yuan & Bauer, 2006; Zhang, 2001). Land cover maps intended for more general purpose uses need comprehensive representative classes, but in order to realize acceptable accuracies the number of classes should be kept as small as possible.

Selection of Imagery for Detailed Urban Mapping

Remotely sensed imagery comes from sensors onboard aerial (sub-orbital) or satellite (orbital) platforms. Images are either panchromatic (a single band covering all visible wavelengths), multispectral (a few wide bands usually including at least blue, green, red, and near-infrared portions of the spectrum), or hyperspectral (many narrow bands covering the visible spectrum and continuing into near-, middle-, and sometimes thermal-infrared wavelengths). In addition to traditional passive optical imagery, other sensors can provide RADAR or LIDAR actively-acquired data. Some remote sensor data are produced and made available by government entities, and some are provided by private commercial firms. Some data can be custom acquired/produced on a contractual paid basis. Some data are available at no cost, some at nominal cost, and some are relatively expensive. For all practical purposes today, all these data are available in digital format, but they are in a variety of file types and structures.

From among the plethora of options decisions need to be made about what data may be best suited for a particular purpose. The problem of selecting imagery for creating urban land cover maps is non-trivial. Key issues and characteristics of the data must be weighed including: spatial, spectral, radiometric, and temporal resolution, availability and cost of the imagery, and what types of preprocessing have already been done or may need to be done. It is highly unlikely that all of these factors can be optimized simultaneously (Baltsavias & Gruen, 2003).

Spatial Resolution

A widely-accepted rule of thumb states that for a remote sensor to detect a feature, the nominal spatial resolution of the sensor should be less than one-half the size of the feature (J. R. Jensen & Cowen, 1999). This is especially important in urban remote sensing applications: the instantaneous field of view (IFOV) or pixel size needs to be fine enough to resolve objects in the urban scenes that are required by end-use applications.

As pertaining to detailed urban remote sensing, Welch (1982) is frequently cited by later authors (e.g., Aplin, 2003) as setting the standard for spatial resolution. In that paper, Welch suggested that resolutions of 0.5 to 10 meters IFOV would be required to adequately resolve features found in urban scenes, and that some cities (especially in Asian areas) might need even finer spatial resolution. For many years only aerial imagery could satisfy this requirement – it was not until 1999 with the successful deployment of IKONOS-2 that commercial satellite systems began to deliver imagery of less than 10 meters spatial resolution (Stoney, 2007).

Notwithstanding Welch’s recommendation, however, many researchers from the 1980’s even up to the present time have used imagery of relatively coarse spatial resolution to study urban land cover (see Table 1). Characteristics other than spatial resolution – such as spectral properties, availability, synoptic coverage, temporal revisit times, etc. – have sometimes made coarse resolution satellite data attractive/suitable for some urban purposes. Of course, prior to the availability of IKONOS data, researchers had limited options: they could use either fine-scale aerial imagery, or coarser resolution satellite data.

Table 1: Examples of remote sensor data used for urban land cover studies (m = meter, pan = panchromatic, m/s = multispectral, h/s = hyperspectral)

<i>Aerial or Satellite</i>	<i>Sensor</i>	<i>Spatial Resolution</i>	<i>Sample Studies</i>
Satellite	Landsat MSS	79m m/s	(J. R. Jensen, 1979)
Satellite	Landsat TM	30m m/s	(Alberti et al., 2004; X. Chen, 2002; Guindon, Zhang, & Dillabaugh, 2004; Phinn et al., 2002; Platt & Goetz, 2004; Pozzi & Small, 2005; Small, 2001; Stefanov, Ramsey, & Christensen, 2001; Stuckens, Coppin, & Bauer, 2000; Wentz et al., 2006; Yang, Xian, Klaver, & Deal, 2003; Yuan, Sawaya, Loeffelholz, & Bauer, 2005)
Satellite	Landsat ETM+	15m pan, 30m m/s	(Alberti et al., 2004; Buyantuyev et al., 2007; Civco et al., 2002; Conway & Hackworth, 2007; Hardin et al., 2008; Islam & Metternicht, 2005; G. Li & Weng, 2007; Lu & Weng, 2004, 2005; Mennis, 2006; Myint, 2006; Park & Stenstrom, 2008; Song, Civco, & Hurd, 2005; Weng & Lu, 2008; Wu & Murray, 2003; Xian & Crane, 2005; Yang et al., 2003; Zoran et al., 2008)

Satellite	EO-1 Hyperion hyperspectral	10m pan, 30m h/s	(Xu & Gong, 2007)
Satellite	SPOT HRV	10m pan, 20m m/s	(Amarsaikhan, Ganzorig, Ache, & Blotevogel, 2007)
Satellite	ASTER	15m m/s	(Y. Chen et al., 2007; R. R. Jensen et al., 2004; Y. Li & Gong, 2006; Stefanov & Netzband, 2005)
Satellite	IKONOS	1m pan, 4m m/s	(Baltsavias & Gruen, 2003; Dare, 2005; Davis & Wang, 2002; Ellis et al., 2006; Grove et al., 2006; Hashiba et al., 2006; Herold, Gardner et al., 2002; Herold et al., 2003; Herold, Scepan et al., 2002; Jain & Jain, 2006; J. R. Jensen et al., 2005; Mathieu et al., 2007; Nichol & Lee, 2005; Platt & Rapoza, 2008; Repaka, Truax, Kolstad, & Hara, 2004; Sawaya et al., 2003; Small, 2003; Stow et al., 2003; Wang & Trauth, 2006; Zoran et al., 2008)
Satellite	QuickBird	0.6m pan, 2.5m m/s	(Carleer & Wolff, 2006; Dare, 2005; Gamba & Dell'Acqua, 2007; Hashiba et al., 2006; J. R. Jensen et al., 2005; Repaka et al., 2004; Schutzberg, 2008; Thanapura et al., 2007; Van de Voorde, De Genst, & Canters, 2007; Yuan, 2008; Yuan & Bauer, 2006)
Satellite	ERS-2 C-band, JERS-1 L-band RADAR	26m, 18m	(Amarsaikhan et al., 2007)
Aerial	panchromatic	<1m	(Choi & Usery, 2004)
Aerial	true color m/s	<1m - 4m	(Akbari et al., 2003; Aplin, 2003; Aplin et al., 1999; Baltsavias & Gruen, 2003; Barr & Barnsley, 2000; Ellis et al., 2006; Hodgson, Jensen, Tullis, Rierdan, & Archer, 2003; Huang, Shyue, Lee, & Kao, 2008; J. R. Jensen et al., 2005; Nowak et al., 2001; Nowak et al., 1996; Phinn et al., 2002; Thomas et al., 2003; Walker & Blaschke, 2008; Walker & Briggs, 2007; Wentz et al., 2006)
Aerial	CIR m/s	<1m - 4m	(Cadenasso et al., 2007; Nichol & Lee, 2005; Ridd, 1995; Zhang, 2001; Q. Zhou, Li, & Kurban, 2008)
Aerial	hyperspectral	3m - 10m	(Gamba & Dell'Acqua, 2007; Gluch et al., 2006; Herold, Gardner et al., 2002; Platt & Goetz, 2004; Roessner et al., 2001)
Aerial	LIDAR	n/a	(Baltsavias & Gruen, 2003; Hodgson et al., 2003; Huang et al., 2008; J. R. Jensen et al., 2005; G. Zhou & Kelmelis, 2007)

One of the main problems with coarse resolution imagery for urban classification is the prevalence of non-pure, or spectrally-mixed pixels, where more than one land cover class or

feature might be represented by the reflectance values of the pixels. Finer resolution imagery reduces but does not eliminate this problem. Very high spatial resolution images contain a relatively larger proportion of spectrally pure pixels; however, other problems such as increased noise are usually introduced with finer resolution scenes. Some researchers have asserted that higher resolution data actually reduces classification accuracy, but this remains a controversial claim and seems to be very dependent on classification methods, class schemes, and other factors (Myint, 2003).

Some sensors provide both panchromatic and multispectral data (e.g., IKONOS), with the pan imagery at finer spatial resolution. A preprocessing technique known as image fusion or pan-sharpening has been used to combine the higher spatial resolution of the pan layer with the spectral properties of the multispectral bands (Ehlers, 2007). Studies that have done this with IKONOS imagery obtained 1-meter spatial resolution multispectral data (Davis & Wang, 2002; Ellis et al., 2006; Jain & Jain, 2006); QuickBird users have obtained sub-meter multispectral imagery (Hester et al., 2008; Van de Voorde et al., 2007). However, Ehlers (2007) points out that most pan-sharpening techniques change the spectral data values of the multispectral bands in the process of fusing them with the panchromatic layer, thus introducing spectral uncertainty and possible errors.

Aerial imagery provides very high resolution data and has been used for decades for urban mapping applications. Aerial imagery was the only viable source for resolving fine details of urban scenes before IKONOS and QuickBird data become available and it continues to have an important role. The United States federal government has implemented several programs featuring aerial imagery, notably the National Aerial Photography Program (NAPP) and the National Agricultural Imagery Program (NAIP), both of which were intended to provide regular synoptic coverage of the country (USDA, 2005; USGS, 1991). Of these, the NAIP program is more recent, and provides 1-meter digital image scene files in both true color (RGB) and color-infrared (CIR) multispectral formats. States, counties, and cities also commission aerial

photography missions from time to time to update land information, and these high spatial resolution data may be available through local government geospatial data clearinghouses.

A blue-ribbon panel commissioned by the American Society for Photogrammetry and Remote Sensing (ASPRS) created an advisory report to the US Geological Survey on the subject of digital aerial orthoimagery (ASPRS, 2006). This report endorsed the position that aerial “orthoimagery is the most cost-effective of all GIS layers in terms of information content, and is the basis of a geospatial program” (p. 100). Further, the report recommended that the federal government sponsor and fund continuous programs to acquire nationwide aerial orthoimagery at 1-meter (sparsely settled areas), 1-foot (moderate density areas), and 6-inch (high density urban areas) resolutions (p. 107).

In summary, source imagery for urban land cover mapping is required to be of very high spatial resolution in order to resolve the heterogenous details of urban features. For a general purpose urban land cover map, the required spatial resolution should probably be no greater than two meters, and preferably one meter or less.

Spectral Resolution

Spectral information plays a vital role in image classification. Indeed, conventional per-pixel classification algorithms rely exclusively on spectral reflectance values. In the context of urban remote sensing, high spectral resolution principally means using many discrete bands of spectral data to help differentiate land cover materials from each other (Herold, Gardner et al., 2002; Herold, Schiefer, Hostert, & Roberts, 2007). In general, the fewer spectral bands used, the harder it may be to discriminate between the spectral profiles/signatures of specific land cover materials. As a practical matter for the purpose of detailed urban land cover mapping, a choice must be made between using multispectral data and hyperspectral (also known as imaging spectrometry) data, and then selecting which available spectral bands to use in the classification.

A paper that was published before very high spatial resolution imagery was widely available suggested that high spectral resolution is generally less important for urban mapping applications than high spatial resolution (J. R. Jensen & Cowen, 1999). However, that assertion was challenged recently in a study that analyzed the relative contributions of high spatial and high spectral resolution to overall classification accuracy (Gamba & Dell'Acqua, 2007). Very high spatial resolution imagery of urban areas reveals comparatively greater variety of surface materials, and the within-class spectral variance of many cover types is also dramatically increased. Thus, greater spectral resolution can help with finer discrimination of urban land cover materials in very high resolution imagery.

Unfortunately, the combination of very high spatial resolution and very high spectral resolution is physically difficult to achieve by remote sensors. The available electro-magnetic energy reflected from earth surface materials is gathered by a sensor and divided up among the bands being imaged. A panchromatic image can have extremely fine spatial resolution because all the available energy is concentrated into one very wide band for each pixel. Multispectral sensors divide the reflected energy into several (typically 3 to 7) separate bands of medium spectral width, thus the total energy is split up and a larger ground IFOV or pixel size is required in order to gather sufficient energy to register a useful image at each pixel. Hyperspectral remote sensing acquires reflectance data in many narrow spectral bands (dozens to hundreds of bands), but since the electro-magnetic energy is divided among the many bands, each band receives only a small fraction of the total available energy. Therefore, the ground IFOV or spatial area of each pixel must be large enough to gather sufficient energy to register a useful signature in each band for each pixel. Due to the underlying physics principles, therefore, it is usually not possible to have both very high spectral and spatial resolution simultaneously in the same remotely sensed data – especially from orbital sensors.

The few available satellite hyperspectral sensors do not provide sufficient spatial resolution for detailed urban mapping applications. However there are many hyperspectral sensors used in

airborne platforms (such as AVIRIS, CASI, DAIS, HyMap, etc.) and these predominate in the literature (e.g., Herold et al., 2007). Examples of studies that have used hyperspectral data for urban land cover discrimination are shown in Table 1. Still, in many cases even airborne hyperspectral sensors cannot provide sufficient spatial resolution for certain urban applications.

In addition, use of hyperspectral imagery usually involves more complicated processing than does multispectral data (Herold et al., 2007; J. R. Jensen, 2005, pp. 433-457). Few commercial software packages are capable of processing hyperspectral data effectively. Selection of useful bands is more complex and data-reduction techniques such as principal components analysis (PCA) may need to be performed (Herold, Gardner et al., 2002; Xu & Gong, 2007). Therefore, users of hyperspectral data for urban land cover mapping will likely face challenges in analysis of the data.

Data/image fusion has been done for the purpose of increasing the spectral resolution of remotely sensed imagery. In one study, SPOT optical imagery was combined with satellite RADAR InSAR data to increase the number of bands useful for land cover differentiation (Amarsaikhan et al., 2007). In a recent Minnesota study, researchers combined pan-sharpened QuickBird imagery with aerial NAIP images to obtain 7 useful bands at 1-meter spatial resolution, and reported enhanced accuracy and other benefits of using the multiple bands (Yuan, 2008).

Aerial digital imagery is typically acquired in 3 or 4 spectral bands. The visible spectrum is captured in blue, green, and red wavelength bands, and a near-infrared (NIR) band may also be imaged. The NIR channel is especially important for discriminating healthy vegetation (Davis & Wang, 2002; W. Zhou et al., 2008) and is required for calculating vegetation indices such as NDVI or LAI. It is common for aerial digital imagery to provide three bands: either visible RGB (called true color imagery), or red and green from the visible spectrum plus NIR. This latter combination of multispectral bands is usually referred to as false-color, color-infrared, or CIR.

Imagery available from the US NAIP program is available as both true color and CIR data (USDA, 2005).

In summary, detailed urban land cover mapping needs to differentiate between the various land cover materials found in urban scenes. Use of many spectral bands (higher spectral resolution) helps with this, but should not be at the expense of adequate spatial resolution. As a minimum requirement, CIR imagery with NIR, red, and green bands can be used, and if more useful bands are available at high spatial resolution then they will likely help to improve the classification accuracy.

Temporal Resolution

In the context of urban land cover mapping, temporal resolution of imagery is primarily concerned with the frequency of acquiring updated source data. This determines a map's temporal relevance – i.e., how current a land cover map is, or how frequently it can be updated or re-created. Many urban areas are experiencing rapid growth and change, so a land cover map could become outdated quickly, losing accuracy and thus value over time. Urban planning activities in particular need to have current and reliable land cover data.

Various update cycles for urban mapping needs have been recommended, generally ranging from 2 to 5 years (ASPRS, 2006, p. 101). Given that urban parcel developmental cycles can occur in one year or less (J. R. Jensen & Cowen, 1999) it may be that municipalities experiencing high rates of rapid growth could demand updates to land cover maps as frequently as one year intervals.

Virtually all satellite sensors can readily fulfill the requirement for frequent updates of source imagery. In the category of very high resolution systems, IKONOS has a revisit period of less than 3 days, and QuickBird from 1 to 5 days (J. R. Jensen, 2007, p. 235). Of course, poor atmospheric conditions over a given urban area (cloud cover, etc.) during a satellite's imaging pass often result in unusable imagery for many dates throughout the year. Nevertheless, the

likelihood of finding cloud-free imagery from these satellite sensors for multiple dates within a year is high.

The temporal frequency of custom-flown aerial imaging missions is dependent on budgets and the availability/scheduling of capable contractors, and also by local weather conditions. Theoretically (with no budget constraints) aerial urban imagery could be updated on demand or as often as desired. In practical reality, of course, annual municipal budgets may not include costs for aerial imagery very often, so the update cycle may be quite sporadic and for some communities may be non-existent.

Aerial programs sponsored and paid for by state or federal funds may offer the promise of regular updates. The NAIP program, for example, was established with the goal of synoptic coverage of the conterminous United States every 2 to 3 years on a state-by-state rotating basis (USDA, 2005). Its performance to date has not quite achieved the intended goal, as renewal of imagery for some states is lagging behind the intended three year interval.

Seasonality can also be a temporal consideration for urban land cover mapping. The time of year that imagery is acquired matters, especially for mapping of vegetation. Summertime images of a city can be strikingly different from wintertime images (for most cities outside the tropics). Deciduous trees will appear either with leaf-on canopy or leaf-off bare branches, and other types of vegetation also exhibit phenological differences depending on the season. The intended end-use of a land cover map might need to dictate the seasonality of its source imagery: if mapping of impervious surfaces is the chief concern, then leaf-off imagery will probably do a better job of accounting for all paved surfaces (Repaka et al., 2004), but if urban forestry or ecological studies are the chief concern then leaf-on imagery might be most appropriate (Grove et al., 2006).

Another temporal consideration is that of continuity and consistency of the imagery data source. Will the imagery selected for today's map production be available in the future, the next time we need to repeat the process? Satellite operations are not guaranteed, in fact it is a virtual certainty that each and every satellite will fail at some point (Stoney, 2007, see chart of expected

satellite operational lifespans). National aerial imagery programs, such as NAIP, are subject to budgetary and policy fluctuations and may be changed or discontinued. Advocates such as the ASPRS committee (ASPRS, 2006) make a strong case for continued refreshment of nationwide orthoimagery into the future but do not control that future.

In summary, urban land cover maps need to be updated regularly, so the temporal resolution of source imagery is an important consideration for appropriate selection. Attention should also be paid to seasonality of the imagery, and potential continuity of the data source.

Radiometric Resolution

Relatively little information appears in the literature with regard to the importance of radiometric resolution (pixel depth, or quantization) for detailed urban studies. Virtually all useful remote sensor data is available in at least 8-bit quantization, with more recent sensors able to provide 11, 12 or even 16-bit data. However few researchers have even mentioned quantization or radiometric resolution, and no studies (found in this literature search) have identified it as a key factor. For example, J Jensen entirely ignores this type of resolution in discussions of resolution requirements for urban remote sensing (J. R. Jensen, 2007, pp. 444-450). Another author notes that higher radiometric resolution may not improve information about urban-scale objects and features (Myint, 2007). From this, one can assume that radiometric resolution is probably not an important factor and should have little influence on selection of imagery for urban land cover maps.

Availability, Accessibility, and Cost

Some remote sensor data are relatively easy to obtain and others are more difficult. Also, costs vary from zero to thousands of dollars for imagery that is useful for urban applications.

In general, imagery that was acquired under US federal government non-security-related programs is made available for little or no cost to US citizens. United States federal law and policy (e.g., the Freedom of Information Act) essentially acknowledges that taxpayers own the

work product of the federal government and are entitled to obtain it (within security limitations). Data from Landsat, ASTER, and other US government-sponsored satellite programs are readily available and usually only cost a nominal fee for media and shipping, or can be downloaded via the internet. Data from aerial programs like NAPP and NAIP are likewise available either by internet download (for free), or media shipping (for a nominal fee). Because states have an option to jointly fund NAIP data acquisition and processing for their state, some states also provide NAIP imagery products. For example, NAIP imagery for the state of Utah is available for free download from the Utah State Geographical Reference Database (SGID) website (<http://gis.utah.gov/download>).

Imagery that is acquired by private commercial firms is usually available only for a fee. The terms of purchase, and the delivery mechanisms, differ based on each company's policies and marketing philosophy. At this time, the only satellite based sensors that can provide very high resolution data suitable for urban mapping (IKONOS and QuickBird) are privately owned by for-profit companies. These data can be expensive, requiring significant budgetary appropriations by municipal agencies or researchers who want to use them. Satellite sensors planned for near future operations (such as GeoEye) are likewise all privately owned, for-profit ventures.

In a positional paper by the WyomingView consortium (associated with AmericaView and sponsored by the USGS), the authors argue for expanded access to free or low-cost remote sensing data (Sivanpillai & Driese, 2007). This paper states the case that free and easy access to remote sensing data archives can be a catalyst to facilitate applications in government agencies and research institutions. Furthermore, barriers (real and/or perceived) often inhibit greater adoption and use of remote sensing data for useful applications at all levels. The authors conclude by saying "Our experience demonstrates that if remotely-sensed data can be obtained for low or no cost, and in a ready-to-use format, more users will adopt remote sensing technology."

Imagery Preprocessing

Another factor to be considered in the selection of remotely sensed imagery is what type of preprocessing will be necessary. The two main categories of image preprocessing are radiometric (or atmospheric) correction, and geometric correction (or geo-rectification) (J. R. Jensen, 2005, pp. 194-250). Additionally, some imagery may need to be topographically corrected (or ortho-rectified) to achieve planimetric accuracy. Most available remotely sensed data is “raw”, or not preprocessed. Some researchers have provided information in their reports regarding the preprocessing they had to perform prior to beginning the central processing methods of their research (Alberti et al., 2004; Davis & Wang, 2002; Hardin et al., 2008; Xu & Gong, 2007).

Some preprocessing may be done as an optional value-added service by the data provider. If the provider is a for-profit commercial firm then this option usually costs extra. In the case of NAIP imagery, the federal program includes in its scope and funding complete preprocessing of the imagery so that it is truly ready-to-use. NAIP imagery is geometrically corrected to the appropriate UTM zone, and it is ortho-rectified for planimetric accuracy. Meta-data is provided with NAIP imagery that documents the preprocessing procedures performed including the accuracy achieved (see Appendix A for a sample NAIP meta-data file).

Automated Processing Methods for Detailed Urban Mapping

The raw data of a remotely sensed image becomes more useful when it is transformed into information. Classification is the primary method used to transform remotely sensed data into a thematic land cover map (J. R. Jensen, 2005, pp. 337-338). A variety of computer algorithms have been developed that essentially attempt to mimic an experienced human analyst to examine the image and recognize patterns, then assign portions of the image to pre-determined classes. No method developed to date is completely automatic – all require input of some type of human *a priori* knowledge. Consequently, these methods can be characterized as computer-aided thematic information extraction systems.

Researchers have applied various types of classification methods to the problem of detailed urban land cover mapping. Also, many researchers have developed modifications or extensions to known methods, devised hybrid approaches that combine processing methods, and even developed new experimental approaches and algorithms. All the methods aim to produce high quality land cover maps or extraction of land cover features; indeed, the nearly exclusive focus of much of the research is on achieving better classification accuracy (sometimes with little regard for operational viability of the method).

Anyone needing to create a detailed land cover map is faced with the non-trivial challenge of selecting and implementing appropriate processing methods. In the subsections that follow, examples of methods found in the literature are reviewed with the intent to focus on those methods that seem to balance high classification accuracy with reasonable operational economics. In general, methods can be grouped into two main categories of classification approaches: pixel-based and object-based.

Pixel-based Classification

Conventional or traditional classification approaches operate on a per-pixel basis. These methods examine each pixel of the source image independently and assign class membership based on the spectral data available in that pixel. The most common per-pixel methods are supervised classification and unsupervised classification.

In a supervised classification procedure the analyst first identifies representative example training sites for each class of interest, and then the software processes the image to match pixels to the defined training examples. Several classification algorithms are available to determine to which class a pixel should belong. These algorithms (or classifiers) include Maximum Likelihood, Parallelepiped, Nearest Neighbor, Minimum Distance to Means, Neural Network, Expert System, and others. The Maximum Likelihood classifier (MLC) is a parametric statistical algorithm that works best with training class data that is normally distributed. Other classifiers are

non-parametric and do not assume normal distributions of class populations (J. R. Jensen, 2005, pp. 370-379).

Many examples are found in the literature of case studies that used a supervised classification procedure; it appears to be the most common per-pixel approach. Following are some examples of case studies that used supervised classification for detailed urban land cover applications:

- A 1999 study that was designed to evaluate the use of high spatial resolution data used 4-meter aerial imagery and a supervised classification method to map land cover in a mixed urban and peri-urban locale in England (Aplin et al., 1999). The per-pixel result was then generalized at the per-field level, and post-classification filters were applied to enhance the accuracy and usability of the classified map.
- Another study done in the UK used 2-meter aerial color imagery and supervised classification to produce a 5-class urban land cover map (Barr & Barnsley, 2000). Further processing was performed using an experimental “reflexive mapping” technique to enhance the accuracy of the map and prepare it for inferential land use analysis.
- In a study done in Columbia, Missouri, pan-sharpened 1-meter IKONOS data were processed using supervised classification and the parallelepiped algorithm to produce a 7-class land cover map with a reported 83% overall accuracy (Davis & Wang, 2002).
- Using aerial hyperspectral data, researchers in Santa Barbara, California, used the maximum likelihood classifier with 10 carefully chosen spectral bands of AVIRIS data to map 20 classes of land cover / land use, and reported 78.4% overall classification accuracy (Herold, Gardner et al., 2002).
- A hybrid approach that included supervised classification and spectral mixture analysis (SMA) was performed using Landsat TM and ETM+ medium resolution data for a land

cover change detection study in the Puget Sound, Washington area (Alberti et al., 2004). The relatively low spatial resolution of the data required the sub-pixel SMA technique to estimate land cover fractional values for each pixel.

- Urban heat island analysis was the object of a study that used aerial ATLAS 10-meter (15 bands) data and supervised classification with the parallelepiped algorithm to map land cover in Salt Lake City, Utah (Gluch et al., 2006).
- Another study done in Columbia, Missouri, extracted impervious surfaces and transportation features using supervised classification with the parallelepiped classifier (Wang & Trauth, 2006).
- Supervised classification using the maximum likelihood classifier was used in an Indian study to create a 3-class urban land cover map using pan-sharpened IKONOS imagery (Jain & Jain, 2006).
- A comparative study performed in the Phoenix, Arizona, area used several types of remotely sensed data, processed by different methods including supervised classification with the maximum likelihood algorithm (Wentz et al., 2006).
- An experimental study that compared per-pixel classification and an object-based method was performed in Mankato, Minnesota, using 2.6-meter QuickBird multispectral imagery as input to both procedures (Yuan & Bauer, 2006). Supervised classification used the maximum likelihood algorithm to create a 5-class land cover map with reported 87% overall accuracy (the object-based method reported 92.5% overall accuracy).
- A study performed using pan-sharpened QuickBird 0.61-meter imagery of a portion of the city of Ghent, Belgium, employed supervised classification with a neural net classifier (Van de Voorde et al., 2007). Three experimental post-classification

processes were then tested to evaluate their effectiveness in improving classification accuracy.

- A hybrid approach that combined supervised and unsupervised classification was done recently in an area of Raleigh, North Carolina (Hester et al., 2008). Pan-sharpened QuickBird 0.61-meter multispectral data was first classified into six high level classes by a supervised method, and then four of the categories were further classified by the unsupervised method to derive more detailed subclasses. Overall accuracy was reported to be 83%, then a GIS-based refinement technique was performed which increased the overall accuracy to 89%.

A problem commonly seen with the output of supervised per-pixel classification is that of isolated pixels, also called speckling or the “salt & pepper effect”. Because each pixel is analyzed independently, the spectral data of a given pixel may vary enough from its immediate neighbors that it gets assigned to a different class and thus stands alone. For many purposes it may be desirable to reduce this effect and produce a map with greater homogeneity. Post-classification processing, using smoothing filters or other techniques, has been done with some success to reduce speckling and increase overall classification accuracy (Aplin et al., 1999; Barr & Barnsley, 2000; Van de Voorde et al., 2007; Zhang, 2001).

Unsupervised classification uses K-means or ISODATA algorithms to create clusters of spectrally-similar pixels. This procedure then requires an analyst to organize, interpret, and label the clusters with meaningful land cover class designations. Following are some examples of studies found in the literature where unsupervised classification was used to derive urban land cover maps:

- A study to extract urban forested areas was performed in Germany with very high resolution aerial CIR imagery, and used unsupervised classification coupled with a texture detection algorithm (Zhang, 2001).

- In a study of imperviousness in Richland County, South Carolina, researchers combined aerial color imagery and LIDAR data and evaluated three classification methods including ISODATA unsupervised classification (Hodgson et al., 2003). Accuracy results for the unsupervised method were lower than for the other two techniques.
- Impervious surface measurements were obtained by unsupervised classification of QuickBird 2.4-meter multispectral imagery of Sioux Falls, South Dakota (Thanapura et al., 2007).
- A medium resolution land cover map of Terre Haute, Indiana was produced from Landsat ETM+ imagery using unsupervised classification, as a basis to calculate land cover metrics for a population estimation research study (Hardin et al., 2008).
- As mentioned above, Hester et al (2008) combined supervised and unsupervised classification methods in a North Carolina study.

A number of urban land cover studies that used medium or low spatial resolution imagery (such as Landsat TM or ETM+) have employed processing methods designed to analyze sub-pixel spectral data. Lower resolution images typically have a large proportion of spectrally-mixed pixels, especially in urban scenes where multiple land cover materials can be represented within the pixel reflectance values. Methods such as spectral mixture analysis (SMA) and variants have been employed with the intent to extract or estimate sub-pixel information from spectrally-mixed pixels (Alberti et al., 2004; Buyantuyev et al., 2007; Lu & Weng, 2004; Myint, 2006; Phinn et al., 2002; Small, 2001; Tang, Wang, & Myint, 2007; Weng & Lu, 2008; Wu, 2004; Wu & Murray, 2003; Xian & Crane, 2005; Yang et al., 2003; Zoran et al., 2008). Sub-pixel analysis techniques are less applicable and usually not needed when using very high spatial resolution imagery. Furthermore, these techniques can only estimate fractional amounts of land cover materials within each pixel and are therefore not useful for detailed urban land cover mapping.

Fuzzy logic has been used in some land cover classification studies. Fuzzy or soft classification approaches recognize the natural gradations of land cover and allow for pixels to be assigned a probability of membership in multiple classes. Some researchers have applied fuzzy classification techniques to urban land cover applications (Islam & Metternicht, 2005; Tang et al., 2007). However, the actual usefulness of soft classifications for making thematic maps is unclear; a fuzzily-classified map could be quite complicated to create and for end-users to interpret and implement for real-world applications. Fuzzy logic has been applied with both per-pixel and object-based classification procedures.

Several advanced classification methods have been developed that use artificial intelligence concepts to imitate the reasoning of an experienced human analyst. Artificial Neural Networks (sometimes abbreviated as NN or ANN) are non-parametric, sophisticated computing environments that try to mimic the structure and reasoning/processing of the human brain. Some researchers have applied ANNs to land cover classification problems (Aitkenhead & Dyer, 2007; R. R. Jensen & Binford, 2004; Van de Voorde et al., 2007). Another sophisticated technique is the use of Expert Systems, which usually employ a rule-based inferencing methodology. Researchers report varied experiences using rule-based or knowledge-based methods, and several have emphasized that building and testing the rules or knowledge base was a difficult and time-consuming effort (Amarsaikhan et al., 2007; Choi & Usery, 2004; Huang et al., 2008; J. R. Jensen et al., 2005; Myint, 2006; Stow et al., 2003; Van de Voorde et al., 2007; Wentz et al., 2006; W. Zhou et al., 2008). It should be noted that ANNs, Expert Systems, rule- or knowledge-based techniques, and decision trees have been adapted for use with both per-pixel and object-based classification approaches.

Conventional per-pixel classification methods may not perform well with imagery that is very high spatial resolution and relatively low spectral resolution (Herold, Gardner et al., 2002; Thomas et al., 2003; Yuan & Bauer, 2006). As noted previously, very high spatial resolution urban imagery is very heterogeneous and exhibits high within-class spectral variances. Because

per-pixel methods use only spectral data they are not always able to make consistent distinctions between classes of land cover with similar reflectance spectra (Herold, Scepan et al., 2002; Myint, 2007).

Despite the implications of its title, an interesting paper titled “Beware of per-pixel characterization of land cover” (Townshend, Huang, Kalluri, DeFries, & Liang, 2000) actually supports the notion that higher spatial resolution imagery can produce higher land cover classification accuracy using per-pixel methods. These researchers focused on low/medium-resolution Landsat TM data, and discussed the phenomenon of “pixel bleed”, i.e., reflectance data for individual pixels includes portions of the signal from surrounding pixels. Researchers have modeled this effect with the Modulation Transfer Function (MTF). The results and conclusions of Townshend et al. (2000) suggest that “land cover properties should be reported at spatial resolutions coarser than the individual pixel”, and “only in those situations where pixel size is small relative to the area of land cover units will these [MTF] effects be unimportant”. However, these conclusions should be interpreted with caution, as the study did not evaluate the MTF effect on high spatial resolution data.

Object-based Classification

In response to the shortcomings of per-pixel techniques, researchers have developed object-based methods that process image objects instead of individual pixels. Image objects are made up of contiguous groups of pixels that ideally perfectly represent real-world objects or homogenous landscape features. Object-based techniques are not new, but are generally considered more recent and innovative than pixel-based methods.

An object-based procedure first segments the image into homogenous image objects, and then applies a classification algorithm to assign class membership to the segments/objects. Whereas per-pixel classification methods can only use spectral data to differentiate between land cover materials, object-based methods can use a richer resource of spectral and spatial

information. A number of spectral and spatial features (including texture, shape, size, etc.) can be calculated for each object or image segment, and used to help differentiate land cover classes.

The texture and pattern of image objects can play an important role in object-based image analysis, and it is discussed by several authors (Aplin et al., 1999; Herold et al., 2003; Myint, 2003, 2007; Myint et al., 2006; Zhang, 2001). The concept of image or object texture can be difficult to precisely define, and likewise is challenging to codify in computer algorithms. Nevertheless, much research has focused on texture, and several texture metrics have been defined that are amenable to realization in software systems (Myint, 2007). The use of texture measures was investigated as early as 1979 as a means to better classify urban-fringe land covers (J. R. Jensen, 1979). However, Myint (2007) suggests that optimum use of texture measures requires the analyst to have a good understanding of the underlying theoretical background and mathematics upon which the techniques are based.

Following are some examples of case studies found in the literature that employed an object-based classification methodology:

- A 2002 study done in Santa Barbara, California, used IKONOS 4-meter multispectral imagery and the object-based methods of image segmentation and classification of image objects (Herold, Scepan et al., 2002). These authors strongly suggested that an object-based method is the only way to achieve high classification accuracy with high spatial resolution urban imagery.
- Mapping of impervious surfaces for storm water management was the purpose of a Scottsdale, Arizona, study that compared three processing methods including object-based classification with decision tree analysis (Thomas et al., 2003). The object-based method performed well, and the authors concluded that “the key to successful mapping from high-resolution imagery can be found in integrating spectral response with additional informational elements such as shape, texture, and context”.

- A study of transportation networks along the Mississippi Gulf Coast compared per-pixel supervised classification with object-based methods using both IKONOS and QuickBird data sources (Repaka et al., 2004).
- QuickBird 2.5-meter multispectral imagery of a portion of Ghent, Belgium, was used for an experimental object-based classification study (Carleer & Wolff, 2006). A focus of this work was to evaluate different segmentation levels and parameters, and to evaluate the selection of the most relevant object features to use for optimum accuracy results.
- Land cover mapping of the city of Beijing, China, was the purpose of a study that used object-based techniques with medium-resolution ASTER data (Y. Chen et al., 2007).
- A study of biodiversity assessment in Dunedin City, New Zealand, used object segmentation and classification with IKONOS imagery to map urban vegetation communities (Mathieu et al., 2007).
- Two related studies performed in the Phoenix, Arizona, metropolitan area used 0.6-meter aerial true-color imagery and object-based methods to map land cover and the urban forest (Walker & Blaschke, 2008; Walker & Briggs, 2007).
- A study compared an object-based approach to a conventional per-pixel supervised classification for land cover mapping of a peri-urban environment around Gettysburg, Pennsylvania, using IKONOS 4-meter multispectral imagery (Platt & Rapoza, 2008).
- An industry on-line magazine reported that a commercial geospatial services firm has used QuickBird 2.4-meter multispectral imagery and object-based feature extraction methods to develop detailed land cover maps of portions of the greater Chicago, Illinois, metropolitan area (Schutzberg, 2008).
- A recent study of the Mankato, Minnesota, area focused on environmental impacts due to land cover changes (Yuan, 2008). This work first fused QuickBird and NAIP

imagery to obtain 7 bands of 1-meter resolution multispectral data, and then applied object-based image segmentation and classification to create 4-class land cover maps for two different dates. The author reports achieving very high classification accuracy, with Kappa values over 0.9.

Similarly to per-pixel supervised classification, object-based procedures also use a specific classification algorithm to assign class membership to objects. A supervised approach is often done, where the analyst identifies representative image segments and identifies specific class membership for the sample segments. The software then uses an algorithm such as Nearest Neighbor to process all segments/objects in the image. This is usually an iterative process, allowing the analyst to adjust and refine the class designations for sample image objects, evaluating the results of each successive classification pass until a satisfactory result is obtained. Another approach can use a knowledge-base or decision tree rules that specify combinations of object features that define each class. Preparation and testing of the rules or knowledge base can be a lengthy iterative process.

Several authors have emphasized the importance of parameters that control the segmentation level, and the judicious selection of object features to be used for object classification. Both over-segmentation (many small segments) and under-segmentation (few, large segments) can result in less-than-optimum classification accuracy. Analysts typically use an iterative trial-and-error procedure to arrive at a 'best' segmentation level for the mapping task at hand; at least two studies have offered semi-automated methods to assist in defining optimal segmentation levels (Carleer & Wolff, 2006; Zhang & Maxwell, 2006). Another factor in resulting classification accuracy is the selection of feature combinations to be used by the classifier. Carleer & Wolff (2006) documented 33 total features in 3 categories (spectral, textural, morphological) that were calculated for each image object, and they evaluated individual features and combinations of features for their contributions to resulting accuracy.

Other Software Techniques

As documented in the literature, researchers are constantly working to develop improved methods – there is no shortage of innovation and experimentation. Many research efforts have sought to expand, extend, vary, and/or combine known methods.

Several studies have used hybrid approaches that combine methods, usually with the goal of getting the best of both techniques (Gamba & Dell'Acqua, 2007; Hester et al., 2008; Hodgson et al., 2003; Thomas et al., 2003; Wentz et al., 2006; Zhang, 2001). Hybrid approaches add increased complexity to the process and have not always demonstrated significant classification improvements.

As noted earlier in the sections on imagery resolution issues, techniques for image fusion have been developed that can contribute to higher mapping accuracy. These methods include pan-sharpening (Davis & Wang, 2002; Hester et al., 2008; Van de Voorde et al., 2007), and fusing data from multiple sensors (Yuan, 2008).

Also discussed earlier, post-classification processing using filters or other techniques have been applied to pixel-based classifications to smooth resulting classified images and reduce the salt & pepper effect.

Some researchers have developed software methods that address the special problems of detailed urban mapping, such as dealing with shadows and tall buildings. These topics are discussed in the following section.

Ancillary Issues Affecting Urban Land Cover Mapping

Shadows

High spatial resolution images of urban environments all contain shadows to some extent. The severity of cast shadows is determined by sun angle, the presence of tall urban objects like buildings and trees, and (sometimes) sensor angle. Shadows in satellite images are generally more severe than those in aerial imagery (Dare, 2005); satellites are in fixed orbits that allow little or no

flexibility in image acquisition, whereas aerial missions can be timed specifically to minimize shadows.

In the context of mapping urban land cover, shadows are a problem since they obscure whatever is actually on the ground in the area covered by the shadow. Some researchers have simply added a 'shadow' class in their classification scheme to help differentiate between shadows and other very dark surface elements such as water or dark impervious surfaces (Davis & Wang, 2002). An urban heat island study used a separate shadow class because shadowed surfaces exhibit separable thermal properties from other land cover types (Gluch et al., 2006).

However, simply classifying an area as 'shadow' is usually insufficient since it provides no useful information about actual land cover materials. A 2003 study in Minnesota discussed accuracy problems caused by shadows and recommended further study of the issue (Sawaya et al., 2003). Several recent studies have experimented with methods to automatically detect shadows in high resolution urban imagery and then remove or mitigate them (Dare, 2005; Y. Li & Gong, 2006; Nichol & Lee, 2005; Tsai, 2006; Van de Voorde et al., 2007; Yuan & Bauer, 2006). In general the methods discussed are complex and/or experimental, and efforts to replace shadows with correct land cover classes are still problematic and inconsistent (Dare, 2005). In a very recent study, it was found that fusing a QuickBird image with an aerial NAIP image had good success in mitigating shadow effects because shadows in the two sets of imagery were at very different angles and thus compensated for each other (Yuan, 2008).

To summarize, shadows exist in high resolution urban imagery, and methods to accurately replace them with true land cover types are difficult to implement and not perfected yet.

Tall Buildings Off Nadir

In addition to casting shadows, tall buildings also cause other problems in urban remote sensing. Unless a building is precisely at the nadir of the photograph or image, it will appear non-vertical or leaning, and will occlude other features on the side of the building furthest from nadir

(i.e., leaning away). The problem is similar to that of shadows in that portions of the land cover are not visible and thus are not accurately classified. In addition, one or two vertical facades of the “leaning” building may be visible and without correction will be classified as land cover features.

A solution has been proposed by G Zhou & Kelmelis (2007) that involves the use of several ancillary data sets: a digital terrain model (DTM), one or more digital building models (DBMs), and one or more ‘slave’ orthoimages. A DBM is required for each building that is to be orthorectified, and the ‘slave’ orthoimages are needed to fill in the image areas that were occluded by the skewed buildings in the original or ‘master’ image. Several complex processing steps are necessary to implement this proposed solution.

In summary, occlusion by off-nadir tall buildings can be a problem in high-resolution urban imagery. Methods to compensate are complex and require use of several ancillary datasets.

Seasonality of Imagery

The time of year that urban imagery is acquired can have a significant impact on a resulting land cover map for most non-tropical cities. Overhead images obtained during the growing season show deciduous trees in leaf-on condition, and the tree canopy will often obscure whatever is on the ground below the trees. By contrast, leaf-off imagery may reveal surface materials under the trees, but the extent of urban tree/forest canopy will be difficult to ascertain. Due to phenological cycles, other types of vegetation also exhibit temporal differences in remotely sensed imagery.

The urban imperviousness work by Hodgson et al (2003) used imagery acquired in early March, which showed trees not yet fully leafed out. A study that was focused on extracting road features in the Mississippi Gulf Coast region reported problems with imagery acquired at different times of the year: leaf-off images allowed good interpretation of road features, while leaf-on images showed full tree canopies but hid some road surfaces and edges (Repaka et al., 2004). Another study that mapped impervious surfaces mentioned leaf-on imagery can obscure

some impervious features, but suggested the difference may not be statistically significant (Sawaya et al., 2003). A study of the urban heat island effect in Sacramento, California, discussed the value of accurate above- and below-canopy land cover metrics and used statistical sampling methods to capture data about both (Akbari et al., 2003).

In summary, a given land cover map will usually reflect the seasonality of its source overhead imagery. Accuracy of areal measurements of specific cover classes and other land cover metrics from these maps will be influenced by the time of year that the imagery was acquired.

Accuracy Assessments of Land Cover Maps

Accuracy of derived thematic maps is very important and has been a key driving factor in research and development efforts. However, it is not easy to precisely define what accuracy means, nor is accuracy a simple thing to measure or interpret. Errors exist in all maps: a map fundamentally is a simplified model of reality, thus it has limitations and imperfections (Foody, 2002). Furthermore, no method of making maps is perfect, whether computer-assisted or entirely done by human expertise.

In spite of the challenges, it is nevertheless essential to make an assessment of the accuracy of a derived land cover map. Foody (2002) probably states it best:

“It is important, therefore, that the quality of thematic maps derived from remotely sensed data be assessed and expressed in a meaningful way. This is important not only in providing a guide to the quality of a map and its fitness for a particular purpose, but also in understanding error and its likely implications, especially if allowed to propagate through analyses linking the map to other data sets.” (p. 186)

Errors in classified maps fall into two categories: errors of commission and errors of omission. In reality, every misclassified pixel or image object is both an error of omission and commission; however, it has been found useful to look at misclassifications from both perspectives (J. R. Jensen, 2005, p. 499). The eventual end uses and users of a map may find certain categories of errors more problematic than others.

Although various methods of assessing accuracy have been employed, the most widely used and accepted practice in recent times is based on an error or confusion matrix (Congalton, 1991; Foody, 2002). This is a fairly simple but comprehensive device for tabulating sampled classification errors, and then deriving meaningful, quantitative, statistical measures of map accuracy. The matrix compares ground reference data (assumed to be the “truth” or reality of what is actually on the ground) with mapped classification results. Where the ground reference information and the mapped information agree there is no error; where they don’t agree it is assumed that the map is in error and has misclassified that point or feature.

To fill out the error matrix, probability-based statistical sampling methods are used to gather data about classification errors. City-wide imagery and maps typically involve extremely large data sets (especially when using very high resolution imagery), so it’s not possible to perform a census of every pixel in the image. Instead, a sound un-biased sampling methodology should be employed: usually either true random sampling or stratified random sampling (Foody, 2002). A statistically-significant number of random samples (pixels) are needed: the minimum number to be used can be calculated using the formula for the binomial probability theory (Fitzpatrick-Lins, 1981). The sample points are to be randomly distributed throughout the study area (for a true random sampling scheme) and should not coincide with training sites to ensure that no bias is introduced. If a stratified random sampling scheme is employed, then a sufficient number of sample points for each class must be distributed randomly within areas representing each of the classes on the map (J. R. Jensen, 2005, pp. 502-504).

At each sample point, it must be determined if what is shown on the classified map matches the ground reference data. If it does not agree, the nature of the misclassification is recorded. Summarized counts of the data obtained from examining all of the sample points are then entered into the error/confusion matrix. Details on construction of a proper error matrix are given by J Jensen (2005, p. 499).

Several measures of error can be derived from the confusion matrix, and can be calculated per class and for the overall map. These include: a measure of omission error called Producer's Accuracy, a measure of commission error called User's Accuracy, and the total percentage of correctly classified points called Overall Accuracy. The aforementioned are typically expressed as percentages. Another useful overall metric is the Kappa statistic, or Kappa Coefficient of Agreement (sometimes notated as K_{hat}). This is a discrete multivariate analytical measure that indicates how much the classified map agrees with the ground reference data compared to pure chance agreement. Calculation of Kappa from data in the error matrix results in a value between 0.0 and 1.0; values closer to 1.0 indicate better agreement/accuracy (J. R. Jensen, 2005, pp. 505-508).

Unfortunately, there is no universally accepted single, all-purpose measure of map accuracy. Some researchers have suggested a (somewhat arbitrary) goal or threshold of 85% overall accuracy for a classified map to be considered acceptably accurate, but these types of proposed standards have not seen wide acceptance (Foody, 2002). Instead, it has been recommended that classification study reports should include the complete raw error matrix, together with computed values for producer's accuracy, user's accuracy, overall accuracy, and Kappa. The eventual users of the report and/or the classified map can then determine their own interpretation and uses for the several reported accuracy measures.

It is worthwhile to note the importance of accuracy assessments for cases where multitemporal land cover maps are to be used for change detection/analysis purposes. This is a situation where 'the chain is no stronger than its weakest link' – in other words, the accuracy of the change detection cannot be any better than the worst accuracy of the input maps, and is usually even lower. Thus, high accuracy of the individual maps is very important as is proper assessment of their accuracies, as these all contribute to the ultimate assessment of the change analysis accuracy. A good example of this, with clear descriptions of accuracy assessment procedures and results, was given by W Zhou et al. (2008).

In the Aspinall (2002) paper, which proposed a comprehensive data and analytical infrastructure for land cover change analyses, the author emphasized capture and storage of land cover map accuracy data within a map metadata repository, and careful management of the accuracy metadata within the overall scheme.

Operational and Cost Issues

It is well beyond the scope and intent of this thesis to do financial analyses, business-case analyses, cost-benefit analyses, or the like. Nevertheless, a discussion of transitioning pure remote sensing research to useful real-world applications necessitates the consideration of cost and operational issues. In the literature, references by authors to these concerns have ranged from non-existent, to brief general comments, to extensive thoughtful treatments.

In an early study, J Jensen (1979) applied some texture measures to better classify urban fringe land cover elements. In his report the author cautioned that there is a cost-benefit trade-off: applying the texture measures improved overall accuracy to some extent, but at the cost of additional expense for data preprocessing. The implication was made that the increased cost may not always be worth the small improvement to the quality of the output map.

The concept of there being a trade-off between quality and cost is not new and not limited to the remote sensing community, of course. Basic project management theory attests there are three competing demands in the completion of any project: quality, cost, and time/schedule; furthermore, all three cannot be optimized simultaneously. If something must be done quickly, then quality and/or budget are sacrificed; if high quality standards are upheld, the project costs more and usually takes longer; if costs are tightly limited, it should be expected that something of less than top quality will be produced.

A thorough treatment of trade-offs between “decision quality” and “information cost” in the context of remote sensing applications was given by de Bruin & Hunter (2003). Their paper discussed the notion of “value of information” and they proposed using a decision method based

on probabilistic cost-benefit analysis to arrive at acceptable trade-offs or balance between competing demands. Although this paper only considered the data acquisition costs, a fuller interpretation of “information cost” perhaps should include both imagery cost and the processing costs needed to transform the data into useful information (i.e., thematic maps).

The Space Studies Board of the National Research Council, under the US National Academy of Sciences, convened a special steering committee in workshops held in 2000 (Steering Committee on Space Applications and Commercialization, 2001). The focus of the workshops and published report was on transfer of remote sensing technology from pure research into practical applications. Findings covered the general areas of life-cycle costs, education and training, outreach, applications research, requirements of application users, and standards and protocols. A fundamental conclusion of this report was that many good research efforts in remote sensing do not transition into useful applications. Gaps must be bridged that encompass both technical and social issues. In particular, there was explicit acknowledgement that research-to-applications models (including funding and incentives) useful in other fields do not (or did not) exist in remote sensing. It is not clear what progress has been made on technology transfer of remote sensing applications since the publication of that report.

The following list is intended to highlight some cases found in the literature where researchers discussed cost and/or operational issues in their reports:

- (Green, Kempka, & Lackey, 1994) stated that their project goal was not to develop new technologies but to tailor existing technologies for commercialization and introduction to the marketplace. They identified key issues in becoming operational for commercialization: product awareness, image cost, and ease of technical implementation.
- (DeFries & Townshend, 1999) addressed the challenges of moving from research to operational implementation for global land cover map production. The four main issues discussed were validation procedures (i.e., accuracy assessment), automation of

methods, continuity of data, and class schemes suitable for a wide range of applications.

- (Foody, 2002) declared that land cover data/maps are not readily available or trivially easy to acquire, and that full potential for creating land cover maps from remotely sensed data has not been realized.
- (Akbari et al., 2003) stated that one objective of their effort was to develop an automated process to obtain accurate land cover data in an efficient, reproducible manner. They also reported relatively low costs for obtaining aerial imagery for the study areas of their research.
- (Thomas et al., 2003) performed three classification methods and evaluated the time and effort required for each. They concluded that the most accurate of the three methods required a large amount of analyst time for preparation and testing of rules. The second most accurate method in their study was object-based classification, which was much more efficient and provided acceptable quality.
- (Wentz et al., 2006) measured and reported on five factors they felt could be used to influence selection of imagery and methods for land cover mapping: spatial and temporal extent, classification, accuracy, cost in analyst hours and money expended, and usability.
- (Grove et al., 2006) performed manual heads-up digitizing of a few sample study areas within the city of Baltimore, Maryland. They concluded the digitizing method was too time-consuming and costly, and that automated techniques are needed to produce land cover data more efficiently.
- (Mathieu et al., 2007) compared using an object-based method of classifying IKONOS data to previous experience performing manual photo interpretation. They concluded

that accuracy of the automated method was not quite as good as photo interpretation, but it was good enough for the purpose and was an order of magnitude more efficient.

- (Nichol et al., 2007) reported on a workshop held in Hong Kong on the subject of remote sensing applications for urban planning. The workshop examined issues that can help to promote practical applications of urban remote sensing. Relevant observations included: “fully automated land use classification in urban areas is not yet operational ... and manual interpretation of aerial photographs or high resolution imagery is still the norm”; also, “impediments to wider use of [remote sensing] data in urban planning and management are educational and institutional, not technical. The technology for image data acquisition is available and its wider utilisation is mainly dependent on increased awareness of its availability among practitioners, cost reductions, and easier integration into existing work procedures”.
- (Sivanpillai & Driese, 2007) called for freely available remote sensing data to foster more research and development and implementation of more practical applications.
- (Van de Voorde et al., 2007) implemented a hybrid classification approach that included neural network and rule-based classification enhancement routines. They reported that definition and testing of rules cost excessive amounts of time, and that the rules were specific for the site, imagery, and types of classification errors encountered, thus not transportable.
- (Walker & Blaschke, 2008; Walker & Briggs, 2007) in two similar studies used custom-flown aerial 0.61-meter color imagery to map urban forest extent. They discussed selection of aerial imagery as being an order of magnitude less expensive than very high resolution satellite data, and easily repeatable.
- (Hester et al., 2008) justified their use of per-pixel classification of very high resolution data. They conclude this method has value because of widespread familiarity and

software accessibility (i.e., the methods are readily available in standard software packages).

- (W. Zhou et al., 2008) used an object-based approach coupled with an expert system classifier, which they reported to be more computationally demanding than other methods. Also creating the knowledge/rule base was reported to be difficult and time-consuming.
- (Schutzberg, 2008) reported in an industry newsletter about the operational achievement of a commercial geospatial services company, which has produced standardized detailed land cover map products for portions of the Chicago, Illinois, metropolitan area. Reportedly, the firm uses QuickBird imagery and object-based feature extraction software to produce the maps.

Aside from the Schutzberg (2008) report, there is little evidence in the research literature that automated urban land cover mapping has become practically operational. This may be due to the very nature of pure scientific research and the purposes for which research studies are published, therefore this absence of evidence is not necessarily a clear indication one way or the other. A study could be done to assess the current state of urban land cover map production, but that is not the focus of this study. It is assumed, based on the limited information reviewed, that automated production of land cover maps for urban areas is not yet a common or routine occurrence.

METHODS

Study Area

The study area, shown in Figure 1, is the combined contiguous urban/suburban area of the neighboring cities of Orem and Provo, Utah (approximate center of the area: 40° 16' N, 111° 41' W). Orem and Provo are the two largest cities in Utah County, and they have a combined population of about 202,000 (according to the 2007 American Community Survey). The average elevation of these two cities is about 4,600 feet (1,402 m). Orem and Provo occupy much of the land area between the eastern shore of Utah Lake and the western slopes of the Wasatch mountain range. The Provo River flows generally southwest from Provo Canyon through this urbanized area and empties into Utah Lake. US Interstate Highway 15 runs generally north-south and is the major transportation corridor connecting this region with Salt Lake City to the north and Las Vegas, Nevada, farther to the south.

For purposes of this study the city boundaries have been modified slightly to exclude large tracts of undeveloped land. For example, the Provo city limits actually include an area that extends eastward into one of the mountain canyons – this section has been removed from the study area because there are no urban features within it. The resulting extent of the study area covers 121.2 square kilometers (about 46.8 square miles).

The study area includes a mix of urban land cover and land use types. Each city has commercial/business districts, and a somewhat continuous strip of businesses along State Street extends through both cities. Industrial enterprises are located primarily near the I-15 corridor. The campus of Brigham Young University, including the football stadium and other outdoor sports facilities, occupies a large area of east-central Provo; the Utah Valley University campus is located in the west-central area of Orem. A majority of the land use is residential, dominated by single family homes on tree-lined suburban streets, with some higher-density apartments/condos in areas near the universities. Very few tall buildings exist in these cities; indeed, the tallest by far

is the 12-story Kimball Tower on the BYU campus. Schools, parks, and recreational land uses are distributed throughout these communities, and some agricultural uses exist that include orchards and field crops. Mountain slopes on the eastern edge of the study area consist of bare earth, rocky outcrops, scrub vegetation and a few native trees.



Figure 1. Study area map: the combined communities of Orem and Provo, Utah (boundaries modified to exclude large non-urbanized areas)

Data

Imagery acquired by the US National Agricultural Imagery Program (NAIP) in early August of 2006 was used for this study. The NAIP data are color-infrared (CIR) images with spectral bands of NIR, red, and green; the spatial resolution is 1-meter ground sampled distance (GSD).

The NAIP aerial images have already been radiometrically corrected, they are ortho-rectified for planimetric accuracy, and they are geometrically rectified to the UTM Zone 12N NAD83 projection and datum. Metadata that accompany the image files document the preprocessing steps and report the accuracy of the geometric rectification (see Appendix A for a sample of a NAIP metadata file). These data were downloaded at no cost from the Utah State Geographic Information Database (SGID) website (<http://gis.utah.gov/download>) in December 2008. Each image tile is provided as a Geo-TIFF fileset (set of three files: *.tif* image file, *.tfw* world file, *.txt* text metadata file). The spatial extent of each NAIP image tile covers a 3.75 x 3.75 minute quarter quadrangle plus a 300 meter buffer (overlap) on all four sides. Synoptic coverage of the selected study area required obtaining and using seven (7) NAIP image tiles.

The NAIP data were selected for use in this study following concepts outlined above in the Literature Review section. The NAIP imagery's spatial resolution of 1-meter GSD is very good for detailed urban mapping purposes. Spectral resolution of three CIR bands might be considered barely adequate, or it may turn out to be not adequate – this concern will be evaluated and discussed later. As for temporal resolution, the NAIP data are just over two years old now – this is within the ASPRS committee's recommended 2-5 year update cycle (ASPRS, 2006, p. 101); however, 2006 imagery may be approaching its limit of usefulness for areas of rapid growth and development (NAIP imagery ideally should be acquired again in Utah in 2008 or 2009). Because NAIP imagery is acquired during the agricultural growing season (in this case August 2006), urban trees are shown with full leaf-on canopy, which supports ecological and urban forestry study purposes but likely obscures some detail of land cover materials directly below the canopy. As pertaining to considerations of cost and accessibility, the NAIP data are ideal: they were easily accessed and downloaded at no cost. Likewise, with respect to preprocessing concerns, the NAIP data are also ideal: all standard and necessary preprocessing has already been completed so the data are truly ready-to-use. Lastly, because the NAIP imagery was acquired near local solar noon, shadows are minimized (though not entirely absent).

Other options for data selection exist and could be considered for the purpose of producing detailed land cover maps of the Orem and Provo communities. Aerial hyperspectral imagery would undoubtedly improve on NAIP imagery's relatively poor spectral resolution, but at the price of degraded spatial resolution and much higher costs to acquire the data and process it. Very high spatial resolution satellite data such as IKONOS or QuickBird (or GeoEye, soon) would offer the advantage of excellent temporal frequency (as compared to NAIP data), but would not significantly improve spatial or spectral resolution and would be expensive to acquire and preprocess. Another possible disadvantage of the satellite imagery is that shadows may be more pronounced and troublesome than those appearing in the NAIP imagery. Lastly, options for data fusion could be considered. Combining two or more sources of data might be able to increase spectral resolution and could help in mitigating shadows (e.g., Yuan, 2008), or, integrating LIDAR data with optical imagery could be helpful in differentiating buildings from paved surfaces and/or dealing with tall building lean (e.g., G. Zhou & Kelmelis, 2008). However, costs for acquiring and preprocessing the data would likely be multiplied by a data fusion approach.

To summarize, it appears that no remotely sensed data are ideal/perfect for the purpose of economical mapping of urban land cover – as previously noted, it is highly unlikely that all important factors can be optimized simultaneously (Baltasvias & Gruen, 2003). NAIP imagery is strong in attributes of spatial resolution, cost and accessibility, preprocessing, and minimized shadows; however, there may be limitations in its spectral and temporal resolution that could impact the useful accuracy of resulting land cover maps.

Classification Scheme

The classification scheme used for this study is based on the HERCULES system (Cadennaso, et al., 2007). As shown in Figure 2, there are three base classes: BuildingRoof, Surface, and Vegetation. The Surface class has three subclasses of Paved, BareSoil, and Water. The Vegetation class has two subclasses of Fine and Coarse vegetation: fine vegetation is

generally low to the ground and of fine texture (such as grass), and coarse vegetation is taller with coarser textures (such as trees and shrubs). For practical reasons that help to improve classification, light- and dark-toned subclasses are used for the BuildingRoof, Paved, and Water classes.

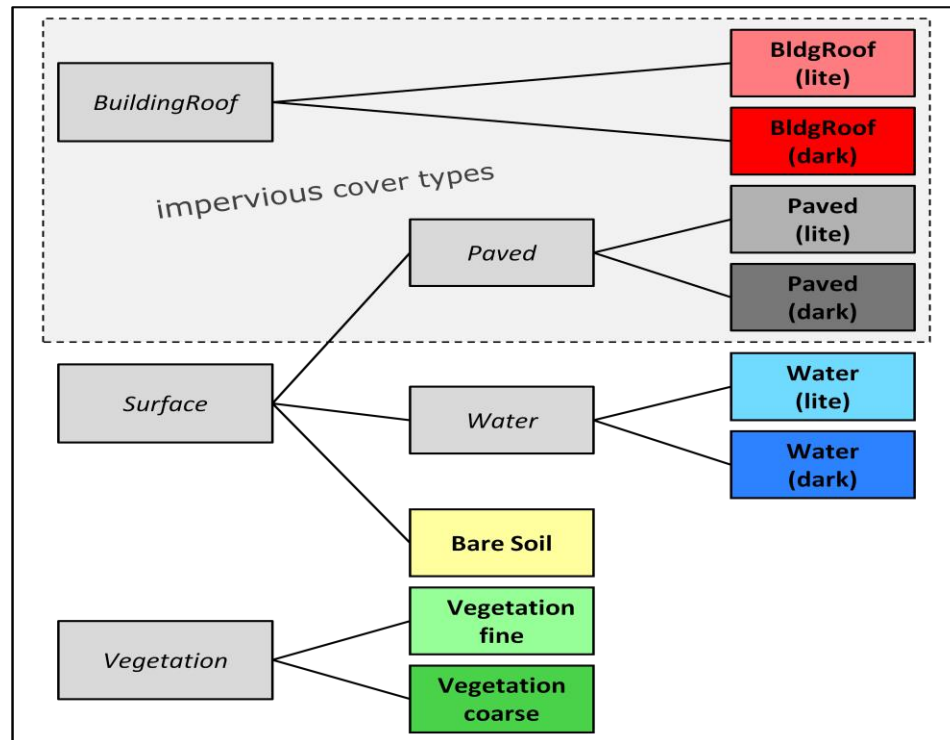


Figure 2. Classification scheme hierarchy, based on HERCULES (Cadenasso, et al, 2007). Light grey boxes are summarization-level classes. Colored boxes show map legend colors used for the nine detailed classes.

This classification scheme was designed with the intent to support multi-purpose end uses of a generic, detailed urban land cover map. Furthermore, the selection of this set of classes was influenced by concepts outlined in the literature and by empirical results from preliminary classification trials using the source NAIP imagery of the study area. The chosen scheme strictly labels classes as land cover types with no inferred land usage whatsoever. Also it follows recommendations for using the fewest classes possible needed to support the map's thematic objectives. The hierarchy of this scheme allows for flexible super-classing or summarization – for

example (as shown by the dashed box in Figure 2), all impervious surfaces can be easily grouped together.

Different types of construction materials that are used for BuildingRoof and Paved urban features cause tonal variations in the imagery that range from very light/bright to very dark. Early classification experiments were attempted using multiple breakdowns of tonal variation (white, light-grey, medium-grey, dark-grey, black, etc.) for these cover types, but it was difficult to maintain consistency of the gradations, and it was observed that using many tonal subclasses did not appear to improve resulting accuracy. In particular (as will be discussed further), confusion between BuildingRoof and Paved classes did not seem to be affected very much by using many or few tonal subclasses. Thus two subclasses – light and dark – for both BuildingRoof and Paved were used.

The Water class was ignored in the Cadenasso, et al. (2007) paper. It was added as a Surface type in this scheme, and because there are two primary subdivisions visually apparent in the imagery it has been subclassed into light and dark types. Lighter-colored water features are mostly man-made objects such as swimming pools, fountains, etc.; natural water features such as rivers, ponds, and lakes are usually very dark in the NAIP imagery.

Shadows are not prominent in the NAIP imagery in this study area, as the scenes were acquired near local solar noon in early August. Using a Shadow class in the scheme was considered and experimented with in trial classifications, with poor results: the small shadowed areas were typically classified correctly, but most natural water features were misclassified as shadow. Without using a Shadow class the opposite result was apparent: water features were correctly classified, but most shadowed areas were then misclassified as one of the Water classes. It was judged that this latter situation was less troublesome and resulted in a more correct and useful map. Also, shadowed areas generally are relatively small in the NAIP imagery of this study area, thus it was decided to ignore shadows and accept any misclassifications of shadowed regions for the purposes of this study.

Software Tools

All image processing methods for this study were performed using ENVI (Environment for Visualizing Images, version 4.5) and ENVI Zoom software products by ITT Visual Information Solutions (<http://www.itvis.com/>). Image mosaicking functions, the supervised classification functions, and accuracy assessment tools are provided in ENVI. An object-based Feature Extraction module is included in the ENVI Zoom product.

The GIS package ArcMap 9.3 by ESRI (<http://www.esri.com/>) was used to prepare the Orem/Provo city boundaries vector data. Also, candidate classified image maps were exported from the ENVI and ENVI Zoom modules to ESRI vector shapefile format and verified in ArcMap.

The Excel spreadsheet program by Microsoft (<http://www.microsoft.com>) was used to tabulate accuracy assessment data, compose error matrices, and calculate map accuracy metrics.

Computer Processing Procedures

Four main processing procedures were performed for this study: preprocessing, per-pixel supervised classification, object-based feature extraction, and accuracy assessments of resulting classified maps. Three candidate output maps were produced for comparison: these were designated as Maps A, B, and C. The main processing steps are shown in a flowchart in Figure 3. For all processing, the input and output data files were always placed on the computer's local C: hard drive to preclude impacts to processing times caused by network issues.

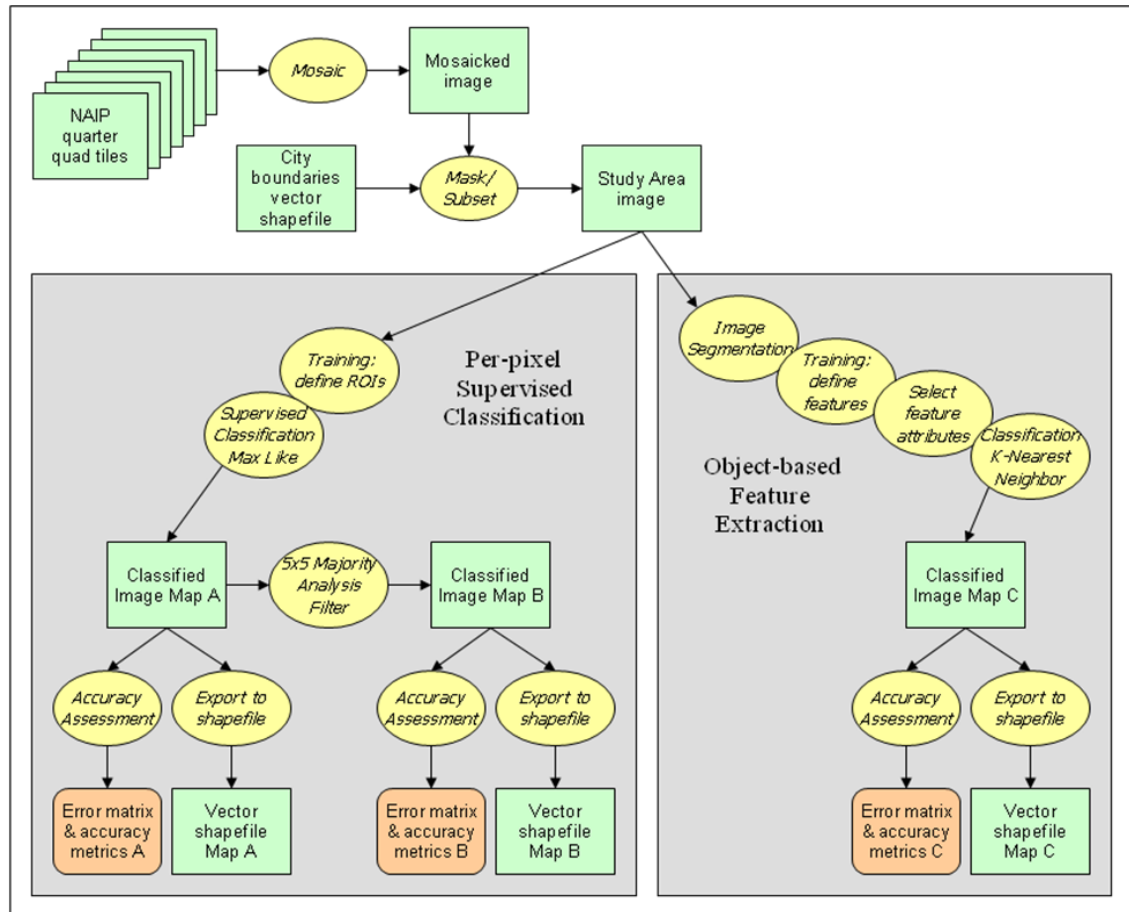


Figure 3. Flowchart depicting processing steps carried out to compare Supervised Classification with Feature Extraction.

Preprocessing

The original seven NAIP image tiles were mosaicked together to create a single large image file. During the mosaic procedure, feathering was performed using 100 pixels of the buffered margins of the source images, and the entire mosaicked output image was color balanced. Then, to reduce and simplify the data, it was masked by the external boundaries of the study area. The city boundary vector data was imported from an ESRI shapefile into an ENVI vector file then used to mask out portions of the mosaicked image that were outside the municipal boundaries. The resulting study area image file occupied 580 MB of disk space. The mosaicked and masked image file is shown in Figure 4. This image file was then used as input to both the supervised

classification procedure and the feature extraction procedure. It was also used to define ground reference data for the accuracy assessments.

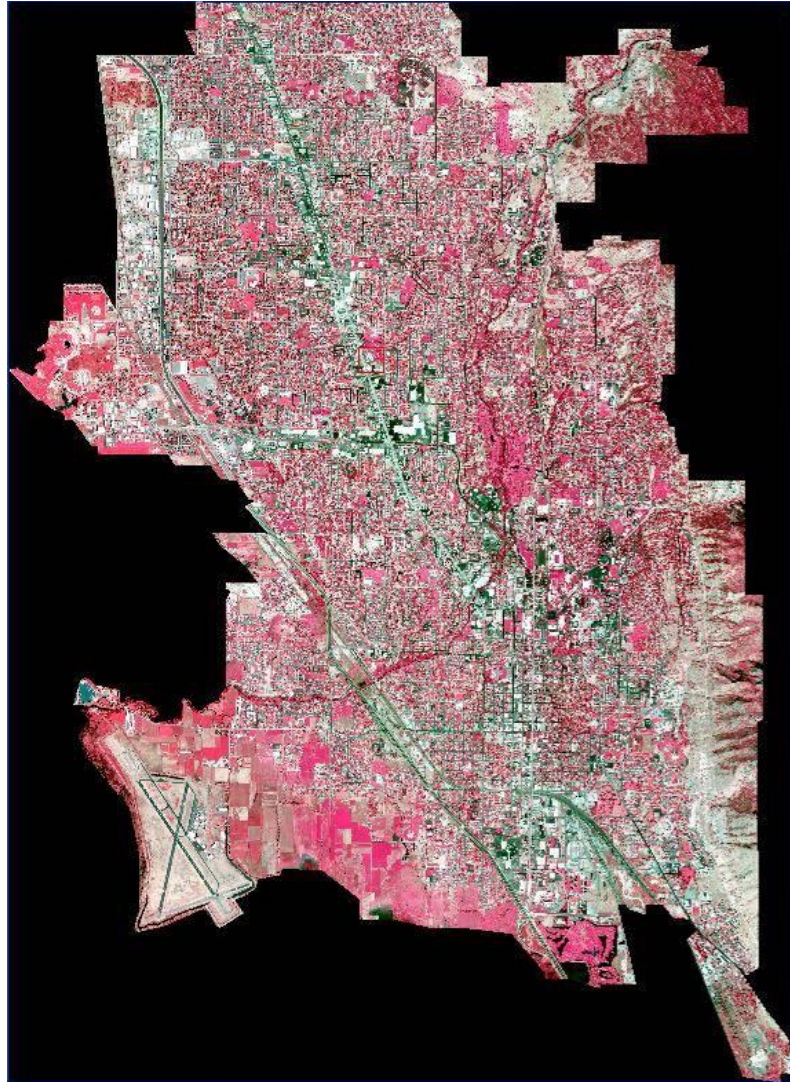


Figure 4: Study Area image, mosaicked and masked by modified city boundaries.

Per-Pixel Supervised Classification

In a supervised classification procedure, the analyst first “trains” the system by identifying sample contiguous pure regions on the image for each of the land cover classes. In ENVI, the Region of Interest (ROI) tool was used to define the set of training sites for the nine land cover classes used for this study. A minimum of six separate polygonal areas were digitized for each of

the nine classes, and many more were identified for most classes. Spectral values (min, max, mean, std dev) and histograms for the class training data were examined to evaluate class separability. Some likely overlaps were observed, especially between the BuildingRoof(light), Paved(light), and BareSoil classes; and between BuildingRoof(dark), Paved(dark), and Water(dark) classes. A smaller overlap appeared between VegetationFine and VegetationCoarse classes. Some adjustments were made to the ROI definitions and sites to try to improve class separations, with only partial effect. The class histograms were also evaluated for their Gaussian normality, as normal distributions are assumed for optimal performance of the maximum likelihood classifier algorithm – some classes exhibited near-normal distributions, and others clearly were non-normal with multiple modes and obvious skewness. The manual process to create the training ROI data required 2.5 hours of analyst time to complete.

When the ROI training data were ready, several experimental classification runs were processed using different classifier algorithms and varying some of their input parameters. No formal accuracy assessments were performed on the results of these preliminary/experimental classifications; instead, visual evaluations were performed to identify error trends and algorithms that had readily apparent problems. The classifiers that were tried and judged to be unsatisfactory were parallelepiped, minimum distance from means, and Mahalanobis distance; each of these (compared to maximum likelihood) exhibited noticeable deficiencies such as leaving many unclassified pixels, or obviously over-classifying one cover type. Trials that used the maximum likelihood classifier appeared visibly better than the others. Some experiments tried using a probability threshold value for maximum likelihood, but these resulted in unclassified pixels/areas, so it was determined that no threshold should be used. The parallelepiped and minimum distance algorithms demonstrated the fastest processing times with each finishing the entire study area in 4 to 5 minutes. The maximum likelihood algorithm was somewhat slower, requiring between 6 and 7 minutes to classify the entire study area image.

The fifth (and final) trial classification using the maximum likelihood algorithm was determined to be acceptable and was designated as candidate classified image Map A (see Figure 5, B). This map was subjected to a formal accuracy assessment procedure (described below in the Accuracy Assessments subsection). The total time required to create this map was 2 hours 30 minutes for training by the analyst plus 7 minutes classification processing time, for a total of 2 hours 37 minutes.

Per-Pixel Supervised Classification plus Post-Classification Processing

Image Map A was used as input for further processing experimentation that tried several post-classification procedures. Simple filters and a few other procedures were applied in attempts to mitigate speckling or the salt & pepper effect that is common with per-pixel classification procedures. Smoothing filters and median filters were tried with both 3x3 and 5x5 kernels; the 5x5 median filter appeared (by visual analysis) to remove much of the speckling and produce more homogenous image objects and a generally more pleasing appearance of the map. In addition, a Majority Analysis procedure using a 5x5 kernel was performed – results of this procedure were similar but appeared preferable to the median filter. Processing time for the various post-classification procedures ranged from less than a minute to about 2 minutes for the majority analyses filter.

Output from the majority analysis 5x5 filter was designated as candidate classified image Map B (see Figure 5, C), and a formal accuracy assessment procedure was performed on it (described below in the Accuracy Assessments subsection). The time required to create this map was just 2 minutes more than Map A, or a total of 2 hours 39 minutes.

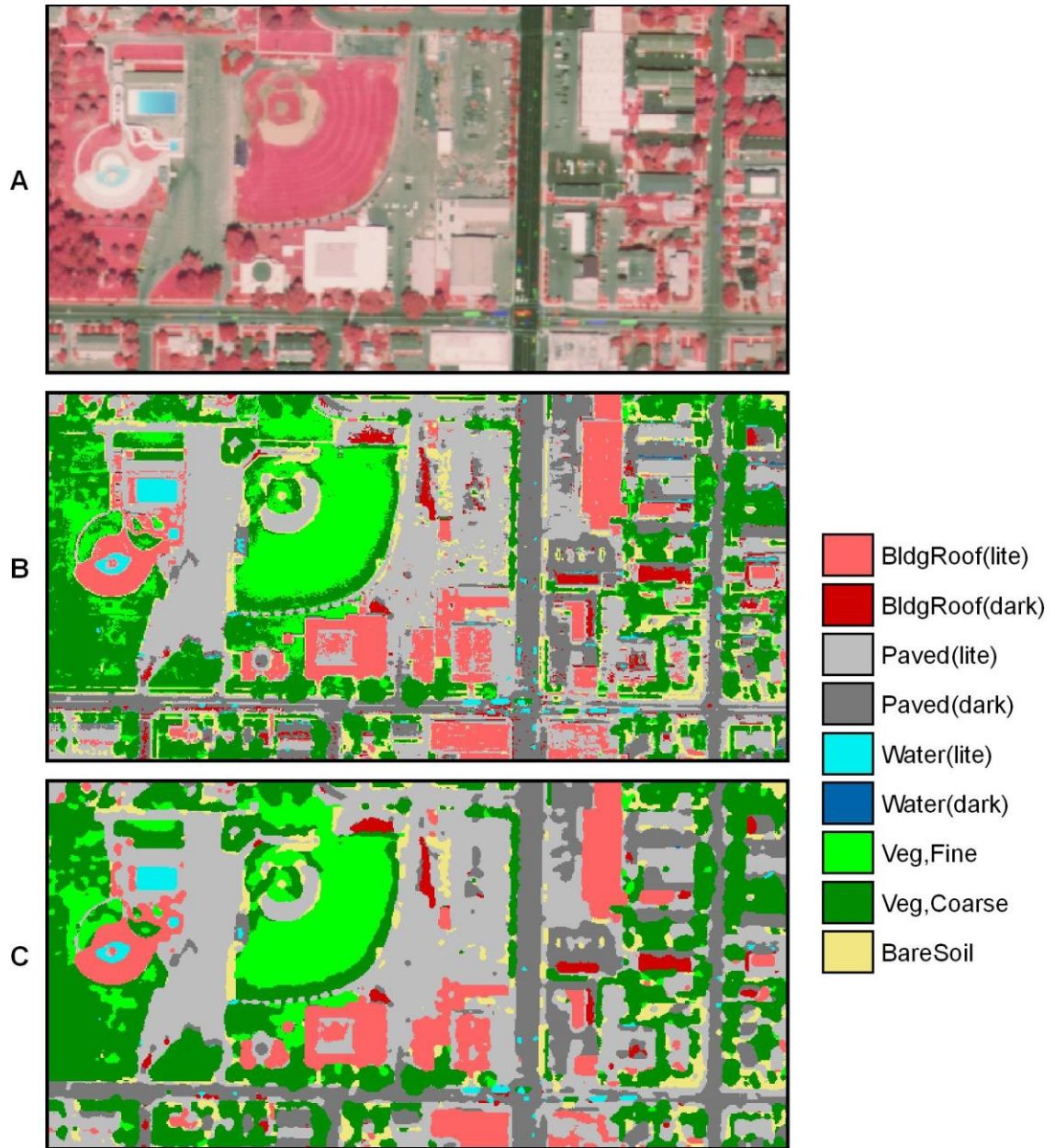


Figure 5: Portion of Pioneer Park and Freedom Blvd in Provo. A) top, NAIP image; B) center, Map A supervised classification; C) bottom, Map B supervised classification + majority analysis 5x5 filter.

Object-Based Feature Extraction

The Feature Extraction module in the ENVI Zoom software package guides the analyst through the steps of the work process. Selection of numerous parameter values and an object-based training procedure must be performed during this process. At a number of steps along the way the system provides a Preview viewing portal that allows immediate visual feedback that is

very helpful for evaluating interim results and refining the controlling parameters and training samples. The software also allows the analyst to move back to previous steps in the work process to reset or adjust parameter settings. This approach is interactive, iterative, and quite flexible; however, it can be difficult for the analyst to determine when an optimal solution has been arrived at and further experimentation would not yield improved results (i.e., the point of diminishing returns is not obvious). At some point the analyst needs to make the decision to move on and complete the classification process to actually generate an output map. Therefore, the time spent in this process can vary widely, depending largely on analyst experience, size of the imagery, number of object classes to be extracted, and how many iterations or interim evaluations are carried out.

In this study, several experimental trials of the feature extraction process were performed using small subsets of the study area imagery. The objective of these trials was to gain experience in using the ENVI Zoom Feature Extraction module and to experiment with the various parameters to evaluate their effects on output classification results. Details of these trials are not documented here, but the empirical experiences gained were applied later when performing feature extraction to classify the complete study area image.

The first major step of the process is segmentation of the image into image objects. This is a crucial step in which pixels are grouped into homogenous contiguous segments that should ideally correspond to real-world land cover features. The segmentation process was the focus of one study (Zhang & Maxwell, 2006) that developed an approach to quickly optimize the segmentation level (the development was done in another software package – it is not available in ENVI Zoom). The study by Carleer & Wolff (2006) also addressed object segmentation and suggested that under-segmentation (too coarse) is probably worse than over-segmentation (too fine), as important boundaries between distinct objects would be missed.

In the first step of the ENVI Zoom work process a segmentation level or scale factor between 0 and 100 is selected and previewed. Smaller values produce more and finer segments,

and larger values result in fewer, coarser segments. Based on empirical results from earlier trial runs and the recommendation to lean towards over-segmentation (Carleer & Wolff, 2006), a segmentation level of 40.0 was selected and processed on the study area image (see Figure 6, A). The time spent on this step was 7 minutes to adjust and preview the segmentation level parameter, plus 20 minutes for the computer to process the entire image then display an interim RegionMeans segmented image, for a total of 27 minutes.

The next step allows refinement of the segmentation through a segment merging process. A merge parameter value between 0 and 100 controls how much merging of segments is to be performed. Using the interactive visual preview pane the merge value was adjusted and set to 90.0. Again, it was assumed that over-segmentation would still be preferable to under-segmentation; however, Carleer & Wolff (2006) also suggested that when texture and/or morphological attributes are important the segmentation level should be set high enough that object shapes are well defined. The setting of 90.0 for the merge parameter appeared to do a good job of placing segment boundaries around building roofs, prominent trees or groves/clusters of trees, lawns, road edges, and so forth (see Figure 6,B). Time spent on this step was 8 minutes to adjust and preview the merge value, plus 31 minutes to compute/process the entire image then display the updated RegionMeans segmented image, for a total of 39 minutes.

The next step in the process is identified (in the ENVI Zoom software) as an advanced option that can apply thresholding parameters. This option was not exercised – the No Thresholding box was selected.

In the next step, a set of feature attributes are computed for each segment/object, to be used in later steps for actual classification of the objects. Categories of feature attributes are presented as options for calculation and include Spatial, Spectral, Texture, Color Space, and Band Ratios. All attributes were selected, and it took the computer 1 hour 2 minutes to finish calculations for all the image segments and advance to the next step of the process.

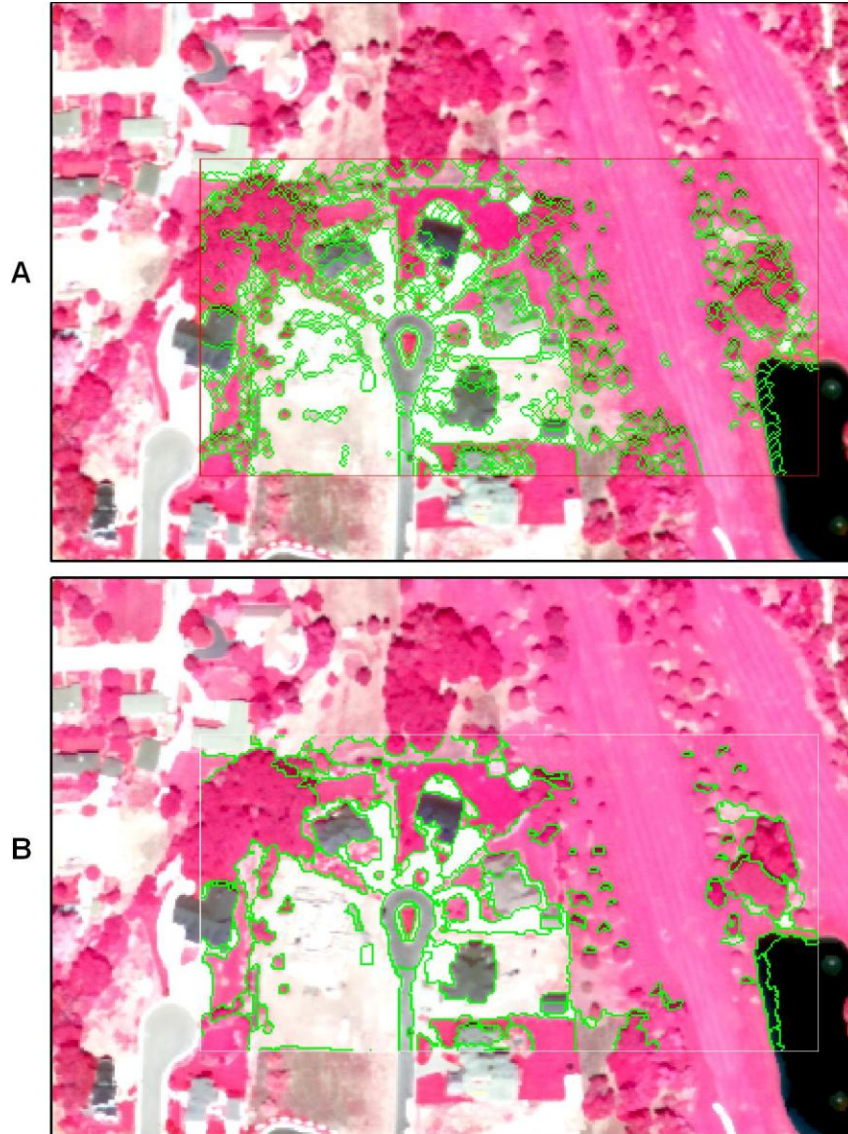


Figure 6: Example of the first two steps of the object segmentation process: A) top, initial segmentation with scale level of 40.0; B) bottom, segments merged with merge level of 90.0.

After indicating that classification is to be performed by selecting examples, the next step of the process presents a dialog box with three tabs. The first tab is used to define classes and select sample objects as training examples for the classes. The second tab is used to choose which of the calculated feature attributes are to be used by the classification algorithm. The third tab is used to select the classification algorithm and its parameters.

On the first tab, the nine classes of the classification scheme were entered into the table and color values were assigned for them. Then for each of the classes, many representative objects from the segmented image were selected as training examples. This is an interactive, iterative process that uses a preview viewing portal to display a sample of interim classification results. As image objects were added to the set of training examples for each of the nine classes, results shown in the preview portal were refreshed to show the effects of the updated training information. Misclassification errors were easily seen, and the set of objects selected were modified by the analyst (objects added or removed) to improve the interim sample result shown in the preview. It should be noted that parameter settings on the other two tabs of the dialog box also factor into the interim classification results displayed in the preview portal.

The second tab of the dialog box allows for selection of the set of feature attributes (previously calculated) that are to be used by the classifier algorithm. The study by Carleer & Wolff (2006) analyzed how various combinations of feature attributes affected resulting classification accuracy. They noted that accuracy can be compromised by using all available attributes, therefore “selection of relevant features [attributes] for each class is essential” (p. 1049). Unfortunately, in the ENVI Zoom work process, this dialog box does not provide the means to select separate sets of attributes per class; rather, one list is selected that applies uniformly across all classes. Based on empirical results from earlier trial runs, the following attributes were selected:

- *Spectral*: avg_band1, std_band1, avg_band2, std_band2, avg_band3, std_band3
- *Texture*: tx_range, tx_mean, tx_variance, tx_entropy
- *Spatial*: length, compact, convexity, solidity, formfactor, elongation, rect_fit
- *Customized*: bandratio, intensity

The third tab of the dialog box is used for selection of the classifier algorithm. The default option to use the K-Nearest Neighbor classifier was chosen with a K parameter value of 1.

At this point in the procedure, the analyst is able to move between all three of the aforementioned dialog tabs to make selections and adjustments and view their effects on the sample interim classification result shown in the preview portal. When all is deemed optimal (or satisfactory), the analyst clicks the Next button which launches the classification computation process on the entire dataset. As mentioned previously, it is possible to spend a large amount of time iteratively trying out options, “tweaking” the training objects, etc.; it’s not easy to discern when one should stop further tweaking and hit the Next button. In this study, the analyst spent 1 hour 53 minutes defining classes, selecting the training objects, making and adjusting other choices and parameter settings, and viewing preliminary classification samples in the preview portal. After clicking the Next button, the computer required 58 minutes to classify the entire study area image and display the resulting classified map image.

The final steps of the ENVI Zoom feature extraction process allow the classified image to be saved to an ENVI image file and/or to create ESRI-compatible vector shapefiles. Both of these options were exercised. The ENVI image file created was designated as candidate classified image Map C. This image was subsequently opened in the ENVI program and was subjected to a formal accuracy assessment procedure (described below in the Accuracy Assessments subsection). The operation to save the classified map as an ESRI shapefile performed a raster-to-vector conversion operation that generated smoothed vector polygons in the output shapefile. Exporting both types of files required 9 minutes of processing time.

The total time spent in the ENVI Zoom feature extraction process to produce the classified image Map C was about 5 hours and 10 minutes.

Accuracy Assessments

A stratified random sampling methodology was employed to assess the accuracies of the three candidate image maps. The minimum number of total sample points needed was determined using the formula for the binomial probability theory (Fitzpatrick-Lins, 1981) as follows:

$$N = \frac{Z^2 (p) (q)}{E^2}$$

where: N is minimum sample size
 Z is 2 (for a 95% confidence level)
 p is expected overall accuracy of the map (percent)
 q is 100 – p
 E is allowable error (percent)

The overall accuracy for Map A (created by the supervised classification procedure) was expected to be about 65%, based on visual evaluations of the map and overall accuracy values reported in the literature. A value of 5% was used for the allowable error (as suggested by Jensen, 2005, p. 501). Using these values in the formula, the required minimum sample size (N) was calculated to be 364 points.

The ENVI software function for generating random points was used to create and randomly distribute the sample points. Most of the classes were allocated between 35 and 68 sample points each, and the two Water classes were allocated about 25 points each. The two Water classes (light and dark) occupy much smaller areas of the map than other classes, therefore proportionally fewer sample points were allocated for them.

A Microsoft Excel spreadsheet was created to record and tabulate accuracy data for the assessment procedure. Rows of the spreadsheet list the sample points. Four additional columns were used to record the land cover type for each sample pixel: one column for the ground reference data, and three columns for each of the three candidate classified image maps A, B, and C. Coded values 1 through 9 were used to represent the land cover classes of the scheme used for this study (see Table 2).

Ground reference data were determined by visual interpretation of the original NAIP study area CIR image. A few points could not be clearly interpreted using the NAIP imagery; in those cases GoogleEarth imagery was consulted to help determine the correct cover type.

Table 2: Class codes used for accuracy assessments

<i>Class code</i>	<i>Class label</i>
1	BuildingRoof(lite)
2	BuildingRoof(dark)
3	Paved(lite)
4	Paved(dark)
5	Water(lite)
6	Water(dark)
7	Vegetation,Fine
8	Vegetation,Coarse
9	BareSoil

In the ENVI program, the original NAIP study area imagery and all three classified image maps were opened in display groups and linked together. The ROI tool and the Cursor Location/Value tool were used to step through the sample points one-by-one and examine how each sample pixel was classified in each image. Corresponding class code values were entered into the spreadsheet in the appropriate columns.

After class codes were recorded for all the sample points, error/confusion matrices were then constructed in the spreadsheet file, following J Jensen (2005, p. 499). A separate error matrix was built for each of the three classified image maps. The resulting error matrices are shown in Tables 3, 4, and 5. Values in the matrices were then used to calculate the accuracy metrics of Producer's Accuracy, User's Accuracy, Overall Accuracy, and Kappa coefficient, for each map.

RESULTS AND DISCUSSION

This section presents the results of accuracy assessments performed on the three classified image maps. Also, the production time metrics (amount of time required for each processing step) are summarized, followed by some interpretation of the results and discussion of possible causes of classification errors exhibited in the output maps. Sample portions of the classified maps created in this study are shown in Figure 7.

Accuracy Metrics

Table 3 shows the error/confusion matrix for Map A, the classified image map created using supervised classification with no post-classification processing. The accuracy results cannot be considered very good, with Overall Accuracy of only 56.5% and a Kappa coefficient of 0.502.

Table 3: Error matrix for Map A (supervised classification)

		Ground Reference Data									UA:	
		1	2	3	4	5	6	7	8	9	tot	pct
Map A - Classified Data	1	9		7						1	17	52.9%
	2		13	3	7	1					24	54.2%
	3	25		37	9					12	83	44.6%
	4	2	18	2	36		5		1		64	56.3%
	5	1		1	3	27	5		3		40	67.5%
	6				1		15			2	18	83.3%
	7			2	1			17	2	4	26	65.4%
	8	2	2	4	4			47	57	4	120	47.5%
	9	4	2	9				1		45	61	73.8%
tot	43	35	65	61	28	25	65	63	68	453		
PA: pct	20.9%	37.1%	56.9%	59.0%	96.4%	60.0%	26.2%	90.5%	66.2%		256	

56.5% Overall Accuracy
0.502 Kappa

Producer's accuracy (PA) values for several classes were extremely poor, particularly BuildingRoof(lite)[1], BuildingRoof(dark)[2], and the Vegetation,Fine[7] classes which all had PA's well below 50%. PA is a measure of errors of omission; thus, a PA value for BuildingRoof(lite)[1] of 20.9% (for example) means that 79.1% of actual light-toned building

roofs were omitted from this class on the map and were misclassified as something else – in this case mostly Paved(lite)[3]. At the high end, the PA value of 90.5% for the Vegetation,Coarse[8] class indicates that less than 10% of actual coarse vegetation were omitted from this class on the map.

User’s accuracy (UA) values were likewise quite poor, especially for the Paved(lite)[3] and Vegetation,Coarse[8] classes. Since UA is a measure of errors of commission, the UA value of 44.6% for the Paved(lite)[3] class means that about 55% of all pixels assigned (committed) to this class were misclassified – they are not actually light pavement features. The best UA value on this map was for the Water(dark)[6] class; its UA measure of 83.3% indicates that less than 17% of the pixels assigned to this class were assigned incorrectly and actually should belong to other classes.

Map B was produced by applying a post-classification majority analysis 5x5 filter to Map A. The result was visually more pleasing, as the speckling or salt & pepper effect was reduced and the map has a more homogenous appearance. Table 4 shows the error matrix for this map.

Table 4: Error matrix for Map B (supervised classification + majority analysis filter)

		Ground Reference Data									UA:	
		1	2	3	4	5	6	7	8	9	tot	pct
Map B - Classified Data	1	11		8						1	20	55.0%
	2		13	2	10	1	1				27	48.1%
	3	27	1	37	7					13	85	43.5%
	4	2	16	1	37		4		1		61	60.7%
	5	1		1	2	27	4		1		36	75.0%
	6						14			2	16	87.5%
	7			1				18	1	2	22	81.8%
	8		3	8	5		1	45	60	5	127	47.2%
	9	2	2	7			1	2		45	59	76.3%
	tot	43	35	65	61	28	25	65	63	68	453	
PA:	pct	25.6%	37.1%	56.9%	60.7%	96.4%	56.0%	27.7%	95.2%	66.2%		262

57.8% overall accuracy
0.517 Kappa

The accuracy values for Map B were only very slightly improved. The Overall Accuracy of 57.8% compares to Map A's value of 56.5%, and the Kappa was improved from 0.502 to 0.517. The pattern of Producer's and User's accuracies was essentially the same, with only slight improvements evident in these measures for a few classes

Accuracy measures for Map C, which was produced using the object-based Feature Extraction method, were significantly better than for the other two maps. Table 5 shows the error matrix for Map C.

Table 5: Error matrix for Map C (feature extraction)

		Ground Reference Data									UA:	
		1	2	3	4	5	6	7	8	9	tot	Pct
Map C - Classified Data	1	34		12						4	50	68.0%
	2	1	23	2	15		2		2		45	51.1%
	3	4		42						9	55	76.4%
	4		11		39						50	78.0%
	5	2		1	4	28				1	36	77.8%
	6			1	3		23	1	15	4	47	48.9%
	7							52	8		60	86.7%
	8		1					11	38		50	76.0%
	9	2		7				1		50	60	83.3%
	tot	43	35	65	61	28	25	65	63	68	453	
	PA: pct	79.1%	65.7%	64.6%	63.9%	100.0%	92.0%	80.0%	60.3%	73.5%		329

72.6% overall accuracy
0.691 Kappa

Overall Accuracy for Map C was 72.6%, almost 15 percentage points better than Map B, and the Kappa statistic of 0.691 was much better than Map B's value of 0.517. While these improvements are significant, the metrics still indicate considerable misclassifications in the map. PA values were better, with the lowest value reported for the Vegetation, Coarse[8] class at 60.3% (meaning almost 40% of coarse vegetation was omitted from this class). UA values also were generally improved over the other maps, but one class, Water(dark)[6], was still below 50% and the BuildingRoof(dark)[2] class was just barely better than 50% for its UA value.

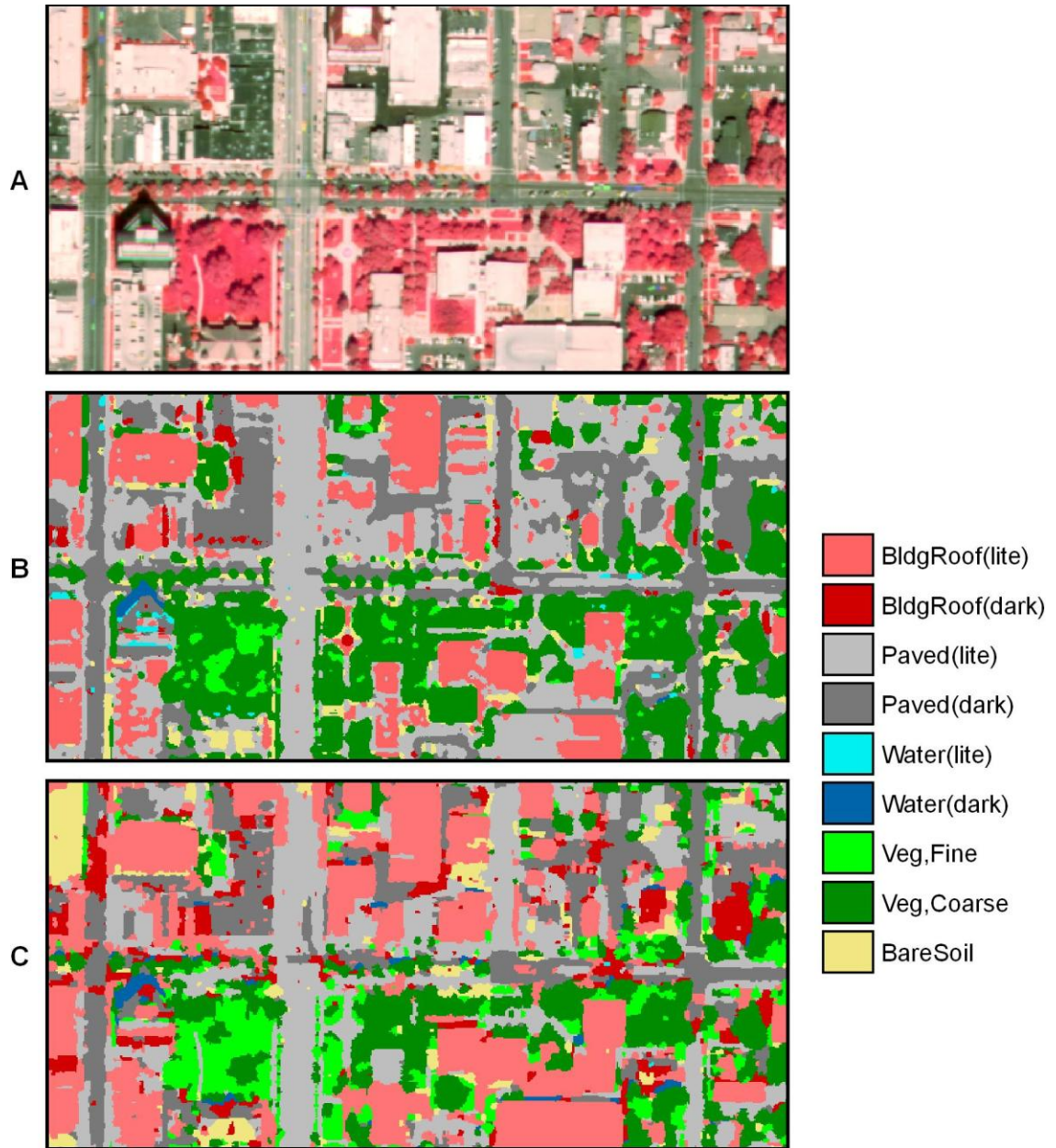


Figure 7: Sample output classified maps, showing a portion of downtown Provo: A) top, original NAIP image; B) center, Map B; C) bottom, Map C.

Cost/Time Metrics

A complete accounting of all possible cost factors to create land cover maps was beyond the scope of this study. Rather, the time that was expended in the implementation of the candidate procedures was used as a simplified proxy for costs.

For the specific purposes of this study, the intent of timing the procedures was to make a side-by-side comparison in a simulated production environment. Accordingly, the time that was spent in obtaining, organizing, and preprocessing (mosaicking and masking) the source imagery was not recorded. Likewise, time expended in the numerous preliminary or experimental runs of classification procedures done in this study was not recorded and not included in the accounting of production times. Also, the time spent performing accuracy assessments on the derived classified maps was not recorded or included in the reported elapsed times. Therefore, the times reported do not represent the total amount of time that would actually be required – start-to-finish – to create classified land cover maps. Rather, they only show the times for the steps that were unique to the performance of each candidate procedure. Moreover, the reported times are intended to represent the efforts of a moderately skilled analyst working in a production environment using a personal computer with adequate hardware and performance characteristics.

The first map (Map A) was created using the supervised classification procedure and the maximum likelihood classifier algorithm; training time by the analyst was 2 hours 30 minutes and computer processing time was 7 minutes, for a total of 2 hours 37 minutes. Map B was created by post-processing Map A, which required an additional 2 minutes to process, for a total of 2 hours 39 minutes. Map C was produced using the Feature Extraction module of ENVI Zoom; training and setup time by the analyst was 2 hours 10 minutes and computer processing for the various steps was 3 hours 0 minutes, for a total of 5 hours 10 minutes.

Processing was performed (in both procedures) on the entire mosaicked and masked image data file at once, instead of in subsets or separate tiles. Due to the large size of the input image file (approx. 580 MB) it is possible that limitations of computer resources – such as main memory and virtual page file size – could have been a factor in computer processing speed and elapsed times. In particular, the ENVI Zoom Feature Extraction work process performed a total of four processing passes through the data (initial segmentation, segment merging, attribute computations, and nearest neighbor classification), compared to just a single pass for per-pixel

supervised classification. It is possible that the total processing time for Map C (feature extraction) would be different than reported in this study if the image were to be processed by subsets or tiles.

The accuracy and time metrics for the three classified image maps are summarized in Table 6.

Table 6: Summary of accuracy and time metrics for the three classified maps

<i>Map</i>	<i>Method</i>	<i>Overall Accuracy</i>	<i>Kappa coefficient</i>	<i>Production Time (hrs:min)</i>
A	Supervised Classification	56.5%	0.502	2:37
B	Supervised Classification + 5x5 Majority filter	57.8%	0.517	2:39
C	Feature Extraction	72.6%	0.691	5:10

Discussion

For purposes of the discussion from this point forward in this paper, Map A will be ignored since Map B essentially embodies everything of Map A but is of slightly better quality. Therefore, Map B will represent output from the per-pixel supervised classification method, and Map C will represent output from the object-based feature extraction method for comparison purposes (see Figure 7).

The relationship between map quality and the time/cost to produce a map is demonstrated by the summary metrics shown in Table 6. Although many of the same classification problems were manifested by both procedures, the object-based method produced a more accurate map. As expected, it also took longer, though the difference in time between the two methods was mostly due to computer processing of the data. Time spent by the analyst in defining parameters and performing training was not significantly different for the two methods and was actually somewhat quicker for the object-based feature extraction method. Computer processing using the feature extraction method – to segment the image, compute object attributes, and classify the

objects – was 3 hours compared to the per-pixel maximum likelihood classification process which took 7 minutes (but as noted above, it may have been slowed by processing the entire large image file at once).

Significant misclassifications are evident in all the maps produced in this study. The most serious confusions were between impervious classes of BuildingRoof and Paved. Neither processing method was able to consistently differentiate between light-toned BuildingRoofs and light-toned Paved surfaces; also, BareSoil was frequently confused with both of those two classes. Likewise, the darker-toned subclasses of BuildingRoof and Paved were often confused with each other, and sometimes were also confused with dark-toned Water. These confusions can be attributed to the fact that similar construction materials are often used for building roofs and pavement, so their spectral reflectance properties are very similar and sometimes identical (Herold, Gardner, et al., 2002). Newly paved asphalt streets have a very dark, nearly black appearance in the imagery, and thus were sometimes confused with natural water features which also have very dark spectral properties.

The Vegetation classes generally were separated quite well from other classes, but exhibited some confusion between the subclasses of Fine and Coarse vegetation. In Map B (supervised classification) the Vegetation,Coarse class dominated over the Fine class – many areas of grass were misclassified as trees/shrubs. The feature extraction method (Map C) generally did a better job of differentiating between Fine and Coarse vegetation, but the opposite misclassifications occurred where some light-colored trees were classified as Fine vegetation. Also, Map C shows confusion between Vegetation,Coarse and dark-colored Water, most likely due to within-canopy shadows.

Shadows in very high spatial resolution imagery of urban areas are a conundrum – they undoubtedly were a cause of classification confusion in this study. Even though shadows in the NAIP data may not be as pronounced as in some satellite imagery, they nevertheless exist and have an important effect. In this study, preliminary classification experiments using a single,

separately-defined Shadow class had poor results as most dark-colored water features were misclassified as shadows. With no shadow class the water features were classified fairly accurately; however, many of the shadows were then classified as water. A major cause of reduced accuracy for the Vegetation,Coarse[8] class in Map C was within-canopy shadows being misclassified as Water(dark) – this can be seen in Table 5, the error matrix for Map C. The

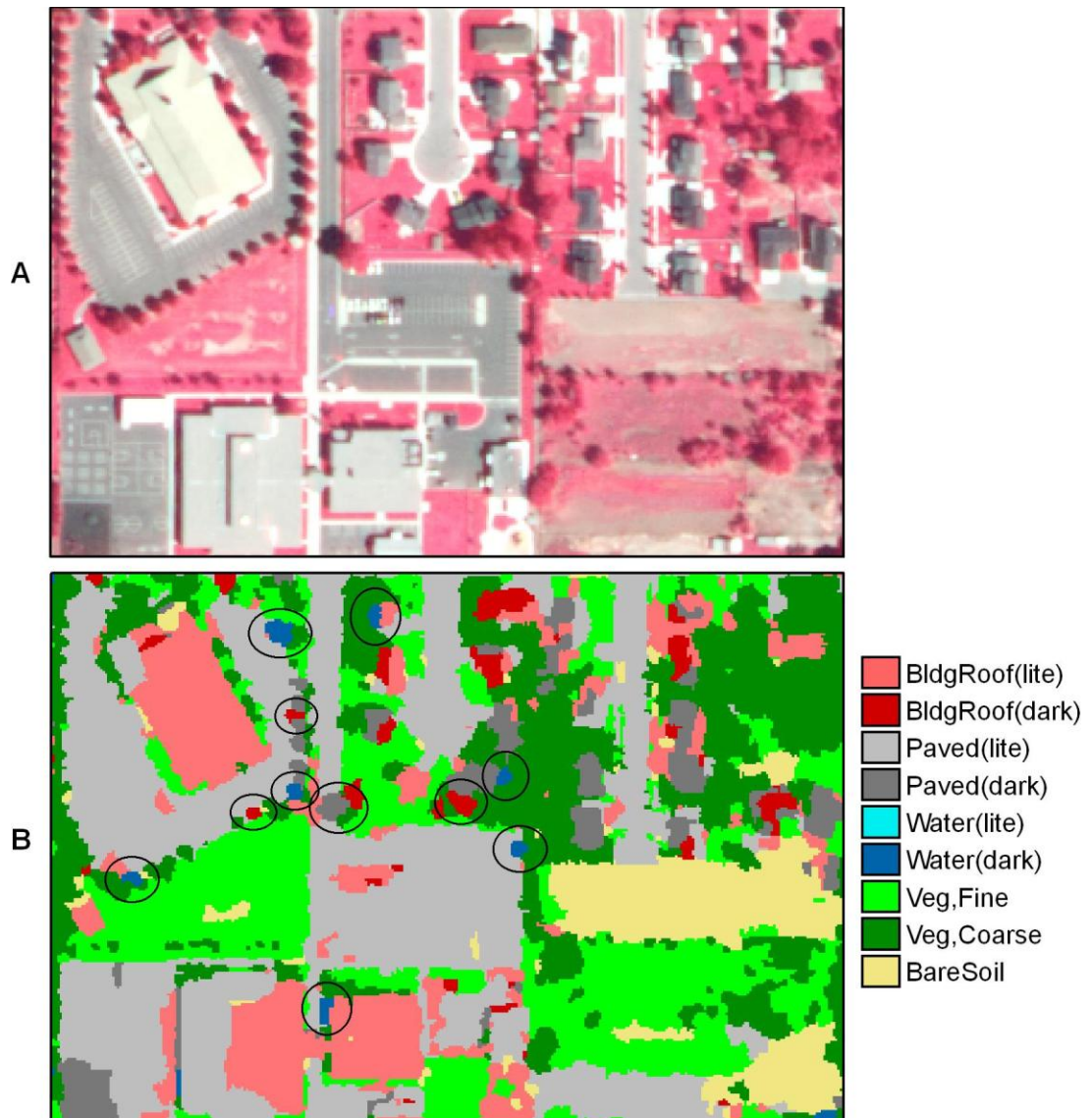


Figure 8: Examples of shadows (cast by trees and buildings) misclassified as BldgRoof(dark), Paved(dark) or Water(dark), in area of north Orem: A) top, original NAIP image; B) bottom, Map C. A few other classification errors are also apparent.

Producer's accuracy for Vegetation,Coarse[8] was severely impacted by 15 omissions that were classified as Water(dark)[6], and the User's accuracy for Water(dark)[6] was severely impacted by incorrectly assigning 15 map objects that should have been Vegetation,Coarse[8]. Other shadow effects were observed while performing the accuracy assessment but are harder to pick out from the error matrices. For example, shadows from both buildings and trees that fell on various other features were often misclassified as either BuildingRoof(dark), Paved(dark), or Water(dark) as shown in Figure 8.

Other consequences of using high spatial resolution imagery also became evident during this study. Generally, the detail available in imagery such as NAIP is welcome and useful. However, "noise" effects frequently interfered with correct classifications and degraded the accuracy and usefulness of the derived land cover maps. Vehicles on roads and parking lots, visible in the NAIP imagery, were one example of this phenomenon. Cars and trucks (which are larger than the 1-meter pixel size of the NAIP imagery) exhibit many different colors and spectral reflectance properties and thus caused anomalous classification results. Vehicles caused pockets and blips to appear on roadways and other paved surfaces, which were classified as Water, Vegetation, BuildingRoof, or BareSoil. These annoying and distracting noise elements affected the accuracy/quality of the maps and their visual appearance, as shown in Figure 9. Similarly, objects on building rooftops such as mechanical and/or HVAC equipment, etc. caused the same kind of noisy classification anomalies. Another situation involved markings on roadways, parking lots, and other surfaces. Even though many painted stripes and other marks on roads are smaller than 1-meter wide, they still show up strongly in the NAIP imagery and caused classification problems.

Various types of synthetic or artificial surface features were also a cause of some classification accuracy problems. In some cases these items did not fit any of the defined classes in the scheme. For example, on the west side of the BYU campus is a large artificial turf field used for sports practices. Due to its synthetic materials it exhibits spectral properties similar to

dark pavement and looks very dark in the CIR NAIP imagery (even though this feature appears green in true color). Not surprisingly, both Map B and C classified it as Paved(dark). However, it is a pervious surface (allows rainwater to drain through it) so for some map purposes such as

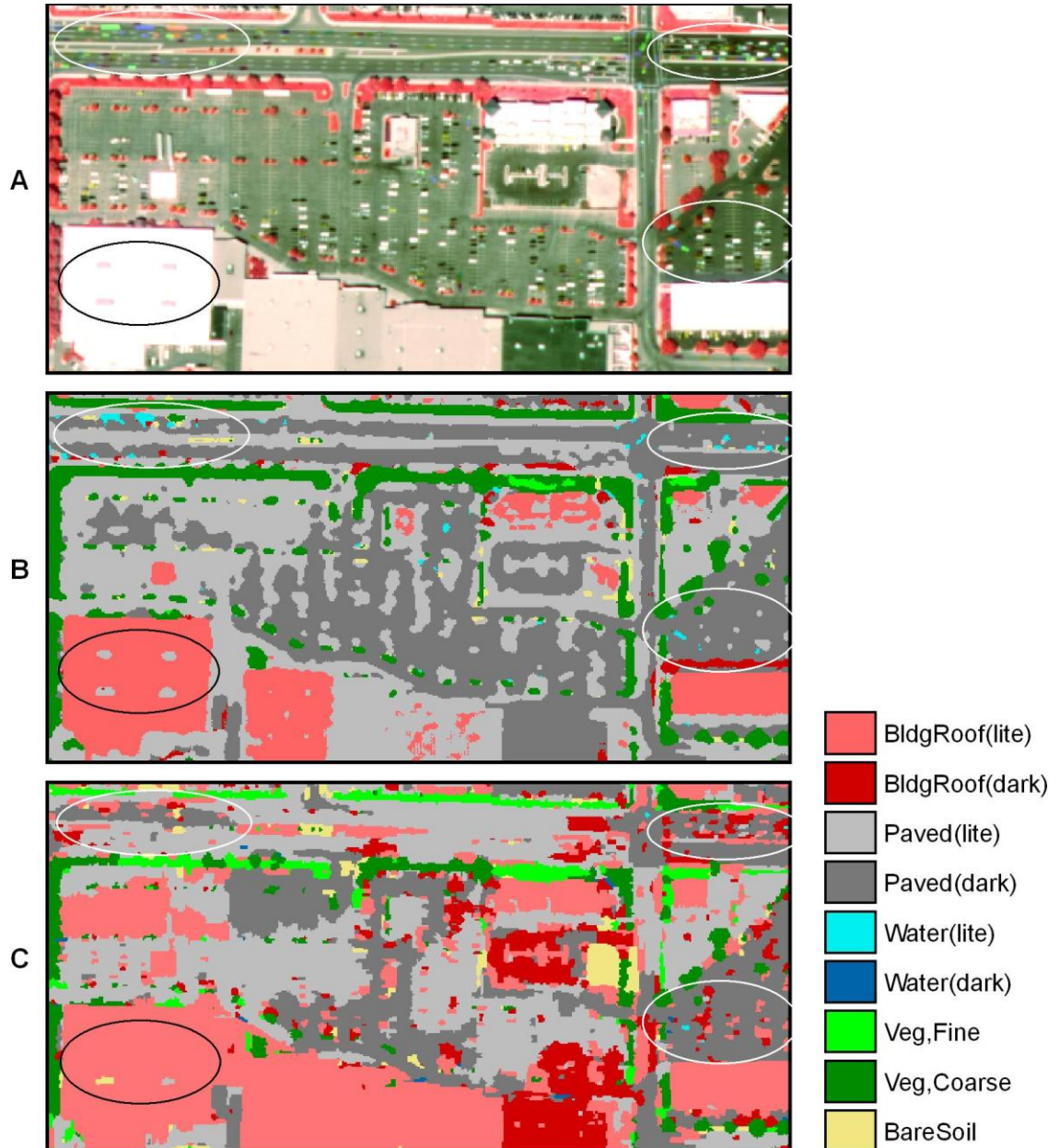


Figure 9: Anomalous classifications of “noisy” objects, along University Parkway in Orem: A) top, original NAIP image; B) center, Map B; C) bottom, Map C. Other classification errors are also apparent.

environmental/ecological studies or imperviousness studies this feature was probably incorrectly classified. Other surface features like this included painted tennis courts that were classified as vegetation, and wooden or composite decks that were classified as bare soil, etc. Adding some specialized classes into the scheme might be helpful to deal with these types of surface materials, but might also introduce other problems (more classes tends toward lower accuracy), or could start crossing the line into defining land use classes.

It is likely that the level of experience and knowledge on the part of the analyst/operator can be a factor in both quality and cost. More experienced and knowledgeable individuals will have developed expertise with the tools and gained empirical understanding of how parameters and variables influence the outcome. Thus, it can be expected that an experienced analyst and user of the software tools can produce more accurate maps in less time than a novice. In this study, relative inexperience may have been a contributing factor in poor classification accuracies and slow performance of some tasks.

CONCLUSIONS

The hypotheses of this study, as stated in the Introduction, have been supported. The object-based feature extraction process did create a more accurate urban land cover map than the per-pixel supervised classification procedure using the same NAIP CIR imagery. And as hypothesized, feature extraction did require more investment of analyst/operator time and computer processing time than supervised classification. It can be concluded that both of these methods are economical, approachable, understandable, repeatable, and thus could be made operational more easily than other more complex processing methods, if accuracy/quality requirements can be met.

This study has demonstrated a clear trade-off between the time/cost expended to execute the two methods and the resulting quality of the maps. The additional time needed to apply post-classification filtering to per-pixel classified Map A was negligible and helped to improve accuracy while also producing a more visually appealing Map B. To make the more accurate Map C, the object-based feature extraction method required more computer processing time than the easier and quicker supervised classification method. In the context of this study it is not appropriate to make value judgments as to which of the two is the better approach; rather, it is the intention to make clear that higher quality land cover maps have cost/time consequences.

Classification accuracies achieved in this study were generally poor and are likely to be unacceptable for most real-world applications of urban land cover maps. The combination of NAIP imagery and the particular implementation of the two processing methods did not achieve the desired goal of economical production of accurate maps. In point of fact, this study emphasized economy (or cost control) over accuracy, and the results clearly mirrored that trade-off. Options for improving accuracy (over what was achieved in this study) are numerous, but they all would involve more effort, time, and/or cost. Some viable approaches for improving accuracy are discussed below along with accompanying cost considerations. Still, it should be

emphasized that if the primary objective is cost containment, then opportunities for improving map quality will be limited.

One of the research questions asked whether NAIP 1-meter CIR imagery would be appropriate and useful for creating high quality maps of urban land cover. Unfortunately this study cannot offer a definite conclusion or make a positive recommendation on this issue. Many of the accuracy problems evident in the derived land cover maps are probably directly attributable to the relatively poor spectral resolution of the NAIP data. Further research could address ways to improve the spectral resolution of such imagery without significantly increasing costs or degrading other important characteristics such as high spatial resolution. It should also be noted that NAIP imagery may not be available for all urban areas, and that the NAIP program could be modified or even discontinued in the future. Low cost alternatives to NAIP data might include custom-flown aerial imagery, as recommended by Walker & Blaschke (2008). However, where budgets allow significant expenditures for imagery, options besides (or in addition to) aerial CIR imagery should be considered and should focus on spectral considerations, including the possibility of using hyperspectral data fused with high spatial resolution multispectral imagery (Gamba & Dell'Acqua, 2007).

A second research question asked whether per-pixel supervised classification is able to produce urban land cover maps of usable accuracy. Unfortunately, based solely on the results obtained in this study and using the NAIP imagery, the answer seems to be “no”. With Map B’s overall accuracy of less than 60% most end-use applications would be unwise to trust it. This result confirms findings of several researchers who noted that conventional per-pixel classification methods may not perform well with imagery that is very high spatial resolution and relatively low spectral resolution (Herold, Gardner et al., 2002; Thomas et al., 2003; Yuan & Bauer, 2006). Because per-pixel methods use only spectral data they are not always able to make consistent distinctions between classes of land cover with similar reflectance spectra (Herold, Scepan et al., 2002; Myint, 2007). Nevertheless, if the classifications in Map B of this study were

summarized into Impervious, Water, Vegetation, and BareSoil, then perhaps some applications (for example, measurement of imperviousness or vegetation cover) might find it acceptably accurate. And as noted above, augmenting the NAIP imagery with better spectral data would likely lead to improvements in classification accuracy by this method and others.

One technique that was not fully implemented in this study, and which could have a positive effect on accuracy, would be to further subdivide the classification scheme into many more subclasses, then do post-classification aggregation into the final high-level end-use classes. This was done only in a very limited sense in this study, with dark and light subclasses of BuildingRoof, Paved, and Water classes. A more complete implementation of this technique could subclass the BuildingRoof and Paved classes into several subclasses that better capture the fine tonal gradations evident in the imagery. It could also subclass BareSoil to better match the variations found in that class (light sand, brown dirt, rock outcrops, etc.), and even the Vegetation classes could possibly benefit from having more defined subclasses to fit variations in color and tonal patterns. Special subclasses for artificial/synthetic surfaces (i.e., artificial turf, painted tennis courts, etc.), and perhaps even for vehicles (as subclasses of Paved) might work in this approach to achieve better accuracy. Costs for employing this technique would mostly be for additional analyst time needed to define the expanded class scheme and perform more detailed training of the system, and more analyst time for the post-classification aggregation into the desired end-use classes.

Many of the classification errors observed in this study were confusions between paved surfaces and building roofs. Due to similarities in construction materials (for example, asphalt shingles on roofs and asphalt paved streets or parking lots) these confusions are understandable, and may not be completely resolvable even with higher spectral resolution data. Given that the chief difference between these two land cover types is that of elevation (building roofs are almost always higher than surrounding paved features), it may be possible to use ancillary LIDAR data

to help discriminate between them. Further research in the area of fusing LIDAR with optical multispectral data could be valuable for urban land cover applications.

Likewise, other ancillary data could be used to supplement the source imagery and assist in the classification process. This might be a realistic and low cost option for municipal agencies that maintain a GIS database for their area of responsibility. One example would be to use a GIS vector layer of city street centerlines: surface pixels or objects could be analyzed for proximity to a street centerline and then assigned to a Paved class if they are within a defined buffer distance. Similarly, GIS data for water bodies could be useful to help properly classify water surface features, and so forth.

Shadows remain a vexing problem in detailed urban remote sensing. Shadows were not dealt with in this study and as a result were a cause of certain classification errors. A simplistic preliminary approach, which experimented with using a defined shadow class, was initially attempted and then discarded. As suggested by some researchers (e.g., Dare, 2005) several detailed shadow subclasses could be used (e.g., shadow in tree canopy, shadow falling on pavement, shadow falling on fine vegetation, etc.), which could then be aggregated post-classification into the appropriate super-classes. This approach would be relatively low cost and would likely yield some accuracy improvements. Another potential help might be to follow the approach of Yuan (2008): fusing two imagery sources such as NAIP and QuickBird that have shadows at different angles which might largely cancel each other out. Other on-going research is mentioned in the literature; further research work to develop cost-effective methods of detecting and mitigating shadows and their effects would be beneficial to urban remote sensing applications.

In summary, automated, detailed urban land cover mapping from remotely sensed imagery is difficult, as mentioned by several researchers (e.g., Mesev, 2003) and confirmed by this study. It is especially challenging to produce accurate urban land cover maps from inexpensive high spatial resolution imagery in an economical process. Although the ultimate goal was not fully

achieved, this study has perhaps established a cost-control baseline. Using NAIP imagery acquired for no cost and methods that are probably the most economical currently in practice, the emphasis on cost containment was well demonstrated – it would be hard to devise a less expensive approach. Modifications can be built on this baseline, to implement some of the numerous options for imagery augmentation and methodology enhancement to achieve better resultant map accuracy.

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APPENDIX A

NAIP Imagery Metadata File (sample)

Shown below is the metadata file `q1721_ne_NAIP2006_CIR.txt` which accompanied the downloaded NAIP image tile for the PROVO NE quarter quad.

Metadata:

Identification_Information:

Citation:

Citation_Information:

Originator: North West Group

Publication_Date: 20070118

Geospatial_Data_Presentation_Form: remote-sensing image

Title: NAIP CIR Digital Ortho Photo Image

Publication_Information:

Publication_Place: Calgary, Alberta

Publisher: North West Group

Description:

Abstract:

This data set contains color infrared imagery from the National Agricultural Imagery Program (NAIP). NAIP acquires digital ortho imagery during the agricultural growing seasons in the continental U.S. A primary goal of the NAIP program is to enable availability of ortho imagery within a year of acquisition. NAIP provides two main products: 1 meter ground sample distance (GSD) ortho imagery rectified to a horizontal accuracy of within +/- 5 meters of reference digital ortho quarter quads (DOQQS) from the National Digital Ortho Program (NDOP); and, 2 meter GSD ortho imagery rectified to within +/- 10 meters of reference DOQQs. The tiling format of NAIP imagery is based on a 3.75' x 3.75' quarter quadrangle with a 360 meter buffer on all four sides. NAIP quarter quads are rectified to the UTM coordinate system NAD83. NAIP imagery can obtain as much as 10% cloud cover per tile.

Purpose:

The 1 meter GSD NAIP CIR is intended as a source for current digital ortho imagery in Utah

GIS and for other uses that require ortho imagery acquired during the agricultural growing season.

Time_Period_of_Content:
Time_Period_Information:
Single_Date/Time:
Calendar_Date: 20060818
Currentness_Reference: Ground Condition
Status:
Progress: Complete
Maintenance_and_Update_Frequency: Irregular
Spatial_Domain:
Bounding_Coordinates:
West_Bounding_Coordinate: -111.6875
East_Bounding_Coordinate: -111.6250
North_Bounding_Coordinate: 40.2500
South_Bounding_Coordinate: 40.1875
Keywords:
Theme:
Theme_Keyword_Thesaurus: None
Theme_Keyword: farming
Theme_Keyword: Digital Georectified Image
Theme_Keyword: Georectified Image
Theme_Keyword: Georectified
Theme_Keyword: Georectification
Theme_Keyword: Georeferenced Image
Theme_Keyword: Georeferenced
Theme_Keyword: Quarter Quadrangle Centered
Theme_Keyword: Color Infrared NAIP
Theme_Keyword: Aerial Compliance
Theme_Keyword: Compliance
Theme_Keyword: North West Group
Theme_Keyword: United States Department of Agriculture (USDA)
Place:
Place_Keyword_Thesaurus: Geographic Names Information System
Place_Keyword: UT
Place_Keyword: Utah
Place_Keyword: 49049
Place_Keyword: UT049
Place_Keyword: UTAH CO UT FSA
Place_Keyword: 4011151
Place_Keyword: PROVO, NE
Place_Keyword: PROVO
Access_Constraints: There are no limitations for access.
Use_Constraints:

None

Point_of_Contact:

Contact_Information:

Contact_Organization_Primary:

Contact_Organization: North West Group

Contact_Address:

Address_Type: mailing and physical address

Address: Suite 212, 5438-11th Street NE

City: Calgary

State_or_Province: Alberta

Postal_Code: T2E 7E9

Country: Canada

Contact_Voice_Telephone: 403-295-0694

Contact_Facsimile_Telephone: 403-295-2444

Contact_Electronic_Mail_Address: info@nwgeo.com

Browse_Graphic:

Browse_Graphic_File_Name: None

Browse_Graphic_File_Description: None

Browse_Graphic_File_Type: None

Native_Data_Set_Environment: Unknown

Data_Quality_Information:

Logical_Consistency_Report:

NAIP 3.75 minute tile file names are based on the USGS quadrangle naming convention.

Completeness_Report: None

Positional_Accuracy:

Horizontal_Positional_Accuracy:

Horizontal_Positional_Accuracy_Report:

The positional accuracy for the digital data is tested by visual comparison to a data source with a higher order of accuracy.

Lineage:

Source_Information:

Source_Citation:

Citation_Information:

Originator: North West Group

Title: PROVO, NE

Publication_Date: 20070118

Geospatial_Data_Presentation_Form: remote-sensing image

Type_of_Source_Media: Digital Linear Tape (DLT)

Source_Time_Period_of_Content:

Time_Period_Information:

Single_Date/Time:

Calendar_Date: 20060818

Source_Currentness_Reference:

Aerial Photography Date for aerial photo source.

Source_Citation_Abbreviation: Georectified Image

Source_Contribution: Digital Georectified Image.

Process_Step:

Process_Description:

Imagery was flown with Leica ADS40 digital sensors to capture 0.9m raw data. Raw data is then downloaded using Leica GPro software into 12 bit TIFF format. The raw TIFF imagery is then georeferenced and reprojected using GPS/INS 200Hz exterior orientation information (x/y/z/o/p/k) to allow stereo viewable imagery. This stereo viewable imagery is processed with the GPro/LPS automatic point matching algorithm to determine common match points every 2000 pixels across the imagery strip and 333 pixels along strip. This pattern includes dual rows of line ties to the adjacent line of imagery. The resulting point data is imported in Leica ORIMA and used to perform a full bundle adjustment of the imagery point data. Any blunders are removed, and weak areas are manually supplemented to ensure good coverage of points. Once the point data is cleaned and point coverage is acceptable vertical control points from the prior generation MDOQQ's are introduced in the corners and center of the block being adjusted. This control is used to perform any datum shift (x/y/z and rotation) to ensure the new adjusted imagery fits the existing MDOQQ reference imagery. The output from this bundle adjustment process is revised exterior orientation data for the sensor with any GPS/INS, datum, and sensor calibration errors modeled and compensated for. Using this revised EO data orthorectified image strips are created using the USGS DEM. The 10m DEM is used where available and 30m DEM is used elsewhere. The orthorectified strips are overlaid over the existing MDOQQ compressed files to ensure accuracy is met by a visual inspection and manually measuring features. Once the accuracy of the orthorectified image strips are validated the strips are processed with a NWG proprietary dodging package that compensates for the bi-directional reflectance function that is caused by the sun's position

relative to the image area. This compensated imagery is then imported into Inpho's OrthoVista 4.0 package which is used for the final radiometric balance, and DOQQ sheet creation. These final DOQQ sheets contain a 300m minimum buffer. These final DOQQ tiles are edge inspected to the existing MDOQQ sheets for accuracy validation. A visual inspection is performed of the DOQQ to ensure the radiometric quality and content of the DOQQ looks good.

Process_Date: 20070118

Spatial_Data_Organization_Information:

Indirect_Spatial_Reference: Utah County, UT

Direct_Spatial_Reference_Method: Raster

Raster_Object_Information:

Raster_Object_Type: Pixel

Row_Count: 1

Column_Count: 1

Spatial_Reference_Information:

Horizontal_Coordinate_System_Definition:

Planar:

Grid_Coordinate_System:

Grid_Coordinate_System_Name: Universal Transverse Mercator

Universal_Transverse_Mercator:

UTM_Zone_Number: 12

Transverse_Mercator:

Scale_Factor_at_Central_Meridian: 0.9996

Longitude_of_Central_Meridian: -111.0

Latitude_of_Projection-Origin: 0.0

False_Easting: 500000

False_Northing: 0.0

Planar_Coordinate_Information:

Planar_Coordinate_Encoding_Method: row and column

Coordinate_Representation:

Abscissa_Resolution: 1

Ordinate_Resolution: 1

Planar_Distance_Units: meters

Geodetic_Model:

Horizontal_Datum_Name: North American Datum of 1983

Ellipsoid_Name: Geodetic Reference System 80 (GRS 80)

Semi-major_Axis: 6378137

Denominator_of_Flattening_Ratio: 298.257

Entity_and_Attribute_Information:

Overview_Description:

Entity_and_Attribute_Overview:

24-bit pixels, 3 band color infrared(RGB)
values 0 – 255

Entity_and_Attribute_Detail_Citation: None

Distribution_Information:

Distributor:

Contact_Information:

Contact_Person_Primary:

Contact_Person: Supervisor Sales Services Branch

Contact_Organization: North West Group

Contact_Address:

Address_Type: mailing and physical address

Address: Suite 212, 5438-11th Street NE

City: Calgary

State_or_Province: Alberta

Postal_Code: T2E 7E9

Country: Canada

Contact_Voice_Telephone: 403-295-0694

Contact_Facsimile_Telephone: 403-295-2444

Contact_Electronic_Mail_Address: info@nwgeo.com

Distribution_Liability:

In no event shall the creators, custodians, or distributors of this information be liable for any damages arising out of its use (or the inability to use it).

Standard_Order_Process:

Digital_Form:

Digital_Transfer_Information:

Format_Name: GeoTIFF – Georeferenced Tagged Image File Format

Format_Information_Content: Color Infrared

Digital_Transfer_Option:

Offline_Option:

Offline_Media: CD-ROM

Recording_Format: ISO 9660 Mode 1 Level 2 Extensions

Fees:

Resource_Description:

n_4011151_ne_12_1_20060818_20070105.tif

Metadata_Reference_Information:

Metadata_Date: 20070118

Metadata_Contact:

Contact_Information:

Contact_Organization_Primary:

Contact_Organization: North West Group

Contact_Address:

Address_Type: mailing and physical address

Address: Suite 212, 5438-11th Street NE

City: Calgary

State_or_Province: Alberta

Postal_Code: T2E 7E9

Country: Canada

Contact_Voice_Telephone: 403-295-0694

Metadata_Standard_Name:

Content Standard for Digital Geospatial Metadata

Metadata_Standard_Version: FGDC-STD-001-1998