ACCURACY ASSESSMENT OF SUPERVISED AND UNSUPERVISED CLASSIFICATION USING LANDSAT IMAGERY OF LITTLE ROCK, ARKANSAS

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REX PEACOCK

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LAND COVER CLASSIFICATION

Accuracy Assessment of Supervised and Unsupervised

Classification using Landsat Imagery of Little Rock, Arkansas

Rex Peacock

Northwest Missouri State University

THESIS APPROVED

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Thesis Advisor, Dr. Ming-Chih Hung Date

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Dr. Patricia Drews Date

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Dr. Yi-Hwa Wu Date

____

Dean of Graduate School, Dr. Gregory Haddock Date

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Abstract

Remotely sensed data is an important component of land use/land cover (LULC) studies. This research utilized the vegetation-impervious surface-soil (V-I-S) model. Using Enhanced Thematic Mapper Plus (ETM+) imagery, this research compared the accuracy of supervised and unsupervised classification by analyzing three study areas in and near Little Rock, Arkansas. The first study area was a homogeneous region comprised primarily of water features. The second study area was a region of an intermediate mix of land cover classes. The third study area was a region of heterogeneous land cover composition between the four land cover classes of the V-I-S model. Upon the completion of supervised and unsupervised classification, 200 points for each area were randomly generated using a stratified random sampling approach. The land cover data associated with these points were then compared to ground truth data derived from higher-resolution imagery from the National Agriculture Imagery Program (NAIP). Based on error matrices, the homogeneous and intermediate study areas featured higher accuracy values for unsupervised classification over supervised classification. For the heterogeneous study area, supervised classification was more accurate than unsupervised classification by one percent.

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LIST OF ABBREVIATIONS

ETM+	Enhanced Thematic Mapper Plus
GloVis	Global Visualization Viewer
ISODATA	Iterative Self-Organizing Data Analysis Technique
LULC	Land Use/Land Cover
MLC	Maximum Likelihood Classification
NAIP	National Agriculture Imagery Program
SLC	Scan Line Corrector
USGS	United States Geological Survey
V-I-S	Vegetation-Impervious Surface-Soil

CHAPTER 1: INTRODUCTION

When identifying land use or land cover for a given area of interest, two common approaches to classify each pixel in an image are supervised classification and unsupervised classification. In supervised classification, an analyst uses previously acquired knowledge of an area, or *a priori* knowledge, to locate specific areas, or training sites, which represent homogeneous samples of known land use and/or land cover types. Based on statistics of these training sites, each pixel in an image is then assigned to a user-defined land use type (residential, industrial, agriculture, etc.) or land cover type (forest, grassland, paved surface, etc.). Unsupervised classification is useful for scenes in which land cover is not well-known or undefined. Computer algorithms group similar pixels into various spectral classes which the analyst must then identify and combine into information classes (Jensen 2005, Thomson *et al.* 1998). Both approaches of classification have strengths and weaknesses associated with the physical execution of the classification process and with the final result of the analysis. It is important to note, however, that no particular classification method is inherently superior to any others (Jensen 2005).

This research did not intend to refute such a claim. Instead, the intent of this research was to determine situations where one classification method is predisposed to be more accurate than the other based on contributing factors such as training site selection, spectral reflectance properties, and land cover composition. Because remote sensing is a powerful tool for studying geospatial phenomena, land use and land cover studies make frequent use of remotely sensed imagery. There are a wide variety of applications for land use and land cover studies to include natural disaster mapping (Borghuis *et al.* 2007), forest management (Mukherjee and Mukherjee 2009), and urban ecosystem analysis (Ridd 1995, Hung and Ridd 2002, Madhavan *et al.* 2001, Ward *et al.* 2000). Possessing accurately classified imagery is paramount to these studies and can affect decisions regarding land development and governmental policy. This is especially true if the analysis is of a time-critical or lifesaving nature.

Before researchers can perform any type of analysis, they must first perform some sort of classification to determine the exact nature of each pixel in a remotely sensed image. Classification error occurs when an image pixel that belongs to one category (as determined by ground truth data) is incorrectly assigned to another category. Classification error does not occur randomly or sporadically. Instead, such errors have several distinct characteristics. First, errors display a systematic and ordered arrangement and are likely associated with certain information classes. Second, incorrectly classified pixels do not occur in isolation. Instead, these erroneously assigned pixels occur in clusters of variable shape and size. Finally, classification errors may follow a distinct spatial pattern. For example, errors may occur at the edges of some classified images or in the interiors of certain land parcels (Campbell 2007). If there are measurable and predictable imagery characteristics that would increase the likelihood of one classification method possessing higher accuracy than others, researchers could save a great amount of time and manpower by utilizing this knowledge before conducting any analysis. This research was meant to provide suggestions for determining a more effective and efficient classification method for different types of land use/land cover studies in order to positively impact any future analysis. There is extensive literature that supports the individual use of both supervised and unsupervised classification approaches in land use and land cover studies. Additionally, there are many studies where both classification approaches are compared to determine which approach is more accurate. Few studies found unsupervised classification to be more accurate than supervised classification (Borghuis *et al.* 2007), while a greater number of studies found the converse to be true (Alrababah and Alhamad 2006, Bahadur 2009, Mukherjee and Mukherjee 2009, Trisurat *et al.* 2000).

1.1 Research Objective

The objective of this research was to assess and compare the accuracy of supervised and unsupervised classification. This research analyzed study areas with homogeneous, intermediate, and heterogeneous land cover compositions. While previous comparative studies have found one classification approach to be more accurate than the other, the authors of those studies did not discuss the implications of their findings outside of the context of their research project, nor did they offer any advice or guidelines for future LULC studies that may use supervised and/or unsupervised classification. In addition to comparing supervised and unsupervised classification, this research aimed to provide guidelines that will allow future researchers to determine which of the two classification approaches is better suited to their own LULC studies.

CHAPTER 2: LITERATURE REVIEW

2.1 Land Use and Land Cover Analyses in Urban Environments

Urban environments provide for complex and challenging geospatial analysis due to the dynamic and interconnected nature of different land use and land cover features. Most remote sensing literature, however, focuses more on natural study areas. After explaining that most remote sensing literature contained very little analysis of urban environments, Ridd (1995) created a standardized classification scheme for urban ecosystems, the vegetation-impervious surface-exposed soil (V-I-S) model, as a basis for standardizing urban area study using remotely sensed data. Ridd developed a pilot project in Salt Lake City, Utah to test the viability of the V-I-S model. Using a sampling frame of a 5.83 hectare square (roughly equivalent to a central city block), a total of 770 points were sampled using high-quality 1:30,000 scale color infrared photographs. Each of these points was classified as vegetation, impervious surface, or soil. Ridd (1995) found a high concentration of impervious surface points in the central business district with a decreasing density of impervious surface as distance from the central business district increased. The opposite trend was true with vegetation as there were high concentrations near the edge of the city and decreasing concentrations toward the center. While there were not a large number of soil points in the study area, there was an interesting correlation between soil points and locations of known construction and/or conversion (i.e. a change from one LULC type to another). While land use is of interest for the V-I-S model, land cover is the true objective for this classification scheme. Water features were treated as special features that were processed separately from the V-I-S model. Water features are important for land cover analysis because water absorbs most visible light and infrared energy, thus providing excellent visual and spectral contrast against other land cover types. While Ridd (1995) did not discuss the use of supervised classification, unsupervised classification, or any other automated classification method, the V-I-S model he proposed provides an excellent framework for any analyst who wishes to conduct a land cover classification study.

Hung and Ridd (2002) expanded on the earlier work of Ridd (1995) by adapting the V-I-S model to subpixel analysis, a technique necessary to address the issue of mixed pixels inherent in a complicated urban environment. While subpixel analysis was beyond the scope of the research in this thesis, the ability to simplify a heterogeneous urban landscape into its V-I-S components is very much relevant. Again, water was treated as a separate and special land cover class. Hung and Ridd (2002) chose to analyze a heterogeneous 10-kilometer by 6-kilometer area of Salt Lake City, Utah. The imagery used in this study included a 5-kilometer Thematic Mapper multispectral image taken in 1990, a 1:8000 panchromatic aerial photograph taken in 1990, and a 1:4600 color infrared aerial photograph taken in 1985. The higher-resolution aerial photographs provided the primary ground truth data during accuracy assessment. A total of six non-water land cover classes were used: green grass vegetation, tree/shrub vegetation, bright impervious surface, medium impervious surface, dark impervious surface, and soil/dry vegetation. Assuming a pixel was not identified as water, the authors assigned a likelihood percentage that matched the land cover of a pixel against its corresponding ground truth. While simplification of land cover types does not handle extreme differences very well, it still allows the study of urban environments in both a qualitative and quantitative manner.

Madhavan *et al*. (2001) was yet another study that used the V-I-S model to analyze changes in an urban environment. The study area was a 617 square-kilometer area in Bangkok, Thailand. Using two Landsat 5 Thematic Mapper scenes taken in the winters of 1988 and 1994, the authors identified a 2 percent decrease in agricultural lands and a 14 percent increase in commercial areas. Madhavan *et al*. (2001) used unsupervised classification to identify seven LULC classes (commercial, high-density residential, medium-density residential, low-density residential, vegetation, open land, water bodies), and then used supervised classification to assign each pixel to one of the LULC classes. Changes detected using the V-I-S model matched well with changes detected by a change-detection map (6.0% versus 5.6%, respectively).

Another study to use the V-I-S model was Ward *et al*. (2000). Ward *et al*. (2000) examined urban growth in southeast Queensland, Australia between 1988 and 1995 with an overall accuracy of 83 percent. The authors used Landsat 5 Thematic Mapper imagery for their analysis. While the authors originally attempted to use supervised classification, the inability to delineate LULC classes led them to use an unsupervised classification that produced 20 spectral classes. Four land cover classes were used in this study: forest, water, a vegetation class that combined exposed agricultural soil with non-woody vegetation areas, and an urban land class that combined exposed soil associated with urban land use as well as landscaped residential areas and impervious surfaces. A total of 385 sample points were used and each class except water contained over 100 sample points. The overall accuracy of the classification was 88% and the Kappa statistic was

83%. The authors noted that the soil class was the most poorly classified and that it was commonly confused with the urban class. Most of this confusion resulted from the inability to distinguish exposed or sparsely vegetated soil from landscaped residential areas. There was also some slight misclassification between the soil and forest classes. In most cases, newly-created impervious surfaces were easier to distinguish from exposed soil and vegetation because of their much higher brightness values. Ward *et al*. (2000) also noted that residential areas further away from the city center were more prone to misclassification due to their heterogeneous composition of buildings, roads, and wooded and non-wooded areas of vegetation.

There are many studies that have directly compared the accuracy of supervised and unsupervised classification. Borghuis *et al.* (2007) is unique in that it is one of the few studies to find unsupervised classification to be more accurate than supervised classification. Using SPOT-5 imagery of the island of Taiwan, the authors used automated and manual classification methods to map the location and intensity of landslides. Though aerial photography was the common data source for mapping landslides, Borghuis *et al.* (2007) chose to use satellite imagery for their analysis for four reasons: aerial photography covers relatively small areas, using photographs for manual analysis takes large amounts of time and money, aerial photographs inevitably feature cloud cover that obscures view of the ground, and the temporal resolution of aerial photography is irregular at best. While conducting unsupervised classification, the authors initially used 8 spectral classes, but then increased this number to 32 due to the spectral similarities between landslides, bare farm fields, dry riverbeds, and roads. Supervised classification used four classes: rock, landslide, forest, and urban areas. The authors also manually classified landslide areas for comparison against the automated methods. Boghuis *et al.* (2007) found the accuracy of supervised classification to range between 15.7 to 39.4 percent while the range of accuracy for unsupervised classification ranged between 53.3 and 63.1 percent.

A larger number of studies, however, found supervised classification to be more accurate. Alrababah and Alhamad (2006) compared supervised and unsupervised classification methods for the highly heterogeneous landscapes in the northern regions of Jordan. Since the authors found paper LULC maps to be lacking in spatial coverage, level of detail, and temporal resolution, they sought to find an effective way to produce accurate and timely electronic LULC maps. Using Landsat Enhanced Thematic Mapper imagery, Alrababah and Alhamad (2006) conducted supervised and unsupervised classification, both with and without spatial enhancement procedures, using 8 land cover classes and 278 sample points. The land cover classes were water, urban, agricultural land, forest land, shrub land, rangeland, olive farms, and bare soil. Alrababah and Alhamad (2006) found that unsupervised classification had an overall accuracy between 69.1% without spatial enhancement and 73.7% with spatial enhancement. The overall accuracy for supervised classification without and with spatial enhancement was 78.8% and 82.7%, respectively.

Bahadur (2009) compared supervised and unsupervised classification schemes in the mountainous regions of Nepal. Bahadur (2009) used five land use classes in his study: forest, scrubland, lowland agriculture, upland agriculture, and vegetables. Using multiple classification schemes, Bahadur (2009) found that the accuracy for unsupervised classification ranged from 45 to 68 percent. An overall accuracy of 82.86% was obtained for supervised classification. Bahadur (2009) noted that ancillary data such as Digital Elevation Model, aspect, and slope decreased the difficulty in differentiating between land use classes.

Mohammed and Rusthum (2008) used pixel-based and object-based approaches to analyze urban structures in Vijayawada, India. The authors derived ground truth data for their study from *in situ* measurements. Four land cover types were used in this study: urban areas, water, vegetation, and rocky areas. Mohammed and Rusthum (2008) achieved 87.67% overall accuracy for unsupervised classification versus 97.5% overall accuracy for supervised classification.

While conducting forest inventory estimation in India, Mukherjee and Mukherjee (2009) used a subpixel analysis method called Spectral Mixture Analysis in both supervised and unsupervised approaches. This study featured only three land cover classes: dense forest, sparse forest, and open bare soil. The authors used 30 training sites (10 for each land cover class) in their supervised classification and 60 spectral classes (20 for each land cover class) in their unsupervised classification.   The authors found the overall accuracy to be 76.67% for supervised classification and 53.33% for unsupervised classification. The most common misclassifications occurred in areas of sparse forest.

Trisurat *et al.* (2000) mapped tropical vegetation in Thailand using both classification approaches. The authors noted two major difficulties in mapping tropical forests: the spectral differences between the many species of vegetation and the problems that shadows can cause in classification. The land cover types featured in this study included dry evergreen rainforest, tropical rainforest, hill evergreen forest, mixed deciduous forest, escarpment vegetation, and grassland. Using 72 sample points, the authors produced a supervised classification with an overall accuracy of 79.16% and an unsupervised classification with an overall accuracy of 65.27%. Escarpment vegetation featured the most misclassification as many of these pixels were classified as denser types of vegetation. Additional confusion occurred between the tropical rainforest and hill evergreen forest classes. Since these two classes occur at different altitudes, the authors suggested that adding a digital elevation model could mitigate any confusion.

Thomson *et al.* (1998) took a different approach and compared how closely supervised and unsupervised classification matched each other in lieu of determining how well the classification results matched ground truth data. After analyzing the eastern coast of England, the authors found that both classification approaches had comparable results in heterogeneous areas, but also noted that areas of homogeneous vegetation produced inconsistent results for unsupervised classification.

Interestingly, all of the referenced instances of supervised classification used the Maximum Likelihood Classification (MLC) algorithm. The majority of unsupervised classification in the studies previously reference used the Iterative Self-Organizing Data Analysis Technique (ISODATA) algorithm. One exception was Mohammed and Rusthum (2008) who did not specify which algorithm they used. MLC and ISODATA appear to be the most common and accurate algorithms for supervised classification and unsupervised classification, respectively. Thus, these two algorithms formed the basis of the supervised and unsupervised classification performed during this research.

After reviewing the literature concerning supervised and unsupervised classification, it became apparent that certain types of land cover are more prone to misclassification than others. Areas of exposed soil can easily be misclassified as roads or riverbeds (Borghuis *et al.* 2007). Vegetation classes can be a source of spectral confusion as some types of shorter, low-density vegetation, such as scrublands, may be misattributed to taller, higher-density vegetation features, such as forests (Bahadur 2009). For both supervised and unsupervised classification processes, there are straightforward methods of mitigating incorrect classifications. When using supervised classification, judicious training site selection is paramount. Using sites of a known and homogeneous land composition can decrease the number of incorrectly classified pixels (Bahadur 2009, Mukherjee and Mukherjee 2009). For unsupervised classification, error propagation is reduced by increasing the number of spectral classes (Mukherjee and Mukherjee 2009). Though the V-I-S model may appear to decrease the chance of error by using a lower number of information classes, the chances of pixel misclassification may actually *increase* in areas where multiple land cover types transition into each other, where there is a large number of instances of mixed pixels (Mukherjee and Mukherjee 2009) or in cases where a feature may be spectrally similar to those of a different land cover type, such as the confused classes identified by Hung and Wu (2005).

2.2 Accuracy Assessment

The increased usage of remote sensing data and techniques has made geospatial analysis faster and more powerful, but the increased complexity also creates increased possibilities for error. In the past, accuracy assessment was not a priority in image classification studies. Because of the increased chances for error presented by digital imagery, however, accuracy assessment has become more important than ever (Congalton 1991). A common tool to assess accuracy is the error matrix. Error matrices compare pixels or polygons in a classified image against ground reference data (Jensen 2005). These matrices can measure accuracy in several ways. The overall accuracy of the classified image compares how each of the pixels is classified versus the actual land cover conditions obtained from their corresponding ground truth data. Producer's accuracy measures errors of omission, which is a measure of how well real-world land cover types can be classified. User's accuracy measures errors of commission, which represents the likelihood of a classified pixel matching the land cover type of its corresponding real-world location (Campbell 2007, Congalton 1991, Jensen 2005). Error matrices have been used in many land classification studies and they were an essential component of this research.

2.3 Sources for Deriving Ground Truth Data

When performing LULC classifications, one needs ground truth data to provide an unbiased reference necessary to conduct accuracy assessments. Because landscapes can change rapidly, it is important that training data and ground truth data are acquired at dates as close to each other as possible. While it is ideal to acquire ground truth data by visiting sites on the ground and performing direct observations, there can be factors that prevent gathering such *in situ* measurements. These limiting factors include prohibitive costs (Alrababah and Alhamad 2006), the sheer size of the study area (Hung and Wu 2005), an inability to temporally match ground truth data with acquisition dates for remotely sensed imagery (Madhavan *et al*. 2001), and inaccessibility to certain parts of the study area (Hung and Wu 2005, Campbell 2007). When *in situ* measurements are not possible, many researchers substitute direct observations with imagery that has a much higher spatial and/or spectral resolution than the imagery used for the LULC classifications (Jensen 2005).

CHAPTER 3: CONCEPTUAL FRAMEWORK AND METHODOLOGY

3.1 Description of Study Area

Little Rock is the capital city of Arkansas and is located near the geographic center of the state. While Little Rock does have a robust urban center expected of a state capital, it also contains many natural features within its city limits. Little Rock lies on the southern bank of the Arkansas River. The western edge of the city rises into the Ozark Mountains while the eastern portion of the city extends towards the Mississippi River Delta. Finally, there are plains that gently roll southwest towards Texas (Bell 2013). With such a diversity of features, Little Rock provides the perfect contrast of land cover types to test the accuracy of supervised and unsupervised classification. Figure 1 shows a visual depiction of the overall study area.

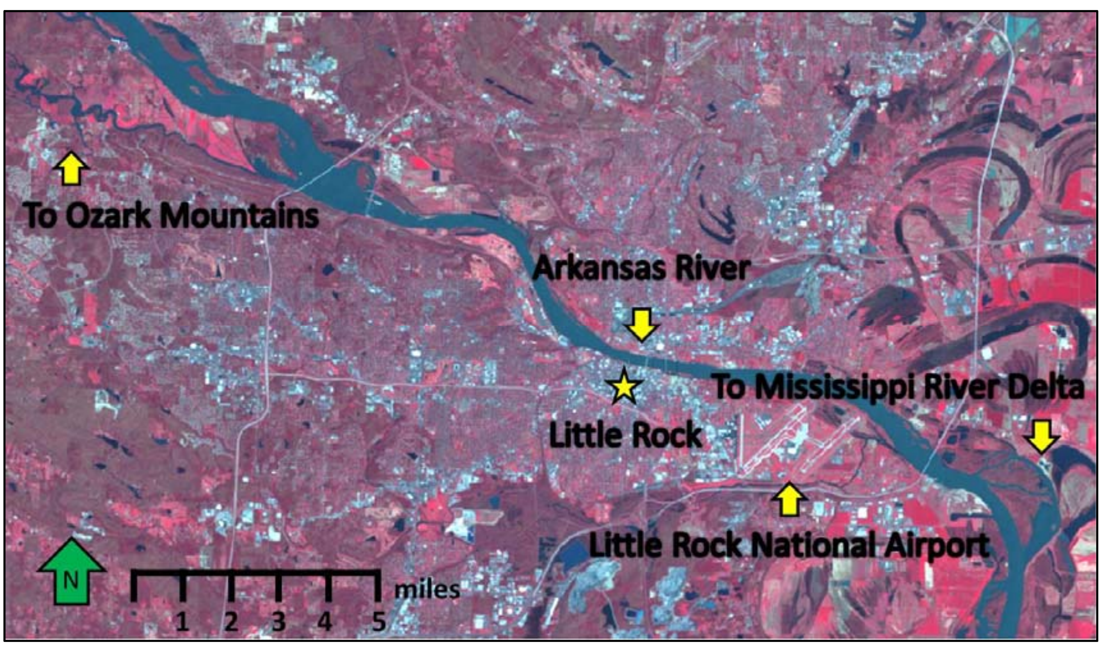


Figure 1. Screenshot of study area with selected features labeled. This figure was derived from Landsat 7 imagery with false color display (R,G,B/4,3,2).

3.2 Description of Data Sources

The main imagery for the land cover classifications performed in this study was Landsat 7 Enhanced Thematic Mapper Plus (ETM+) imagery. ETM+ features eight spectral bands: three in the visible spectrum (Bands 1-3), two near-infrared (Bands 4-5), one thermal (Band 6), one mid-infrared (Band 7), and one panchromatic (Band 8). Band 6 has a spatial resolution of 60 meters, Band 8 has a spatial resolution of 15 meters, and the remaining bands have spatial resolutions of 30 meters. A Landsat 7 image, or scene, is approximately 170 kilometers by 185 kilometers (106 miles x 115 miles) (United State Geological Survey 2013). Because of their differing spatial resolutions, Bands 6 and 8 were omitted from any analysis (Hung and Ridd 2002). Additionally, Landsat 7 scenes with the Scan Line Corrector (SLC) off were not suitable for this research. Therefore, the Landsat imagery was limited to a scene with the SLC on. The ETM+ imagery used in this study was acquired on April 1, 2003 at 1631 hours Coordinated Universal Time (UTC). ETM+ imagery was chosen for this research due to the rich spectral information contained within, the stability of data availability, and the fact that the imagery is available at no cost.

Ground truth data is essential to performing accuracy assessment. Because of the time elapsed from the ETM+ imagery to the present, obtaining ground truth data through *in situ* readings may have resulted in inaccurate findings. Instead, ground truth was derived from higher resolution National Agriculture Imagery Program (NAIP) imagery. The NAIP imagery was acquired in 2006 and has a spatial resolution of two meters.

3.3 Methodology

3.3.1 Conceptual Overview

There were three phases in conducting this research: initial image processing, supervised/unsupervised classification, and accuracy assessment. Initial image processing involved obtaining the necessary ETM+ and NAIP imagery, then identifying and isolating suitable homogeneous, intermediate, and heterogeneous study areas. The classification phase involved performing supervised and unsupervised classification on each of the study areas. For accuracy assessment, 200 stratified random points were created for each study area and then LULC class was retrieved from each of the classified images. In the meantime, ground truth data at locations corresponding to these sampling points were visually interpreted from the NAIP image. Finally, all points were put into error matrices to assess the accuracy of each classification approach in each study area. Figure 2 provides a graphical representation of the conceptual overview.

3.3.2 Initial Image Processing

As previously mentioned, the first phase of analysis involved the initial processing of ETM+ and NAIP imagery. A single ETM+ scene was downloaded from the United States Geological (USGS) Global Visualization Viewer (GloVis) website. Using a total of four land cover classes (vegetation, impervious surface, soil, and water), the ETM+ scene was then loaded into ERDAS Imagine where it was subdivided into three study areas: one of homogeneous land cover, one heterogeneous, and one intermediate. The homogeneous area was defined as an area where 50% of the pixels are classified as one land cover type. A study area comprised mostly of water features was ideal for the homogeneous area because it absorbs most of the energy from the visible light and infrared bands, thus making it easier to distinguish from other types of land cover. The intermediate area was defined as one where two of the four land cover types each comprised at least 35% of the pixels. Water and vegetation were the two land cover classes chosen to comprise the majority of the intermediate study area. High accuracy for classifying water features was possible due to its previously mentioned spectral properties while high accuracy for classifying vegetation features was possible due to its high reflectance in the near-infrared spectrum and relatively low reflectance in visible light (red edge). The heterogeneous area was defined as an area where all four land cover classes each comprised at least 20% of the total pixels in the study area. The homogeneous, intermediate, and heterogeneous areas were approximately 2 square miles (5.3 square kilometers). There are 5,893 pixels in each study area. After performing visual analysis and then supervised and unsupervised classifications, the percentage of pixels for each land cover class in each study area were computed in order to ensure that the study areas met the previously mentioned criteria. Unfortunately, there was one study area and classification combination that was slightly below the criteria – the supervised classification of the intermediate area. For the supervised classification of the intermediate area, the percentage breakdowns were 27.0% for vegetation, 7.2% for impervious surfaces, 24.6% for soil, and 41.2% for water. Because these percentages were close to the prescribed criteria and radically different from the unsupervised classification percentages, this area was maintained because of its potential for interesting and meaningful analysis. Figures 3 and 4 show the locations of each study area overlaid on ETM+ and NAIP imagery, respectively.

3.3.3 Supervised Classification

Once the homogeneous, intermediate, and heterogeneous areas were defined, supervised classification was performed on each of the study areas. All pixels were assigned to one of four land cover classes: vegetation, impervious surfaces, soil, and water. The Maximum Likelihood Classification (MLC) algorithm was the chosen method for supervised classification. For the homogeneous study area, a minimum of twelve training sites (three for each LULC class) were created based on pixel clusters that corresponded to pre-defined four LULC classes. The same process was repeated for the intermediate and the heterogeneous study areas. Each set of twelve training sites was exclusive to its respective study area; a training site that was used in one study area was not used in either of the remaining two study areas. Spectral signatures of like land cover type were then merged so that each study area would only have four spectral signatures – one for each land cover class. Figure 5 shows the supervised classification and associated training sites for the homogeneous, intermediate, and heterogeneous study areas. Spectral signature plots were then produced from the merged training site signatures of the homogeneous, intermediate, and heterogeneous study areas. The spectral signature plots for these LULC classes in each of the sub-areas are shown in Figure 6.

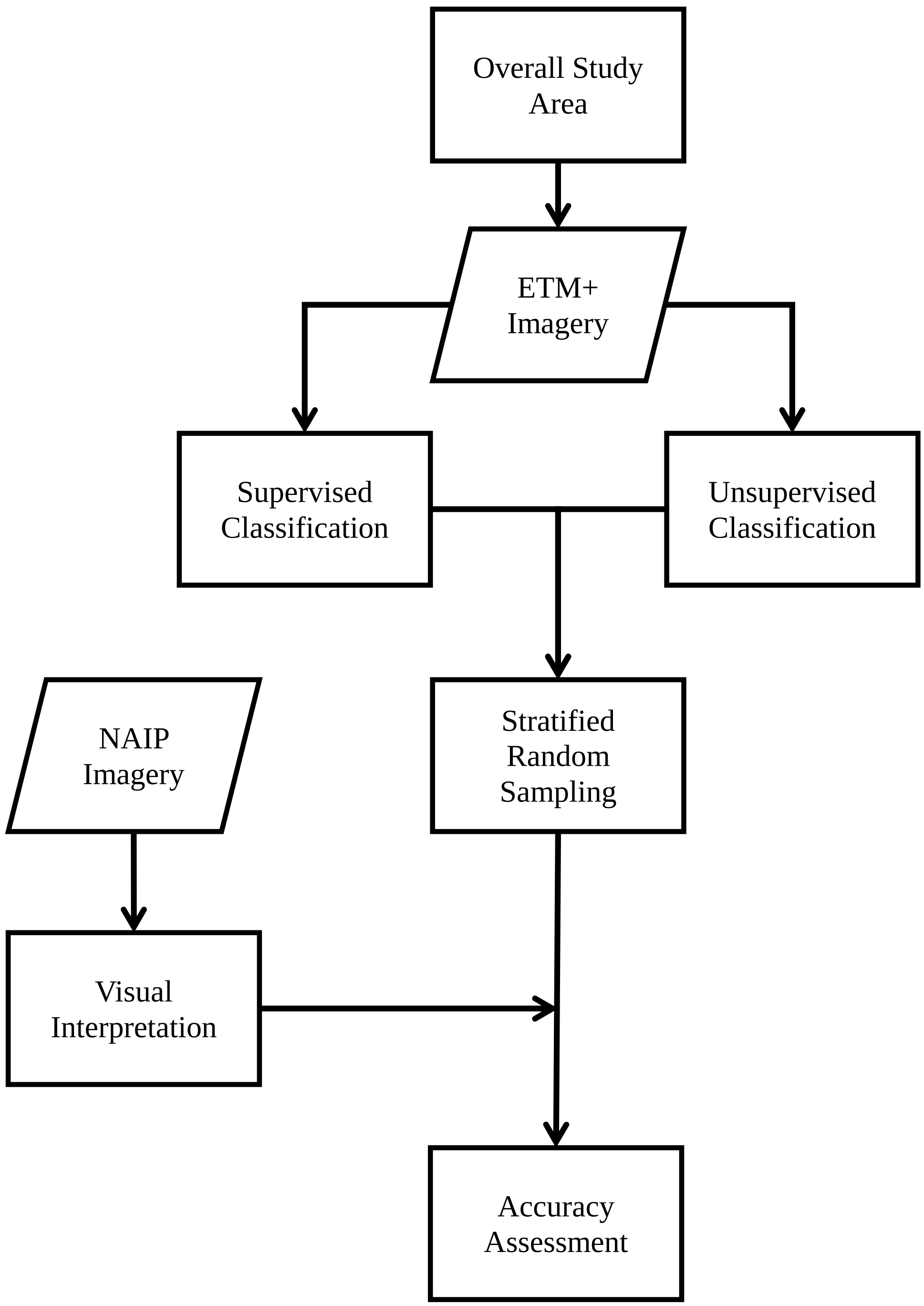


Figure 2. Workflow process

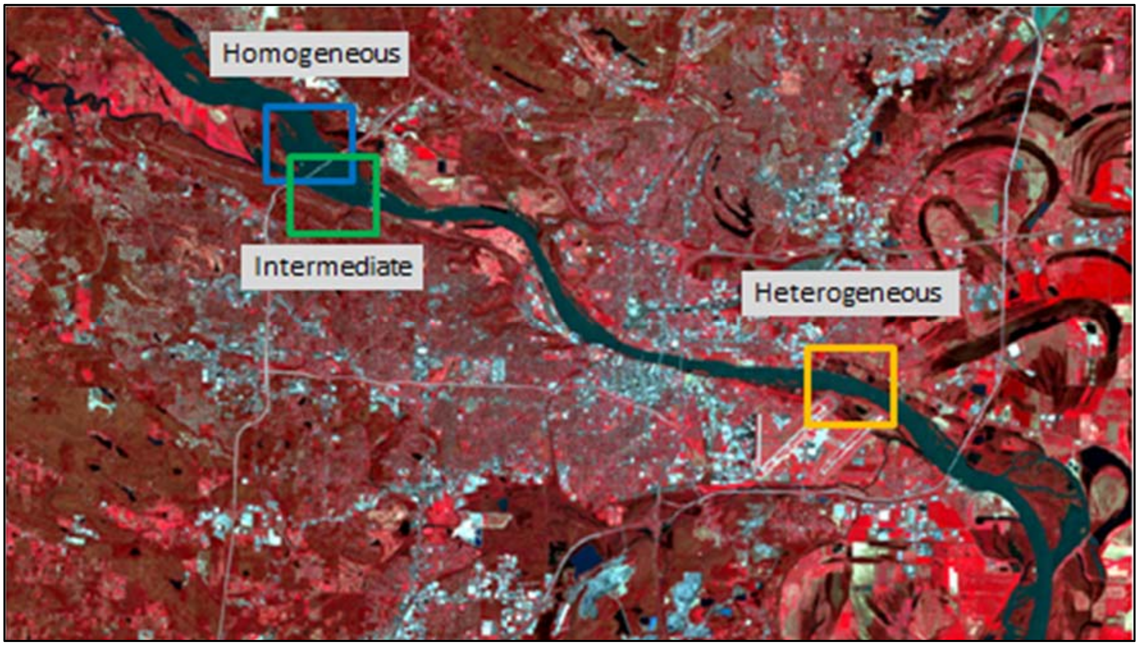


Figure 3. Screenshot of homogeneous, intermediate, and heterogeneous study areas (ETM+ overlay). This figure was derived from Landsat 7 imagery false color display (R,G,B/4,3,2).

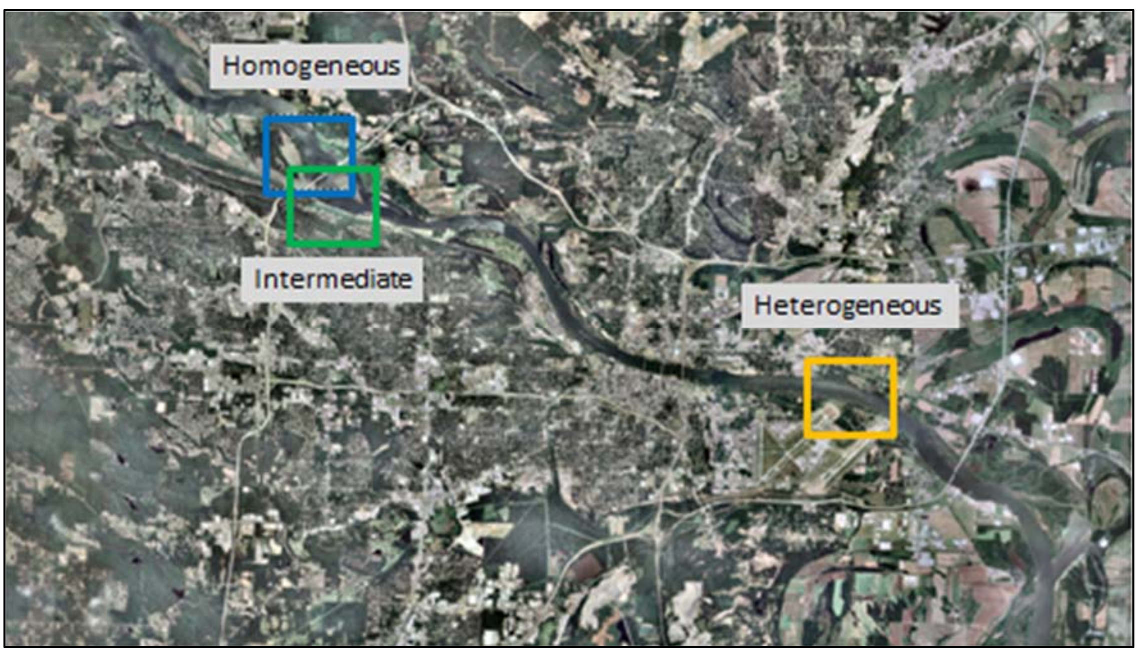
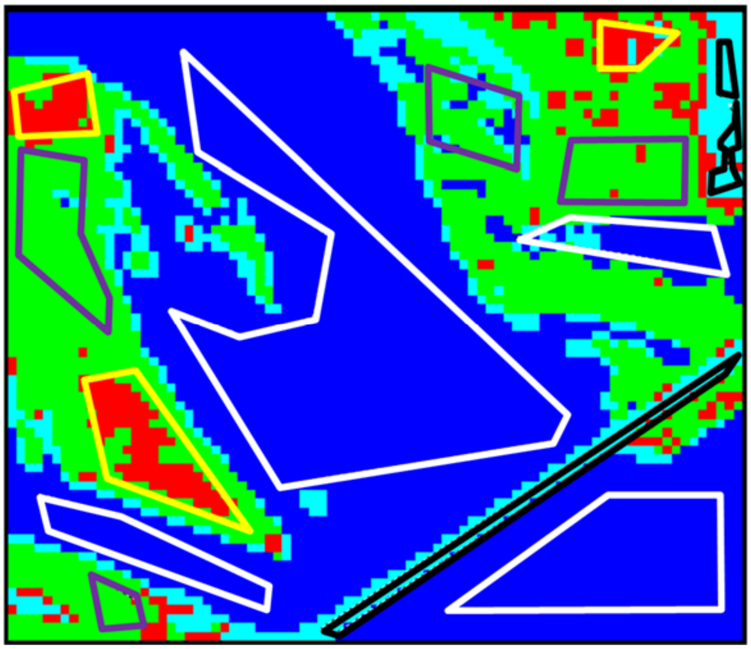
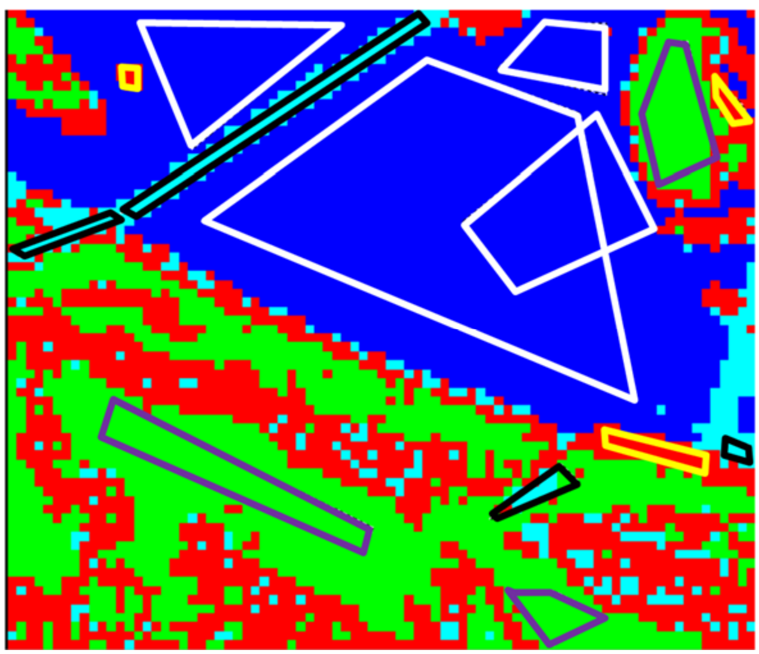


Figure 4. Screenshot of homogeneous, intermediate, and heterogeneous study areas (NAIP overlay).

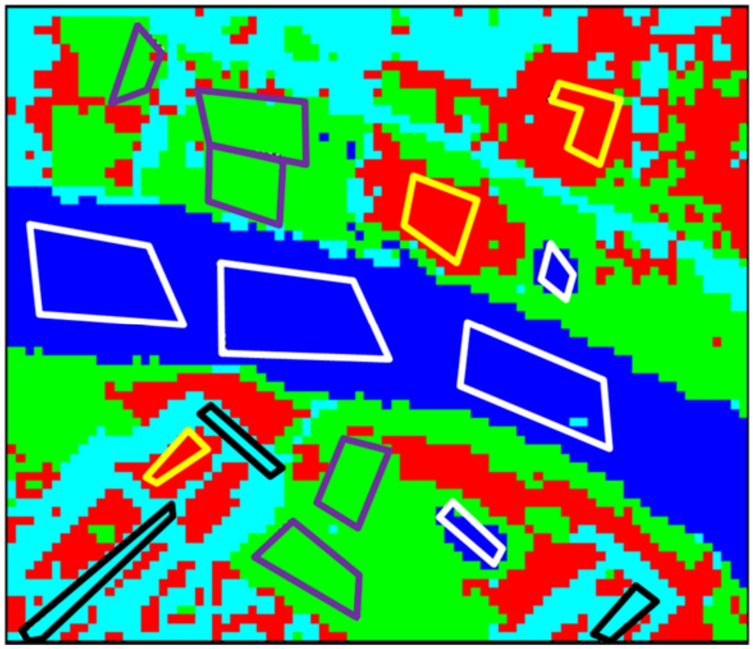


(a) Homogeneous study area



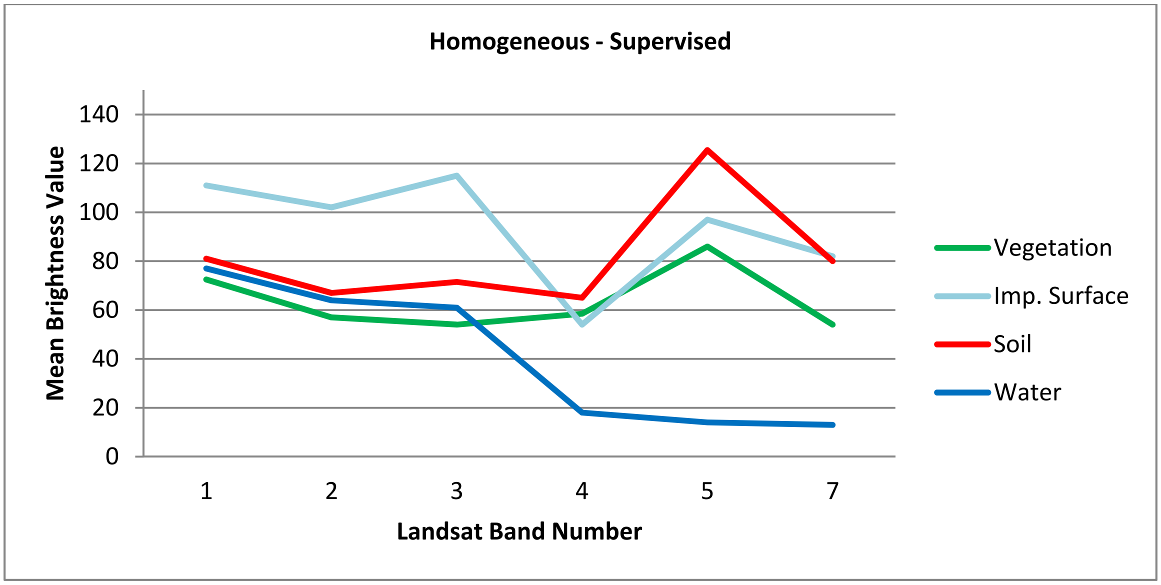
(b) Intermediate study area

Figure 5. Supervised classification with delineated training sites for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. Purple lines represent vegetation training sites, black lines represent impervious surface training sites, yellow lines represent soil training sites, and white lines represent water training sites.

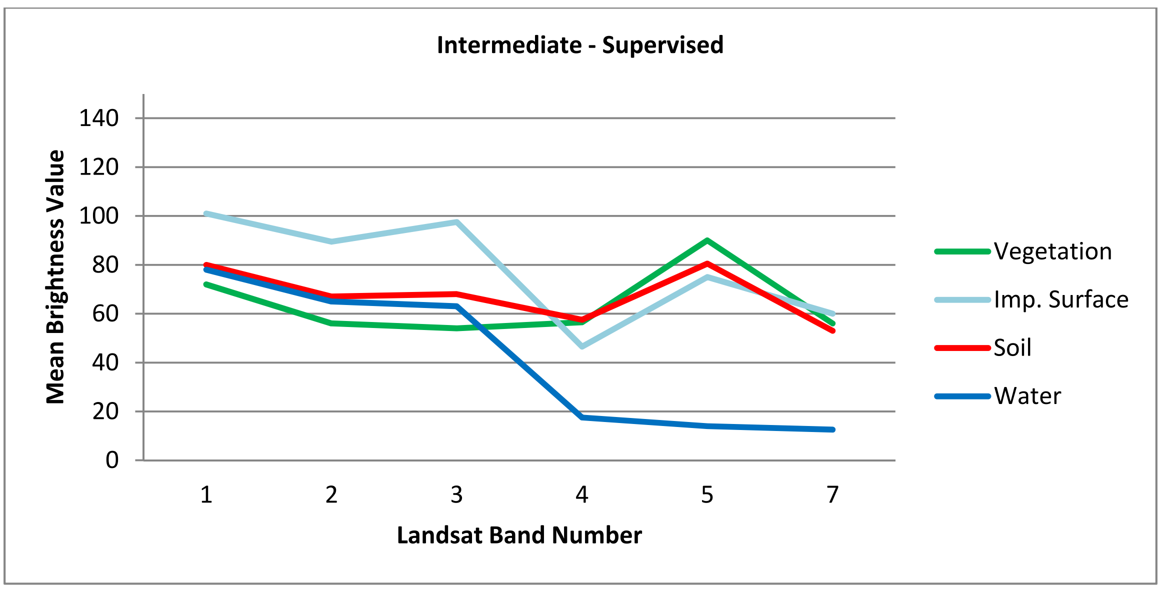


(c) Heterogeneous study area

Figure 5 (continued). Supervised classification with delineated training sites for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. Purple lines represent vegetation training sites, black lines represent impervious surface training sites, yellow lines represent soil training sites, and white lines represent water training sites.

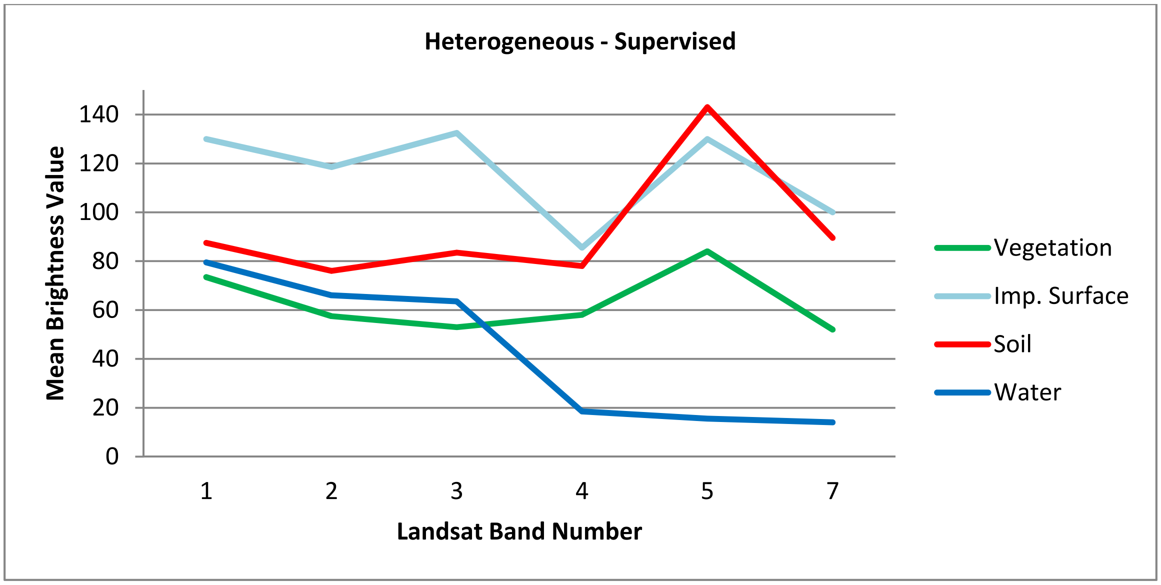


(a) Homogeneous study area



(b) Intermediate study area

Figure 6. Supervised classification signature mean plots for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. The x-axis represents Landsat bands 1-6 and the y-axis represents a mean brightness value.

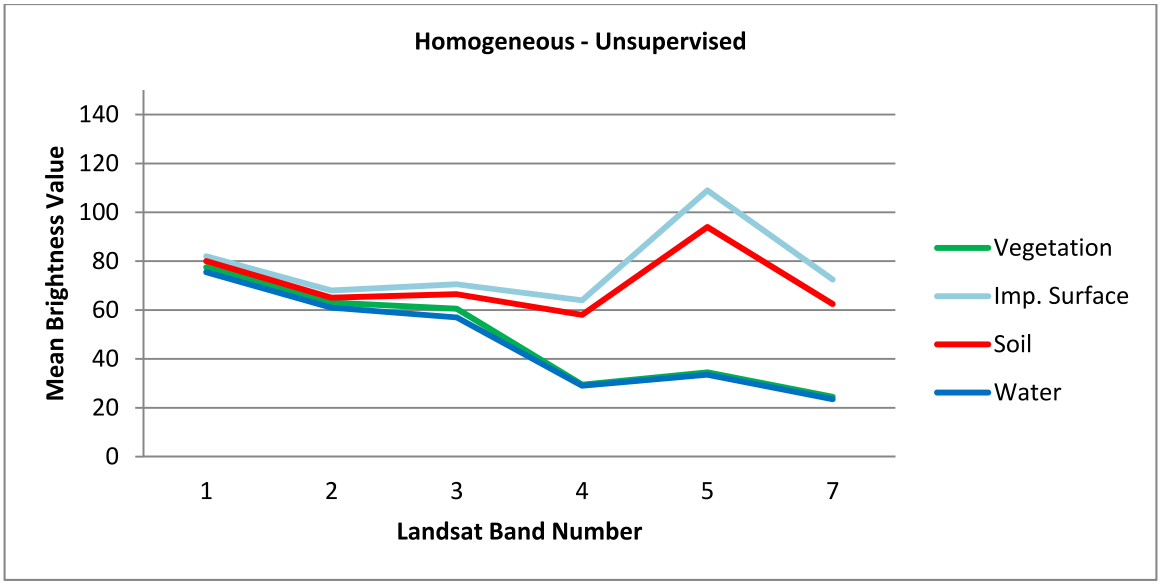


(c) Heterogeneous study area

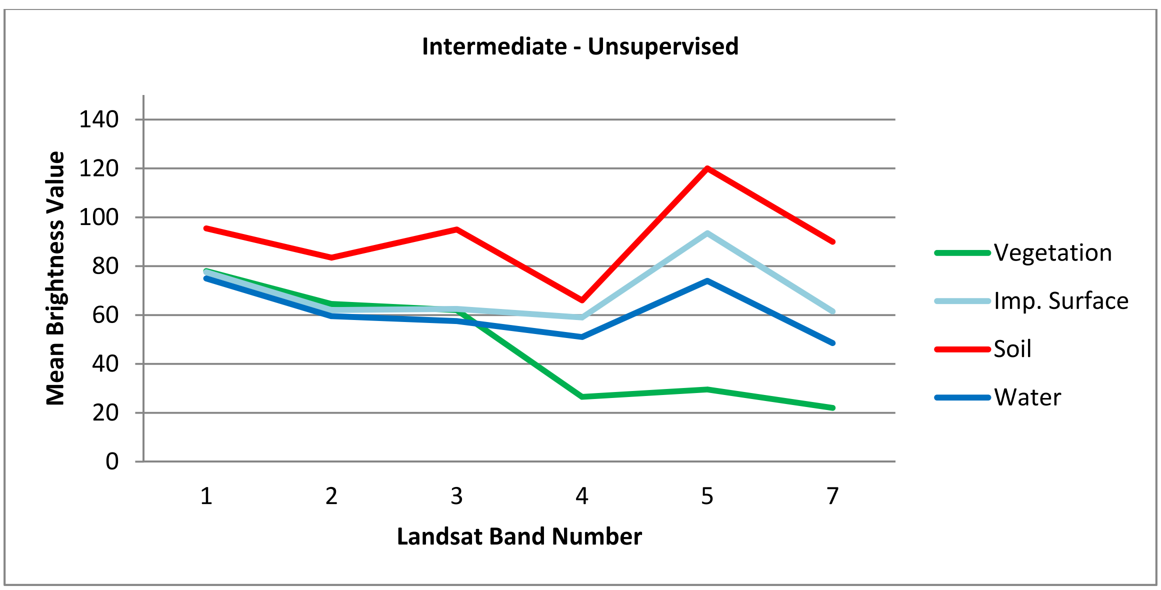
Figure 6 (continued). Supervised classification signature mean plots for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. The x-axis represents Landsat bands 1-6 and the y-axis represents a mean brightness value.

3.3.4 Unsupervised Classification

Using the ISODATA algorithm, unsupervised classification was conducted using 100 spectral classes, 20 maximum iterations, and a convergence threshold of 0.950. The convergence threshold of 0.950 stopped processing when 95% or more of the pixels remained in the same cluster between iterations. After the completion of the unsupervised classification process, each of the 100 spectral classes was assigned to the most appropriate land cover class. For comparison purposes, the spectral signature mean plots derived from the unsupervised classification for these LULC classes in each of the sub-areas are shown in Figure 7.

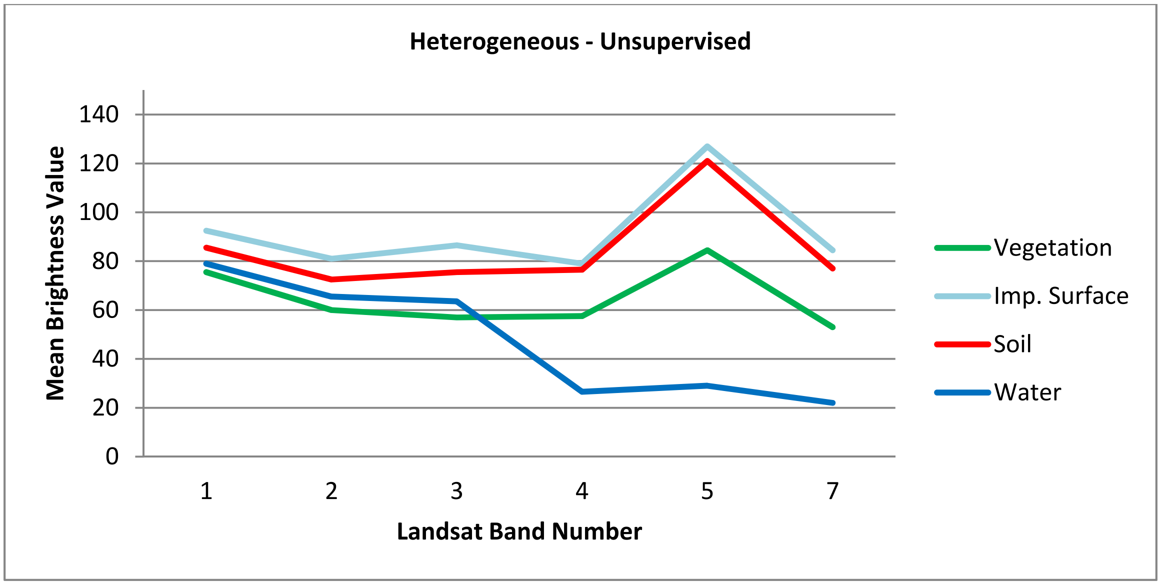


(a) Homogeneous study area



(b) Intermediate study area

Figure 7. Unsupervised classification signature mean plots for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. The x-axis represents Landsat bands 1-6 and the y-axis represents a mean brightness value.



(c) Heterogeneous study area

Figure 7 (continued). Unsupervised classification signature mean plots for (a) homogeneous study area, (b) intermediate study area, and (c) heterogeneous study area. The x-axis represents Landsat bands 1-6 and the y-axis represents a mean brightness value.

3.3.5 Accuracy Assessment

Once both classification methods were complete, accuracy assessment was the final portion of this research. For each study area, 200 points using a stratified random sampling approach were created. A minimum threshold of 30 points for each land cover class was used. For each point, the appropriate land cover type was identified from the supervised and unsupervised classification images. Ground truth for each of these points was then derived from higher resolution NAIP imagery. Figure 8 provides a graphical depiction of the result of this process. Higher resolution imagery is a suitable substitute for *in situ* data gathering (Bahadur 2009). In order to ensure an objective identification of ground truth data, the ETM+ pixels (with a pixel size of 30 meters x 30 meters) were analyzed using a 15 x 15 majority filter. Upon identifying the supervised classification, unsupervised classification, and ground truth land cover classes for each point in each study area, these data were then compiled into error matrices. While ERDAS Imagine allowed for automated accuracy assessment for each supervised classification, the software was unable to import the points necessary for accuracy assessment for each unsupervised classification. To mitigate this technical difficulty, all accuracy assessment was completed in Microsoft Excel.

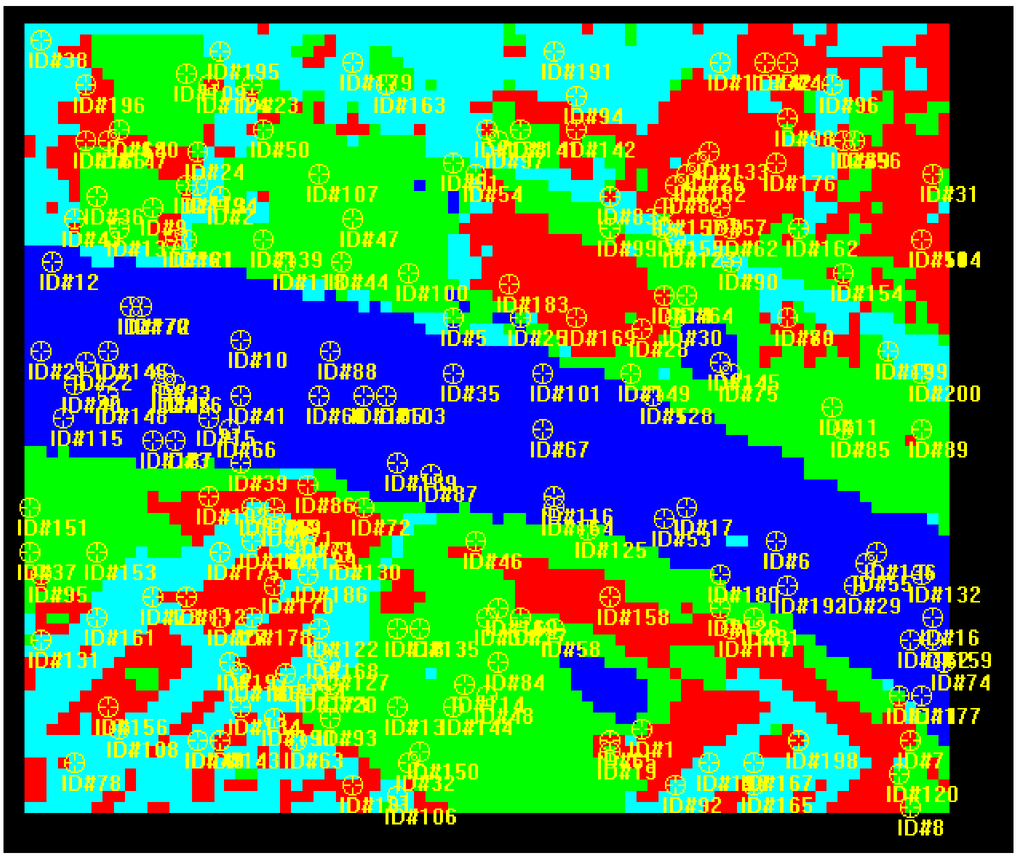


Figure 8. ETM+ (supervised classification) image of the heterogeneous study area overlaid with 200 points from stratified random sampling. The same process was conducted for the homogeneous and intermediate study areas.

CHAPTER 4: ANALYSIS RESULTS AND DISCUSSION

4.1 Classification Results

For each of the study areas (homogeneous, intermediate, and heterogeneous), there were a total of 5983 pixels. In the homogenous study area, the number of water pixels was 3284 and 3644 for supervised classification and unsupervised classification, respectively. This resulted in water coverage of 55.7% for supervised classification and 61.8% for unsupervised classification. For the intermediate study area, there were 1591 pixels (27.0%) of vegetation and 2428 pixels (41.2%) of water for the supervised classification. For the unsupervised classification of the intermediate study area, there were 2434 pixels (41.3%) and 2581 pixels (43.8%) for vegetation and water, respectively. In the heterogeneous study area, the percentage range for the land cover classes was between 21.9% to 32.2% for supervised classification and 20.3% to 29.6% for unsupervised classification. Table 1 provides a visual summary for the pixel numbers and percentages for each combination of study area and classification approach. The column labeled "# Pixels" shows the number of pixels assigned to each land cover class for each combination of study area and classification approach while the column labeled "% Pixels" coverts the aforementioned numbers into a percentage out of 5983 total pixels. Figure 9 shows the supervised classification results for the study area and Figure 10 shows the unsupervised classification results for the study area.

Table 1. Pixel count/percentage for each study area/classification method combination

(a) Pixel count/percentage of homogeneous study area using supervised classification

Homogeneous Supervised	# Pixels	% Pixels
Vegetation	1633	27.7
Impervious Surface	640	10.9
Soil	336	5.7
Water	3284	55.7

(b) Pixel count/percentage of homogeneous study area using unsupervised classification

Homogeneous Unsupervised	# Pixels	% Pixels
Vegetation	1878	31.9
Impervious Surface	241	4.1
Soil	130	2.2
Water	3644	61.8

(c) Pixel count/percentage of intermediate study area using supervised classification

Intermediate Supervised	# Pixels	% Pixels
Vegetation	1591	27.0
Impervious Surface	424	7.2
Soil	1450	24.6
Water	2428	41.2

Table 1 (continued)

(d) Pixel count/percentage of intermediate study area using unsupervised classification

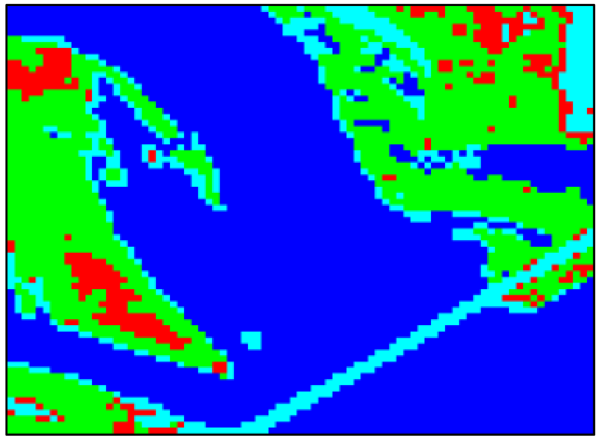
Intermediate Unsupervised	# Pixels	% Pixels
Vegetation	2434	41.3
Impervious Surface	843	14.3
Soil	35	0.6
Water	2581	43.8

(e) Pixel count/percentage of heterogeneous study area using supervised classification

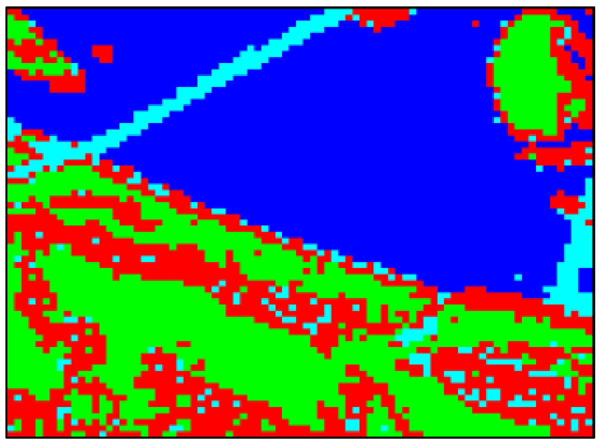
Heterogeneous Supervised	# Pixels	% Pixels
Vegetation	1896	32.2
Impervious Surface	1291	21.9
Soil	1312	22.3
Water	1394	23.7

(f) Pixel count/percentage of heterogeneous study area using unsupervised classification

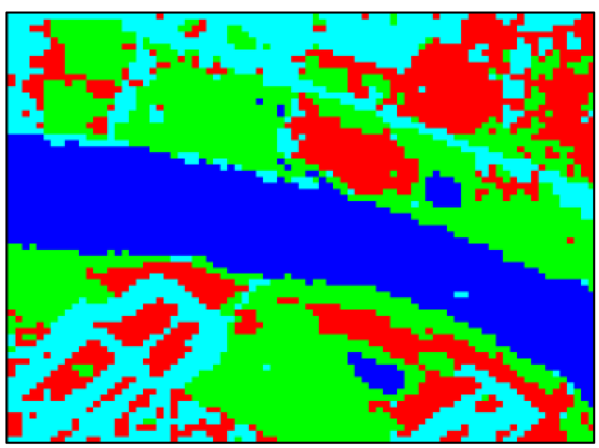
Heterogeneous Unsupervised	# Pixels	% Pixels
Vegetation	1744	29.6
Impervious Surface	1237	21.0
Soil	1198	20.3
Water	1714	29.1



(a) Homogeneous study area

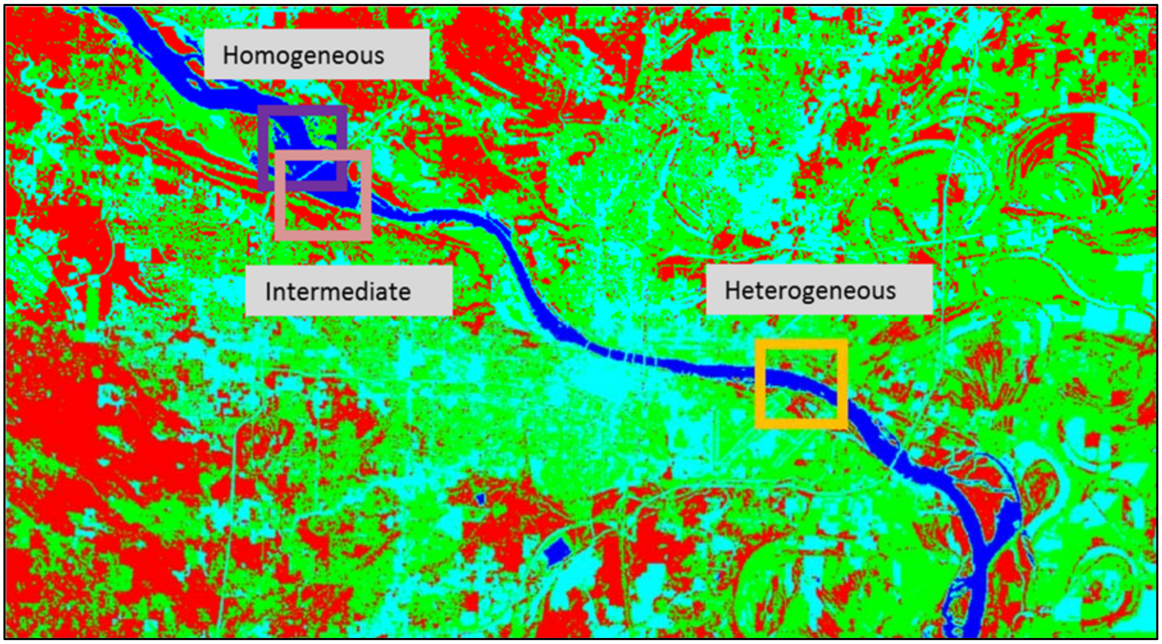


(b) Intermediate study area



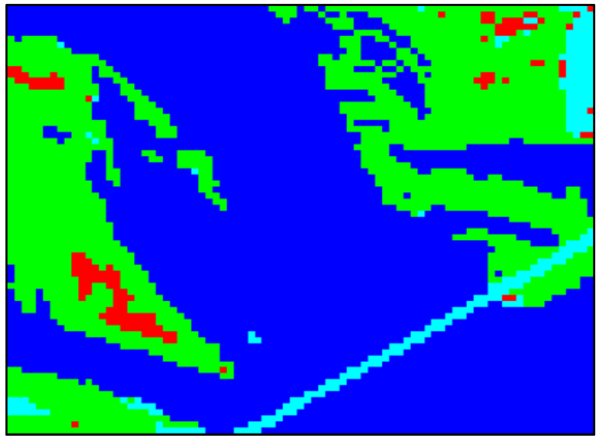
(c) Heterogeneous study area

Figure 9. Supervised classification results of (a) homogeneous, (b) intermediate, (c) heterogeneous and (d) overall study areas. Green areas represent vegetation, cyan areas represent impervious surfaces, red areas represent soil, and blue areas represent water.

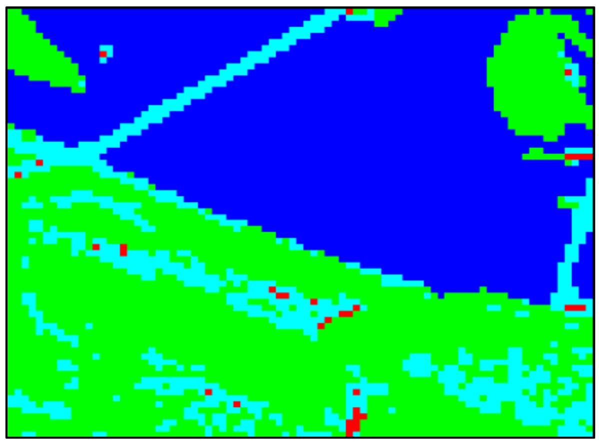


(d) Overall study area with sub-areas delineated

Figure 9 (continued). Supervised classification results of (a) homogeneous, (b) intermediate, (c) heterogeneous and (d) overall study areas. Green areas represent vegetation, cyan areas represent impervious surfaces, red areas represent soil, and blue areas represent water.

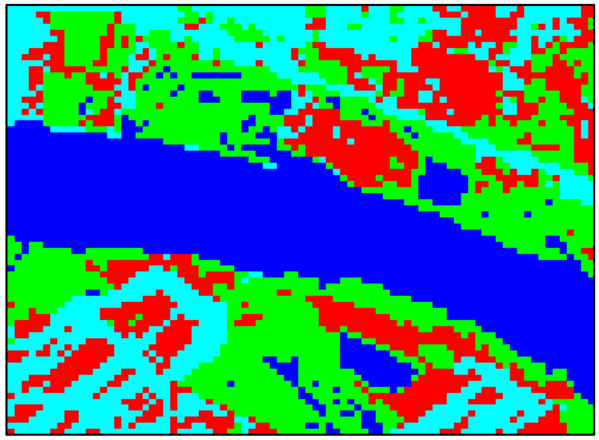


(a) Homogeneous study area

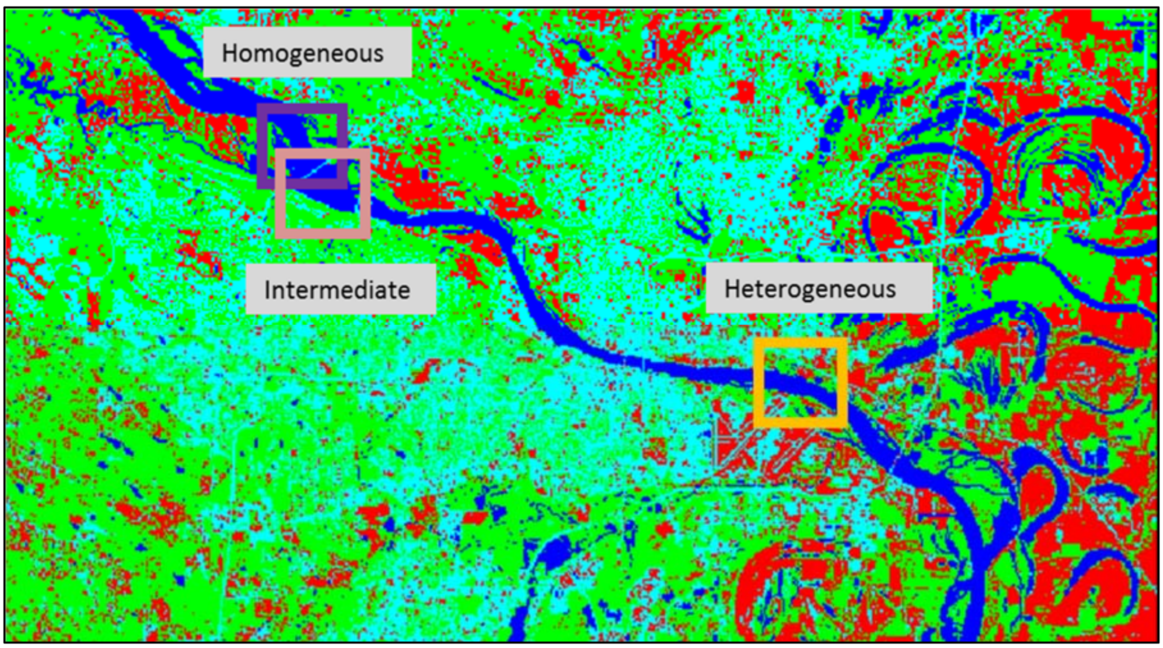


(b) Intermediate study area

Figure 10. Unsupervised classification results of (a) homogeneous, (b) intermediate, and (c) heterogeneous and (d) overall study areas. Green areas represent vegetation, cyan areas represent impervious surfaces, red areas represent soil, and blue areas represent water.



(c) Heterogeneous study area



(d) Overall study area with sub-areas delineated

Figure 10 (continued). Unsupervised classification results of (a) homogeneous, (b) intermediate, and (c) heterogeneous and (d) overall study areas. Green areas represent vegetation, cyan areas represent impervious surfaces, red areas represent soil, and blue areas represent water.

4.2 Error Matrices

For two of the three study areas, unsupervised classification was more accurate than supervised classification. For the homogeneous area, the overall accuracy for supervised classification and unsupervised classification was 74.5% and 86.5%, respectively. For the intermediate area, the overall accuracy for supervised classification and unsupervised classification was 67.0% and 83.0%, respectively. While supervised classification was more accurate than unsupervised classification in the heterogeneous area, the difference in accuracy between the two classification approaches was only one percent. The supervised classification had an overall accuracy of 72.0% while the unsupervised classification had an overall accuracy of 71.0%.

Regarding user's accuracy and producer's accuracy, the water land cover class had consistently high values over all three study areas. As stated previously, water has radically different spectral properties than the other land cover classes in the V-I-S model. In the signature mean plots, the brightness values for water are much lower in bands 4, 5, and 6 when compared to the other land cover classes. This spectral difference allowed water to be readily identified and thus resulted in higher accuracy values.

For vegetation, user's accuracy was in the mid-80s or higher for all three study areas, but producer's accuracy was lower ranging from low-50s to mid-80s. The disparity in user's accuracy and producer's accuracy indicates a tendency to overestimate the number of vegetation pixels. Soil and impervious surfaces were commonly misclassified as vegetation in almost all of the error matrices. In the signature mean plots, vegetation and impervious surfaces had overlapping brightness values mostly in bands 4 and 5 during supervised classification and bands 1, 2, and 3 during unsupervised classification. These overlapping brightness values occurred only in the homogeneous and intermediate study areas. The heterogeneous study areas had distinctly different brightness values. Regarding the brightness values for vegetation and soil, there were similar values for bands 1 and 4 in the supervised classification of the homogenous and intermediate study areas. There were also similar brightness values for vegetation and soil in bands 1 and 2 of the unsupervised classification of the homogenous area. No other combination of classification approach and study area displayed similar brightness values. It was interesting to note, however, that none of the signature mean plots for vegetation displayed the expected spike in brightness from band 3 to band 4. In fact, there was a near-overlap of the vegetation and soil graphs in Figure 6b, an even closer overlap of the vegetation and water graphs in Figure 7a, and a drop in brightness values from band 3 to band 4 in Figure 7b. The near-overlap of vegetation and soil in Figure 6b could explain why nearly 50 percent of the vegetation pixels in the error matrix for supervised classification of the homogeneous area were misclassified as soil. The error matrix for unsupervised classification of the homogeneous study area featured nine vegetation pixels misclassified as water – an error which could have been reflected by the overlap of vegetation and water in Figure 7a. Finally, the drop in vegetation brightness values from band 3 to band 4 could explain why nearly a quarter of the vegetation pixels for the unsupervised classification of the intermediate study area were misclassified as impervious surfaces.

The lowest producer's accuracy for impervious surfaces was 68.75% while all of the other values ranged between low-80s to 100%. The user's accuracy for impervious surfaces ranged between low-30s to 50%. The large difference between user' accuracy and producer's accuracy indicates a tendency to overestimate the number of impervious surface pixels. In every signature mean plot, impervious surfaces and soil had similar brightness values in band 4. Band 6 was another area of common brightness values in all but one of the signature plots.

Accuracy values for soil displayed much more variance. User's accuracy ranged from 0 to 53.3% while producer's accuracy ranged from 0 to 100%. The wide range of accuracy indicates a severe confusion of soil with other land cover classes. Soil pixels were both overestimated and underestimated in the various study areas. The majority of overestimation was due to the misclassification of vegetation as soil, particularly in regards to supervised classification. Conversely, an underestimation of soil occurred where soil pixels where mainly misclassified as impervious surfaces, particularly in the heterogeneous study area. In the signature mean plots, soil and water had similar brightness values in bands 1 and 2, while the brightness values in bands 3 through 6 displayed anywhere from small to great divergence.

Based on the supervised classification signature mean plots produced in ERDAS Imagine (see figure 6), the reflectivity in bands 4, 5, and 6 was similar between impervious surfaces and soil in the homogeneous and heterogeneous study areas. This could explain the instances of soil being misclassified as impervious surfaces as well as contributing to user's accuracy values below 50 percent. In the intermediate study area, impervious surfaces had similar reflectance in bands 4, 5, and 6 with both soil and vegetation. Consequently, all three land cover classes showed a wide variance of user's accuracy ranging from 6 to 100 percent and producer's accuracy ranging from 53.06 to 100 percent. Soil and vegetation had similar reflectance in band 4 in the homogeneous and heterogeneous study areas. While vegetation had user's accuracy above 80 percent, all other user's and producer's accuracy values for vegetation and soil were 70 percent or less.

For the unsupervised classification, the signature mean plots also show similar reflectivity in bands 4, 5, and 6 between impervious surfaces and soil in both the homogeneous and heterogeneous study areas (see figure 7). In the heterogeneous area, impervious surfaces and soil actually have similar reflectivity in all six bands. In the intermediate study area, impervious surfaces and water share similar reflectivity in all six bands. While the user's accuracy for impervious surfaces was 36.84%, the other user's and producer's accuracy values were 89% or higher. Also in the intermediate study area, vegetation exhibits similar reflectivity with impervious surfaces and water in bands 1, 2, and 3. Both user's and producer's accuracy for vegetation were high at 94.87% and 75.51%, respectively. In the heterogeneous area, vegetation and water feature similar reflectivity across bands 1, 2, and 3. The producer's accuracy for vegetation is 59.52% while the other accuracy values for vegetation and water are greater than 86%. Table 2 shows the full error matrices for the homogeneous, intermediate, and heterogeneous study areas.

Table 2. Error matrices

(a) Error matrix for supervised classification of the homogeneous study area

Supervised Classification (Homogeneous)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	51	0	0	2	53	96.23%
Imp. Surface	13	11	3	8	35	31.43%
Soil	23	0	7	0	30	23.33%
Water	2	0	0	80	82	97.56%
Total	89	11	10	90	200	
Producer's	57.30%	100.00%	70.00%	88.89%		

Overall Accuracy = 74.50%

Kappa Coefficient = 62.52%

(b) Error matrix for unsupervised classification of the homogeneous study area

Unsupervised Classification (Homogeneous)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	73	0	0	1	74	98.65%
Imp. Surface	1	9	4	4	18	50.00%
Soil	6	0	6	0	12	50.00%
Water	9	2	0	85	96	88.54%
Total	89	11	10	90	200	
Producer's	82.02%	81.82%	60.00%	94.44%		

Overall Accuracy = 86.50%

Kappa Coefficient = 77.92%

Table 2 (continued)

(c) Error matrix for supervised classification of the intermediate study area

Supervised Classification (Intermediate)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	52	0	0	0	52	100.00%
Imp. Surface	6	11	0	13	30	36.67%
Soil	40	5	3	2	50	6.00%
Water	0	0	0	68	68	100.00%
Total	98	16	3	83	200	
Producer's	53.06%	68.75%	100.00%	81.93%		

Overall Accuracy = 67.00%

Kappa Coefficient = 53.89%

(d) Error matrix for unsupervised classification of the intermediate study area

Unsupervised Classification (Intermediate)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	74	2	2	0	78	94.87%
Imp. Surface	23	14	1	0	38	36.84%
Soil	1	0	0	5	6	0.00%
Water	0	0	0	78	78	100.00%
Total	98	16	3	83	200	
Producer's	75.51%	87.50%	0.00%	93.98%		

Overall Accuracy = 83.00%

Kappa Coefficient = 73.08%

Table 2 (continued)

(e) Error matrix for supervised classification of the heterogeneous study area

Supervised Classification (Heterogeneous)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	54	0	4	6	64	84.38%
Imp. Surface	10	19	15	0	44	43.18%
Soil	20	1	24	0	45	53.33%
Water	0	0	0	47	47	100.00%
Total	84	20	43	53	200	
Producer's	64.29%	95.00%	55.81%	88.68%		

Overall Accuracy = 72.00%

Kappa Coefficient = 61.80%

(f) Error matrix for unsupervised classification of the heterogeneous study area

Unsupervised Classification (Heterogeneous)

	Vegetation	Imp. Surface	Soil	Water	Total	User's
Vegetation	50	1	5	2	58	86.21%
Imp. Surface	11	18	14	0	43	41.86%
Soil	21	1	23	0	45	51.11%
Water	2	0	1	51	54	94.44%
Total	84	20	43	53	200	
Producer's	59.52%	90.00%	53.49%	96.23%		

Overall Accuracy = 71.00%

Kappa Coefficient = 60.64%

4.3 Comparisons between Supervised and Unsupervised Classifications

Supervised and unsupervised classifications each have their own strengths and weaknesses. Supervised classification is advantageous because it uses a relatively small number of classes to determine the appropriate land cover for each pixel. This allows for a streamlined and focused analysis. The disadvantage of supervised classification is that it requires much user input prior to performing any classifications. This portion of the analysis is time-consuming and, if there are any user-induced errors, the user will have to restart the training site selection process, possibly more than once. The effectiveness of supervised classification increases if the analyst is more familiar with a particular study area (Jensen 2005).

The much larger number of spectral classes in unsupervised classification allow for a more detailed and nuanced approach to assign land cover classes to smaller groups of pixels. Unfortunately, the increased number of pixel clusters can make it difficult to decide exactly what feature a particular cluster represents. This is especially apparent in areas with mixed pixels or with clusters that appear to cover multiple, yet distinctive, land cover types. Unsupervised classification may be suitable for analysts who are unfamiliar with a study area (Jensen 2005) or as a way to identify land cover classes suitable to conduct supervised classification at a later time (Mohammed and Rusthum 2008). Table 3 provides a summary of the overall accuracy and kappa coefficient for each classification approach in each study area. The overall accuracy is a measure of how well the classified pixels match the ground truth data while the Kappa coefficient measures how well the classification in question would compare to a chance arrangement of pixels to each land cover class.

Regarding LULC composition, the water features in all study areas displayed high producer's accuracy in excess of 80 percent for supervised classification and 90 for unsupervised classification. These findings for water are expected considering how the spectral properties are different compared to the other three land cover classes. Impervious surfaces had the second highest producer's accuracy which ranged from 68.75 to 100 percent for supervised classification and 81.82 to 90 percent for unsupervised classification. While the number of misclassified pixels was low overall, impervious surfaces were mostly misclassified as soil. The classification of vegetation was only moderately accurate with producer's accuracy ranging from 53.06 to 64.29 percent for supervised classification and 59.52 to 82.02 percent for unsupervised classification. Vegetation was mainly misclassified as soil. For the homogeneous and the heterogeneous areas, producer's accuracy for soil ranged between 55.81 to 70 percent for supervised classification and 53.49 to 60 percent for unsupervised classification. Soil was mostly misclassified as impervious surfaces in the homogeneous and heterogeneous areas. In the intermediate study area, the producer's accuracy for soil was 100 percent and 0 percent for supervised and unsupervised classification, respectively. Of note, however, is the fact that there were only three soil pixels in the intermediate study area for each classification approach. Unless an analyst has vast knowledge of a study area and extensive research with LULC classification, unsupervised classification will most likely provide the most effective means of delineating between land use and land cover classes. The analyst can always use the unsupervised classification results as a starting point for supervised classification, as well as any of the hybrid or object-based approaches not covered in this thesis.

Table 3. Overall accuracy and Kappa coefficient percentages

Study Area	**Classification Approach**	**Overall Accuracy (%)**	**Kappa Coefficient (%)**
Homogeneous	Supervised	74.50	62.52
Homogeneous	Unsupervised	86.50	77.92
Intermediate	Supervised	67.00	53.89
Intermediate	Unsupervised	83.00	73.08
Heterogeneous	Supervised	72.00	61.80
Heterogeneous	Unsupervised	71.00	60.64

CHAPTER 5: CONCLUSION

The primary objective of this research was to contrast the accuracy of supervised classification and unsupervised classification using the V-I-S model. In the homogeneous and intermediate study areas, unsupervised classification was more accurate than supervised classification. In the heterogeneous study area, supervised classification was more accurate by a mere one percent. These findings were contrary to the reviewed literature.

Another objective of this research was to determine guidelines for choosing supervised or unsupervised classification for future LULC studies. The most important factor in deciding which classification to use is the amount of *a priori* knowledge an analyst has about a study area. If the analyst is not intimately familiar with the LULC patterns of an area, unsupervised classification would most likely be more effective. While this thesis research was conducted by a resident of the Little Rock area, the lack of experience in identifying local LULC patterns most likely led to the decreased accuracy of the supervised classifications. Regardless of *a priori* knowledge, an analyst may want to use unsupervised classification as a means to identify LULC classes, which can then be applied to a supervised classification. In some situations, unsupervised classification may be the only method capable of producing viable LULC classes.

5.1 Research Limitations

This is an experimental project from which many lessons can be learned. The ability to obtain ground truth data was the largest limiting factor in this research. Since obtaining *in situ* ground truth data was not possible for this research, using higher resolution imagery was the best alternative method. Unfortunately, the amount of no-cost and/or low-cost high resolution imagery was limited, which resulted in using an NAIP image acquired three years after the SLC-on ETM+ imagery used in this research. It was fortunate, however, that the images were taken at the same time of the year, thus resulting in few differences between the environmental composition and spectral characteristics of the NAIP and ETM+ imagery. Also fortunate was the fact that there was very little change in the urban landscape between the two images, thus resulting in a more consistent comparison between the classified pixels and their associated ground truth.

Another limitation in this research was inexperience in conducting real-world land cover classification and deriving ground truth from remotely sensed imagery. If individuals with greater remote sensing experience and proficiency were to conduct similar studies, they would most likely achieve more accurate results in a shorter period of time. These limitations, however, did not have any significant impact on achieving the objectives of this research.

5.2 Suggested Areas for Further Research Study

There are many possible areas for further research based on the findings and results of this study. One possible avenue of expanding on this research would be to use a larger number of study areas with a wider variety of land cover compositions. For example, future researchers could analyze homogenous areas where water does not comprise the majority of the land cover or they could analyze intermediate areas where the majority land cover combination is something other than vegetation and water. Additionally, researchers could use a greater number of land cover classes than that offered by the V-I-S model, or they could use object-based and/or sub-pixel analysis in lieu of the relatively simple supervised and unsupervised classification approaches described in this research.

In addition to image classification methods and classification scheme, ground truth data is another avenue for future research. This study used ETM+ and NAIP imagery with acquisition dates that were approximately three years apart. Using a wider variety of imagery with closer dates of acquisition could possibly lead to more objective evaluation of the classification accuracy. By acquiring more recent imagery for analysis, it could also be possible to compare *in situ* ground truth data with that of high-resolution imagery. Again, this could lead to more objective evaluation of the classification accuracy.

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