University of Southern Queensland
Faculty of Engineering and Surveying

Extracting Spatial Information from Aerial Video Imagery for Monitoring Riparian Areas

A dissertation submitted by

Daniel Boitshoko

In fulfilment of the requirements of

Courses **ENG4111** and **ENG4112** Research Project

Towards the degree of

Bachelor of Spatial Science (Geographic Information Systems)

Submitted: 1st November, 2007

ABSTRACT

There are many different techniques being used in remote sensing to capture data for natural resource management. Aerial video mapping is a relatively new technique that is gaining popularity because of its non invasiveness, relative cost-effectiveness and timeliness.

The Queensland Murray Darling Committee (QMDC) has collected video footage of rivers within its catchment area to facilitate their river management activities. It endeavours to ascertain the usefulness and reliability of information provided by aerial video mapping technology for riparian management.

The aim of this project was to develop object-oriented image processing techniques and GIS based techniques for extracting riparian area parameters from aerial video imagery. Specifically, the objectives were to a) use traditional image processing techniques to extract the identified riparian parameters; b) identify and test object-oriented image processing techniques that may be suitable for mapping the selected riparian variables; and c) assess the accuracy of the results generated from both the traditional per-pixel and object-oriented image processing techniques.

Four images were extracted from the aerial video footage. Each image represented a dominant land cover/use type (i.e. agriculture, urban, pasture and forest). For each image, a set of classes representing various riparian parameters were created. These were then used for classifying the images using the maximum likelihood algorithm in ERDAS IMAGINE 9.1, and the object-oriented classification techniques in Definiens Professional 5.

The object-oriented approach achieved results with accuracies ranging from 90% up to 97% while the pixel-based approach managed accuracies ranging from 69% up to 82%. The data was found to have two major limitations. It had only three spectral bands, red, green and blue. Accurate measurements could not be made from the imagery because it was collected at an oblique angle.

University of Southern Queensland

Faculty of Engineering and Surveying

ENG4111 & ENG4112 Research Project

Limitations of Use

CERTIFICATION

I certify that the ideas, designs and experimental work, results, analyses and conclusions set out in this dissertation are entirely my own effort, except where otherwise indicated and acknowledged.

I further certify that the work is original and has not been previously submitted for assessment in any other course or institution, except where specifically stated.

Daniel Boitshoko

Student Number: 0050030444

____

Signature

____

Date

ACKNOWLEDGEMENTS

I would like to thank my supervisor, Associate Professor Armando Apan for his support and guidance throughout my project.

I would also like to thank my project sponsors: QMDC for providing the data used in the project and USQ for providing the software I needed to complete my project.

TABLE OF CONTENTS

ABSTRACT .... **II**

LIMITATIONS OF USE .... **III**

CERTIFICATION .... **IV**

ACKNOWLEDGEMENTS .... **V**

LIST OF FIGURES .... **IX**

LIST OF TABLES .... **XI**

GLOSSARY .... **XII**

CHAPTER 1 INTRODUCTION **1**

1.1. INTRODUCTION 1
1.2. PROBLEM 2
1.3. PROJECT AIM AND SPECIFIC OBJECTIVES 2
1.4. JUSTIFICATION 3
1.5. DISSERTATION STRUCTURE 3

CHAPTER 2 LITERATURE REVIEW **4**

2.1. INTRODUCTION 4
2.2. RIPARIAN AREAS 4
2.3. THE IMPORTANCE OF MONITORING RIPARIAN AREAS 5
2.4. IMAGE ANALYSIS TECHNIQUES 6
2.4.1. Pixel-Based Image Analysis *6*
2.4.2. Object-Oriented Image Analysis *6*
2.4.3. Object-Oriented vs. Pixel-Based Approach *8*
2.5. AERIAL VIDEO MAPPING 9
2.6. THE POTENTIAL OF AERIAL VIDEO IMAGERY AS A SOURCE OF SPATIAL INFORMATION FOR MONITORING RIPARIAN AREAS 11
2.7. OBJECT-ORIENTED PARADIGM AND AERIAL VIDEO MAPPING AS APPLIED TO RIPARIAN MONITORING 11
2.8. CONCLUSION 12

CHAPTER 3 RESEARCH METHODS **13**

3.1 INTRODUCTION 13
3.2 STUDY AREA 13
3.3 METHODS 16
3.3.1 Data Capture *16*
3.3.2 Data Pre-processing *17*

3.3.3 Software Used ... *17*
3.3.4 Video Imagery Sampling ... *19*
3.3.5 Study Site Selection ... *19*
3.3.6 Identification of riparian parameters to be extracted ... *19*
3.3.7 Image Analysis ... *20*
3.3.8 Accuracy Assessment ... *20*
3.3.9 Methodology Flow Chart ... *21*
3.3.10 Image Extraction ... *22*
3.3.11 Image Classification ... *22*
3.3.12 Identification of classes ... *23*
3.3.13 Pixel-Based Classification ... *25*
3.3.14 Unsupervised Classification ... *25*
3.3.15 Supervised Classification ... *27*
3.3.16 Training Samples ... *28*
3.3.17 Object-Oriented Classification ... *29*
3.3.18 Image Segmentation ... *29*
3.3.19 Nearest Neighbour Classification ... *32*
3.3.20 Creating Class Hierarchies ... *33*
3.3.21 Image Object Feature Space ... *34*
3.3.22 Classification ... *35*
3.3.23 Refining Classification using rule sets ... *36*
3.3.24 Accuracy Assessment ... *39*
3.3.25 Pixel-based classification results ... *39*
3.3.26 Object-oriented classification results ... *40*
3.4 CONCLUSION ... 40

CHAPTER 4 RESULTS ... 41

4.1 INTRODUCTION ... 41
4.2 PIXEL-BASED IMAGE CLASSIFICATION RESULTS ... 41
4.2.1 Supervised Classification Results - Agriculture ... *42*
4.2.2 Supervised Classification Results - Urban ... *43*
4.2.3 Supervised Classification Results - Forest ... *44*
4.2.4 Supervised Classification Results - Pasture ... *45*
4.3 OBJECT-ORIENTED IMAGE CLASSIFICATION RESULTS ... 46
4.3.1 Object-Oriented Classification Results - Agriculture ... *46*
4.3.2 Object-Oriented Classification Results - Forest ... *47*
4.3.3 Object-Oriented Classification Results – Urban ... *48*
4.3.4 Object-Oriented Classification Results – Pasture ... *49*
4.4 ACCURACY ASSESSMENT RESULTS ... 50
4.5 CONCLUSION ... 50

CHAPTER 5 ANALYSIS AND DISCUSSIONS **51**

5.1. INTRODUCTION 51
5.2. INTERPRETATION OF CLASSIFICATION RESULTS 51
5.3. DATA LIMITATIONS 53
5.3.1. Lack of Near Infrared Band *53*
5.3.2. Oblique Nature of the Imagery *54*
5.4. CONCLUSION 54

CHAPTER 6 CONCLUSIONS **56**

6.1. INTRODUCTION 56
6.2. CONCLUSIONS 56

REFERENCES **58**

APPENDIX A **61**

APPENDIX B **62**

APPENDIX C **65**

APPENDIX D **68**

APPENDIX E **71**

APPENDIX F **74**

APPENDIX G **77**

APPENDIX H **81**

APPENDIX I **89**

LIST OF FIGURES

Figure 2-1: Riparian Area 5
Figure 2-2: Unsegmented Image 7
Figure 2-3: Segmented Image 7
Figure 2-4: Aerial Video Mapping Setup 10
Figure 3-1: Agriculture 14
Figure 3-2: Pasture 14
Figure 3-3: Urban 14
Figure 3-4: Forest 14
Figure 3-5: Study Area Location 15
Figure 3-6: Video Camera mounted on a Helicopter 16
Figure 3-7: Methodology Flow Chart 21
Figure 3-8: Unsupervised classification dialogue box 26
Figure 3-9: Supervised Classification dialogue box 27
Figure 3-10: Histogram for Tree Cover 1 training sample 28
Figure 3-11: Signature File 29
Figure 3-12: Scale parameter 10 30
Figure 3-13: Scale parameter 50 31
Figure 3-14: Scale Parameter Analysis 32
Figure 3-15: Defining Feature Space for Nearest Neighbour Classification 33
Figure 3-16: An example of a class hierarchy 34
Figure 3-17: Image Object Features 35
Figure 3-18: Nearest Neighbour Classification Settings 36
Figure 3-19: Image Object Features used when classifying the Agriculture image . 37
Figure 3-20: Setting conditions for a custom rule set 38
Figure 3-21: Process Tree 39
Figure 4-1: Agriculture – Supervised classification results 42
Figure 4-2: Urban – Supervised Classification Results 43
Figure 4-3: Forest – Supervised Classification Results 44
Figure 4-4: Pasture – Supervised Classification Results 45
Figure 4-5: Agriculture – Object Oriented Classification Results 46
Figure 4-6: Forest – Object Oriented Classification Results 47

Figure 4-7: Urban – Object Oriented Classification Results 48
Figure 4-8: Pasture – Object Oriented Classification Results 49

LIST OF TABLES

Table 3-1: Study Area Images and their associated informational categories.......... 25

Table 4-1: Accuracy Assessment Results.. 50

GLOSSARY

Accuracy assessment: use of different techniques to assess the quality of a classification

Image classification: this is a process of associating or linking image objects or pixels with particular informational class (Definiens, 2006).

Image object: this refers to a group of pixels in an image that represent a particular feature. Each image object has a wide range of properties that can be used in the classification process (Definiens, 2006).

Image segmentation: refers to the use of different algorithms to break an image into image objects which are then used in image classification (Definiens, 2006).

Object-oriented image classification: an image classification technique that uses image objects rather than pixels as the basic unit of classification.

Pixel: picture element: the smallest element in an image

Pixel-based image classification: an image classification technique that uses pixels as the basic unit of the classification. During classification, each pixel is assigned to a particular class (Mather, 2004).

Riparian area: an area of land bordering a water body such as a river.

Scale parameter: an arbitrary value used to determine the size of image objects and the upper limit for a permitted change of heterogeneity during image segmentation (Definiens, 2006).

Chapter 1 INTRODUCTION

1.1. Introduction

The Queensland Murray Darling Committee (QMDC) is a non-profit natural resource management organisation that strives to ensure the sustainable management of natural resources in the Queensland Murray Darling Basin (QMDB) (QMDC, 2007). QMDC, a co-sponsor for this research project, is concerned with the timeliness and adequacy of the data that it has for river management. It seeks to ensure that it has adequate and timely data to facilitate river management activities (in this case, riparian area management) in the QMDB.

To this end, the QDMC has collected video footage of selected catchments in the QMDB. It endeavours to ascertain the usefulness and reliability of aerial video mapping technology and the quality and usefulness of the information that can be extracted from the aerial video imagery for managing riparian areas.

Upon establishing the usefulness of the data, the QMDC hopes to use the data in many different mapping applications. These include riparian condition mapping, riparian corridor connectivity and riparian width mapping. They also want to map vegetation species, bank stability, and stream width and identify erosion points. The data will also be shared with other land care groups and organisations to be used as an educational and capacity building tool for the community.

In previous research efforts, the use of spatial technologies (e.g. geographic information systems (GIS) and remote sensing (RS)) in monitoring riparian areas has been limited to using the pixel-based approach for analysing high resolution satellite imagery. Limited studies have been done using high spatial resolution imagery acquired from aerial video footage for monitoring riparian areas. New techniques, particularly the use of multi-resolution object-oriented image analysis approach, applied to aerial video imagery, have not been incorporated in methods or techniques recommended for monitoring riparian areas.

This study, which is a part of QDMC's Aerial Video Mapping Project (AVM), seeks to develop image processing and GIS based techniques for extracting spatial information from imagery acquired from the aerial video footage, for use in monitoring and managing riparian areas in the QMDB.

1.2. Problem

QMDC is concerned with the lack of timely and adequate data necessary for the apt, effective and efficient management of rivers within its catchment area. The data that is currently available to QMDC for management of riparian areas is inadequate and often not available when needed or not in a usable form, hence hindering the effective management of riparian zones.

1.3. Project Aim and Specific Objectives

The aim of this research project was to develop object-oriented image processing techniques and GIS based techniques for extracting riparian parameters from aerial video imagery.

The specific objectives of this study were to:

a. Identify riparian parameters to be extracted from the aerial video imagery.

b. Use traditional image processing techniques to extract the identified riparian parameters.

c. Develop object-oriented image processing techniques that may be suitable in mapping the selected riparian variables.

d. Assess the accuracy of the results generated using the selected image processing techniques.

1.4. Justification

The need for this project arose because the QMDC was looking for different ways it could tackle its problem of inadequate and untimely data for riparian area management. Also, limited studies have been done using high spatial resolution imagery acquired from aerial video footage for monitoring riparian areas. New techniques, particularly the use of multi-resolution object-oriented image analysis approach, applied to aerial video imagery, have not been incorporated in methods or techniques recommended for monitoring riparian areas.

1.5. Dissertation Structure

This dissertation is made up of six chapters. Chapter 1 introduces the project, gives a brief outline of the project background. It provides a justification for the project and presents the project aims and objectives. Chapter 2 deals with the literature review. It presents a summary of similar work done in the past and creates a working foundation for this project.

Chapter 3 describes the study area and outlines the research methodology and techniques used to process the data. Chapter 4 provides an analysis and interpretation of the results achieved using the techniques described in chapter 3. Chapter 5 discusses the findings of the project and chapter 6 provides conclusions and recommendations based on the discussions in previous chapters.

The dissertation is also made up of ancillary material: appendices, list of tables and figures.

Chapter 2 LITERATURE REVIEW

2.1. Introduction

This chapter presents a summary of the literature that was reviewed before undertaking the research work discussed in this paper. It starts by giving a brief description of riparian areas, their importance and the current spatial techniques used in managing them.

It then presents a discussion on pixel-based image analysis and object-oriented image analysis techniques and a comparison between these two techniques. A brief summary of aerial video mapping is also provided here. The chapter concludes by discussing the usefulness of aerial video mapping technology coupled with object-oriented image classification in riparian area management.

2.2. Riparian Areas

An area of land is referred to as a riparian area if it borders a natural water body. The width of the riparian area is defined in accordance with the objectives of the purpose for which it is being delineated (Price & Lovett, 2002). Figure 2-1 depicts an example of a riparian area. It shows a natural water body, a river in this case, and the land adjacent to it.

Figure 2-1: Riparian Area

2.3. The Importance of Monitoring Riparian Areas

It is important to monitor the condition of riparian areas in order to know the extent of damage or alteration on these areas due to human activities (Goetz, 2006). The availability of timely and adequate data about the state of riparian areas in the Murray Darling Basin will enable QMDC to take appropriate action to keep the riparian areas in good health.

Riparian areas play an important role in river ecosystem health and diversity. They help maintain river bank stability by anchoring the stream banks with their roots and thus decreasing the rate of soil erosion (Congalton et al., 2002; Price & Lovett, 2002). Riparian vegetation provides shade which regulates water temperate and thus improving water quality by reducing the rate of growth of algae (Congalton et al., 2002; Neale, 1997; Price & Lovett, 2002). Healthy riparian areas also have socio-economic benefits for people residing in their vicinity. Price and Lovett (2002), give a detailed account of the importance of correctly managing riparian lands for both economic and ecological reasons.

2.4. Image Analysis Techniques

2.4.1. Pixel-Based Image Analysis

A picture element (pixel) is defined as the smallest unit that can be displayed on a computer screen (Clarke, 2003). In remote sensing terms, a pixel is the smallest unit in an image. Thus, a remotely sensed image is an array of pixels. Each pixel contains a value that represents the amount of electromagnetic energy reflected or emitted by one or more geographic features in the area covered by the image (Mather, 2004).

Pixel-based image classification techniques use pixels as the base elements in the classification process. During classification, each pixel is assigned to a particular class. For example, the maximum likelihood classifier will assign a pixel to a class which it has highest likelihood of being a member (Mather, 2004; Yan et al, 2006). If a pixel represents more than one geographic feature, the pixel is usually assigned to the class of the more dominant feature (Mather, 2004).

2.4.2. Object-Oriented Image Analysis

Object-oriented image analysis is a relatively new image processing technique that is used to extract spatial information from remotely sensed images.

The basic operating principle of object-oriented image analysis is the breakdown of an image into smaller segments known as objects (Benz et al., 2004), hence the name object-oriented. This process of dividing an image into objects is known as image segmentation (Mather, 2004). It is the initial step in object-oriented image classification. Each object is made up of a group of pixels that represent a homogeneous area (Definiens AG, 2006).

Figure 2-2 shows an unsegmented image and Figure 2-3 shows the same image with images objects created after segmenting the image.

Figure 2-2: Unsegmented Image

Figure 2-3: Segmented Image

2.4.3. Object-Oriented vs. Pixel-Based Approach

The advent of high resolution imagery and the availability of better image processing technologies have led to a paradigm shift in image classification techniques used in remote sensing applications (Lang & Blaschke, 2006).

Recent research shows that the object-oriented approach to image processing is becoming the method of choice for many applications that require analysis of imagery with a very high spatial resolution. For example, Zhang and Feng (2005) used the object-oriented approach to map the distribution of urban vegetation from IKONOS imagery. Chubey, Franklin and Wulder (2006) devised a method for extracting forest inventory data from IKONOS-2 imagery using the object-oriented approach to image analysis. Recent undertakings in land use/cover mapping and change detection have favoured the use of the object-oriented approach rather than the pixel-based approach (Walter, 2006).

In the research studies mentioned in the previous paragraph, the authors opted to use the object-oriented approach over conventional classification methods (i.e. the pixel-based approach) because such methods have severe limitations when it comes to dealing with very high spatial resolution imagery. The inability of pixel-based classifiers to incorporate contextual data and other aerial photo interpretation elements during the classification process can lead to inaccurate results (Benz et al., 2004). Riparians areas exhibit a relatively high degree of spatial heterogeneity. In order to map these areas accurately, imagery with very high spatial resolution must be used (Neale, 1997). However, if the pixel-based approach is used to classify such imagery, the results obtained will have lower accuracy because pixel-based classifiers can be easily misled by the heterogeneity inherent in high spatial resolution imagery (Hay & Castilla, 2006).

When mapping vegetation, the pixel-based approach may be unable to differentiate between different types of vegetation which have similar spectral signatures. This problem can be overcome by using the object-oriented technique, which allows the incorporation of texture (Zhang & Feng, 2005) and other image object characteristics such as shape, size and context into the classification process(Hay & Castilla, 2006).

The pixel-based approach has been proven to produce results with lower classification accuracy when compared to the object-oriented approach in a variety of applications. For example, Yan et al. (2006) undertook a study to compare the accuracy of pixel-based and object oriented image classification techniques for mapping land-cover in a coal fire area. Their findings indicate that the accuracy achieved using the object-oriented methodology (83.25%) was considerably higher than that achieved when using the pixel-based approach (46.48%). Yuan and Bauer (2006) used object-based and pixel-based image classification techniques to map impervious surface areas. They applied both techniques to medium resolution Landsat TM imagery and found that the object-based approach produced results with a higher accuracy than those obtained from the pixel-based approach.

2.5. Aerial Video Mapping

Aerial video mapping, also known as aerial videography, is a technique used in remote sensing and other disciplines to gather data about geographic phenomena (Mausel et al., 1992;).

In its simplest form, an aerial video mapping system comprises of a standard home use video camera mounted on a platform such as a helicopter or a small plane. Figure 2-4 shows an example of an aerial video mapping system.

Figure 2-4: Aerial Video Mapping Setup
Source: Peter Smith (http://www.petersmith.com)

The complexity and sophistication of the camera used depends on the application and budget of the researcher. Positional data is recorded for each video frame using a GPS receiver linked to the video camera (Mausel et al., 1992; Neale 1997).

Data collected using aerial video mapping technology can be used in a variety of natural resource management applications. It also has uses in other non-remote sensing disciplines.

The aerial video mapping technique is gaining popularity in natural resource management because it is relatively inexpensive to use and provides coverage of large areas in a short period of time (Mausel et al., 1992). It produces data that is compatible with image processing systems(Richardson, Menges & Nixon, 1985).These data can, in some cases, be processed immediately without need for pre-processing and correction to remove or minimise instrument errors (Mausel et al. 1992).

2.6. The Potential of Aerial Video Imagery as a source of Spatial Information for Monitoring Riparian Areas

A review of previous studies into the use of aerial video mapping technology has revealed that the technique has been used to solve a variety of natural resource management problems, including riparian area mapping, restoration and monitoring. This is because the technique is relatively cost effective, timely and non-invasive (Lamb & Brown, 2000).

For example, Wulder et al. (2007) used airborne digital video in a study aimed at validating a large area land cover product. The authors chose to use the aerial video mapping technique over other approaches because it provided a timely and cost effective solution for their application.

Aerial video mapping has been used in the past for riparian area mapping and restoration activities. Neale (1997) gives a description of airborne multispectral videography and examples of its application in mapping riparian systems. In a study to select sites for riparian restoration, Russell et al. (1997), manually interpreted aerial video imagery in an attempt to verify the results they obtained by classifying Landsat imagery.

Solving spatial problems requires a technique that provides timely, adequate and accurate data. Aerial video imagery can be used to assess the condition of riparian areas both visually and automatically using image classification techniques. The studies discussed above have shown that aerial video mapping is a technique that has produced positive results when used in natural resource management, hence its potential suitability as a source of data for riparian monitoring in the Queensland Murray Darling Basin.

2.7. Object-Oriented Paradigm and Aerial Video Mapping as Applied to Riparian Monitoring

Remote sensing techniques have been and are still widely used in natural resource management. Past research shows that the main remote sensing approach used in natural resource management is the extraction of data from satellite imagery, aerial photographs (Goetz, 2006) or aerial video imagery using the pixel-based image classification approach.

For example, Goetz et al. (2003) used IKONOS imagery to map tree cover within riparian buffer zones using the pixel-based approach. In their study, (Congalton et al., 2002) mapped riparian vegetation from aerial photos and Landsat imagery using traditional image classification methods. In a study conducted by Neale (1997), the supervised pixel-based image classification technique was used to extract riparian variables from digital video imagery. Hawkins, Bartz and Neale (1997) undertook a study to assess the vulnerability of riparian vegetation to flooding. They used supervised pixel-based classification on aerial video images acquired before and after the flood event to map the effects of the flood on riparian vegetation.

Very few studies have been conducted using the object-oriented approach in riparian management. Johansen et al. (2007) applied the object-oriented approach to high spatial resolution imagery in a study aiming to discriminate vegetation structural stages in riparian and adjacent forested ecosystems.

2.8. Conclusion

This chapter set the technical background for this research project. It presented a summary of similar research work conducted in the past using both the pixel-based image processing and object-oriented image processing techniques in natural resource management. Results from previous research show that the object-oriented approach tends to produce more accurate results than the pixel-based approach, especially when working with imagery that has a high spatial resolution.

Chapter 3 RESEARCH METHODS

3.1 Introduction

This chapter discusses the research methodology used in this project. First, a brief introduction of the study area is presented. This is then followed by a summary of the techniques used during data capture and pre-processing. A detailed description of the pixel-based and object-oriented image techniques is then presented. The chapter concludes by providing an accuracy assessment report of the results obtained using both the pixel-based and object-oriented image classification approaches.

3.2 Study Area

The study area for this project is comprised of four images extracted from the video footage captured along the Macintyre and Dumaresq rivers in the Borders River Catchment. Each image represents a different riparian land use/cover. For this study, the land cover/use types selected were agriculture, pasture, forest and urban.

The images chosen as the study areas for this project are shown in Figure 3-1 to Figure 3-4.

Figure 3-1: Agriculture

Figure 3-2: Pasture

Figure 3-3: Urban

Figure 3-4: Forest

The agriculture, forest and urban images were extracted from video footage captured along the Macintyre River on the 23rd of September 2005 while the pasture image was obtained from video footage captured over the Dumaresq River on the 24th of September 2005.

The map in Figure 3-5 below shows the location of the Macintyre and Dumaresq rivers.

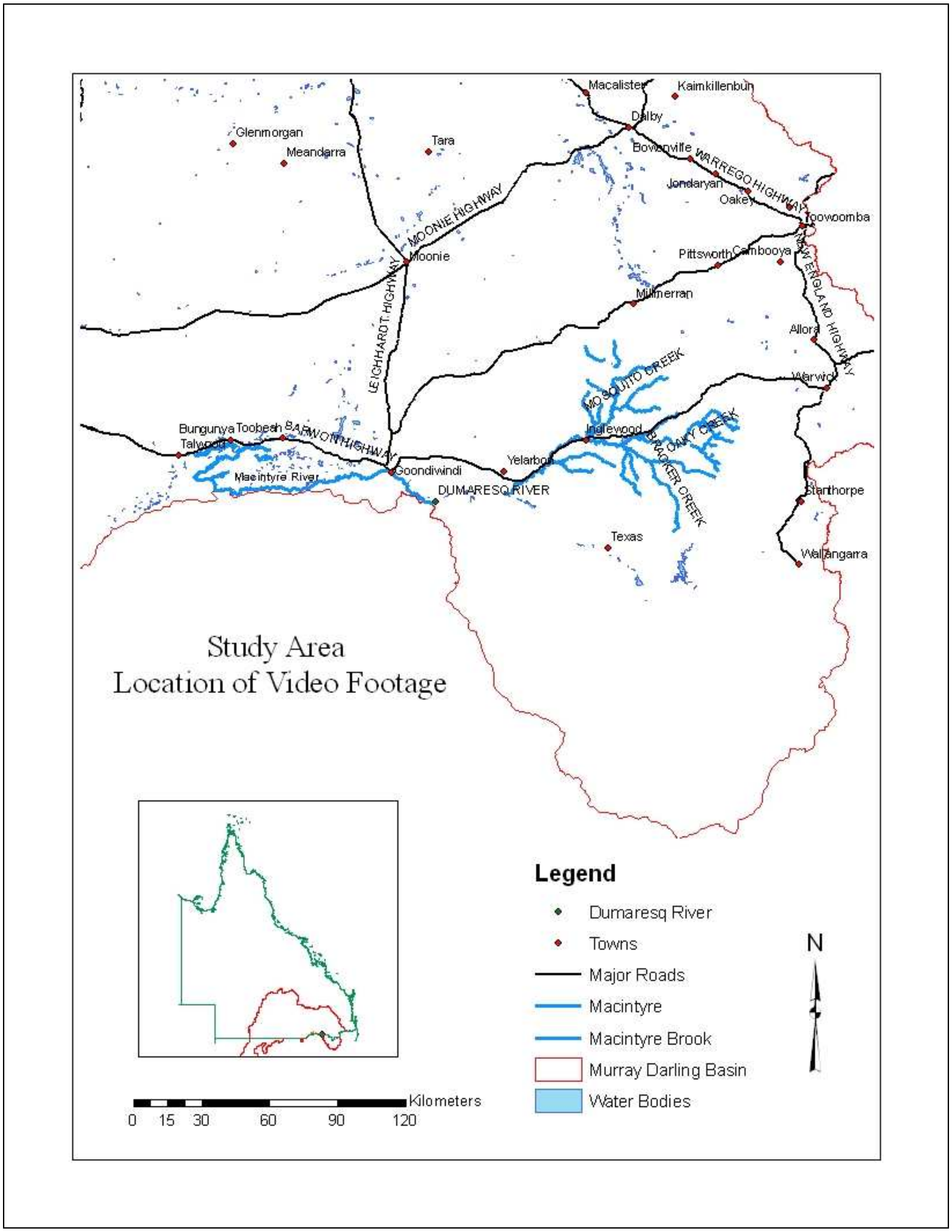

Figure 3-5: Study Area Location

3.3 Methods

3.3.1 Data Capture

The data used in this project was captured from the 23rd of September 2005 to the 29th of September 2005 by Gyrovision, a company that provides aerial stabilised camera solutions to clients such as QMDC.

The data was captured using a digital video camera mounted to the front of a helicopter. Figure **3-6** below is an illustration of a typical aerial video mapping system.

Figure 3-6: Video Camera mounted on a Helicopter
Source: Gyrovision (http://www.gyrovision.com.au)

The camera used captured data in the visible band i.e. data was collected using only the red, green and blue bands of the electromagnetic spectrum. The helicopter was also fitted with GPS equipment to facilitate the recording of positional data for each video frame captured. Flying heights varied between 50m and 400m along the course of the river.

3.3.2 Data Pre-processing

Once the data was captured and recorded on digital media, it was transferred to spatial DVD (sDvD) using GeoVideo, an extension tool for the ArcGIS environment from Red Hen Systems (Red Hen Systems, 2007). This was done to enable QMDC staff to interact with the video data within ESRI's ArcGIS (ArcMap) environment.

The data used in this project was provided by QMDC in sDVD format. Two sDVD disks were provided, one had video captured on the 23rd of September 2005 and the other had footage captured on the 24th of September 2005. The video footage in each disk was about an hour long and it was accompanied by other GIS datasets. The datasets included in the disk were rivers, major and minor roads, towns and state of the rivers sites (SOR) data and other water bodies.

3.3.3 Software Used

Three different types of software were used to accomplish the aims and objectives of this research project. The different types were GIS software, Image processing software and Video processing software:

a. ArcGIS 9

Product Version: ESRI ArcMap 9.2 Build (1324)
License Type: ArcView Student Edition
Copyright © 1999 – 2006 ESRI Inc. All Rights Reserved

This software was used to perform GIS-based analysis and to prepare the final results for presentation

b. ERDAS IMAGINE 9

Product Version: 9.1

This software was used to extract information from the video imagery using the traditional pixel-based image classification techniques. It provided algorithms for performing both the supervised and unsupervised image classification and the associated accuracy assessments. It was also used to perform an accuracy assessment of the results generated using the object-oriented image classification software.

c. Definiens Professional 5

Product Version: Definiens Professional 5

This software was used to classify images using object-oriented techniques. It provided a wide variety of object-oriented functionality that made the classification process more flexible and more accurate as compared to the traditional approach of classifying images.

d. VideoLAN – VLC Media Player

Product Version: 0.8.6c
VideoLAN Software Project

VLC is a free cross-platform media player from the VideoLAN software project. It was chosen for use in this project because it has the functionality for capturing still images from video footage. It was also chosen because it was a cheaper, less restricted alternative to GeoVideo.

3.3.4 Video Imagery Sampling

This step involved watching the video footage to identify potential study sites i.e. the video footage was assessed to locate sections which could be extracted as still images and used as a study site. After an area was identified as a potential site for study, it was extracted using VLC media player.

3.3.5 Study Site Selection

The study site was selected by analysing the video footage from both disks and extracting still images that represented a particular dominant riparian land use/cover type. Four images were selected, each image representing one of pasture, agriculture, forest and urban land use/cover types.

3.3.6 Identification of riparian parameters to be extracted

Once the images were extracted from the video footage, the riparian parameters to be extracted were identified for each image. Since each image represented a different land use/cover type, the types of parameters identified for extraction were different for the four images, although there were common parameters across all images.

3.3.7 Image Analysis

The imagery selected as study sites were analysed to extract the identified riparian parameters. First, before the images were analysed, the parameters identified for each image were used to create classes. These classes were then used in the classification process to extract spatial information from the images. The images were classified using both the traditional pixel-based algorithms and the new object-oriented algorithms. Section 3.3.11 gives a detailed description of how each of these methods was used to extract information from the four images.

3.3.8 Accuracy Assessment

The results obtained from the classification process were analysed and an accuracy report generated to determine the quality of the classification. This was done for both the pixel-based classification and the object-oriented classification. An extensive discussion of how the accuracy assessment was performed is given in sections 3.3.24, 3.3.25 and 3.3.26.

3.3.9 Methodology Flow Chart

Figure 3-7 below is a depiction of the methodology used in this project.

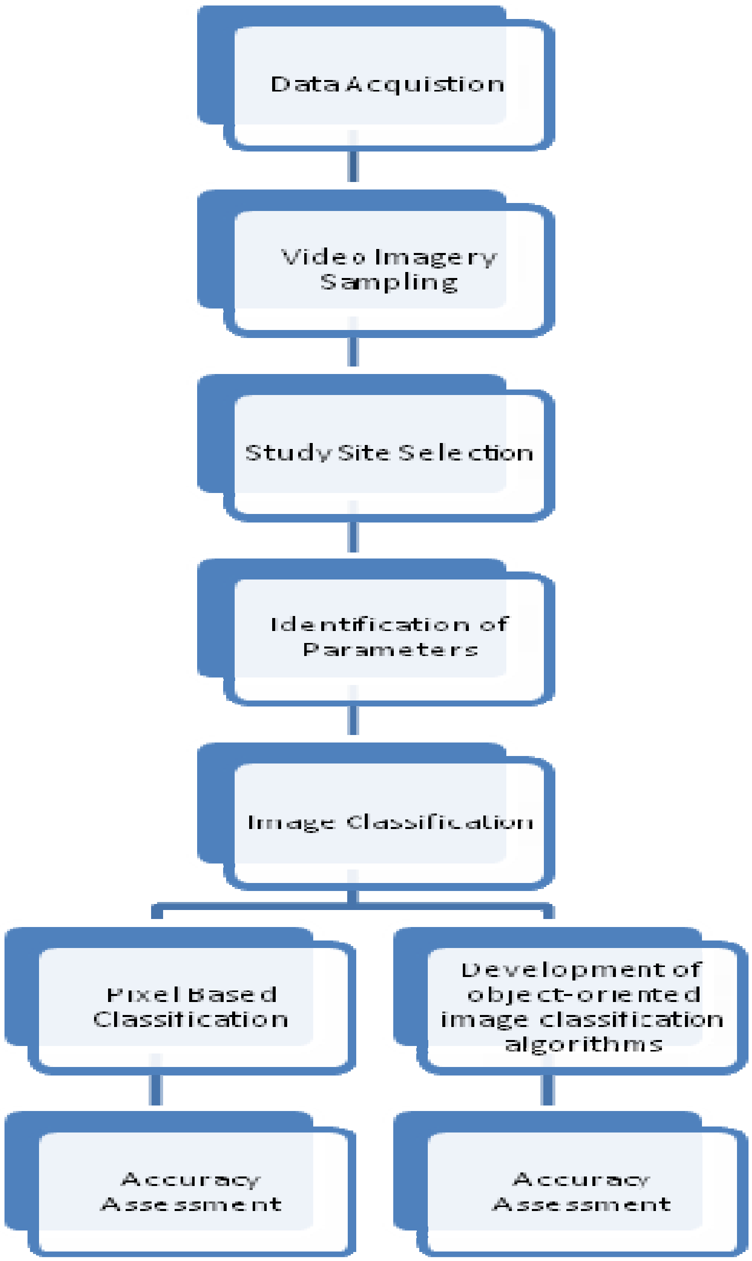

Figure 3-7: Methodology Flow Chart

3.3.10 Image Extraction

The images were extracted from the video footage using VLC. VLC is a freely available media player that allows the extraction of still images from video. This player was chosen because GeoVideo and Pixpoint, the more suitable applications for this project, could not be acquired due to financial and licensing constraints. Only trial versions of these products could be accessed but they had limited functionality and hence were not suitable as the critical functionality needed for extracting images was disabled.

A series of images were extracted from the video footage. Once the entire video footage was examined, the images were assessed and those that were most representative of a particular land use/cover type were chosen as the study area.

3.3.11 Image Classification

Image classification is a process of grouping pixels in an image into informational categories identified by the image analysts.

Two image classification approaches were used in this study: pixel-based approach and object-oriented approach. For the pixel-based approach, both supervised and unsupervised classification techniques. The unsupervised classification was performed first to help identify the natural grouping of features in the image. The results produced aided the process of determining the number of classes necessary for supervised classification. The object-oriented approach involved the use of rule sets to classify image objects.

3.3.12 Identification of classes

For all of the four images used in this project, the classes of features present in each image were identified by visual inspection. Where necessary, each class was broken down into subclass to aid the classification process. Table 3-1 below shows the four images and the informational categories identified for each of them.

Land Use/Cover Type	Classes/Sub - Classes
1. Agriculture  Figure 3-2: Pasture	• Crops o Crops 1 o Crops 2 o Crops 3 • Water o Water 1 o Water 2 o Water 3 • Tree Cover o Tree Cover 1 o Tree Cover 2 o Tree Cover 3 • Shadow o Shadow 1 o Shadow 2 • Grass Cover o Grass Cover 1 • Soil o Soil 1 o Soil 2 o Soil 3 o Soil 4
2. Forest	• Water o Water 1 o Water 2

 Figure 3-4: Forest	o Water 3 • Tree Cover o Tree Cover 1 o Tree Cover 2 o Tree Cover 3 o Tree Cover 4 • Shadow o Shadow 1 o Shadow 2 • Grass Cover o Grass Cover 1
3. Urban  Figure 3-3: Urban	• Buildings o Buildings 1 o Buildings 2 • Water o Water 1 o Water 2 o Water 3 • Tree Cover o Tree Cover 1 o Tree Cover 2 o Tree Cover 3 • Shadow o Shadow 1 o Shadow 2 • Grass Cover o Grass Cover 1 • Bitumen o Bitumen 1 o Bitumen 2
4. Pasture	• Water o Water 1 o Water 2 • Tree Cover

 Figure 3-2: Pasture	○ Tree Cover 1 ○ Tree Cover 2 ○ Tree Cover 3 • Shadow ○ Shadow 1 ○ Shadow 2 • Grass Cover ○ Grass Cover 1 ○ Grass Cover 2 ○ Grass Cover 3 ○ Grass Cover 4 • Soil ○ Soil 1 ○ Soil 2

Table 3-1: Study Area Images and their associated informational categories

3.3.13 Pixel-Based Classification

The pixel-based classification was performed using both the unsupervised and supervised approaches. These are described in the sections 3.3.14 and 3.3.15.

3.3.14 Unsupervised Classification

This technique was used in order to get a feel for the natural groupings of features present in the images.

The Iterative Self Organising Data Algorithm (ISODATA) in ERDAS IMAGINE 9 was used to perform unsupervised classifications. The ISODATA algorithm loops until the maximum number of iterations have been completed or when the convergence threshold is reached between two iterations. A more detailed description of the ISODATA algorithm can be found in Mather (2004).

Figure 3-8 shows the interface provided by ERDAS IMAGINE 9 for setting the parameters to be used during the unsupervised classification process. The number of classes or groupings was set to 50. This number tells the algorithm to group the features in an image into 50 different classes.

The maximum iterations value was set to 6. This number determines the number of cycles that the algorithm goes through while re-clustering the data. It prevents the algorithm from looping continuously without reaching the convergence threshold. The convergence threshold determines the maximum percentage of pixels whose cluster assignments can go unchanged between each clustering cycle. The X and Y skip factors were each set to 1 so that all pixels in the image are included in the classification (ERDAS, 2007).

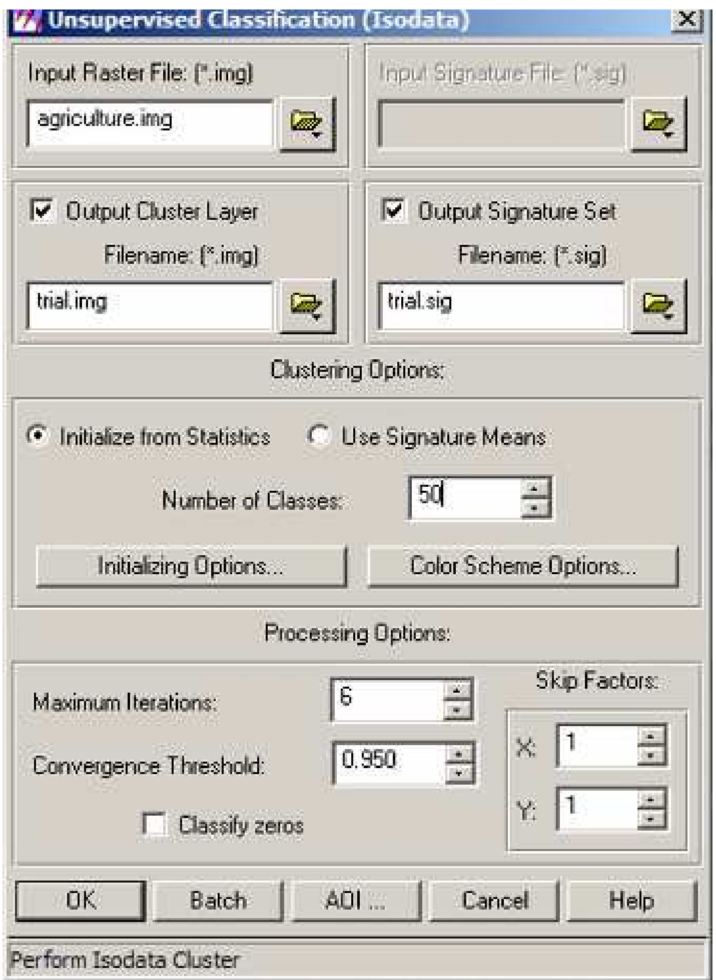

Figure 3-8: Unsupervised classification dialogue box

3.3.15 Supervised Classification

This technique is heavily dependent on user input and knowledge of the area represented by the image being classified. Prior to classifying an image, training samples were selected for each of the riparian parameters identified for that image. The algorithm used to perform the supervised classifications was the maximum likelihood parametric rule. This rule requires training data to compute the likelihood of a pixel belonging to a particular class. It uses mean values from the training samples to classify pixels in the image (Campbell, 2007). A more detailed description of the inner workings of the maximum likelihood algorithm can be found in Mather (2004). Figure **3-9** shows the interface used to set the parameters for supervised classification.

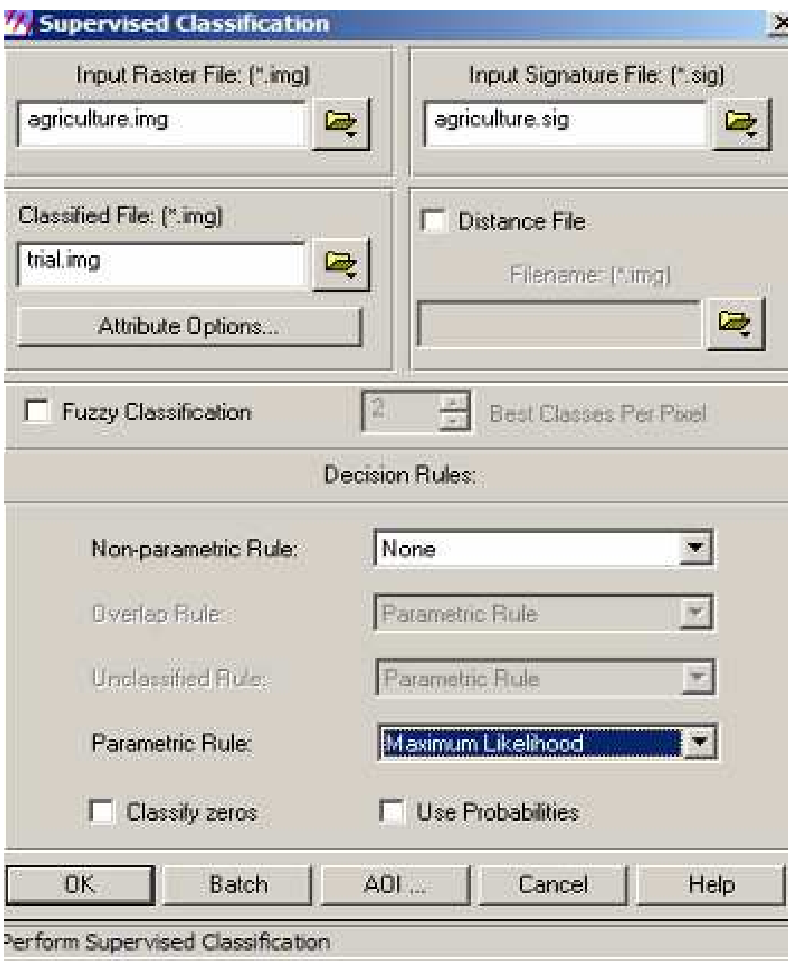

Figure 3-9: Supervised Classification dialogue box

3.3.16 Training Samples

Before commencement of the classification process, samples were selected for each of the sub-classes associated with a particular super class for each of the four images. No samples were selected for the super classes as these were only used on a nominal scale. Care was taken to ensure that the samples selected were representative of their classes. The representativeness of samples was checked by inspecting their spectral curves to ensure that they resembled a Gaussian distribution, indicating that the sample represented only one feature class. Figure 3-10 below shows a histogram of a training sample selected to represent the subclass tree cover 1. The histogram has a single peak indicating that the selected sample represents one feature only.

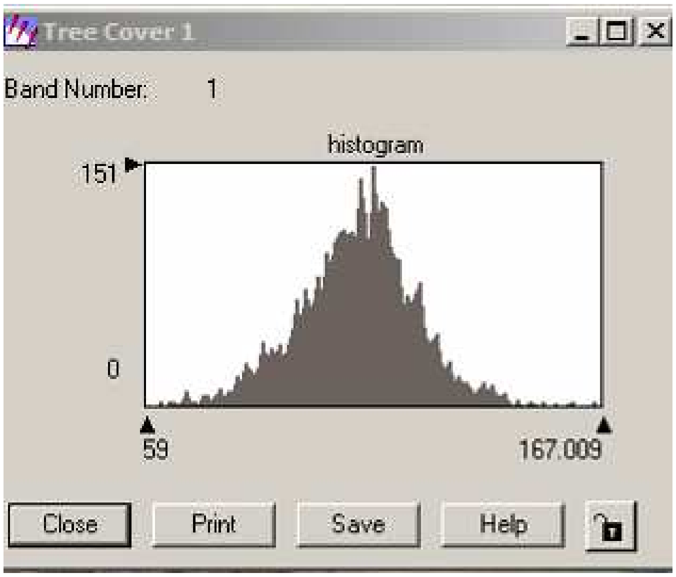

Figure 3-10: Histogram for Tree Cover 1 training sample

Figure **3-11** below shows the signature file containing the samples from which the histogram in Figure 3-10 was generated. The histogram in Figure 3-10 belongs to the highlighted class (Tree Cover 1) in Figure **3-11**.

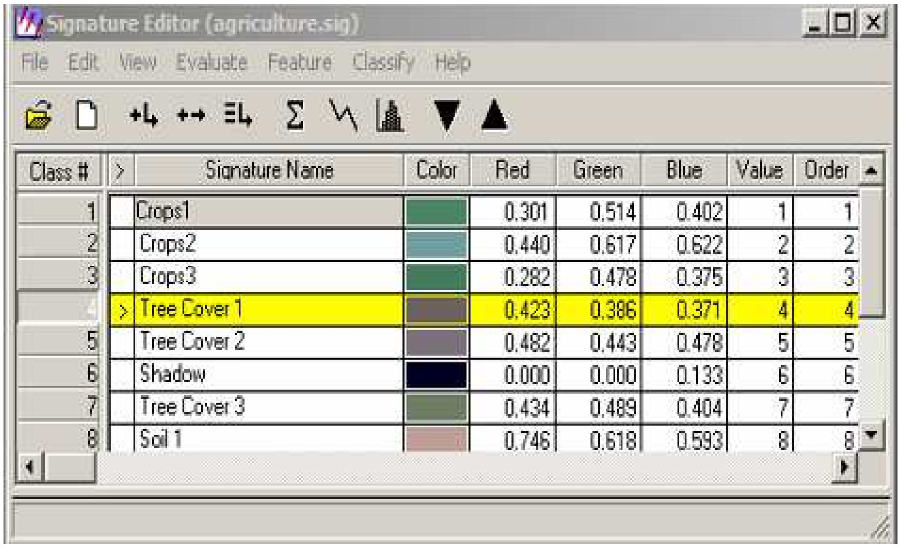

Figure 3-11: Signature File

3.3.17 Object-Oriented Classification

Object-oriented classification is a relatively new image processing technique that works on image objects rather pixels. Pixels are the lowest level in the image object hierarchy. Once an image has been segmented and image objects created, the classification process focuses on the image objects and uses them as the basic unit of the classification.

3.3.18 Image Segmentation

This was the first step performed during object-oriented image classification. During this step, the image was broken down into image objects. The size of the image objects depended on the chosen scale parameter. The scale parameter determines the maximum allowed heterogeneity for the resultant image objects (Definiens, 2006).

For this project, scale parameters of 10 and 50 were used to extract different riparian parameters. The appropriate scale parameter to use was determined by the trial and error approach. The images were segmented and classified using different scale parameters until an appropriate or satisfactory scale parameter was found. Figure **3-12** shows an image segmented with a scale parameter 10 while Figure **3-13** shows an image segmented with a scale parameter 50. As can be seen from Figure **3-12**, a scale parameter of 10 resulted in a large number of small sized objects while Figure **3-13** shows that a scale parameter of 50 resulted in small number of large image objects.

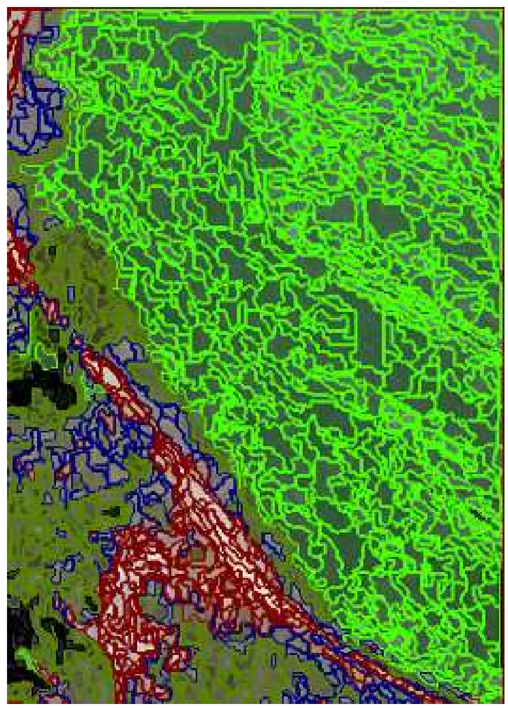

Figure 3-12: Scale parameter 10

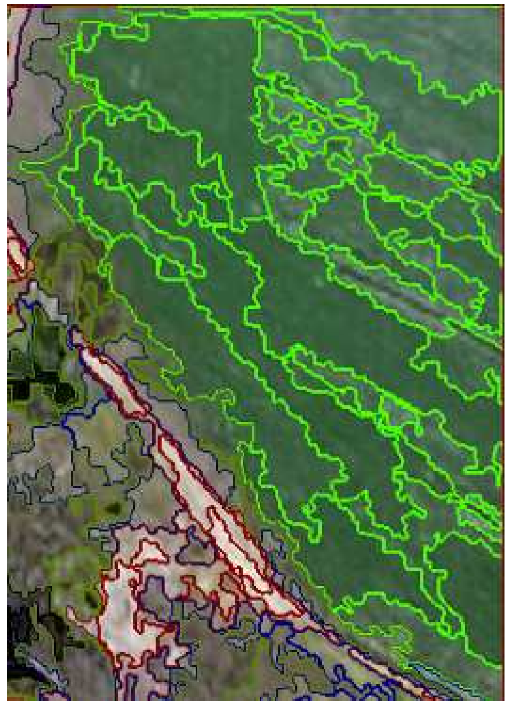

Figure 3-13: Scale parameter 50

The images used in this project were segmented using the multi-resolution segmentation algorithm. This algorithm used a heuristic optimization procedure which minimizes the average heterogeneity of image objects for a given resolution (Definiens, 2006). The images analysed in this project had a spatial resolution of 1m.

Figure **3-14** shows the interface provided by the software for setting the parameters used during the image segmentation process. The homogeneity criterion is a set of parameters (colour and shape) used to minimize the heterogeneity within image objects. The shape criterion is made up of compactness and smoothness (Definiens, 2006). The value assigned to the shape criterion was kept to a minimum in order to preserve the spectral homogeneity of image objects (Definiens, 2006).

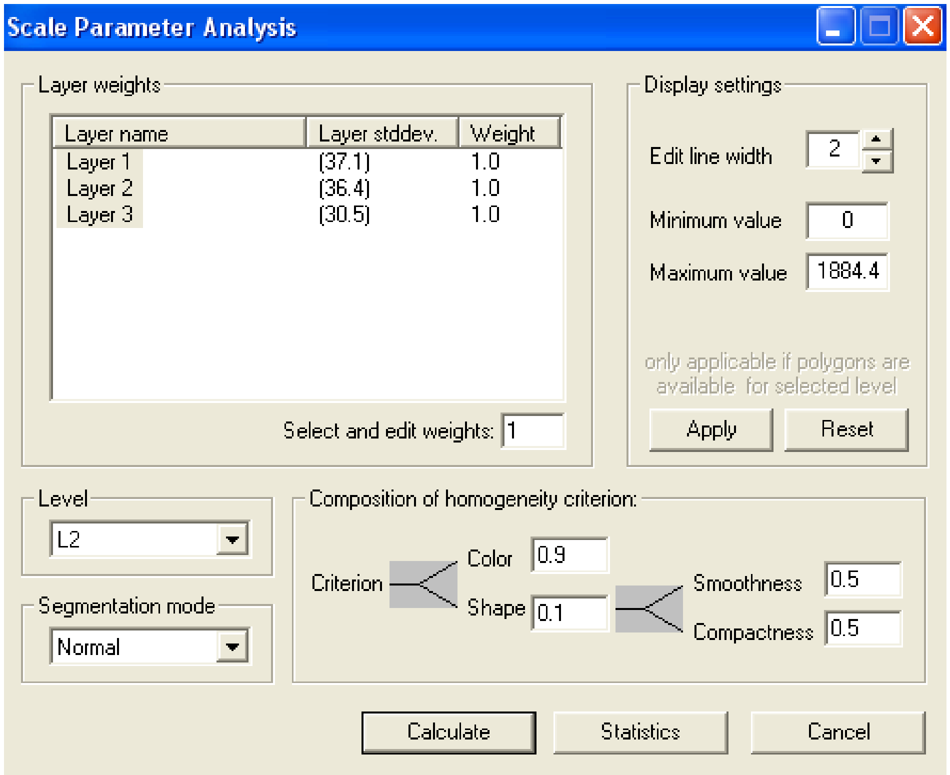

Figure 3-14: Scale Parameter Analysis

3.3.19 Nearest Neighbour Classification

This object-oriented image classification technique is similar to the pixel-based supervised classification technique in that it also requires samples to classify images. The samples used in nearest neighbour classification are based on image objects rather than pixels as in supervised classification. The nearest neighbour algorithm works by computing the distance (in the defined feature space) to the nearest sample image object for each image object in the image. An image object is assigned a class represented by the closest or nearest sample object (Definiens, 2006). Figure 3-165 shows a dialogue box used to specify the image object features chosen to define the feature space for nearest neighbour classification. Once the feature space was defined, it was applied to the classes present in the class hierarchy.

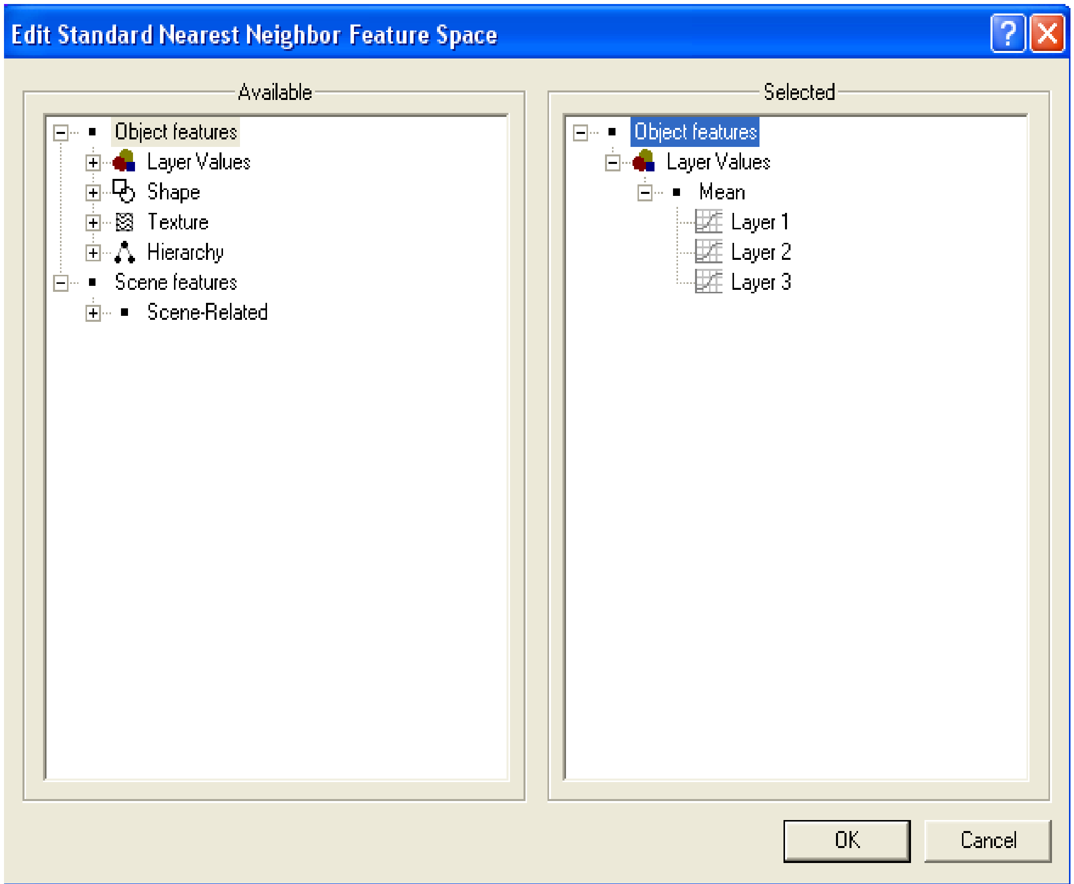

Figure 3-15: Defining Feature Space for Nearest Neighbour Classification

3.3.20 Creating Class Hierarchies

Class hierarchies were created by identifying the appropriate informational categories (classes) for each image. These classes were then broken down into subclasses to accommodate the within class variability. The software provided a drag and drop mechanism for creating a class hierarchy. Figure 3-16 below shows an example of a class hierarchy.

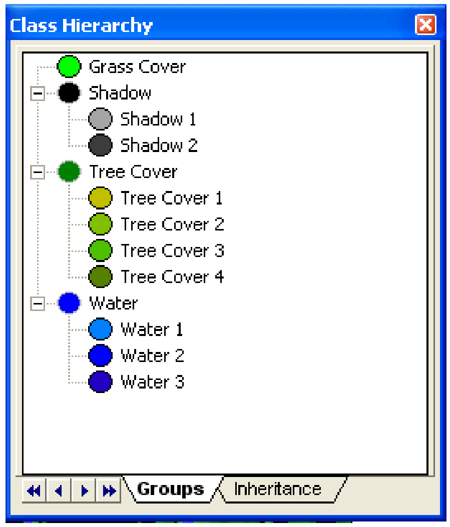

Figure 3-16: An example of a class hierarchy

3.3.21 Image Object Feature Space

The feature space refers to the characteristics of the image objects that were included in the classification process. The software provided a range of features to choose from. Figure 3-17 shows an example of the different image object features that were available for use during image classification.

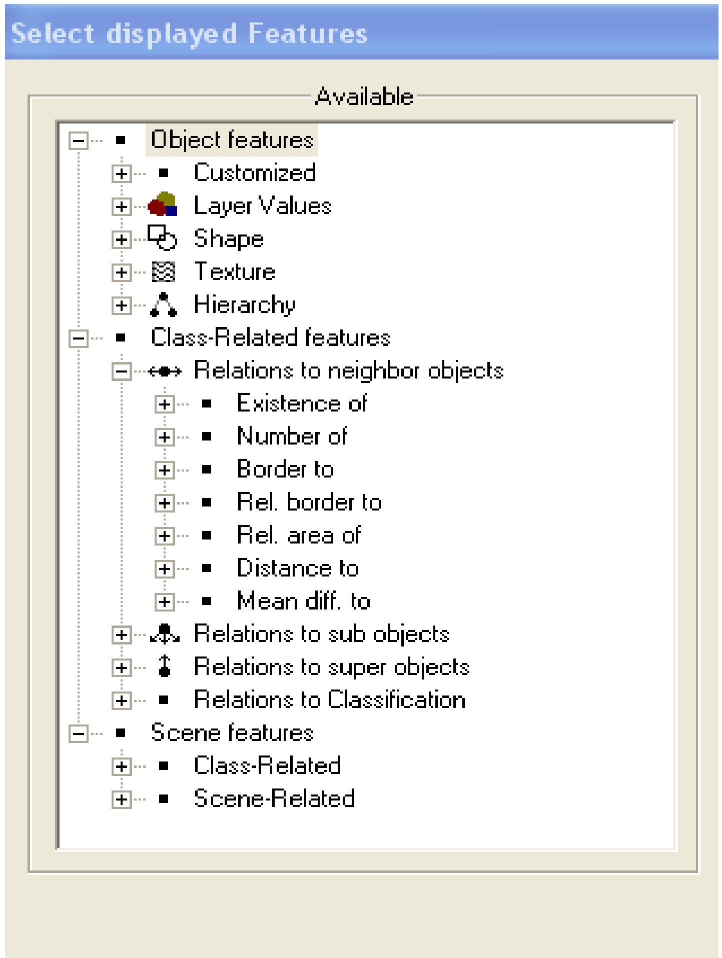

Figure 3-17: Image Object Features

3.3.22 Classification

Definiens Professional 5, the software used for object-oriented classification in this project, provided a simple 'click and classify' mechanism for performing nearest neighbour classification. Figure 3-18 is an illustration of the interface provided by the software for performing nearest neighbour classification.

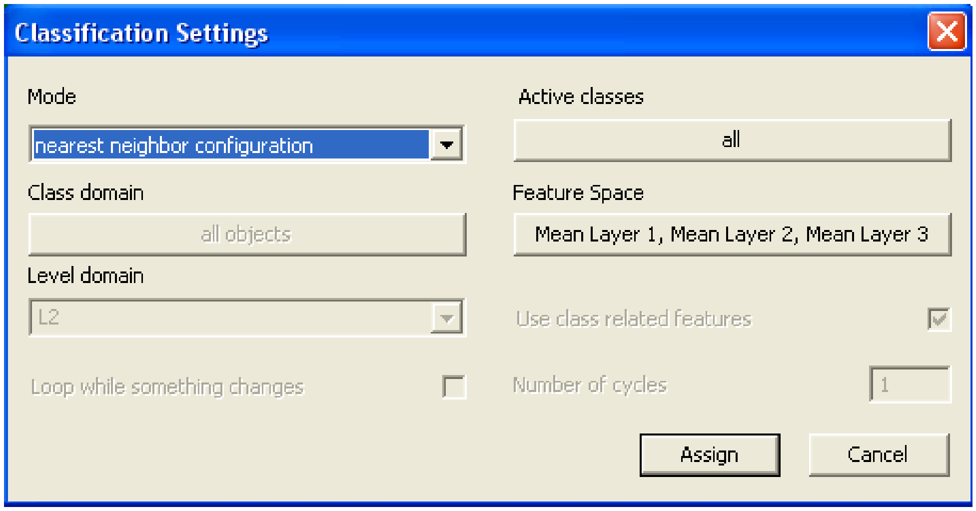

Figure 3-18: Nearest Neighbour Classification Settings

Prior to performing the classification, the feature space was defined and applied to the classes defined in the class hierarchy. The image objects were then assigned to their respective classes using the nearest neighbour algorithm. A custom algorithm was used to assign subclasses to their super class. For example, image objects classified as Tree Cover 1 and Tree Cover 2 were assigned to the super class Tree Cover by use of an algorithm defined in the process tree.

3.3.23 Refining Classification using rule sets

The classification results obtained using the Nearest Neighbour approach were not 100% accurate. These results were further refined using custom made rule sets.

Using rule sets to refine classification results allows for the incorporation of other image object characteristics in the classification process. Characteristics or image object features such as area, border to neighbour objects, relative border to neighbour objects and distance to neighbour objects were used to refine the classification results.

Figure 3-19 shows the features used when classifying the agriculture image. The values associated with each feature gave an indication of how the selected image object relates to its neighbours. For example, some tree cover objects (incorrectly classified) bordering crop image objects had a "distance to crops" value of zero. This statistic was used as a criterion for classifying those objects as crops. This was validated against the original image to ensure that image objects were assigned to the correct class. The shadow image objects that were misclassified as tree cover were reclassified as shadow using the assign class algorithm. The area and "distance to neighbour objects" features were used to set the conditions for the algorithm, so that only those objects that met the criteria could be classified as shadow. Besides the use of conditions to automatically exclude some objects during classification, the algorithm was also used to classify manually selected (highlighted) image objects.

Feature	Value
Layer Values	**Mean**
Layer 1	173.12
Layer 2	169.55
Layer 3	147.64
Shape	**Generic**
Area	58607
Relations to neighbor objects	**Border to**
Crops	1421
Soil	0
Tree Cover	5409
Water	487
Relations to neighbor objects	**Rel. border to**
Crops	0.1390
Shadows	0.031794
Soil	0
Tree Cover	0.5292
Water	0.047642
Relations to neighbor objects	**Distance to**
Crops	0
Shadows	0
Soil	13.07
Tree Cover	0
Water	0

Figure 3-19: Image Object Features used when classifying the Agriculture image

The process of refining classification results using rule sets is iterative and was repeated until the results obtained were deemed satisfactory. Figure 3-20 shows a dialogue box used to set conditions for using the area of an image object in the classification process. In this case, only those image objects whose area is less than the one specified in the dialogue box were included in the classification.

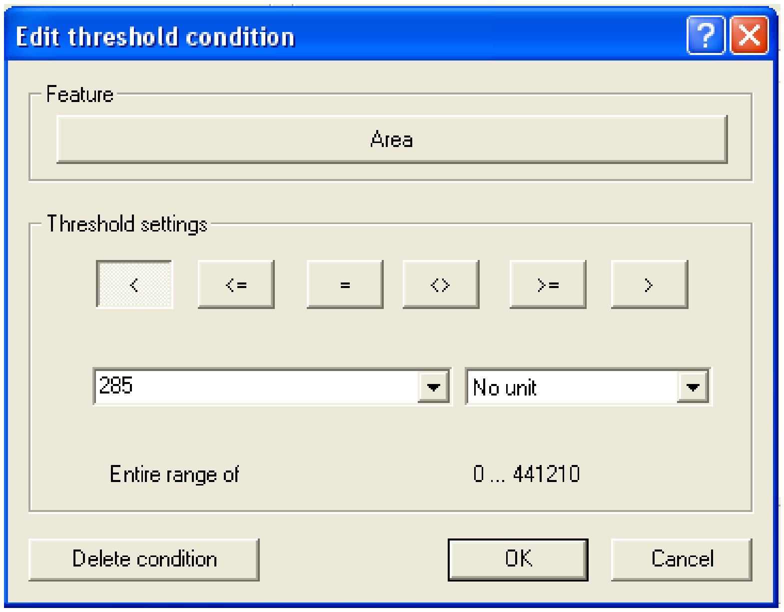

Figure 3-20: Setting conditions for a custom rule set

The rule sets used to improve the classification were grouped together in a process tree. Figure 3-21 is an example of a process tree. It lists out all the algorithms (rule sets) used to classify the urban study area image. Similar process trees were used during the classification of the other images in the study area.

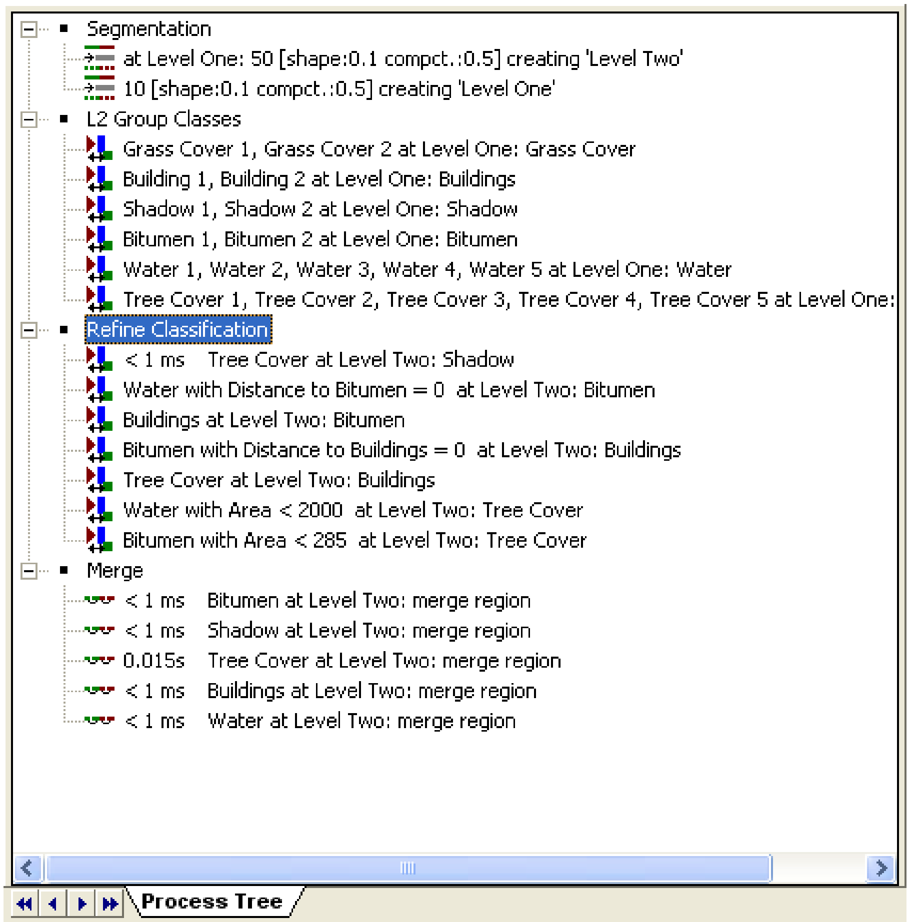

Figure 3-21: Process Tree

3.3.24 Accuracy Assessment

The quality of the classification results was assessed for both the object-oriented classification results and the pixel-based classification results using ERDAS. Refer to sections 3.3.25 and 3.3.26 for more information about the accuracy assessment procedure used.

3.3.25 Pixel-based classification results

The accuracy assessment for the pixel-based classification was performed using the accuracy assessment tool in ERDAS. For each image, a 100 random points were used in the accuracy assessment process. Each of these random points was assigned a class value (reference value). The assigned class value was compared to the value automatically assigned to the random point. Any mismatch between the manual and automatically assigned values represented a classification error.

3.3.26 Object-oriented classification results

The accuracy assessment for the results obtained from the object-oriented classification was performed using the same technique as that used for those from pixel-based classification. This was accomplished by exporting the object-oriented classification results from Definiens Professional 5 to ERDAS IMAGINE 9 and then using ERDAS' accuracy assessment tool to perform the accuracy assessment.

3.4 Conclusion

This chapter described the research methods used during this project. It described the data capture and pre-processing techniques used to prepare the data for analysis. The two image classification techniques: object-oriented and pixel-based and the algorithms used by each technique to analyse the video imagery were also discussed. The next chapter presents the image classification results obtained from these two methods.

Chapter 4 RESULTS

4.1 Introduction

The four images that made up the study area for this project were classified using pixel-based image classification and object-oriented image classification techniques. The object-oriented classification approach produced results with greater accuracy than those obtained from pixel-based analysis. The object-oriented approach achieved results with accuracies greater than 90% while the pixel-based approach managed accuracies ranging from 69% up to 82%.

Please note that the imagery in the maps presented in this chapter was taken at an oblique angle, hence the absence of a scale bar in the maps.

4.2 Pixel-Based Image Classification Results

The classification results shown below were obtained by classifying the four study area images (agriculture, urban, forest and pasture) using the maximum likelihood algorithm (supervised classification).

4.2.1 Supervised Classification Results - Agriculture

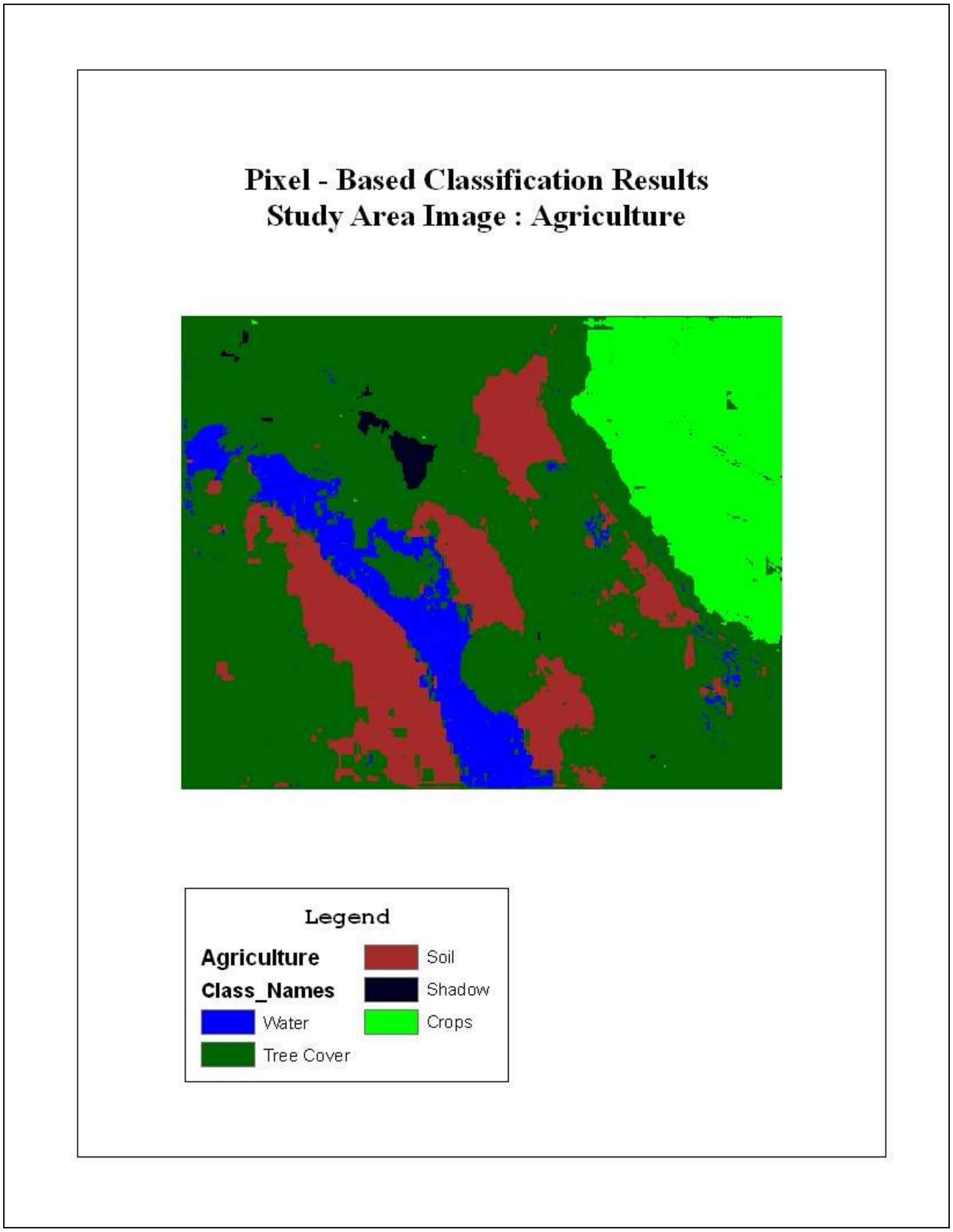

Figure 4-1: Agriculture – Supervised classification results

4.2.2 Supervised Classification Results - Urban

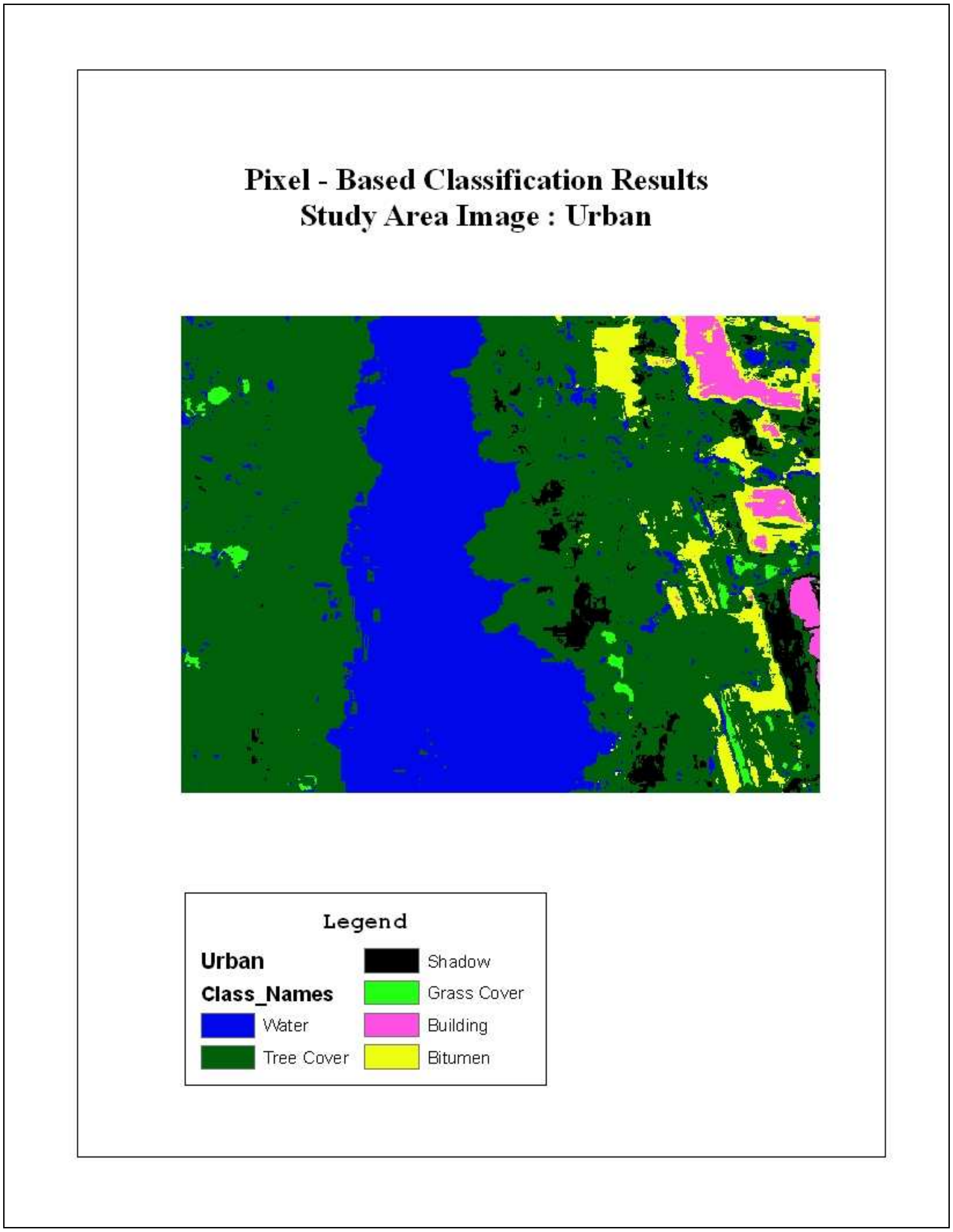

Figure 4-2: Urban – Supervised Classification Results

4.2.3 Supervised Classification Results - Forest

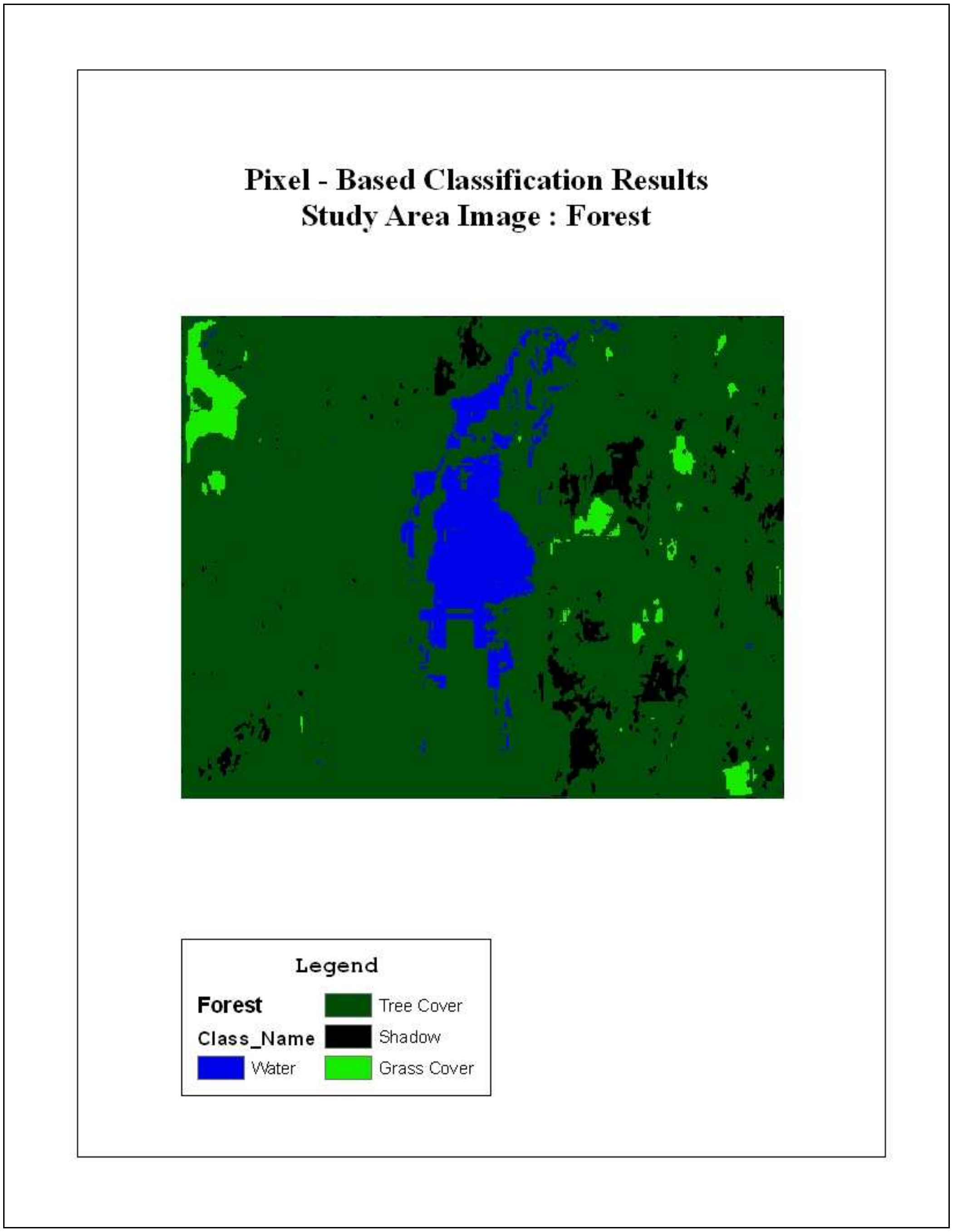

Figure 4-3: Forest – Supervised Classification Results

4.2.4 Supervised Classification Results - Pasture

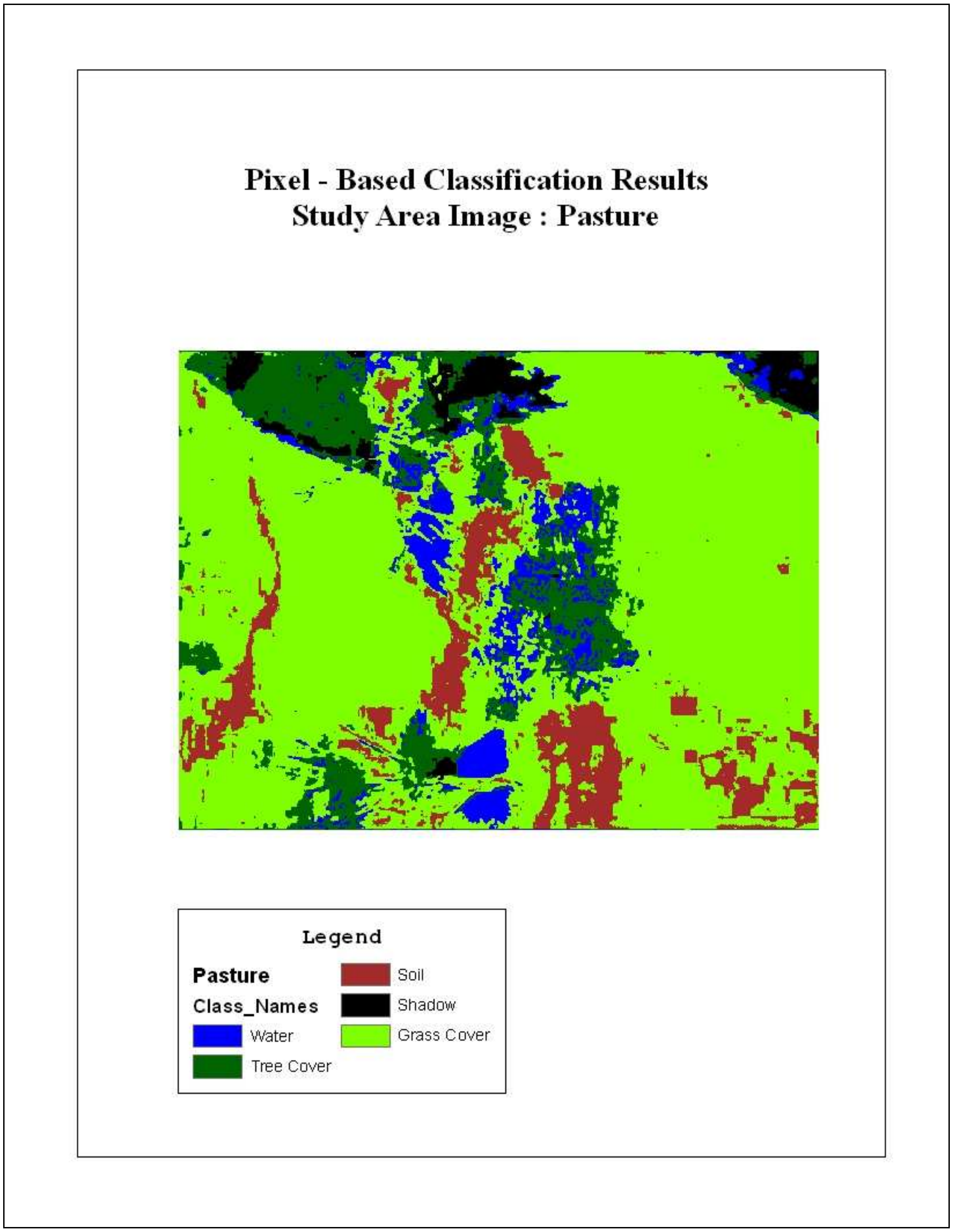

Figure 4-4: Pasture – Supervised Classification Results

4.3 Object-Oriented Image Classification Results

The classification results shown below were obtained by classifying the four study area images using object-oriented techniques.

4.3.1 Object-Oriented Classification Results - Agriculture

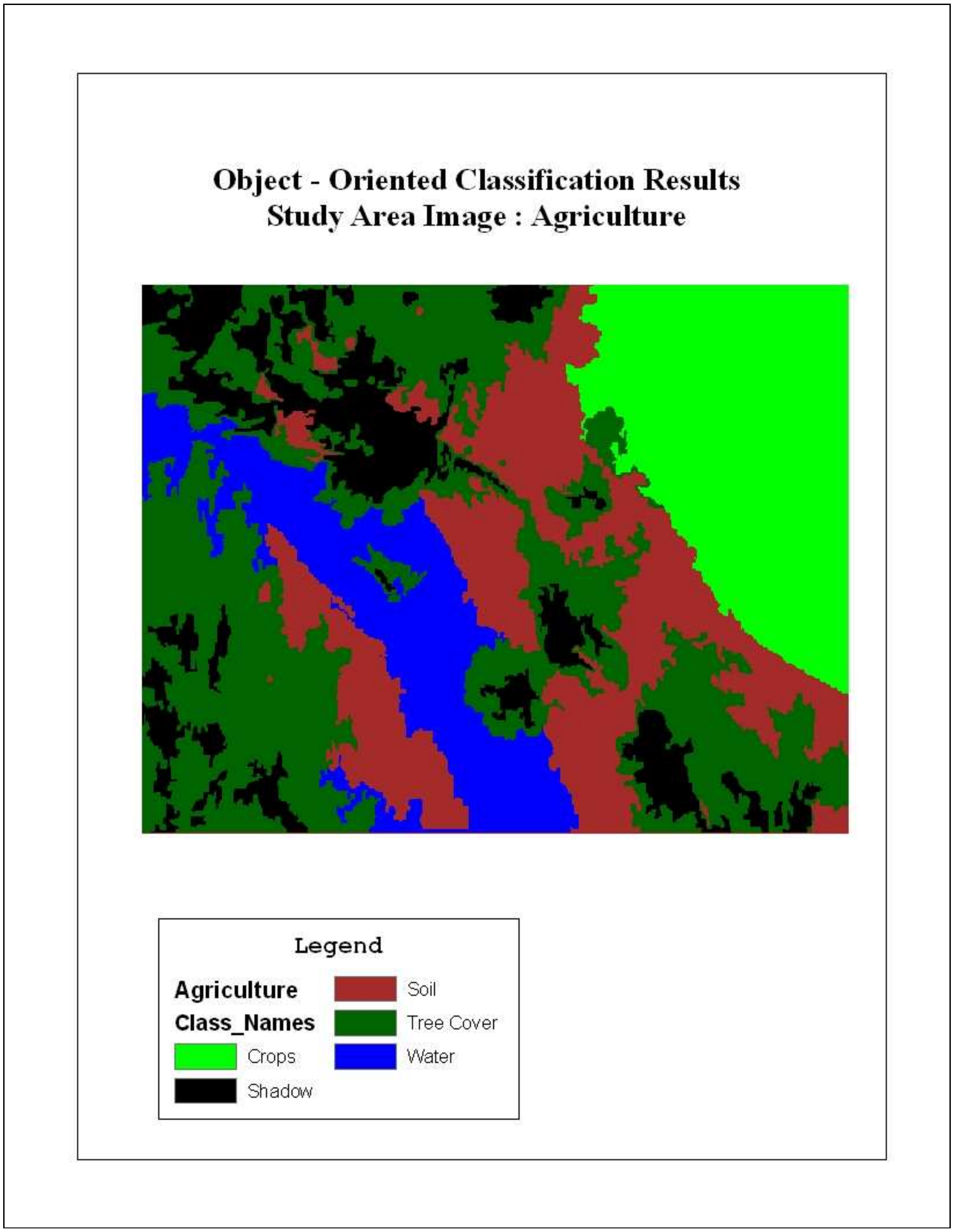

Figure 4-5: Agriculture – Object Oriented Classification Results

4.3.2 Object-Oriented Classification Results - Forest

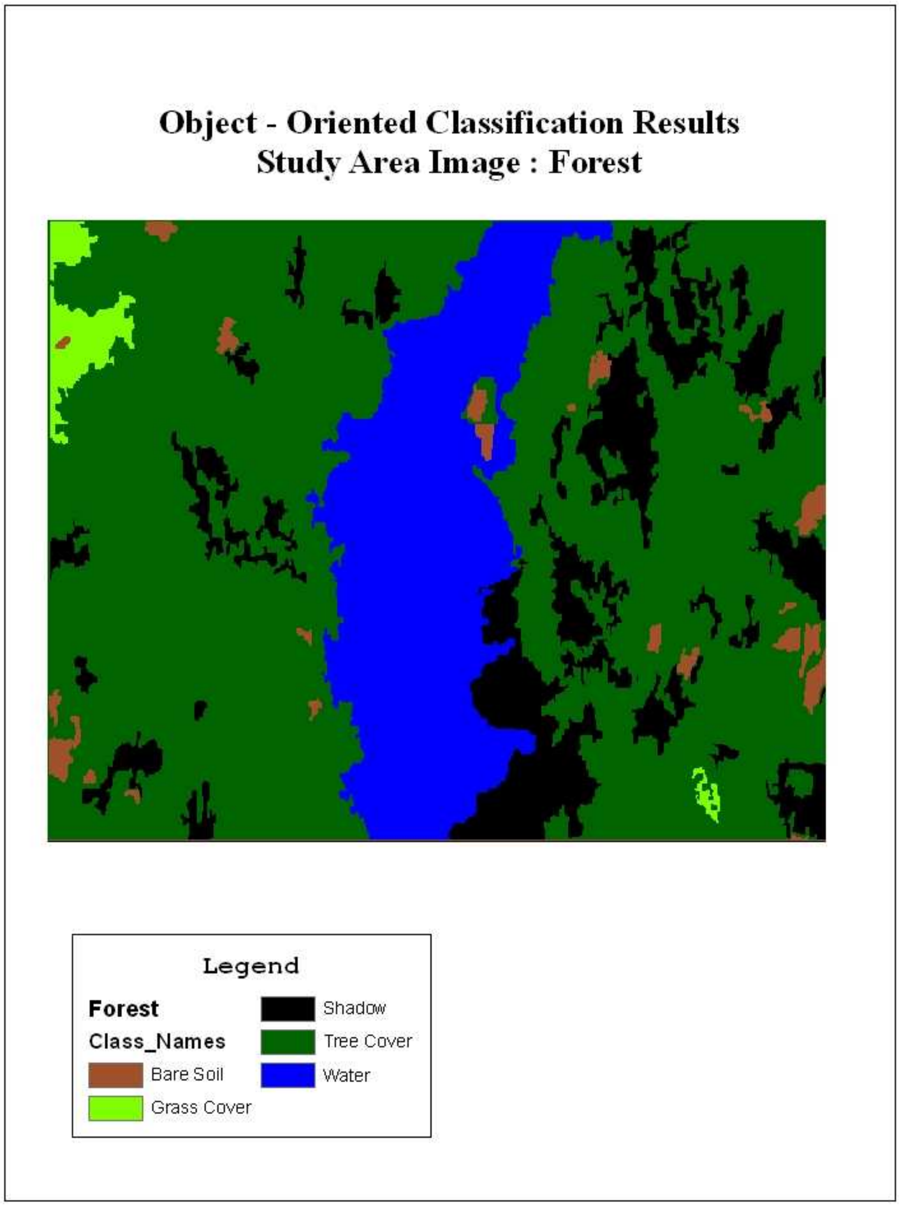

Figure 4-6: Forest – Object Oriented Classification Results

4.3.3 Object-Oriented Classification Results – Urban

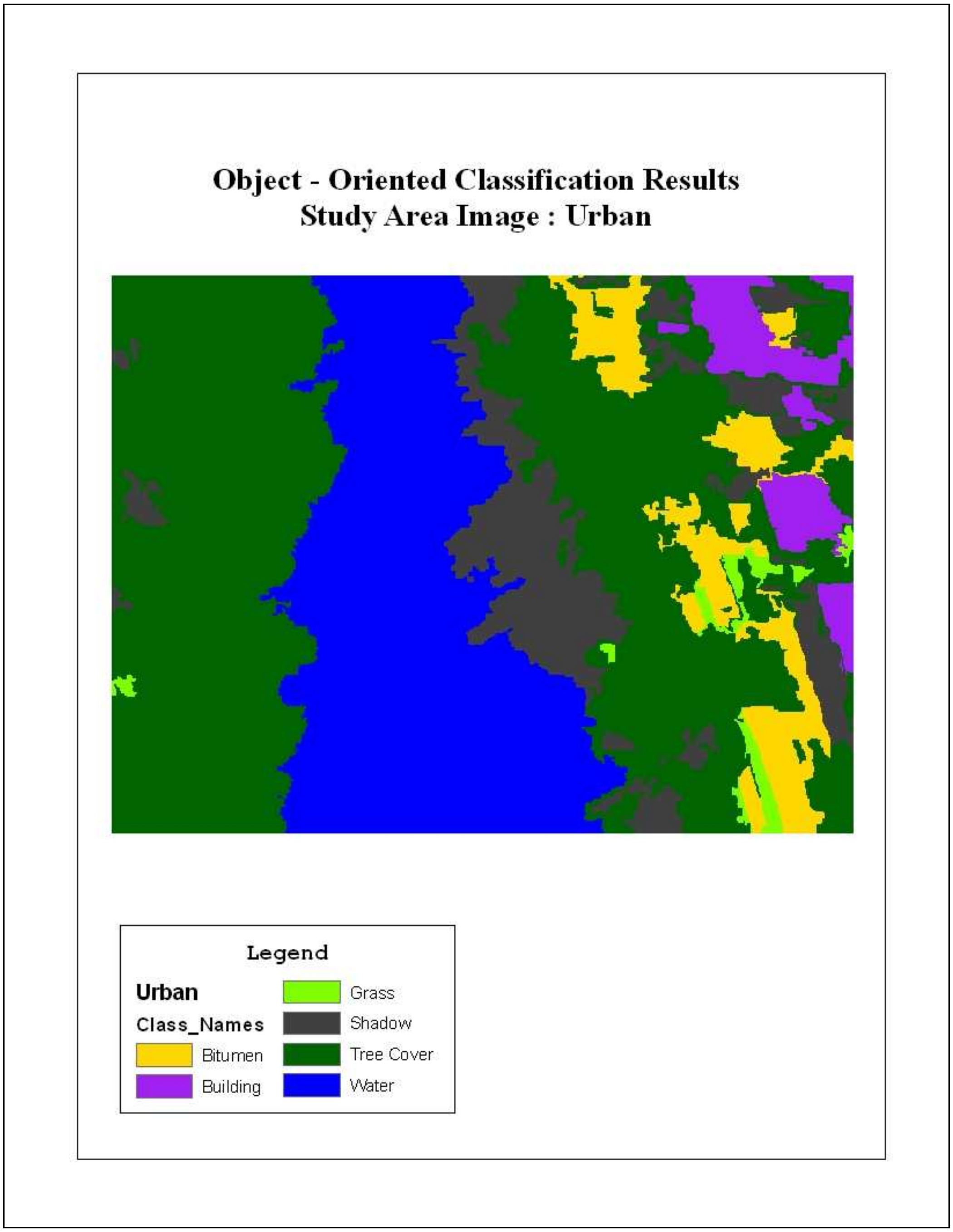

Figure 4-7: Urban – Object Oriented Classification Results

4.3.4 Object-Oriented Classification Results – Pasture

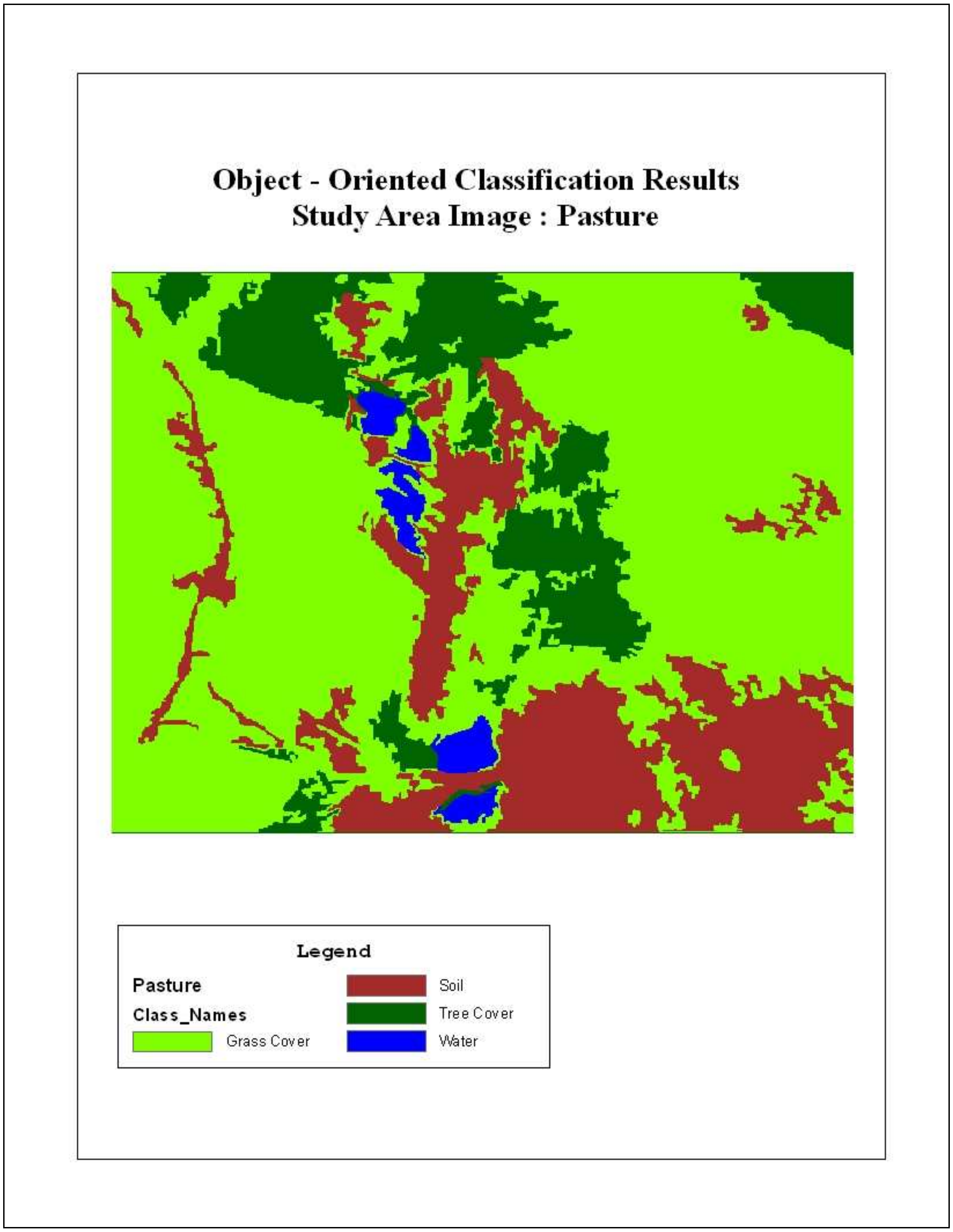

Figure 4-8: Pasture – Object Oriented Classification Results

4.4 Accuracy Assessment Results

Table 4-1 shows the accuracy assessment results obtained from both the pixel-based image classification and object-oriented classification for each of the images that made up the study area. It shows the overall classification accuracy and the overall Kappa statistics for each method for each of the four images that make up the study area. The complete error matrices for the classification results listed in Table 4-1**: Accuracy Assessment Results** are in appendices B to I.

	Pixel-Based Classification		Object-Oriented Classification	
Image	**Overall Classification Accuracy**	**Overall Kappa Statistics**	**Overall Classification Accuracy**	**Overall Kappa Statistics**
Agriculture	69.00 %	0.5098	97.00 %	0.9600
Urban	80.00 %	0.7737	92.00 %	0.8810
Forest	82.00 %	0.7321	93.00 %	0.8682
Pasture	73.00%	0.5065	90.00 %	0.8332

Table 4-1: Accuracy Assessment Results

4.5 Conclusion

The results indicate that the object-oriented image classification approach is more accurate than the traditional pixel-based image classification approach. The overall classification accuracies achieved using object-oriented classification techniques were 97%, 92%, 93% and 90% for the agriculture, urban, forest and pasture images respectively. The corresponding overall kappa statistics for these images were 0.9600, 0.8810, 0.8682 and 0.8332. The pixel-based image classification approach produced overall classification accuracies of 69%, 80%, 82% and 73% for agriculture, urban, forest and pasture respectively. The associated overall kappa statistics were 0.5098, 0.7737, 0.7321 and 0.5065. An in-depth analysis and interpretation of these results is presented in chapter 5.

Chapter 5 ANALYSIS AND DISCUSSIONS

5.1. Introduction

The purpose of this chapter is to provide an in-depth analysis and interpretation of the image classification results presented in the previous chapter. The classification results were as expected, with the object-oriented classification techniques achieving greater classification accuracies than the traditional pixel-based image classification approach.

5.2. Interpretation of classification results

The object-oriented approach produced results with greater accuracy than those attained by the pixel-based approach. This was the expected outcome since the object-oriented approach has been proven to have a superior ability of handling high resolution imagery. High resolution imagery is made up of pixels with a higher degree of spectral variability which makes the statistical classifiers used in pixel-based classification less effective when dealing with high resolution imagery (Zhang & Feng, 2005).

The pixel-based approach uses only the spectral values contained in each pixel during classification. The inability of pixel-based classifiers to incorporate contextual data and imagery interpretation elements during the classification process can lead to inaccurate results (Benz et al., 2004). With the object-oriented approach, image object features such as area, relative border to neighbour objects, distance to neighbour objects and border to neighbour objects were used to enhance the final classification outcome. Their incorporation into the classification process resulted in the achievement of greater classification accuracies.

Problems inherent in the classification of high spatial resolution imagery using pixel-based classification were evident from the results obtained. Figures Figure 4-1, Figure 4-2 and Figure 4-4 show the salt and pepper effect that appears on high resolution images classified using the pixel-based techniques. This salt and pepper effect was due to the incapacity of pixel-based classifiers to deal with the increased variability embedded in high spatial resolution imagery (Hay & Castilla, 2006).

Table 4-1 shows the accuracy assessment results of the classifications performed using the pixel-based maximum likelihood technique and object-oriented techniques for all four images in the study area. It shows the overall classification accuracy and the overall Kappa statistics achieved using both the techniques mentioned above for each of the images that made up the study area. The kappa coefficient is a statistical measure of classification accuracy (Mather, 2004). A kappa value of zero means that there is no agreement between the reference data and the classifier output while a value of 1.000 shows perfect agreement (Mather, 2004). The Kappa coefficient endeavours to provide a measure of agreement between the reference data and the classifier output that has been adjusted for chance agreement (Campbell, 2006).

The Kappa statistics obtained using the object-oriented approach for the agriculture, urban, forest and pasture images were 0.9600, 0.8810, 0.8682 and 0.8332 respectively. These statistics indicate or imply a high level of agreement between the reference data used and the classifier output. For the pixel-based classification, the Kappa statistics were 0.5098, 0.7737, 0.7321 and 0.5065 for the agriculture, urban, forest and pasture images respectively. Compared to those obtained using the object-oriented approach, the Kappa statistics for the pixel-based approach were found to be lower. This was due to the fact that only pixel values were used in the pixel-based classification whereas the object-oriented approach incorporated other elements in the classification process. Other factors such as imperfect reference data and the increased spectral variability within each pixel may have contributed to the achievement of lower classification accuracies.

The classification results achieved in this research project were found to be consistent with results obtained from previous studies that used both the pixel-based image classification approach and the object-oriented image classification approach to classify imagery with a high spatial resolution. Yuan and Bauer (2006) used object-based and pixel-based image classification techniques to map impervious surface areas. They applied both techniques to medium resolution Landsat TM imagery and found that the object-based approach produced results with a higher accuracy than those obtained from the pixel-based approach. Yan et al. (2006) undertook a study to compare the accuracy of pixel-based and object oriented image classification techniques for mapping land-cover in a coal fire area. Their findings indicate that the accuracy achieved using the object-oriented methodology (83.25%) was considerably higher than that achieved when using the pixel-based approach (46.48%).

5.3. Data Limitations

The data used in this research project was found to have two major limitations. It lacked some spectral bands which would have made it possible to extract more information from the imagery and it was collected at an oblique angle.

5.3.1. Lack of Near Infrared Band

The aerial video footage from which the imagery was extracted was collected in three spectral bands only: red, green and blue. The absence of the near infrared band proved to be a major limitation during the classification process.

The near infrared band is a crucial component in the computation of vegetation indices and ratios (Campbell, 2007). It was not possible to use the infrared-to-red band ratio to separate vegetated areas from non-vegetated areas during image classification. Healthy vegetation has a high reflectance in the near infrared band and low reflectance in the red band (Campbell, 2007). This contrasting spectral behaviour would have made it easier to distinguish between actively growing vegetation and dead vegetation (logs) in the imagery. The lack of the near infrared band also hindered the use of vegetation indices and ratios to distinguish between native and exotic vegetation species in the riparian zones.

5.3.2. Oblique Nature of the Imagery

The video data used in this project was captured at an oblique angle. This in turn meant that the imagery extracted from the video footage was oblique. In an oblique image, the scale is constant along any line parallel to the true horizon but differs from point to point along any other line (Moffit & Mikhail, 1980).

Since the scale in the imagery acquired from the video footage varied continually from point to point, it was not possible to take measurements from the imagery. The inability to take measurements from the imagery hindered the extraction of some riparian parameters. For example, it was impossible to determine the total area covered by bare soil patches, which serve as an indicator of soil erosion along the riparian corridor. Other parameters which could not be extracted from the imagery due to the changing scale were the width of the riparian zone and the stream width.

5.4. Conclusion

This chapter presented a discussion of the results achieved in this project. It was found that the results achieved were as expected, with the object-oriented approach achieving greater classification accuracies than the pixel-based approach. The results were also found to be consistent with those obtained from similar studies. The chapter concluded by identifying and discussing the limitations found in the data. These limitations were found to have greatly reduced the amount of useful spatial information that could be extracted from the video imagery.

Chapter 6 CONCLUSIONS

6.1. Introduction

This chapter presents the conclusions derived from the analysis of the results achieved in this project. The specific objectives of this study were to:

a. Identify riparian parameters to be extracted from the aerial video imagery.

b. Use traditional image processing techniques to extract the identified riparian parameters.

c. Develop object-oriented image processing techniques that may be suitable in mapping the selected riparian variables.

d. Assess the accuracy of the results generated using the selected image processing techniques.

These objectives were successfully completed although the data limitations identified in chapter 5 hindered the extraction of some riparian parameters using the object-oriented approach. The pixel-based approach was successfully used to extract the identified riparian parameters albeit with a lower degree of accuracy compared to the object-oriented approach.

6.2. Conclusions

The conclusions drawn from the findings of this study are;

a. The object-oriented approach produced more accurate results than the pixel-based approach in the extraction of riparian parameters from the video imagery.

b. The lack of the near infrared band hindered the extraction of certain riparian parameters. This limited the amount of useful information that could be extracted from the video imagery.

c. The oblique nature of the imagery inhibited the accurate measurement of riparian variables. This characteristic of the imagery also limited the amount of useful information that could be extracted for riparian area management.

REFERENCES

Benz, U.C, Hofman, P, Willhauck, G, Lingenfelder, I & Heynen, M, 2004, 'Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information', *ISPRS Journal of Photogrammetry and Remote Sensing*, vol. 58, pp. 239-258.

Campbell, J.B, 2007, Introduction to Remote Sensing, 4^{rd} Edition, The Guildford Press

Chubey, M.S, Franklin, S. E, & Wulder, M.A, 2006, `Object-based Analysis of Ikonos-2 Imagery for Extraction of Forest Inventory Parameters`, *Photogrammetric Engineering and Remote Sensing*, vol.72, no.4, April 2006, pp. 383-394.

Clarke, K.C, 2003, *Getting started with Geographic Information Systems*, 4^{th} Edition, Upper Saddle River, N.J, Pearson Education

Congalton, R. G., Birch, K., Jones, R. & Schriever, J, 2002, 'Evaluating remotely sensed techniques for mapping riparian vegetation', *Computers and Electronics in Agriculture*, 37, 113-126.

Definiens AG, 2006, *Definiens Professional 5 User Guide*, Definiens AG, Germany
Goetz, S. J., Wright, R. K., Smith, A. J., Zinecker, E. & SchauB, E, 2003, IKONOS imagery for resource management: Tree cover, impervious surfaces, and riparian buffer analyses in the mid-Atlantic region. *Remote Sensing of Environment*, 88, 195-208.

Goetz, S.J, 2006, Remote Sensing of Riparian Buffers: Past Progress and Future Prospects, *Journal of the American Water Resources Association*, vol. 42, no. 1, February 2006, pp. 133-143.

Gyrovision – Aerial Stabilized Camera Solutions, viewed 2 October 2007, http://www.gyrovision.com.au/

Hawkins, C.P, Bartz, K.L. & Neale, C.M.U, 1997, Vulnerability of Riparian Vegetation to Catastophic Flooding: Implications for Riparian Restoration, *Restoration Ecology*, vol.5, no.4S, December 1997, pp 75-84.

Hay, G.J & Castilla, G, 2006, Object-Based Image Analysis: Strengths, Weaknesses, Opportunities and Threats (SWOT), OBIA, 2006: *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences.*

Johansen, K., Coops, N. C., Gergel, S. E. & Stange, Y. Application of high spatial resolution satellite imagery for riparian and forest ecosystem classification. *Remote Sensing of Environment*, In Press, Corrected Proof.

Lamb, D. W & Brown, R.B, 2001, Remote Sensing and Mapping of Weeds in Crops, *Journal of Agricultural Engineering Research*, vol. 78, no.2, pp. 117-125.

Lang, S & Blaschke, T, 2006, Bridging Remote Sensing and GIS-What are the main supportive pillars?, *1st International Conference on Object-Based Image Analysis* (OBIA, 2006)

Mather, P. M, 2004, *Computer Processing of remotely sensed images: an Introduction*, 3rd Edition, Chichester, West Sussex, England

Mausel, P.W, Everitt, J.H, Escobar, D.E, & King, D.J, 1985, Airborne Videography: Current Status and Future Perspectives, *Photogrammetric Engineering and Remote Sensing*, vol. 58, no.8, August 1992, pp 1189-1195.

Neale, C.M.U, 1997, Classification and Mapping of Riparian Systems Using Airborne Multispectral Videography, *Restoration Ecology*, vol.5, no.4S, December 1997, pp 103-112.

Peter Smith – Ultramedia, Aerial Photography & Video Specialists, viewed 2 October 2007, http://www.petersmith.com/

Price, P & Lovett, S, 2002, 'Managing Riparian Land', Fact Sheet 1, Land & Water, Canberra, Australia.

Queensland Murray Darling Committee, viewed 12 April 2007, http://www.qmdc.org.au/about-qmdc.html

Red Hen Systems, viewed 2 October 2007, http://www.redhensystems.com/products/multimedia_mapping_software/geovideo/default.asp?sm=2

Richardson, A.J, Menges, R.M. & Nixon, P.R, 1985, Distinguishing weed from crop plants using video remote sensing, *Photogrammetric Engineering and Remote Sensing*, vol. 51, no.11, November 1985, pp 1785-1790.

Russel, G.D, & Hawkins, C.P. & O'Neill, M.P, 1997, The Role of GIS in Selecting Sites for Riparian Restoration Based on Hydrology and Land Use, *Restoration Ecology*, vol.5, no.4S, December 1997, pp 56-68

Walter, V, (2004), Object-based classification of remote sensing data for change detection, ISPRS *Journal of Photogrammetry and Remote Sensing*, vol.58, pp. 225-238.

Wulder, M. A, White, J.C, Magnussen, S. & McDonald, S, 2007, Validation of a large area land cover product using purpose-acquired airborne video. *Remote Sensing of Environment*, 106**,** 480-491.

Yan, G, Mas, J.F, Maathuis, B.H.P, Xiangmin, Z & Van Dijk, P.M, 2006, Comparison of pixel-based and object-oriented image classification approaches – a case study in a coal fire area, Wuda, Inner Mongolia, China, *International Journal of Remote Sensing*, vol. 27, no.18, 20 September 2006, pp. 4039-4055.

Yuan, F & Bauer, M. E, 2006, Mapping Impervious surface area using high resolution imagery: a comparison of object-based and per pixel classification, *ASPRS 2006 Annual Conference*, Reno, Nevada

Zhang, X & Feng, X, (2005), 'Detecting Urban Vegetation from Ikonos Data Using an Object-Oriented Approach', *Geoscience and Remote Sensing Symposium, 2005. IGARSS Proceedings,* 2005 IEEE International, vol. 2, 25-29 July 2005 pp. 1475 - 1478

APPENDIX A

University of Southern Queensland
Faculty of Engineering and Surveying

ENG 4111/2 Research Project
PROJECT SPECIFICATION

FOR: Daniel **BOITSHOKO**

TOPIC: **Extracting Spatial Information from Aerial Video Images for Monitoring Riparian Areas**

SUPERVISOR: Dr Armando Apan

SPONSOR: Queensland Murray Darling Committee - QMDC
University of Southern Queensland - USQ

PROJECT AIM: To develop image processing and GIS based techniques for extracting spatial information from aerial video images for monitoring riparian areas

PROGRAMME: **Issue A, 21st March 2007**

1. Conduct literature review on:
   a. Riparian area monitoring.
   b. The potential role of using aerial video images for extracting spatial information
2. Select a suitable study site and identify riparian parameters to be extracted from the aerial video images for that site. Carry out field data collection as necessary.
3. Acquire the necessary spatial datasets (aerial video imagery) for the study site.
4. Prepare the data for analysis.
5. Use appropriate image processing techniques to extract the identified riparian parameters. Identify and test selected object oriented image processing techniques that may be suitable in mapping the riparian variables identified in step 2.
6. Assess the accuracy of the results generated using the methods used in step 5.
7. Write, revise and submit final dissertation.

Agreed : ______________________ (Student) ______________________ (Supervisor)
Date: – / 03 /2007 Date: 28 / 03 /2007

Co – Examiner ______________________
Date: 29 / 03 /2007

APPENDIX B

Object – Oriented Classification Error Matrix
Study Area Image: Agriculture

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/ecog/agriculturereclass.img
User Name  : w0030444
Date       : Wed Oct 17 21:34:23 2007
```

ERROR MATRIX

Reference Data

Classified Data	Unclassifi	Water	Tree Cover	Crops
Unclassified	0	0	0	0
Water	0	10	1	0
Tree Cover	0	0	37	0
Crops	0	0	0	21
Shadow	0	1	0	0
Soil	0	0	0	0
Column Total	0	11	38	21

Reference Data

Classified Data	Shadow	Soil	Row Total
Unclassified	0	0	0
Water	0	0	11
Tree Cover	1	0	38
Crops	0	0	21
Shadow	9	0	10
Soil	0	20	20
Column Total	10	20	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water	11	11	10	90.91%	90.91%
Tree Cover	38	38	37	97.37%	97.37%
Crops	21	21	21	100.00%	100.00%
Shadow	10	10	9	90.00%	90.00%
Soil	20	20	20	100.00%	100.00%
Totals	100	100	97		

Overall Classification Accuracy = 97.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.9600

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water	0.8979
Tree Cover	0.9576
Crops	1.0000
Shadow	0.8889
Soil	1.0000

----- End of Kappa Statistics -----

APPENDIX C

Object – Oriented Classification Error Matrix
Study Area Image: Forest

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/ecog/forestreclass.img
User Name  : w0030444
Date       : Wed Oct 17 20:23:29 2007
```

ERROR MATRIX

Reference Data

Classified Data	Unclassifi	Water	Tree Cover	Bare Soil
Unclassified	0	0	0	0
Water	0	24	0	0
Tree Cover	0	1	60	0
Bare Soil	0	0	0	0
Grass Cover	0	0	1	0
Shadow	0	1	2	0
Column Total	0	26	63	0

	Reference Data		
Classified Data	Grass Cove	Shadow	Row Total
Unclassified	0	0	0
Water	0	1	25
Tree Cover	0	1	62
Bare Soil	0	0	0
Grass Cover	0	0	1
Shadow	0	9	12
Column Total	0	11	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water	26	25	24	92.31%	96.00%
Tree Cover	63	62	60	95.24%	96.77%
Bare Soil	0	0	0	---	---
Grass Cover	0	1	0	---	---
Shadow	11	12	9	81.82%	75.00%
Totals	100	100	93		

Overall Classification Accuracy = 93.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8682

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water	0.9459
Tree Cover	0.9128
Bare Soil	0.0000
Grass Cover	0.0000
Shadow	0.7191

----- End of Kappa Statistics -----

APPENDIX D

Object – Oriented Classification Error Matrix
Study Area Image: Urban

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/ecog/urbanreclass.img
User Name  : w0030444
Date       : Wed Oct 17 19:51:18 2007
```

ERROR MATRIX

Reference Data

Classified Data	Unclassifi	Water	Tree Cover	Bitumen
Unclassified	0	0	0	0
Water	0	27	2	0
Tree Cover	0	1	44	2
Bitumen	0	0	0	7
Building	0	0	1	0
Shadow	0	0	0	0
Grass	0	0	0	1
Column Total	0	28	47	10

Classified Data	Reference Data Building	 Shadow	 Grass	 Row Total
Unclassified	0	0	0	0
Water	0	0	0	29
Tree Cover	0	1	0	48
Bitumen	0	0	0	7
Building	2	0	0	3
Shadow	0	11	0	11
Grass	0	0	1	2
Column Total	2	12	1	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water	28	29	27	96.43%	93.10%
Tree Cover	47	48	44	93.62%	91.67%
Bitumen	10	7	7	70.00%	100.00%
Building	2	3	2	100.00%	66.67%
Shadow	12	11	11	91.67%	100.00%
Grass	1	2	1	100.00%	50.00%
Totals	100	100	92		

Overall Classification Accuracy = 92.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8810

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water	0.9042
Tree Cover	0.8428
Bitumen	1.0000
Building	0.6599
Shadow	1.0000
Grass	0.4949

----- End of Kappa Statistics -----

APPENDIX E

Object – Oriented Classification Error Matrix
Study Area Image: Pasture

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/ecog/pasturereclass.img
User Name  : w0030444
Date       : Wed Oct 17 21:03:57 2007


ERROR MATRIX
-------------

                        Reference Data
                        --------------
Classified Data   Unclassifi       Water  Tree Cover  Grass Cove
---------------   ----------  ----------  ----------  ----------
   Unclassified            0           0           0           0
          Water            0           2           0           0
     Tree Cover            0           0          15           1
    Grass Cover            0           0           4          52
           Soil            0           0           0           0

Column Total               0           2          19          53
```

Classified Data	Reference Data: Soil	Row Total
Unclassified	0	0
Water	0	2
Tree Cover	0	16
Grass Cover	1	57
Soil	21	21
Column Total	22	96

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water	2	2	2	100.00%	100.00%
Tree Cover	19	16	15	78.95%	93.75%
Grass Cover	53	61	52	98.11%	85.25%
Soil	22	21	21	95.45%	100.00%
Totals	96	100	90		

Overall Classification Accuracy = 90.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.8332

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water	1.0000
Tree Cover	0.9228
Grass Cover	0.6861
Soil	1.0000

----- End of Kappa Statistics -----

APPENDIX F

Pixel - Based Classification Error Matrix
Study Area Image: Agriculture

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : c:/temp/agric9.img
User Name  : w0030444
Date       : Fri Oct 19 16:00:31 2007


ERROR MATRIX
-------------

                        Reference Data
                        --------------
Classified Data   Unclassifi      Shadow       Crops       Water
---------------   ----------  ----------  ----------  ----------
   Unclassified            0           0           0           0
         Shadow            0           1           0           0
          Crops            0           0          15           0
          Water            0           0           0           4
           Soil            0           0           1           1
     Tree Cover            1          12           1           4

Column Total               1          13          17           9
```

Classified Data	Reference Data: Soil	Tree Cover	Row Total
Unclassified	0	0	0
Shadow	0	0	1
Crops	0	0	15
Water	0	0	4
Soil	6	5	13
Tree Cover	6	43	67
Column Total	12	48	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	1	0	0	---	---
Shadow	13	1	1	7.69%	100.00%
Crops	17	15	15	88.24%	100.00%
Water	9	4	4	44.44%	100.00%
Soil	12	13	6	50.00%	46.15%
Tree Cover	48	67	43	89.58%	64.18%
Totals	100	100	69		

Overall Classification Accuracy = 69.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.5098

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Shadow	1.0000
Crops	1.0000
Water	1.0000
Soil	0.3881
Tree Cover	0.3111

----- End of Kappa Statistics -----

APPENDIX G

Pixel - Based Classification Error Matrix
Study Area Image: Forest

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/aerial video  mapping project/image classification/supervised classification/forest_sup.img
User Name  : w0030444
Date       : Wed Sep 05 21:45:38 2007


ERROR MATRIX
-------------
                        Reference Data
                        --------------
Classified Data   Unclassifi      Water1      Water2      Water3
---------------   ----------  ----------  ----------  ----------
   Unclassified            0           0           0           0
         Water1            0           7           0           0
         Water2            0           0           0           0
         Water3            0           0           0           3
        Shadow1            0           0           0           0
        Shadow2            0           0           0           0
     TreeCover1            0           0           0           0
     TreeCover2            0           2           5           4
     TreeCover3            0           1           0           0
     TreeCover4            0           0           0           0
     GrassCover            0           0           0           0

Column Total               0          10           5           7
```

	Reference Data			
Classified Data	Shadow1	Shadow2	TreeCover1	TreeCover2
Unclassified	0	0	0	0
Water1	0	0	0	0
Water2	0	0	0	0
Water3	0	0	0	0
Shadow1	3	0	0	0
Shadow2	0	0	0	0
TreeCover1	0	0	5	0
TreeCover2	0	0	2	47
TreeCover3	0	0	0	0
TreeCover4	1	0	0	0
GrassCover	0	0	0	0
Column Total	4	0	7	47

	Reference Data			
Classified Data	TreeCover3	TreeCover4	GrassCover	Row Total
Unclassified	0	0	0	0
Water1	0	0	0	7
Water2	0	0	0	0
Water3	0	0	0	3
Shadow1	0	0	0	3
Shadow2	0	0	0	0
TreeCover1	0	0	0	5
TreeCover2	1	2	0	63
TreeCover3	6	0	0	7
TreeCover4	0	10	0	11
GrassCover	0	0	1	1
Column Total	7	12	1	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water1	10	7	7	70.00%	100.00%
Water2	5	0	0	---	---
Water3	7	3	3	42.86%	100.00%
Shadow1	4	3	3	75.00%	100.00%
Shadow2	0	0	0	---	---
TreeCover1	7	5	5	71.43%	100.00%
TreeCover2	47	63	47	100.00%	74.60%
TreeCover3	7	7	6	85.71%	85.71%
TreeCover4	12	11	10	83.33%	90.91%
GrassCover	1	1	1	100.00%	100.00%
Totals	100	100	82		

Overall Classification Accuracy =   82.00%

----- End of Accuracy Totals -----

```
KAPPA (K^) STATISTICS
---------------------

Overall Kappa Statistics = 0.7321

Conditional Kappa for each Category.
------------------------------------

    Class Name              Kappa
    ----------              -----
  Unclassified             0.0000
        Water1             1.0000
        Water2             0.0000
        Water3             1.0000
       Shadow1             1.0000
       Shadow2             0.0000
    TreeCover1             1.0000
    TreeCover2             0.5208
    TreeCover3             0.8464
    TreeCover4             0.8967
    GrassCover             1.0000

            ----- End of Kappa Statistics -----
```

APPENDIX H

Pixel - Based Classification Error Matrix
Study Area Image: Urban

```
            CLASSIFICATION ACCURACY ASSESSMENT REPORT
            -----------------------------------------
Image File : e:/aerial video  mapping project/image classification/supervised classification/urbansup2.img
User Name  : w0030444
Date       : Sat Aug 18 13:19:59 2007


ERROR MATRIX
-------------

                        Reference Data
                        --------------
Classified Data   Unclassifi      Water1      Water2      Water3
---------------   ----------  ----------  ----------  ----------
   Unclassified            0           0           0           0
         Water1            0           4           0           0
         Water2            0           0           4           0
         Water3            0           0           0           0
         Water4            0           0           0           0
         Water5            0           0           0           0
        Shadow1            0           0           0           0
        Shadow2            0           0           0           0
        Shadow3            0           0           0           0
     TreeCover1            0           0           0           0
```

TreeCover2	0	0	0	0
TreeCover3	0	0	0	0
TreCover4	0	0	0	0
TreeCover5	0	0	0	0
Building1	0	0	0	0
Building2	0	0	0	0
Bitumen1	0	0	0	0
Bitumen2	0	0	0	0
Bitumen3	0	0	0	0
GrassCover1	0	0	0	0
GrassCover2	0	0	0	0
Column Total	0	4	4	0

Reference Data

Classified Data	Water4	Water5	Shadow1	Shadow2
Unclassified	0	0	0	0
Water1	0	0	0	0
Water2	0	0	0	0
Water3	0	0	0	0
Water4	12	0	0	0
Water5	1	5	0	0
Shadow1	0	0	0	0
Shadow2	0	0	0	1
Shadow3	0	0	0	0
TreeCover1	0	0	0	1
TreeCover2	0	0	0	0
TreeCover3	0	2	0	0
TreCover4	0	0	0	5
TreeCover5	0	0	0	1
Building1	0	0	0	0
Building2	0	0	0	0
Bitumen1	0	0	0	0
Bitumen2	0	0	0	0

Bitumen3	0	0	0	0
GrassCover1	0	0	0	0
GrassCover2	0	0	0	0
Column Total	13	7	0	8

Reference Data

Classified Data	Shadow3	TreeCover1	TreeCover2	TreeCover3
Unclassified	0	0	0	0
Water1	0	0	0	0
Water2	0	0	0	0
Water3	0	0	0	0
Water4	0	0	0	0
Water5	0	0	0	0
Shadow1	0	0	0	0
Shadow2	0	0	0	0
Shadow3	1	0	0	0
TreeCover1	0	4	1	0
TreeCover2	0	0	7	0
TreeCover3	0	0	0	14
TreCover4	0	0	0	3
TreeCover5	0	0	0	0
Building1	0	0	0	0
Building2	0	0	0	0
Bitumen1	0	0	0	0
Bitumen2	0	0	0	0
Bitumen3	0	0	0	0
GrassCover1	0	0	0	0
GrassCover2	0	0	0	0
Column Total	1	4	8	17

Reference Data

Classified Data	TreCover4	TreeCover5	Building1	Building2
Unclassified	0	0	0	0
Water1	0	0	0	0
Water2	0	0	0	0
Water3	0	0	0	0
Water4	0	0	0	0
Water5	0	0	0	0
Shadow1	0	0	0	0
Shadow2	0	0	0	0
Shadow3	0	0	0	0
TreeCover1	0	0	0	0
TreeCover2	0	1	0	0
TreeCover3	0	0	1	0
TreCover4	18	0	0	0
TreeCover5	0	6	0	0
Building1	0	0	1	0
Building2	0	0	0	1
Bitumen1	0	0	0	0
Bitumen2	0	0	1	1
Bitumen3	0	0	0	1
GrassCover1	0	0	0	0
GrassCover2	0	0	0	0
Column Total	18	7	3	3

Reference Data

Classified Data	Bitumen1	Bitumen2	Bitumen3	GrassCover
Unclassified	0	0	0	0
Water1	0	0	0	0
Water2	0	0	0	0

Water3	0	0	0	0
Water4	0	0	0	0
Water5	0	0	0	0
Shadow1	0	0	0	0
Shadow2	0	0	0	0
Shadow3	0	0	0	0
TreeCover1	0	0	0	0
TreeCover2	0	0	0	0
TreeCover3	1	0	0	0
TreCover4	0	0	0	0
TreeCover5	0	0	0	0
Building1	0	0	0	0
Building2	0	0	0	0
Bitumen1	0	0	0	0
Bitumen2	0	1	0	0
Bitumen3	0	0	1	0
GrassCover1	0	0	0	0
GrassCover2	0	0	0	0
Column Total	1	1	1	0

	Reference Data	
Classified Data	GrassCover	Row Total
Unclassified	0	0
Water1	0	4
Water2	0	4
Water3	0	0
Water4	0	12
Water5	0	6
Shadow1	0	0
Shadow2	0	1
Shadow3	0	1
TreeCover1	0	6
TreeCover2	0	8

TreeCover3	0	18
TreCover4	0	26
TreeCover5	0	7
Building1	0	1
Building2	0	1
Bitumen1	0	0
Bitumen2	0	3
Bitumen3	0	2
GrassCover1	0	0
GrassCover2	0	0
Column Total	0	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Water1	4	4	4	100.00%	100.00%
Water2	4	4	4	100.00%	100.00%
Water3	0	0	0	---	---
Water4	13	12	12	92.31%	100.00%
Water5	7	6	5	71.43%	83.33%
Shadow1	0	0	0	---	---
Shadow2	8	1	1	12.50%	100.00%
Shadow3	1	1	1	100.00%	100.00%
TreeCover1	4	6	4	100.00%	66.67%
TreeCover2	8	8	7	87.50%	87.50%
TreeCover3	17	18	14	82.35%	77.78%
TreCover4	18	26	18	100.00%	69.23%

TreeCover5	7	7	6	85.71%	85.71%
Building1	3	1	1	33.33%	100.00%
Building2	3	1	1	33.33%	100.00%
Bitumen1	1	0	0	---	---
Bitumen2	1	3	1	100.00%	33.33%
Bitumen3	1	2	1	100.00%	50.00%
GrassCover1	0	0	0	---	---
GrassCover2	0	0	0	---	---
Totals	100	100	80		

Overall Classification Accuracy = 80.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.7737

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Water1	1.0000
Water2	1.0000
Water3	0.0000
Water4	1.0000
Water5	0.8208
Shadow1	0.0000
Shadow2	1.0000
Shadow3	1.0000

TreeCover1	0.6528
TreeCover2	0.8641
TreeCover3	0.7323
TreCover4	0.6248
TreeCover5	0.8464
Building1	1.0000
Building2	1.0000
Bitumen1	0.0000
Bitumen2	0.3266
Bitumen3	0.4949
GrassCover1	0.0000
GrassCover2	0.0000

----- End of Kappa Statistics -----

APPENDIX I

Pixel - Based Classification Error Matrix
Study Area Image: Pasture

```
             CLASSIFICATION ACCURACY ASSESSMENT REPORT
             -----------------------------------------
Image File : c:/temp/pasture5.img
User Name  : w0030444
Date       : Fri Oct 19 16:34:38 2007


ERROR MATRIX
-------------

                         Reference Data
                         --------------
Classified Data   Unclassifi  Grass Cove      Shadow       Water
---------------   ----------  ----------  ----------  ----------
   Unclassified            0           0           0           0
    Grass Cover            0          58           2           0
         Shadow            0           0           2           0
          Water            0           0           3           0
     Tree Cover            0           1           5           0
           Soil            0           2           0           0

Column Total               0          61          12           0
```

Classified Data	Reference Data		
	Tree Cover	Soil	Row Total
Unclassified	0	0	0
Grass Cover	4	5	69
Shadow	0	0	2
Water	5	0	8
Tree Cover	7	0	13
Soil	0	6	8
Column Total	16	11	100

----- End of Error Matrix -----

ACCURACY TOTALS

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified	0	0	0	---	---
Grass Cover	61	69	58	95.08%	84.06%
Shadow	12	2	2	16.67%	100.00%
Water	0	8	0	---	---
Tree Cover	16	13	7	43.75%	53.85%
Soil	11	8	6	54.55%	75.00%
Totals	100	100	73		

Overall Classification Accuracy = 73.00%

----- End of Accuracy Totals -----

KAPPA (K^) STATISTICS

Overall Kappa Statistics = 0.5065

Conditional Kappa for each Category.

Class Name	Kappa
Unclassified	0.0000
Grass Cover	0.5912
Shadow	1.0000
Water	0.0000
Tree Cover	0.4505
Soil	0.7191

----- End of Kappa Statistics -----