Landcover Classification in a Heterogeneous Savanna Environment:

Investigating the performance of an Artificial Neural Network and the effect of image resolution

by

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DECLARATION

This study was undertaken in fulfilment of a Geography Masters Degree and represents the original work of the author. Any work taken from other authors or organisations is duly acknowledged within the text and references chapter.

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ABSTRACT

The aim of this study was to investigate the role of spatial and categorical resolution of satellite images in landcover classification. Three images namely, SPOT 5, Landsat TM, and MODIS were used, each of varying spatial resolution. Landcover classes were chosen for each of the classifications, were placed into groups of 11, and then merged to 8. This was to evaluate the effect that the categorical resolution plays on the final classification algorithm. Three traditional classifiers were used to create landcover maps. It was found that the higher resolution imagery produced higher accuracies at the 11 class level and these accuracies were improved by reducing the number of classes to 8. The coarser resolution imagery was able to classify larger features more accurately than the smaller features. This allowed the conclusion to be drawn that, before classifications are to be done, the size of the features to be detected should be considered when deciding which imagery to use. To improve upon the accuracy of the maximum likelihood classifier, an Artificial Neural Network was trained using ancillary data and the SPOT 5 image. Results showed an increase of over 30% in the classification accuracy of the ANN. Specific classes were easily identified, showing the ability of the ANN to classify imagery from a complex savanna environment. Experiments with various parameters of the neural network confirmed that there are no general guidelines that can be applied to a neural network to obtain high classification accuracy.

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Chapter 1. INTRODUCTION

1.1 BACKGROUND

Satellite remote sensing has been widely used in landuse and landcover studies (Shoshany, 2000, Franklin and Wulder, 2002, Omasa *et al.*, 2003, Potter *et al.*, 2003, Rwetabula and De Smedt, 2005, Song *et al.*, 2005, Yuan *et al.*, 2005), since the data in many cases is very cost effective (Song *et al.*, 2005). It has been estimated that a third of the earth's surface has in some way been changed due to the actions of mankind (Brovkin *et al.*, 2004). Remote sensing allows for large-scale derivation of landcover types and with a temporal sequence of images, changes within the system can be calculated (Nabuurs *et al.*, 2000, Brovkin *et al.*, 2004).

Satellite remote sensing can be seen as being an important tool in the quantification of many landscape elements, due to the scales at which the system can operate. There have been many studies on the application of remotely sensed images for use at varying scales. One such study was conducted for the monitoring of estuarine environments and the effects of landuse change around these estuaries. Such a study was aimed at improving the management of the estuary system (Yang and Liu, 2005). Landcover mapping can also be used in the study of heterogeneous environments such as savannas, where many different landcover types may exist (Korontzia *et al.*, 2004, Stuart *et al.*, 2006). These landcover maps can also be used in the formulation and implementation of policies and management plans. Examples can be found in some urban environments, where the growth of cities has been monitored for a number of years, allowing for the quantification of changes to the landscape. These quantifications can be used in the estimation of pollution, traffic, and housing policy problems (Yang and Lo, 2002, Sunar Erbek *et al.*, 2004, Yuan *et al.*, 2005).

Satellite remote sensing allows for the monitoring of large expanses of spatial areas making it an invaluable tool for the monitoring of large-scale problems. An example of this is the use of satellite remote sensing in the quantification of carbon sinks and sources, and examining the effects of the large-scale burning of certain land cover classes. RADAR remote sensing techniques have been used within the forest environments for the quantification of carbon sinks (le Toan *et al.*, 2004).

Although many studies have characterised landcover and landuse mapping using remotely sensed data, very little is known about optimal resolution for specific environments. There are various scales and resolutions at work within the realm of remotely sensed data, each with its own advantages and disadvantages depending on the types of data needed for the particular study (Franklin and Wulder, 2002). Resolution can be divided into three classes, namely Temporal Resolution, Spectral Resolution, and Spatial Resolution. Temporal resolution is the time period in which a sensor re-visits a given area i.e. one week, 24 hours, (Lillesand *et al.*, 2004). Spectral resolution refers to the ability of a sensor to define different wavelength intervals (Ju *et al.*, 2005). Spatial Resolution refers to the smallest object that is possible to detect with the sensor i.e. Landsat – 30 m (Lillesand *et al.*, 2004).

Spatial resolution can be divided into a further three groups. These groups describe the size of the resolution and can aid in determining the optimal sensor to use for a specific use. These are High, Low, and Medium Resolution imagery. Low spatial resolution can be used to describe imagery that has a resolution greater than 100 m. Medium spatial resolution refers to imagery of between 10 m and 100 m. High spatial resolution refers to imagery with resolutions of less than 10 m (Franklin and Wulder, 2002).

The issues of spatial, spectral and categorical scales play an important role in the accuracies of landcover classification (Ju *et al.,* 2005). It has been seen in some studies done in the past (Markham and Townshend, 1981, Irons *et al.*, 1985 cited in Ju *et al.,* 2005) that attempts to define a single optimal scale for a remote sensing application, can leave many classes not represented in the final classification (Ju *et al.*, 2005). One of the most often used methods of altering the categorical scale is the aggregation of classes. This can be done through the application of a roving window over the image, aggregating spectral classes. The other and more popular method (and the one used within this study) is that of aggregating classes using the labels of those classes (Ju *et al.*, 2005).

An issue within the remote sensing school of thought is determining the correct scales or resolutions for each study. Reasons for this are features greater than 30 m in area are likely to be detected by a sensor with a resolution of 30 m, however, features smaller than 30 m in area may not be detected. Depending on what size the feature that is to be studied is, the correct resolution must be used (Cao and Lam, 1997). For the present study the SPOT 5, Landsat TM and the MODIS sensors were used to evaluate the effect that spatial and categorical resolutions play in relation to the accuracy of the final landcover classification.

As remote sensing technology increases in its complexity, it becomes more difficult to acquire the desired information from the data. As more bands become available and the spatial resolutions become higher, the user of the images has difficulty in processing the imagery (Qiu and Jensen, 2004). Current techniques of image classification can fail to detect potential overlaps within the data and so inaccuracies in the classifications can become a problem (Linderman *et al.*, 2004, Qiu and Jensen, 2004). Linderman *et al.*, (2004) found that the understorey of a forest environment can have a detrimental effect on the reflectance properties of the canopy and so can cause problems in the classification of forest canopies (Linderman *et al.*, 2004). Examples of this may be found in the way in which statistical classifiers will classify an image:

A **minimum distance to means** classifier will calculate the distance that a pixel is from the closest class mean and will classify that pixel accordingly (Lillesand *et al.*, 2004).

A **parallel piped** classifier uses a set of digital number ranges to define 'boxes' that define the classes of the classification and so will classify those pixels accordingly (Lillesand *et al.*, 2004).

The **maximum likelihood** classifier evaluates the probability of a pixel occurring within a class. If the probability is high, the pixel is classified accordingly, if it is low, the classification process continues until it is classified (Lillesand *et al.*, 2004).

Problems with these traditional classifiers occur when pixels fall out of the system defined parameters, especially in areas of high spectral variability – heterogeneous savanna environments – and thus the classification accuracy may be reduced (Lillesand *et al.*, 2004). Other problems occur with the detection of features within a complex environment with different linear and non-linear contributions to the reflectance. An example of this can be seen in the detection of understorey vegetation where some of the reflectance is able to be detected through gaps in the canopy. However, due to scattering of light at the canopy, the understorey vegetation is not detected when using traditional classification techniques (Linderman *et al.*, 2004). Because of this, other methods of landcover classification can be explored.

In order to overcome the limitations of the statistical classifiers that focus on the spectral properties of classes, Artificial Neural Networks (ANNs) have been shown to greatly improve the accuracy of image classifications (Linderman *et al.*, 2004, Qiu and Jensen, 2004, Sunar Erbek *et al.*, 2004). ANNs do not require *a priori* knowledge about the class' statistical properties. ANNs have the ability to 'learn' with the use of external sources of data which allows for better classifications (Linderman *et al.*, 2004, Qiu and Jensen, 2004, Sunar Erbek *et al.*, 2004). Various data sources (ancillary data) can be used in the classification, focusing more on spatial elements within the image, whereas classical statistical classifiers focus on the spectral information within the image (Qiu and Jensen, 2004, Sunar Erbek *et al.*, 2004).

This study will look at the various aspects of landuse classification and some of the problems associated with the generalisation of the various features in the landscape. In light of the problems, this study aims to investigate the effect of spatial resolution as well as the classification algorithms in landcover mapping accuracy.

1.2 LOCATION OF THE STUDY AREA

Figure 1.1 displays a map of the study site. The image itself is the SPOT 5 image and its boundaries formed the boundaries of the study. The study area is around the city of Pietermaritzburg, KwaZulu-Natal. Pietermaritzburg (29°35'54"S 30°22'53"E) is the main urban centre in the study area. However, other smaller towns include Camperdown to the south-west, Richmond to the south-east and Howick to the north. The average annual temperature varies between 16.3° C and 17.9° C. There are, however, areas in the study area that have mean annual temperatures slightly higher. The mean average rainfall for the region is between 747 mm and 1389 mm, however, for the specific study area it is roughly between 748 mm and 1017 mm. The topography in the study area is generally hilly, with an increase in altitude from the south-west to the north-east of the city of Pietermaritzburg. Agriculturally, the area is diverse, with sugar cane being cultivated to the north and north-east of the city, and with cattle farming on grasslands being found to the north-west beyond the Midmar Dam. Subsistence farming is practised in the tribal areas surrounding Camperdown. Plantations can be found extensively in the high rainfall areas which are near the Albert Falls dam around Pietermaritzburg and Richmond. Natural vegetation can be found extensively in some areas. Around Richmond, natural forests are found primarily on the south facing slopes. Near Camperdown and west of Pietermaritzburg, the vegetation is primarily thicket and bushland (GAEA Projects, 2002).

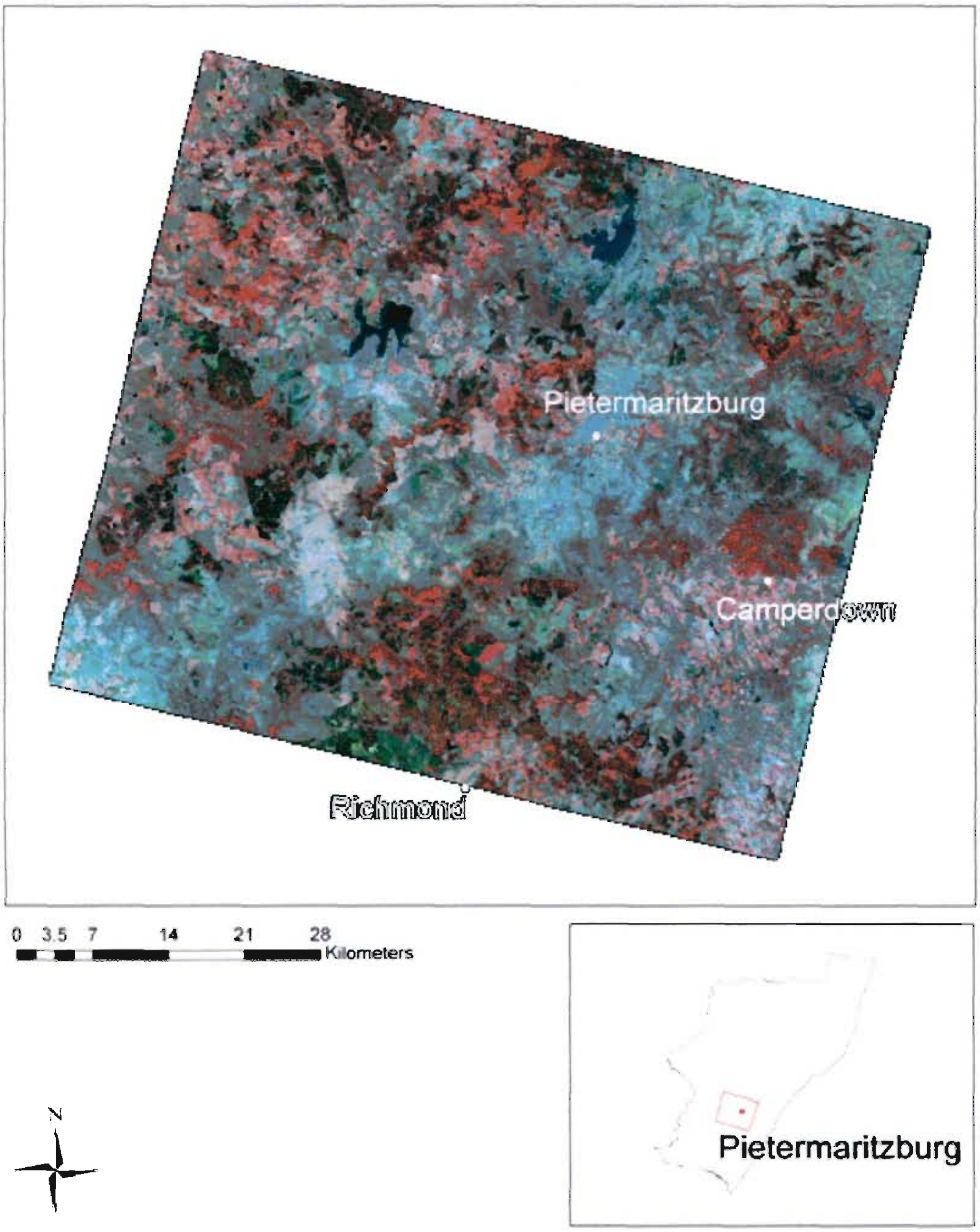

Figure 1.1: Location of the study area in relation to the rest of the KwaZulu-Natal province, an insert of a SPOT 5 image is provided.

1.3 AIM AND OBJECTIVES OF THE PRESENT STUDY

1.3.1 Aim

The aim of this study is to examine the effect of spatial resolution on landcover mapping using various techniques available for research. Attempts were made to study the effect that the varying scales and resolutions of different remote sensing sensors can have on the final classification accuracies. The role played by scale and classification methods used was studied to determine the technique best suited for each sensor. An artificial neural network (ANN) was tested to evaluate its potential in improving classification mapping accuracy.

1.3.2 Objectives

In order to reach the aims of this study, various objectives must be met. These objectives are as follows:

1. To test the accuracy of Landcover Classification at three different spatial resolutions, each resolution being taken from three remotely sensed images (SPOT 5, Landsat TM, and MODIS).
2. To evaluate the effect of the number of classes on the final classification accuracies.
3. To evaluate the differences between the classification accuracy of an image using fine class definitions and traditional algorithms; and then to compare this to a neural network.
4. To test the ability of a more computationally intensive Artificial Neural Network to improve the accuracy of the classification.

1.4 RESEARCH QUESTIONS

During the study, various questions needed to be answered to aid in the completion of the main aim and objectives.

These questions can be grouped into those concerning **Broad Landcover Classifications** and **Specific Landcover Classifications**. Broad landcover classifications refer to the overall classification of the images, focusing on the overall accuracies of the classifications. Specific landcover classifications refer to the focused investigation of the ability of specific features to be classified accurately.

1.4.1 Broad Landcover Classification

1. Of the various traditional statistical classifiers (Maximum Likelihood, Minimum Distance to Mean, and Parallel Piped) which will produce the most accurate classification at each of the different scales?
2. Of the three images (SPOT 5, Landsat TM, and MODIS) at the various resolutions, which image produces the most accurate classification?
3. Are the differences in the classifications so distinct that a high cost, high resolution image is best?

1.4.2 Specific Landcover Classification

1. Is it possible to discern differences between the various target classes using the basic classifiers such as Maximum Likelihood and Parallel Piped techniques?
2. What effect does the number of available classes have with regard to the overall accuracy of the classification?
3. Can an ANN technique be implemented using ancillary data to provide an accurate distinction between the various target classes?

4. What properties of the neural network play the most important role in determining the accuracy of the neural network?

1.5 Outline of Chapters

In the following chapter, Chapter 2, the concepts of landcover classification will be outlined, as well as the basic theory behind the traditional classifiers. The influence of resolution on classification accuracy will be explored. The final concept introduced is the expansion on the theory behind artificial neural networks. Examples are given of the use of a neural network for landcover classifications.

In chapter 3 the methods used within this study to achieve the defined aims and objectives are presented. The chapter is divided into the preparation of the data for classification, the classification of the images with the traditional classifiers, and the training and final classification of the SPOT 5 image using the trained artificial neural network.

In chapters 4 and 5 the results obtained through the study are presented and discussed. Where possible, data are displayed in graphical format, and the error matrices are contained within the appendices.

Chapter 6 contains the conclusion to the study. The aims and objectives are re-examined to assess how successful or unsuccessful the study was. Limitations of the study and recommendations for future studies are made.

Chapter 2. LITERATURE REVIEW

As has been stated in the first chapter, the effect of different resolutions and classification algorithms on the accuracy of landcover mapping will be studied. For best results, the subject should be viewed within its theoretical context, hence in this section the background to landcover mapping will be looked at.

2.1 LANDCOVER MAPPING

The mapping of landcover using remotely sensed imagery has been practised since the 1940s, with aerial photography being used as the source data (Lillesand *et al.*, 2004). With the increase in availability of satellite remotely sensed imagery, the extraction of landcover features from these sources has increased (Cihlar, 2000, Lillesand *et al.*, 2004). Landcover can be defined as the type of feature(s) that cover the surface of the earth. This can be man-made or natural (Cihlar, 2000, Foody, 2002, Lillesand *et al.*, 2004).

Due to the high amount of information contained within a remotely sensed image and the speeds at which this data can be processed, the efficiency of landcover mapping has increased with time (Franklin and Wulder, 2002, Yang and Liu, 2005). Due to this, the use of remote sensing for landcover classification by government organisations has increased. Many governments have started landcover and landuse mapping on a large scale for the management and planning of the use of natural resources as well as the monitoring of environmental degradation (Franklin and Wulder, 2002, Yang and Liu, 2005).

2.1.1 Application of Landcover Mapping

Cihlar (2000: 1094) outlines seven important considerations for the characteristics of a good landcover classification. These are **Purpose**, **Thematic Content**, **Scale**, **Data** and **Processing and analysis algorithms**.

1. **Purpose:** this refers to what the final product will be used for. Generally landcover maps can be used for management, policy planning and scientific research; each of these has in turn its own requirements for completion. An example would be a vegetation model that may require certain landcover types and so would need to be included within the final landcover classification (Cihlar, 2000).
2. **Thematic Content:** this refers to how many classes of features need to be identified within the final map (Cihlar, 2000).
3. **Scale (Resolution):** this refers to how large an area will be mapped during the landcover mapping process. Scale can be divided into three categories: Low, Medium and High. Low spatial scales refer to mapping at the small scales (large features). Medium spatial scales refer to mapping where the features being mapped can be relatively small (areas of 10s to 100s of metres squared). High spatial scales refer to the smallest features which can be at the centimetre level (Cihlar, 2000, Franklin and Wulder, 2002). In the present study, scale refers to the resolution of the image being classified.
4. **Data:** refers to the type of data obtained from the sensor, and how the accuracy of the data might affect the accuracy of the final map produced (Cihlar, 2000).
5. **Processing and analysis algorithms:** refers to the types of algorithms used within the classification process. Each algorithm has its own positive and negative aspects for the final accuracy of the map (Cihlar, 2000).

Factors in points three and five are critical for obtaining high classification accuracies and thus these factors will be focused on in the present study.

Changes to the natural environment can vary in how long they take to happen. Changes due to major catastrophes can take a few hours to alter the landscape, whereas changes due to climate can take many decades. As has been stated, satellite remote sensing allows for quick and easy access to data and because most sensors pass a point of the earth's surface in a given timeframe, changes can be detected and quantified (Foody, 2002, Lillesand *et al.*, 2004, Stefanov and Netzband, 2005, Yuan *et al.*, 2005).

2.1.2 Examples of Landcover mapping

A few examples of the uses for landcover mapping will be discussed and, where possible, examples will be described.

2.1.2.1 Urban Environmental Mapping

The use of satellite imagery has been used extensively to study the expansion of man-made settlements into the surrounding areas of cities and towns. Due to increases in economic growth in some cities, people are being drawn into the city seeking economic opportunities. This increase in the number of people can put strain on a city's infrastructure: overcrowding and lack of access to services can cause people to move onto the fringe of a city and so expand the boundary of the city. This can create problems for the city planners (Sunar Erbek *et al.*, 2004, Yuan *et al.*, 2005).

City planners need to understand trends in city growth to allow for better policy planning and management plans. Satellite remote sensing allows for accurate, cost-effective, and timely data to be obtained, thus allowing for plans to be made to avoid problems (Yuan *et al.*, 2005). A study completed by Yuan *et al.*, (2005) looked at three different images from three time periods. The aim of Yuan's study was to display the growth of a city (Twin Cities, Minnesota). Results from this study showed extensive expansion along the fringes of the city into the rural areas, and thus the loss of agricultural land. City planners can therefore use data like this to attempt to slow the loss of important agricultural land (Yuan *et al.*, 2005).

A similar study was undertaken in Istanbul, Europe, in an attempt to monitor the considerable growth of the city after major increases in economic activity. Problems arose from this growth in the form of increased congestion and pollution. In order for city planners to gain a greater understanding of the problem, a classification and time series analysis was performed to display the growth of the urban environment. From the final classification, planners were able to make adjustments to policies and management plans for the city (Sunar Erbek *et al.*, 2004).

With an increase of population within a city, the impacts of the growth can alter the natural environment in and around the city for the worse. A study in Atlanta, Georgia, USA, attempted to evaluate the effect of the city's growth on increases in temperature and on air quality within the city. The researchers used a model to accurately model the air temperature and quality. Satellite remote sensing techniques were used to produce an accurate landcover map, and this formed the base from which the model would run. The final images produced were used and illustrated how remote sensing can provide a cost-effective and efficient process from which a base for other studies may use (Yang and Lo, 2002).

2.1.2.2 Vegetation Environmental Mapping

In areas of little water supply, the need to calculate the amount of water for specific landuse types becomes paramount. A study undertaken within Iran attempted to classify agricultural land or areas that were under irrigation for agricultural purposes. The outcome of this produced a classification using multi-temporal images and a minimum distance classifier to produce a classified image with accuracy of between 60% and 70% (Akbari *et al.*, 2006).

Because satellite remote sensors follow set paths, this means an area can be re-visited, which allows a researcher to expand on the body of knowledge for a set subject

(Lillesand *et al.*, 2004). An example of this can be seen in the mapping of savanna in Belize, Central America by Plane *et al* (2006), where many coarse landcover maps have been produced over the years. Plane's study increased the resolution of the landcover maps using Landsat images. Results from the study showed that the use of the Landsat images provides managers of these savannas with an affordable and reliable way to monitor changes over time (Plane *et al.*, 2006)

2.1.2.3 Landcover mapping in the southern African Context

Southern Africa is an area full of differing demands on the natural environment and it has many different features on its surface, thus creating many research opportunities to study these various landforms with remotely sensed imagery.

In areas of low rainfall, the need for water amongst the local communities can pose problems for the management of water resources. In Zambia, satellite remote sensing using the Landsat MSS platform was used to detect the changes within a wetland as a result of the construction of a dam upstream. This, in conjunction with water extraction from the wetland, put pressure on the wetland system. Remote sensing allows for the monitoring of the area which would otherwise be difficult to reach and so monitor. Lessons learnt from this study could be applied to the study of other wetlands within southern Africa (Munyati, 2000).

Changes to the global climate have sparked the formation of policies to monitor, and to enforce regulations regarding the emission of greenhouse gases (Robertson, 1998, Pearce, 2005). Due to these policies it is now becoming necessary to report on emissions produced by a country, and therefore reliable information on the emissions from the burning of biomes in needed. A study, the SAFARI 2000 study, attempted to use remotely sensed data in conjunction with emission factors from the International Panel on Climate Change (IPCC) to estimate the emissions from the burning of grasslands and woodlands in southern Africa. Satellite remote sensing using coarse imagery enabled estimates over large areas to be made for emissions from the burning of vegetation. It was seen, however, that the smaller countries in the study area were usually not mapped correctly and so the estimates were not accurate enough to be considered reliable (Korontzia *et al.*, 2004).

Landuse and landcover mapping can be used not only to estimate the effect of human population growth and how it affects the distribution of animal species, but also to evaluate the landcover and landuse types within an area. A study conducted in KwaZulu-Natal, South Africa, evaluated the species richness of the province using the database from a landcover map. Using indicators in conjunction with statistical methods, it was found that during the time of the study species richness increased. Reasons for this increase in species richness could be attributed to better management of change in landcover types or species of birds taking advantage of the changed landcover types (Fairbanks, 2004). The Fairbanks study shows the possible use for a landcover map after it has been made and distributed.

From the above examples, it was seen that there was no comparison of results at differing spectral and spatial resolutions. There was a study undertaken by Atkinson (1997) in which the optimal resolutions for specific mapping needs were explored. In this context, however, mapping was undertaken using Airborne MSS for determining the optimal resolution for remotely sensed images from airborne sensors (Atkinson, 1997). Another study, undertaken by McCabe and Wood in 2006, discovered that coarse resolution imagery cannot compete with medium resolution imagery when mapping at a local spatial scale. Thus it can be said that coarse imagery is best for regional mapping (McCabe and Wood, 2006).

2.2 IMAGE CLASSIFICATION

Landcover is often seen as the dominant feature within an area, for example vegetation type, rock, and water (Franklin and Wulder, 2002).

Franklin and Wulder (2002) outline a set of nine tasks or procedures that should be followed during the process of image classification. These will be listed and discussed in the following sections.

Table 2.1: List of procedures to complete for the undertaking of multiple image land cover classification (after Franklin and Wulder, 2002)

Tasks to be completed:
1. Selection of landcover classification classes.
2. Acquiring of the imagery.
3. Geometric processing.
4. Radiometric correction, calibration, and standardisation of the imagery.
5. Choosing mapping variables.
6. Choosing the classification approach
7. Completion of pre-classification procedures.
8. Selection of the decision rule.
9. Validation – Accuracy assessment.

2.2.1 Selection of land cover classes

As has been stated by Franklin and Wulder (2002:185) "land cover is almost always used in the sense of the dominant physiographic attribute for a given parcel of land…" In other words, the landcover feature for a given piece of land should be the dominant feature within the parcel of land. When choosing the classes to be used within the landcover classification, this should be kept in mind. At smaller spatial scales, the classes can be broad and offer very little spatial detail, and this is usually the case when looking at the continental or global scales. As the spatial scale increases, more detail is required to differentiate the classes. The fundamental approach to choosing classes is to keep class consistency over large areas, by choosing classes that can be easily distinguishable in the coarsest resolution, e.g. MODIS (Franklin and Wulder, 2002).

Problems arise in the landuse and landcover classifications when specific covers are used for two purposes. For example, a forest may be classed as a natural forest but may be used by external entities as recreational or conservation. This is where it becomes important to clearly define what classes and definitions are to be used in the classification (Anderson *et al.*, 1976). Another problem is that of areas of transition between one class and another. For example, at the boundary of land and water there is generally not a single definitive line dividing the two. There may be a wetland, or in the case of ocean or tidal estuaries the land/water boundary changes hourly (Anderson *et al.*, 1976).

Anderson *et al.* (1976) define a set of criteria that should be met when creating the landuse and landcover classes for satellite imagery (Table 2.2).

For the present study it was felt that the definition given by Anderson *et al.* of the criteria was too detailed. Consequently, the criteria used in this study were derived from the National Land Cover project (NLC 2000) (CSIR, 2002).

2.2.2 Acquiring Imagery

When obtaining the image, it is necessary to note the time at which the image was taken. Some features will be different depending on the time of year and season. This is especially true when looking at time series and change detection because features may be detectable at a given season (Franklin and Wulder, 2002).

Table 2.2: List of criteria for the formation of a landuse and landcover classification (after Anderson et al., 1976)

Classification Criteria	
1.	The minimum level of classification accuracy of classes should be 85%
2.	The level of accuracy of the classification classes should be equal for several of the classes.
3.	Results should be repeatable from one interpreter to another, at different times.
4.	The classification system should be applicable over large areas.
5.	Categorisation should allow for vegetation and other types of landcover to be used as substitutes for other activities.
6.	The classification system should be able to function within different seasons within the year.
7.	Formation of sub-classes from other data sets should be obtainable.
8.	Some classes should be able to be aggregated.
9.	Comparison of future images with present images should be possible.
10.	When possible, multiple uses of land should be recognisable.

Other parameters to consider when acquiring the imagery are the selection of which classes or features are to be mapped. Franklin and Wulder (2002) neglect an important issue. The size of the features to be studied may be viewable only at specific resolutions, or may be detectable only at specific spectral resolutions (Atkinson, 1997, McCabe and Wood, 2006). McCabe and Wood (2006) showed that certain processes may be detected only at or below a certain resolution. Thus the choosing of the correct imagery plays an important role in landcover classification.

2.2.3 Geometric Processing

Geometric correction refers to the processes by which errors within an image are removed. These errors can arise from many different factors, including elevation of the senor, motion of the sensor, and the curvature of the earth (Lillesand *et al.*, 2004). Errors obtained through the collection of reflectance by the sensor can be divided into two categories. The first is one of random errors that cannot be predicted and are corrected using ground control points. The second is one of errors that are systematic, that are generally known, and can be predicted and corrected using mathematical methods (Lillesand *et al.*, 2004).

The image has to be projected. This is the process by which the image is placed into a geographic location on the earth's surface by means of mathematical algorithms (Lillesand *et al.*, 2004).

2.2.4 Radiometric Processing

Within a raw, remotely sensed, image there are errors and distortions that occur due to either the sensor or the atmosphere. Some of these errors can be removed with the use of mathematical algorithms. An example of radiometric corrections would be found in the case of the angle of the sun during different seasons. A satellite sensor measures the amount of solar reflection from the earth's surface. It is well known that the angle that the sun makes with the earth's surface varies, depending on the season. It is because of this that standardisation of the pixel brightness of images must be achieved using mathematical equations, thus allowing for the comparison or mosaicing of scenes from different temporal sequences (Lillesand *et al.*, 2004).

There are other corrections that need to be looked at and corrected including distortions created by the atmosphere which interferes with the reflectance of the sun's light on the surface of the earth or scatters the reflectance of light. A way to correct for haze is to take reflectance values from a known source and subtracting them from the entire image. Lillesand *et al.* (2004) use the example of reflectance over deep water and estimate the reflectance to be essentially zero in the Near-Infrared band. Thus any value recorded here represents interference and so can be subtracted from the rest of the image to remove this interference (Lillesand *et al.*, 2004).

2.2.5 Choosing Mapping Variables

When looking at the mapping variables to use within a land cover classification one can divide the variables into two categories, namely: Spectral and Ancillary.

Spectral variables primarily refer to using the reflectance values within the image to accomplish the classification (Franklin and Wulder, 2002).

Ancillary variables refer to the use of external data sources with the spectral information. This allows for a more accurate classification (Franklin and Wulder, 2002). Work done by Bolstad and Lillesand in Wisconsin shows that by including external data sources such as soil types and elevation, the quality of the classification is improved by 16% over previous classifications in that area (Bolstad and Lillesand, 1992). The present study used a DTM to create a slope and aspect map for the study area. The ancillary data was therefore the DTM, the aspect and slope maps, and an Normalised Differential Vegetation Index (NDVI) created from the red and NIR bands from the image used.

2.2.6 Choosing a Classification Approach

Due to the inherent errors and differences within an image, there is no single classification technique that can perform the best classification. Each technique must find a common ground among the desired classes, spectral and other information available, and the ability for the technique to derive the desired classes. The different pieces of information are rarely able to overlap each other exactly and so ambiguity within classes exists (Franklin and Wulder, 2002).

2.2.7 Selection of Decision Rule

Decision rules refer to the approaches used to identify the structures within the data usually by employing clustering methods. These clustering methods use measures of distance and statistical rules to identify trends within the data (Franklin and Wulder, 2002).

One of the most powerful classifiers available is the maximum likelihood algorithm (Franklin and Wulder, 2002). Examples of other classifiers include the discriminant function, minimum distance to means, and parallel piped classifier. These classifiers are widely used and provide predictable results and are easy to use (Franklin and Wulder, 2002).

2.2.8 Accuracy Assessment

Accuracy assessment is the assessment of how accurate the final created product is compared to reality (Foody, 2002). Error can therefore be seen as the inability of the final product to represent reality (Foody, 2002).

Accuracy assessment has its inherent problems such as: the overestimation of chance agreement between pixels which will underestimate the final accuracy; and problems with the sample size used for the classification (Foody, 2002). Accuracy assessment seems to be constrained by what resources are available to undertake the assessment. There have been suggestions as to how to overcome constraints, such as the use of other imagery, but in the end the assessment methods are a result of the compromise between the statistically sound and the practical (Cihlar, 2000).

2.2.9 Summary

Examining the relevant literature, one can conclude that specific important factors need to be addressed in this study. The selection of the appropriate classes is vital. The reason for this is due partly to the type of resolutions of the imagery being used. The classes being selected need to be broad enough so that even the coarsest imagery is able to detect these classes. It must, however, be noted that the selection of the classes must not be so broad that the ability to detect specific classes is removed.

The mapping variables are important to the classification. These will be the inputs into the classification algorithms from which the classification will be completed. It is best to choose variables that therefore allow for the best detection and so classification of the classes chosen. Where necessary, some variables may have to be created. For this study an NDVI image was used in many of the classifications in an attempt to improve the performance of the classification algorithms.

The classification of an image is governed by the classifier used. It is therefore important to decide which of the different classification techniques are best for the specific situation. Each of the classifiers has its own set of rules which it applies to an image, thus the output from these classifications can be very different. This study will look at the performance of three of the traditional classifiers as well as the performance of a trained neural network.

2.3 NEURAL NETWORKS

2.3.1 Introduction to Neural Networks

As technology within the sector of remote sensing increases, so does the amount of data a single image can hold. More bands and higher resolutions mean that there can be an increase in the amount of data that are repeated within the image, increasing the chances for classes within an image to overlap (Qiu and Jensen, 2004). This in turn increases the complexity of the classification of an image and creates problems within the current statistical classification techniques (Qiu and Jensen, 2004).

Most statistical classifiers rely on assumptions about the data and so are limited in their applicability in complex scenes (Linderman *et al.*, 2004). Limitation of these types of classifiers, namely the minimum distance to means, and maximum likelihood classifiers, are due to the assumptions and restrictions on the input data types (Kavzoglu and Mather, 2003). Examples of this limitation have been seen in the classification of understorey vegetation cover within a forest environment. The complex understorey vegetation affects the reflectance properties and scattering of light and so it can be difficult to obtain accurate and repeatable results from statistical classifiers (Linderman *et al.*, 2004).

Neural networks have proven that, in the study of complex and variable features, they are invaluable in their accuracy in classification over other statistical classification techniques (Kavzoglu and Mather, 2003, Linderman *et al.*, 2004, Qiu and Jensen, 2004, Sunar Erbek *et al.*, 2004). A neural network is defined as being a mathematical model of brain activity, featuring corresponding characteristics of a working brain represented mathematically (Sunar Erbek *et al.*, 2004). A neural network is made up of many components called neurons; each of these neurons performs a simple computational procedure (Qiu and Jensen, 2004).

Neural networks work by creating neurons that act as simulators of multivariant linear regression models that make no assumptions about the distribution of the data. Neural networks are able to 'learn' from set parameters for the classification, making it possible for the classification of complex datasets (Linderman *et al.*, 2004, Qiu and Jensen, 2004). There are two ways for neural networks to 'learn', these are, as with classifications, supervised and unsupervised. Supervised 'learning' occurs when the final desired values for output are known and used in the network during its training. Unsupervised learning occurs when the final output values are not known and so are not used in the network during training (Sunar Erbek *et al.*, 2004).

A neural network will usually have an input layer and an output layer. There are also nodes and connectors that play a role in the development of the network. Information is distributed and encoded through the neurons by nodes that act as connectors within the system. The connection methods within a neural network can either be unidirectional or multidirectional. Networks with a single direction of information movement, inter-nodal or intra-nodal flows are known as a Feedforward neural networks (Figure 2.2) and a network with multiple directions of information flow is known as a Recurrent Neural Network (Figure 2.1) (Murphy *et al.*, 2003, Mutanga and Skidmore, 2004).

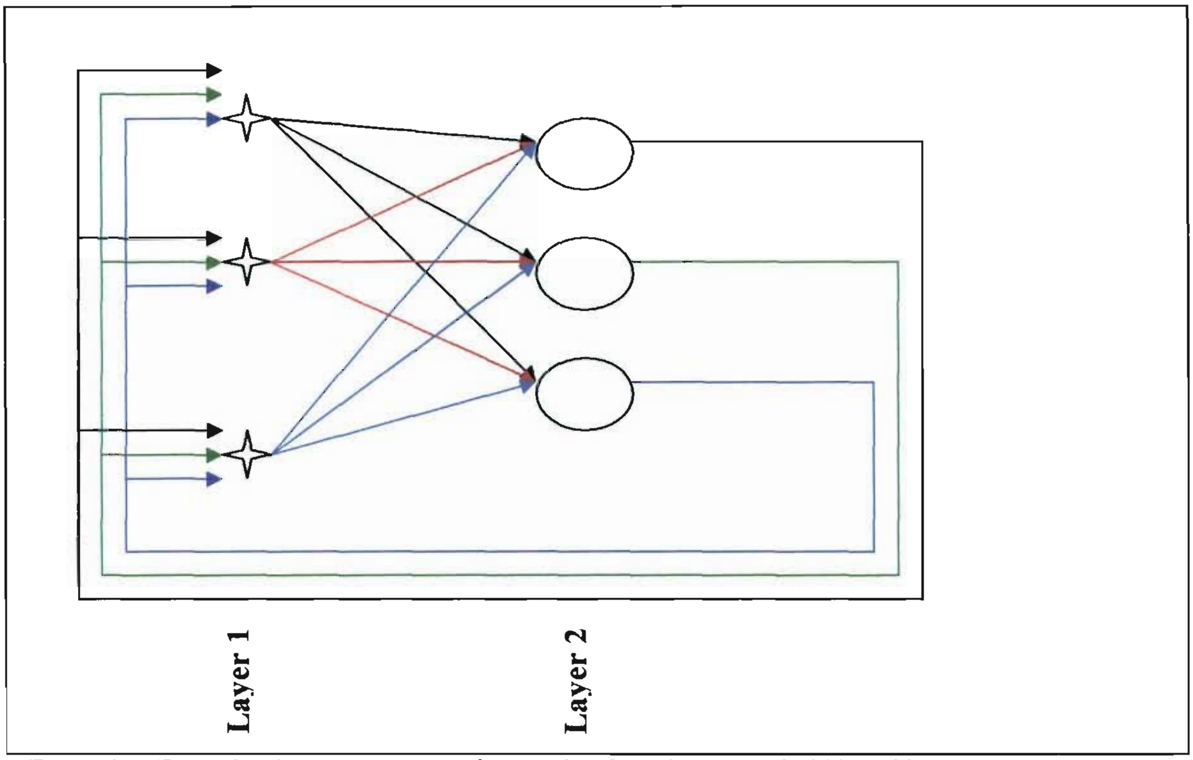

Figure 2.1: Example of a recurrent neural network (after Murphy et al., 2003: 4886).

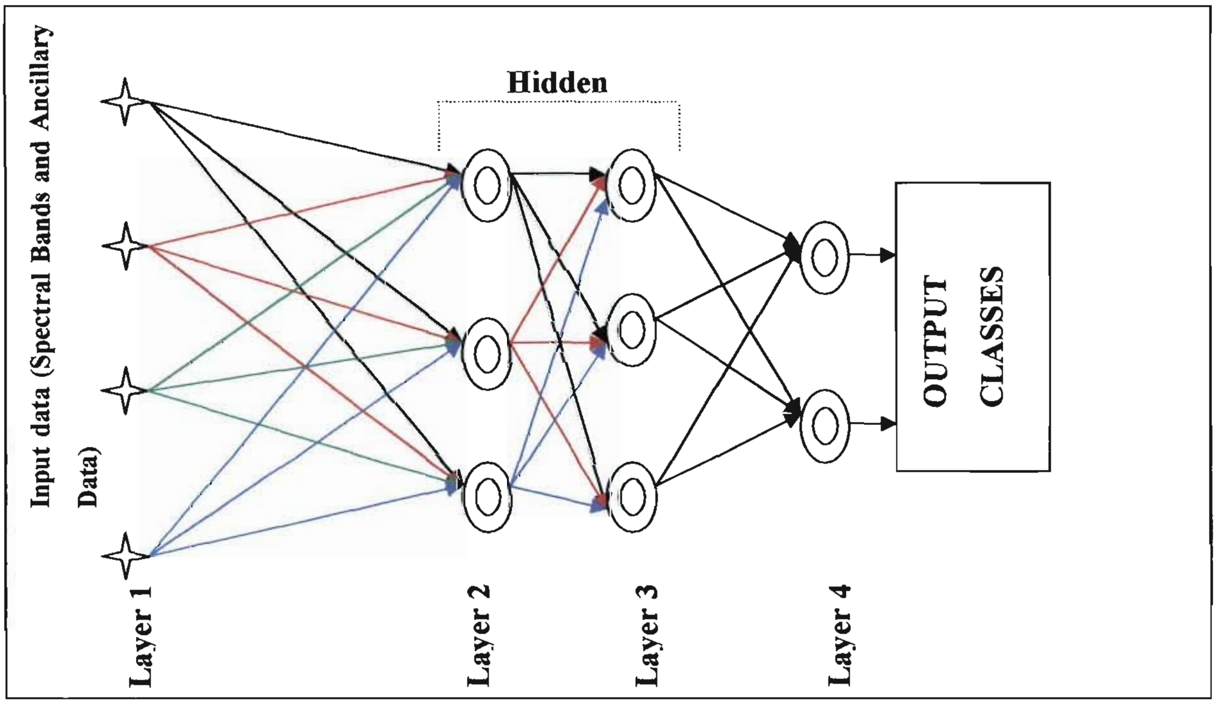

Figure 2.2: Example of a feedforward neural network (After Murphy et al., 2003: 4886 and Kazoglu and Mather, 2003).

2.3.2 Feedforward Neural Networks and Backpropagation

One of the most common neural networks used is that of the Multilayer Perceptron (MLP) model. This is a feedforwad artificial neural network model (Kavzoglu and Mather, 2003, Foody, 2004). Another type of feedforward neural network is that of the Radial Basis Function (RBF) (Foody, 2004).

A MLP model comprises different layers: these layers can be classed as the input, hidden, and output layers. Each layer consists of nodes and each node is connected by a user defined weighted function. Nodes from the same layer cannot be connected to another node within the same layer. The function of the node is to perform a simplified mathematical algorithm (Foody, 2004). Information from spectral bands and ancillary data are fed into the model through the one input layer into the hidden layers. The hidden layers perform the mathematical analysis on the input data to create the output layer or the specific classes for the classification. The flow of information is in one direction, hence the feedforward model (Kavzoglu and Mather, 2003).
MLP models have been described in literature as a supervised type of model (Kavzoglu and Mather, 2003, Foody, 2004). Because that information is already known about the classes and other information involved within the model and, the model is 'taught' to the network (Kavzoglu and Mather, 2003). One of the most popular teaching methods is known as the 'backpropogation learning algorithm' (Kavzoglu and Mather, 2003).

Backpropogation is a learning technique that aids in the accuracy of the final result of running the model. (Kavzoglu and Mather, 2003, Foody, 2004). Backpropogation works in two stages.

> Stage 1: Initially, network weights are put through the network and estimates of the output values are made for each set of data input into the network (Kavzoglu and Mather, 2003, Foody, 2004).

Stage 2: Once the values have been estimated, they are compared to known values and the errors between these values are calculated and sent backwards through the network. The weights between the nodes are adjusted to create minimal error. The whole process is repeated until the error reaches a designated value or a value as close to zero as possible (Kavzoglu and Mather, 2003, Foody, 2004).

The Radial Basis Function (RBF) is another type of feedforward neural network. It is similar to the MLP model in that it contains specific layers connected by weighted functions and nodes. However, whereas the MLP model has an infinite number of hidden layers, the RBF has only one. Within the single hidden layer of the RBF is a statistical function; this function 'looks' at a specific small area within a defined input layer. This layer will calculate the location of a specific point from the input layer and calculate the deviation of an input layer vector from the designated centre for the RBF. The points closest to the centre of the designated radial point have a maximum value of 1.0, whilst those furthest will be 0.0, the layer is thus divided into zones (Foody, 2004).

A problem that is contained within the neural network algorithms is that the actual algorithms used are very complex. This means that the relationship between inputs and outputs are very difficult to obtain. It is noted by Qiu and Jensen (2004:1750) that "a neural network is often accused of being a black box", due to these relationships being complex and hidden. The number of designated hidden layers within the network is vital to the accurate classification of an image (Kavzoglu and Mather, 2003). Problems with the MLP neural network can be caused by the use of the weighted connections between nodes. These weights affect the rates of error calculations and thus the learning properties of the network. It has often been seen that the derivation of many of the values used in a successful classification stems from trial and error. Another problem stems from the correct use of the best number of training samples (Kavzoglu and Mather, 2003), and this will be discussed further.

It is thus difficult to gain an understanding of the characteristics of a given dataset and so simplification of and improvement of the efficiency of a classification is near impossible.

Essentially, every neural network created has to learn from the beginning of every problem (Qiu and Jensen, 2004).

2.3.3 Factors Affecting the Accuracy of Neural Networks

The overall accuracy of neural networks when compared to that of conventional statistical classifiers is generally greater. There have been many studies undertaken that confirm this (Foody and Arora, 1997, Yool, 1998, Kavzoglu and Mather, 2003, Qiu and Jensen, 2004, Sunar Erbek *et al.*, 2004). There are, however, difficulties with the use of neural networks.

The complexity of the network is a factor which affects the accuracy of the network's classification. The more connections and layers within the network the more these will govern the overall accuracy of the classification. The number of connections and layers will also govern the effective generalisation and classification of pixels not incorporated in the supervised data set. The more connections there are, the more accurate the classification of these 'seen' pixels, but there is a reduction in the ability of the network to generalise and so classify the 'unseen' pixels or the pixels not within the supervised data set (Foody and Arora, 1997).

A study by Foody and Arora in 1997 identified four possible factors that could affect the classification accuracy and thus the accuracy of a neural network. The following section will attempt to briefly evaluate the factors which affect the accuracy of image classifications.

The **first factor** identified is that of the structure of the network. This refers to the structures of the layers within the network, and how many hidden layers and nodes are contained within that network. It is generally seen that the more complex the network, the more accurate the output classes are, when compared to smaller and less complex networks. The structure alone cannot be viewed as the deciding factor when assessing the accuracy of a network, because the structure combined with the other factors bears a greater influence on the accuracy (Foody and Arora, 1997).

The **second factor** identified is that of the training set size. It is accepted by advocates of remote sensing that for an accurate classification to occur, a representative sample of the required classes be obtained. "To yield acceptable classification results, training data must be both representative and complete" (Lillesand *et al.*, 2004). In other words, the reference data obtained, in order to train the classifier (Statistical or Neural Network), should represent all the classes that are to be created in the output. It has, however, been seen that because a neural network makes no assumptions about the distribution of the samples, a neural network can still be accurate without requiring as many training datasets as a statistical classifier does (Foody and Arora, 1997). It has been shown that the greater the number of samples are used, the more accurate the classification. However, as the sample set is increased so too is the amount of time needed to perform the classification. In their study Foody and Arora (1997) showed that the number of training samples can increase the accuracy of the output classification.

The **third factor** identified is that of discriminating among variables. This is the ability of the system to distinguish between classes based on the characteristics of the data for those classes. Traditionally, for statistical classifiers the main discriminating variable has been that of spectral separability or the ability to discriminate among classes based upon the spectral bands within an image (Foody and Arora, 1997, Lillesand *et al.*, 2004). Within a neural network, the discriminating variables are not limited to just the spectral bands of an image. The bands can not only be used to aid in the classification but also used for ancillary or extra. These data can be in the form of aspect, slope, soil types, and rainfall to name a few variables. (Foody and Arora, 1997, Foody, 2004, Lillesand *et al.*, 2004, Mutanga and Skidmore, 2004). Caution must be exercised regarding the use of too many spectral bands within the classification. A phenomenon known as the Hughes phenomenon is known to occur when too many bands are used. Adding bands to a classification aids in identifying different classes up to a point, but thereafter the addition of more bands has no effect on increasing the accuracy of the classification and in some cases can reduce the accuracy of the final classification (Foody and Arora, 1997).

The **fourth factor** identified is that of testing data characteristics. The final output of the classification must be tested for its accuracy compared to real-life situations. This is usually done by means of an error matrix, also known as a confusion matrix. Within this matrix, values from the classification are compared with known values from reality and are plotted in the matrix comparing what was classified correctly against what was not. An ideal determination of accuracy is the inclusion of samples representing the statistical representation of all the classes and so classified pixels (Foody and Arora, 1997, Lillesand *et al.*, 2004).

Neural networks allow for the identification of complex spectral and spatial patterns (Paola and Schowengerdt, 1995). Studies have shown the ability of a neural network to detect different wheat crops at various stages of their growth cycles (Murphy *et al.*, 2003). Studies comparing the performance traditional classifiers with that of a neural network have shown that the neural network performs better with the complex scenes when compared with the traditional classifier. This is primarily due to the ability of the neural network to model non-linear features (Murphy *et al.*, 2003, Sunar Erbek *et al.*, 2004). The present study will add to the studies of the performance of traditional classifiers in heterogeneous environments and to the improvement of these classifications using a supervised neural network.

2.3.4 The Importance of Resolution in Classification Accuracy

For the present study, the term 'resolution' can refer to the spatial resolution of an image, the spectral resolution of an image, and the categorical or number of classes in the image. The term 'scale', in this study, is often used in the context of spatial resolution, or the minimum spatial extent of a pixel. 'Spectral resolution' refers to the number of spectral ranges or the number of different wavelengths that the image may have. 'Categorical resolution' refers to the number of classes and how much descriptive detail those classes may have. Examples would be a fine categorical resolution which may have hardwood and softwood trees, and a coarse resolution which may combine the two to create a forest class (Lillesand *et al.*, 2004, Johnson, 2005)

2.3.4.1 Spatial Resolution

Features at different spatial resolutions take on different properties, depending on the scale at which these features are analysed. Scale can determine how much generalisation can occur within and around the feature: some features may be very detailed at one scale, but at another they may be generalised. In cartographic scale, a large scale means that the images are smaller and portrayed in more detail and the smaller scales will have larger extents and show less detail. An example of this can be seen within remote sensing. Scale (resolution) in remote sensing is often seen as the smallest pixel size within the image; the size of this pixel on the earth's surface can determine how much of a feature is shown (Quattrochi and Goodchild, 1997, Lillesand *et al.*, 2004).

One of the most concerning factors within remote sensing is the determination of which spatial resolution is best to be used in a study. Resolution of an image is important, for example an image with a resolution of 30 m can identify features larger than 30 m, however, the number of pixels within that feature will determine whether that feature can be correctly identified/ A higher resolution is needed to identify more of these features and how they may relate to each other (Cao and Lam, 1997).
Scale plays an important role in the extrapolation of results. Differences in scales within the extrapolation can have a detrimental effect on the results obtained. An example of this occurs within landcover classification. Data are lost between classes as the resolution of the image becomes coarser. Landcover types gradually disappear as the resolution of the image increases (Cao and Lam, 1997).

2.3.4.2 Categorical Resolution

As has been stated, categorical resolution refers to the amount of detail an image may portray post-classification. This generally refers to the labels of the classes (Ju *et al.*, 2005)

It has been seen that as the spatial resolution of an image becomes coarser, so the amount of spectral mixing increases, necessitating more broad categorical labels. Generally, to allow for the changes in spatial resolution, classes are joined together to form more generalised classes. This can create problems in that areas where one class is dominant there can be a large loss of categorical information (Ju *et al.,* 2005)

2.3.4.3 Spectral Resolution

Spectral resolution refers to the number of spectral bands or ranges that an image may have. Using the Landsat TM sensor as an example, it has 6 bands and detects 3 bands within the visible spectrum and 4 bands in the Near InfraRed (NIR), Shortwave InfraRed (SIR), Thermal Spectrum, and Mid InfraRed (Akbari *et al.*) bands (Lillesand *et al.*, 2004)

The spectral resolution of an image can aid in the detection of specific features. Some images with high spectral resolutions, as in hyperspectral images, allow for the detection of specific types of chemicals within vegetative matter. This can then allow for the detection of specific species of vegetation (Dungan *et al.*, 1996). Other uses for specific spectral bands include the detection of crop residues for agricultural land management (Bannari *et al.*, 2006), the monitoring and estimation of water content within vegetation (Claudio *et al.*, 2006) and the mapping of vegetation in highly complex areas such as salt marshes (Belluco *et al.*, 2006).

2.3.5 Selection of Resolution

During previous studies of different scales within remote sensing, an ideal resolution (spatial and categorical) was sought for landcover mapping. It must, however, be noted that there is not any one set or defined optimal resolution for the study of a specific situation. The reason for this is that at different spatial resolutions it is difficult to accurately portray all of the features that need to be studied, due to the heterogeneity of the different features (Ju *et al.,* 2005).

When undertaking a landcover classification, deciding on of the correct resolution therefore becomes a very important factor in determining the accuracy of the final output of the classification. A study conducted by Markham and Townshend (1981) determined that the accuracy of a classification is governed by two factors, namely the amount of pixels falling on the boundary of features and the spectral variation of classes. 'Boundary pixel' refers to the proportion of pixels that fall on the boundary of the classes. Mixed pixels, or the number of pixels that contain more than one class, increase as the spatial resolution of the image increases and thus decreases as the resolution of an image becomes finer. The spectral variation within a class increases with the increase in the resolution of an image. Thus the spectral separability of the classes is reduced, creating problems in determining the nature of the class (Cao and Lam, 1997).
There have been studies comparing the accuracy of landcover classification at various resolutions. One such study took an image of 1 m x 1 m resolution and aggregated and resampled the image to various resolutions from 4 m x 4 m to 24 m x 24 m. It was found that as the resolution of the image became coarser so the standard deviation between pixel values decreased; also the spatial autocorrelation between adjacent pixels decreased. It was found that the rates of decrease were related to the type of feature within the classes (Chen *et al.*, 2004).

Modern remote sensing offers many opportunities for the expansion of knowledge about the earth's surface. These opportunities also add problems to the researchers' studies. The problems of scale can become evident with regard to the resolution at which the study is being conducted. Some features can be studied only at the finer resolutions; whilst others will not show any major changes in the finer resolutions, but as the resolution becomes coarser so the amount of change becomes more apparent (Franklin and Wulder, 2002, Ju *et al.*, 2005).

2.4 CONCLUSION

The literature has shown the extent to which a neural network is able to operate and the improvements that a neural network can make, especially in spectrally complex areas.

Foody and Arora (1997) identified the various factors that may affect the classification accuracy of a neural network. The present study will investigate these factors to evaluate the specific neural network used within the study and identify which variables are important.

The performance of the neural network has been studied by various authors (Foody and Arora, 1997, Kavzoglu and Mather, 2003, Foody, 2004, and Qiu and Jensen, 2004), although the performance of these networks compared with traditional classifiers has not been studied as much. This study aims to determine if the neural network can substantially improve on a traditional classifier.

Resolution plays a large role in this study. The two resolutions investigated are the spatial and categorical resolutions. The effect these resolutions have on the classification accuracy will be examined. To test the conclusions reached by researchers in the reviewed literature, these resolutions and the affect they have on the landcover accuracy will be investigated.

This chapter has outlined some of the major themes for the study. Chapter three will outline the techniques used in the study.

Chapter 3. METHODS

The information in the chapter follows the order in which the study was undertaken: starting with the creation of the random points from which the spectral signatures were created, followed by the classification of the images, and finally the use of the neural network.

3.1 BASELINE DATA COLLECTION

The base for all the data in this study relies on the GPS points collected from the field. In order for these points to be collected, it was decided to use randomly generated points.

For this study, 11 classes were used to classify the image; these 11 classes were derived from the National Landcover classification definitions of South Africa (CSIR, 2002). The first step in the study was to collect the GPS points to be used for training of imagery. A random sample list had to be created to ensure a random sampling strategy for collecting the GPS points. In order to generate the random sample listings, it was decided that 15 random samples would be taken from each of the classes. The decision to use 15 random samples was made to ensure a wide spread of samples across the spatial extent of the class. It was known that not all of the sample points would be reached, and thus the higher the number of sample points the greater the chance of acquiring those points in the field.

To decide on the classes, an unsupervised classification was performed using ERDAS Imagine 8.4 (Geosystems, 2003). A simple ISODATA unsupervised classification technique was used. Figure 3.1 outlines the process used. Franklin and Wulder (2002) identified this technique as a method to increase the efficiency with which data is collected in the field. In the present study, however, the unsupervised classification was undertaken to attempt to acquire an idea of the class separation for the collection of randomly generated training site data.

It was decided that, due to the large spatial area of some of the classes e.g. Grassland, it was best to fragment these classes by increasing the number of classes in the unsupervised classification; hence, the number of classes chosen was 13. Once the 13 classes were created, the created image was imported into ESRI's ArcGIS 9.1. For the generation of the random points, the program Hawth's Analysis Tools, was used. Hawth's Analysis Tools can create a set number random of points per polygon defined by the user (Beyer, 2004). Initial testing with the generation of these points revealed that the generation of the random points on the first created image would create 15 points for each polygon on the image. Not only was this highly computationally intensive, but also it was too extensive for the study. In order to counteract the creation of too many points, it was decided that each class would be dealt with individually.

Using ArcGIS 9.1, each class from the unsupervised classified image was extracted into a separate feature; in total 13 new features were created. Hawth's Analysis Tools program was run on each of the separate classes. A total of 15 points were then generated for each class. Each of these separated classes was merged to create a single file containing 195 points. These points were overlaid onto a 1:50 000 topographical map of the study area. These points formed the foundation from which the GPS points for the training sites were collected. Due to the small size of the study area, and the best dispersion of the sampling points, 60 points were chosen randomly for the collection of the training site information.

The CSIR has defined, for the National Land Cover 2000 (NLC 2000) project, a set of class definitions. It was decided that for the present study the definitions used for the NLC 2000 study would be modified and used when collecting data for the training sites. Initially, 11 classes were identified, in order to determine what effect the reduction in the categorical scale would have on the final accuracies of the classification process; these 11 classes were susequently merged.

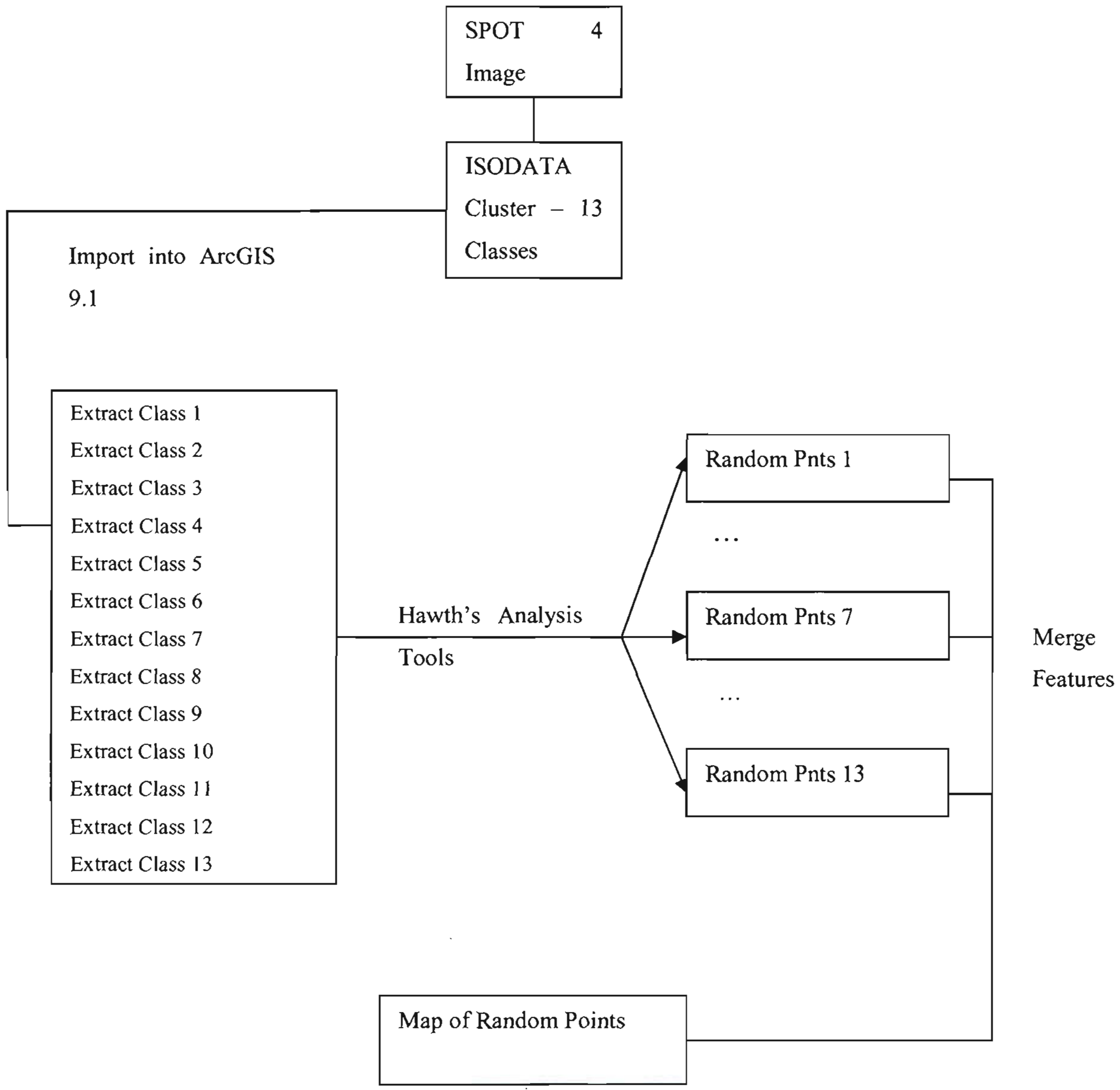

Figure 3.1: The process by which random points were generated for identification of the training sites.

Table 3.1 The definitions used for each of the classes (after CSIR, 2002 and Anderson et al., 1976)

Class	**Class Name**	**Class Description**
1	Agriculture	All land under any type of agricultural activity that is not used for sugar cane and grazing
2	Bush	Dense natural vegetation, consisting of shrubbery and natural forest communities
3	Cane	Sugar cane plantations
4	Gum Plantations	Any area under Eucalypt Plantation
5	Urban	Areas that are inhabited by man. Combining the classes defined by the CSIR" residential, commercial, and industrial areas.
6	Wattle Plantations	Any area under Acacia Plantation
7	Wetland	Areas in and around water bodies. The CSIR defined wetlands as areas where water is either at or close to the surface. Cover usually woody or herbaceous. Examples being papyrus type vegetation (CSIR, 2002)
8	Woodland	Natural areas where the cover of tree is between 10% and 70% of the total cover (CSIR, 2002)
9	Grassland	By combining the CSIR's definitions, a broad definition of grassland was created. Defined as an area with less than 10% tree or shrub cover, containing grass as the dominant species, this included planted grass types
10	Pine Plantation	Any area under pine plantation
11	Water	All open bodies of water, including streams and rivers.

In total, 45 points were collected from the field. Attempts were made to ensure that all classes were correctly represented in the collection process. Owing to the location of some of the points and their inaccessibility, some that were initially decided upon were not collected. To counteract this, using 1:50 000 map data and SPOT 5 Panchromatic image interpretation, more training points were added to the initial 45. In total, 76 points were collected for use in the classification process, and 22 were put aside for use in the final accuracy assessment.

Using ArcGIS 9.1, shapefiles were made according to the class of the point collected. Using attribute data collected (Table 3.2), such as the class type and class description, 11 classes were created to follow the initially decided upon classes. These individual class shapefiles were the base from which all classifications and accuracy assessments were made. Merging of classes to create broader classes was done once the creation of the signature files was completed.

Table 3.2: Example of database created

FID	GPS_Point	X Coords	Y Coords	Class	Descript
1	P1	29.001	-30.25	Urban	Pmb CBD
2	P2	29.65	-30.65	Cane	Sugar Cane

The merging of classes occurred during the classification stage of the study. The 11 classes were reduced to 8 by merging classes that were seen to be similar. The classes that were merged were the Gum, Pine and Wattle classes, which became the Plantation class. The Wetland and Grassland classes were merged to form the new Grassland class. Classes were merged to evaluate the effect that different resolutions – Categorical and Spatial, would have on the final classifications using various classification algorithms.

The procedure used for the classification was kept the same for all images used. Alterations were, however, made to the actual images used, based upon the spectral bands available for use in the classification. The broad approach is outlined below, followed by an in depth look at each image separately.

3.2 IMAGES USED

During the study, three images were used. These were the Satellite Pour l'Observation de la Terre (SPOT 5), Landsat TM and the Moderate Resolution Image Spectroradiometer (MODIS). These images were chosen due to the different characteristics of the images. The SPOT 5 image had the highest resolution of all the images acquired for use in this study, this presented for an opportunity to determine the extent of accuracy differences between the higher resolution image and other lower resolution images.`Landsat TM is widely used for landcover classification, and so was a necessity for the study. The MODIS images are readily available to the public and if the results from the image are satisfactory, costs of landcover classification may be reduced. Attempts were made to keep the images from the same periods in an effort to reduce the effects that changes in the season may have on certain features. It was however difficult to acquire the imagery from the same periods and images were chosen from 2001 and 2004. These images were received pre-processed. This section will briefly outline what steps were taken for the pre-processing of the images.

Figures 3.2 and 3.3 displays some landcover classes from two periods, namely 2000 and 2004, close to the periods from which the satellite images were acquired. An exercise was undertaken to determine what possible changes, if any, happened to the landcover classes during that time period.

It can be seen in Figure 3.2 that the plantation class does go through some minor changes, however, the changes are not changes in the landcover type, namely the amount of cover. Once a plantation lot is cleared, it is quickly replaced with more plantation type vegetation. During the GCP collection stage of the study, it was seen that a plantation had recently been cleared, it was still recorded as a plantation. It can be seen in Figure 3.3 that the agricultural lands identified did not change over the 4 year period. It is possible that land may have been harvested, but the land remained as agricultural.

Using these small samples of the study area, it was assumed that over the entire study area, the amount of change between the landcover classes for imagery from different time periods was minimal, and thus could be used for the study.

While efforts were made to keep the dates of the acquisition of the imagery close together, it was also important to keep the seasons of the acquisition similar. It was seen that the Landsat TM and MODIS imagery were both acquired during winter, the SPOT image was acquired during summer. Although it is possible for some landcover classes to become less prominent during the winter months, it was assumed that this decrease in prominence occurred for all landcover classes of the same period. Thus it was assumed that the ability of the classifier to classify imagers from different seasons was considered to remain consistent.

3.2.1 SPOT 5

The SPOT 5 image was acquired in January 2004. It consists of 4 bands (1 to 4) at different spectral ranges. Table 3.3 displays the spectral ranges for each of the bands used. These bands are at 10 m resolution, band 4 was 20 m, but resampled to 10 m. The image was geometrically and spectrally pre-processed at level 2B in WGS 84 (Pasquilini, 2005).

3.2.2 Landsat TM

The Landsat TM was acquired in July 2001. Although there is a difference in years between the MODIS and the SPOT image, it was felt that the classes used within the classification would not have significantly changed during that period. The image was received pre-processed, with geometric and spectral corrections completed. The image was projected using the UTM and WGS84 datum. The image consists of 7 bands, each at 30 m resolution. Table 3.3, page 50, displays the spectral ranges of the Landsat TM image (Xiao *et al.*, 2002).

3.2.3 MODIS

The MODIS image was recorded during the early part of July 2004. The image is a composite of the best images from an eight-day collection period of a gridded level 2 surface reflectance. The final product is a level 3 reflectance product known as MOD09 A1 (Mutanga and Rugege, 2006). Atmospheric correction was undertaken using the Bidirectional Reflectance Distribution Function (BRDF)/Albedo Product, which is a MODIS-specific input. Profiles for ozone, aerosols, and clouds were also completed. The image was reprojected into the Universal Transverse Mercator (UTM) Zone 36 projection, using the WGS 84 datum (Mutanga and Rugege, 2006).

Figure 3.4 displays all three of the images that were used in the study. It is seen that the MODIS image is less clear than the other two images, primarily because of the spatial resolution differences between the images.

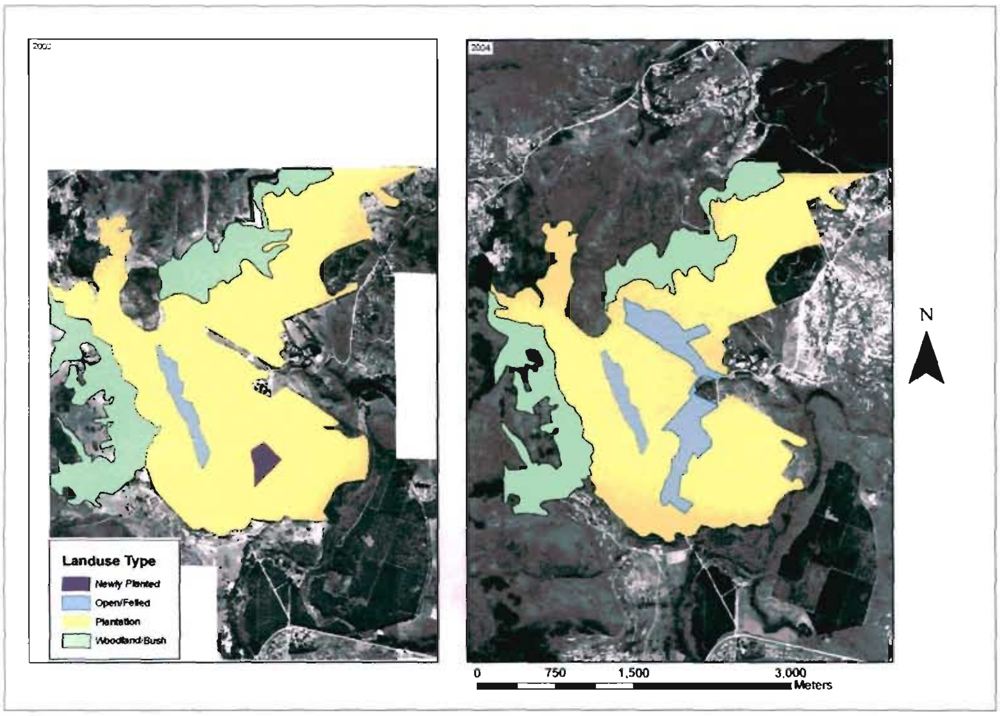

Figure 3.2: Comparison of a plantation stand from 2000 and 2004.

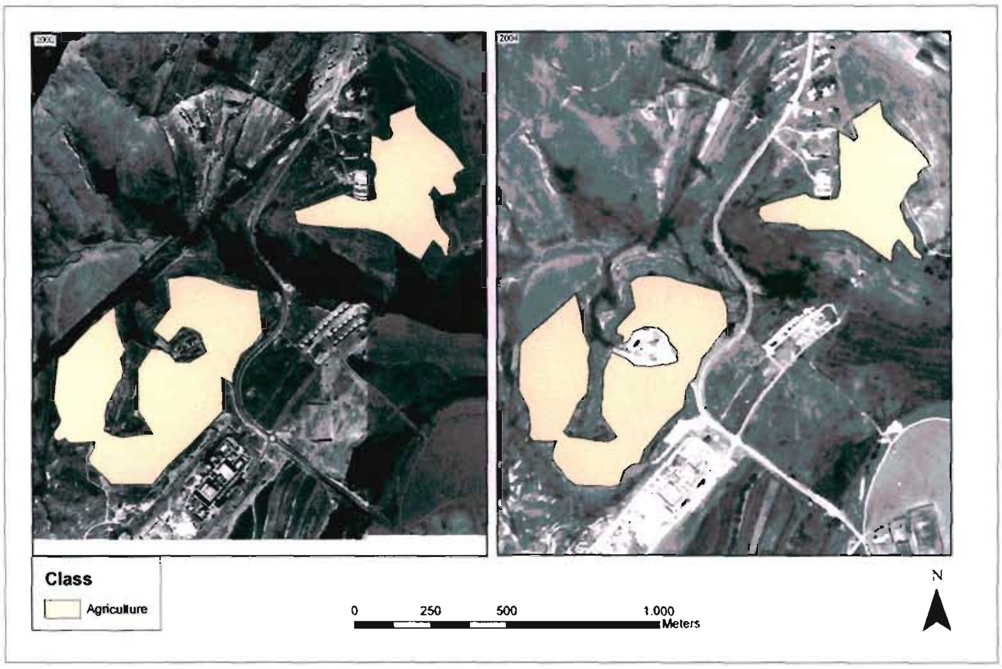

Figure 3.3: Comparison of an agricultural field from 2000 and 2004

3.2.4 Impacts of using different resolutions for image classification

One of the critical factors involved in the classification of remotely sensed images, is the factor of image resolution (Markham and Townshend, 1981 and Chen *et al.*, 2004). This is partly due to the concentration of pixels along the boundaries of the classes being classified and the finer the imagery the more spectral variation can occur over the study area, because of the increased number of pixels per given area (Chen *et al.*, 2004). Studies have shown that changes in the spatial resolution of an image affect the classification accuracy more than changes in the number of classes (Chen *et al.*, 2004).

Studies have been conducted evaluating the effect of changing spatial resolution of a single fine resolution image to coarser resolutions using aggregating averaging windows (Bian, 1997 and Chen *et al.*, 2004). By applying the roving window to the image it is possible to average the surrounding pixels values to create coarser grids and thus coarser resolutions (Bian, 1997). The study conducted by Chen *et al.*, (2004, showed that using the Maximum Likelihood Classification algorithm on an image that had been progressively made coarser, the accuracies were not significantly changed, although some classes were classified with different accuracies. It must however be noted that a study conducted by Bian, 1997, showed that by slowly increasing the coarseness of an image, the actual values of the pixels are altered and in some cases, lost. It is for this reason that the present study used 3 separate images to evaluate the effect of image resolution on image classification accuracy. It was decided that the native pixel reflectance values would be used and thus evaluated and not the altered values that occur when an image is aggregated.

3.2.5 Impacts of using images from different seasons for comparing classification accuracies

Depending on the season and so the time of the year, the physical environment will be different. This poses problems for remotely sensed image acquisition due the variations in the conditions, thus changing the spectral reflectance properties of the image. This can create accuracy issues when looking at features across different times over a given period, as there is no guarantee that the spectral properties of the image will be the same when the site is revisited (Lillesand and Kieffer, 2000).

Changes in the soil moisture content and evapotranspiration demands of a season can place stress on a plant that may not usually occur during other seasons. The increased stress can alter the reflectance properties of a plant to the point where it may not be recognised during a classification as to belong to a particular class type (Sabins, 1997 and Lillesand and Kieffer, 2000).

For the present study, the three images used were taken from summer and winter seasons. Although they are potentially different with regards to the reflectance properties of the images, these differences occur across the entire image and thus will not affect the overall classification of the image. One of the objectives of the study is to determine the accuracy of the classifications using different classification algorithms, not the actual reflectance values themselves. Thus any reflectance differences there may be due to seasonal variations are not taken into account and thus negated.

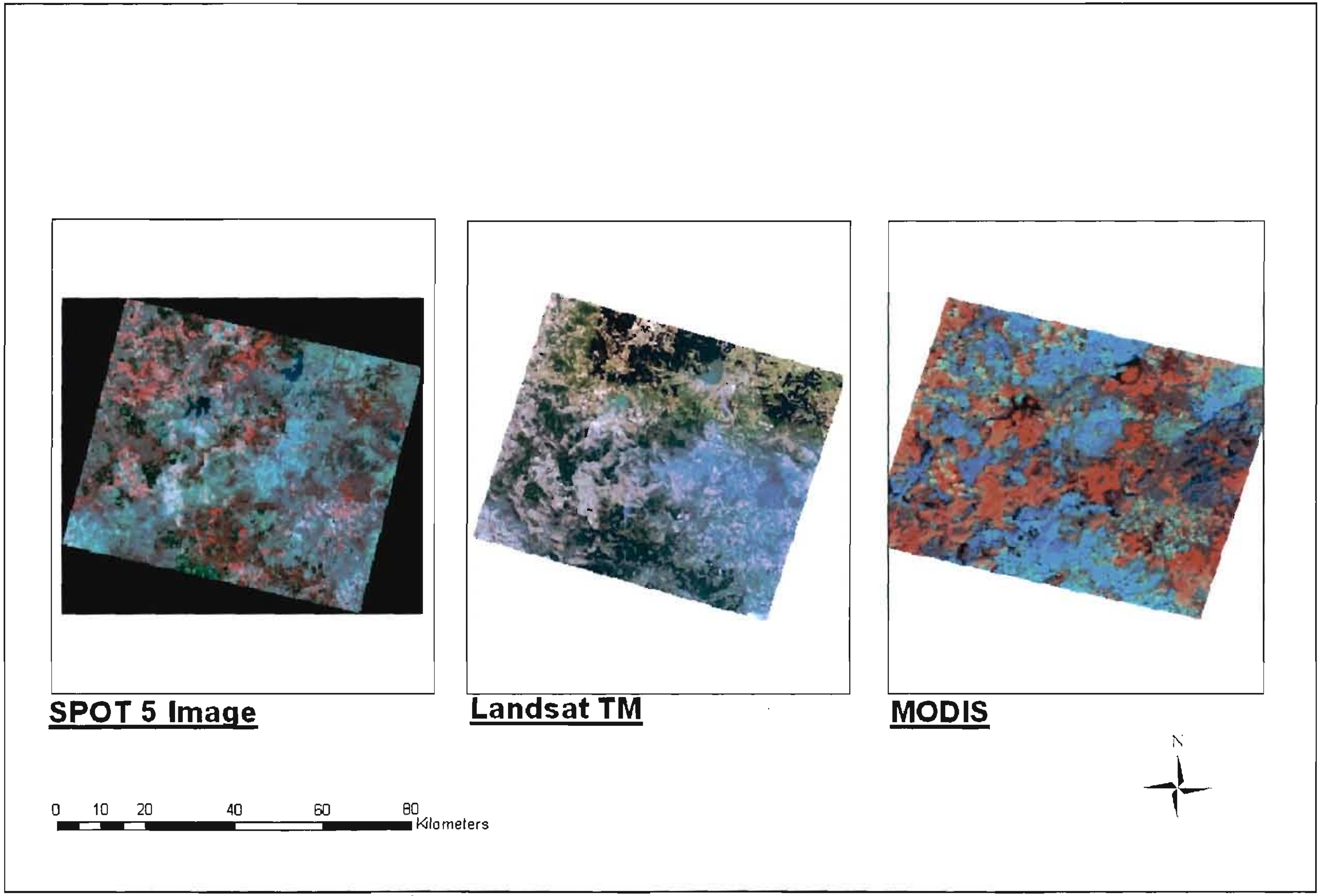

Figure 3.4: Displays the three images used in this study.

Table 3.3: The bands and resolutions of the images used for classification (after Lillesand et al., 2004, Pasquilini, 2005, Mutanga and Rugege, 2006)

Sensor	Bands	Spectral Ranges (nm)	Resolution
SPOT 5			
	1 – Green	500 – 590	10 m
	2 – Red	610 – 680	10 m
	3 – NIR	780 – 890	10 m
	4 – MIR	1 580 – 1 750	20 m (resample to 10 m)
Landsat TM			
	1 – Blue	450 – 515	30 m
	2 – Green	525 – 605	30 m
	3 – Red	630 – 690	30 m
	4 – NIR	760 – 900	30 m
	5 – MIR	1 550 – 1 750	30m
	6 – Thermal	10 400 – 12 500	60 m
	7 – MIR	2 080 – 2 350	30 m
MODIS			
	1 -	620 - 670	250 m
	2 -	841 – 876	250 m
	3 -	459 – 479	500 m
	4 -	545 – 565	500 m
	5 -	1 230 – 1 250	500 m
	6 -	1 620 – 2 155	500 m

3.3 SIGNATURE CREATION

The process by which signature creation was completed was kept uniform for all three of the images. Each image did, however, present problems, and each problem was unique due to both the resolution and spectral qualities of the image. These problems will be outlined later within this chapter.

Each of the class vector files was imported into ERDAS Imagine 8.4. These vector files were the base from which the rest of the classification was made.

Using the vector files overlaid on the image, polygons were created around the point for the creation of signatures from which the classification would be made. The procedures for signature creation have been laid out by Leica Geosystems (2003). The procedures set out within the tour guide were followed in order to produce the signatures for the classification (Geosystems, 2003).

3.4 IMAGE CLASSIFICATION

As the objectives of this study were to determine which resolution could produce the best classifications, and which of the traditional statistical classifiers creates the most accurate classifications, the same signatures were used for each image and in turn the type of classifier was changed accordingly. The spectral ranges used within the classification focused on having some bands within the visible range and the invisible range, so the Red, Green, Blue or NDVI bands were used in conjunction with the NIR bands where possible. In order to allow for the comparison of the effect of spatial resolution on the accuracy of the image classifications, the NIR and visible bands were used for the image classifications, since they were common to the three images used. Thus the MIR, bands were not used in the classifications. By changing the images used, the resolution of the classification would change; and by changing the signatures only after each classification was completed, consistency was kept for each image.

In some cases, to improve upon the classification accuracy, it was necessary to create a NDVI to add to the images. Equation 3.1 displays the equation used to create the NDVI. The NDVI uses the NIR and Red bands to apply an index to the image showing the concentration of vegetative matter. The NIR reflects higher electromagnetic radiation due to the multiple scattering effects of vegetation whereas the red is absorbed by chlorophyll in vegetation. These bands are used because of the reflective reactions of vegetation matter to these bands. The index ranges from 1.0 to -1.0, the higher the values the greater the amount of vegetation (Lillesand and Keifer, 1994).

3.4.1 Challenges with Image Classification: Landsat TM

It has been reported that Landsat TM has a spatial resolution of 30 m (Lillesand *et al.,* 2004). The classification of the Landsat TM image has been well documented (Shoshany, 2000, Price, 2003, Powell *et al.*, 2004, Small, 2004, Sunar Erbek *et al.*, 2004, Yuan *et al.*, 2005). The procedure for the classification was therefore already set out and so was followed.

Initially, bands 4, 3, and 2 (NIR, R, and G) were used for the first classifications. The outputs for these classifications were, however, not acceptable. Problems occurred with the identification and confusion was experienced by the system with regards to the Urban and Water classes. Bands 4, 3, and 1 (NIR, R, and B) were used in an attempt to counteract the confusion. The ability of the system to distinguish between certain classes was still insufficient for what was needed. It was therefore decided that an additional band to the 7 bands within the Landsat image was to be created. An NDVI (Normalised Differential Vegetation Index) was created. Table 3.4 displays the spectral ranges for the bands used in the NDVI equation.

$$\text{NDVI} = \frac{NIR - \text{Re}d}{NIR + \text{Re}d} \qquad \text{Equation 3.1}$$

The NDVI image was rescaled using the 'Rescale' function within ERDAS Image. The image was rescaled to an unsigned 8-bit data format. This new image was added to the Landsat TM image to create an additional band. This was done through the process of a 'Layer stack', and this new band easily identified the vegetation of the image. A classification was undertaken using the new NDVI band, Red, and Blue bands.

3.4.2 Challenges with Image Classification: SPOT 5

The SPOT 5 image was acquired during January 2005, and consists of 4 bands and 1 panchromatic band. Bands 1 - 4 (Green, Red, Near Infrared, and Short Wave Infrared) are 10 m resolution and the panchromatic image is 5 m resolution (Pasqaulini *et al.*, 2005). Because of the high resolution of the image, it is possible to discriminate between different patterns and therefore different features on the surface. This made identification of training site easier.

The initial classification was done using bands 1, 3, and 4; the results obtained during the classification were satisfactory. In order to be consistent, an NDVI image was created using Equation 3.1. Table 3.4 displays the spectral ranges for the bands used in the NDVI equation. This NDVI image was rescaled to an unsigned 8-bit data format and added to the original SPOT 5 image. The classification process was repeated using the new NDVI band, Green, and Red bands.

The time period during which the image was recorded was after a period of very little rainfall. This posed a problem with regard to the identification of the water class. Because the level of water bodies was very low, exposing the underlying features, thus confusing the spectral reflectance response for that class.

An example can be seen in Figure 4.2, page 69, where a comparison of the classifications reveals that the water level in the Landsat TM image is higher than that in the SPOT 5 image. It can be seen that a large area of bedrock has been exposed and was thus confused during the classification process with the Urban class.

Table 3.4 : The spectral ranges for the bands used to create the NDVI images

Sensor	NIR Band (nm)	Red Band (nm)
SPOT 5	780 – 890	610 – 680
Landsat TM	760 – 900	630 – 690
MODIS	841 – 876	620 – 670

3.4.3 Challenges with Image Classification: MODIS

The MODIS image used consists of 6 bands, each of different resolutions, thus causing problems during the creation of the signature development phase of the classification. The 6 bands can be seen in Table 3.3, page 50.

The differing resolutions of the image increased the difficulty in creating the signatures for the image. Due to Bands 1 and 2 having the same resolution (250 m), these bands were used to create the signatures. The MODIS NDVI can be created using bands 1 and 2, however the NDVI band was not used in the classification due to the poor performance of the SPOT 5 image when the NDVI band was added.

When one uses Franklin and Wulder's (2002) definition of coarse, medium, and fine resolutions, MODIS can be defined as a coarse resolution image. This creates problems in the creation of signatures for the image in the amount of spectral mixing within the pixel. Large classes such as the plantations and grassland can be detected due to the large spatial area that these classes occupy; the smaller classes such as wetlands and some urban classes make the detection of these spectral signatures very difficult to accomplish.

3.5 ACCURACY ASSESSMENT

Once the classifications were completed, it was necessary to determine the accuracy of the final image. This was done using the 22 GPS points set aside during the data collection. These 22 points are a collection of the various classes used in the classification.

The system compares the classified image with these known points to determine the accuracy of the user and producer classification. With the lower resolution imagery, classes were merged and the number of classes was reduced to create broader classes in an attempt to increase the accuracy of the final classifications.

3.6 NEURAL NETWORKS

Neural networks differ from traditional statistical classifiers in that ancillary data (additional data) can be incorporated into the classification process (Linderman *et al.*, 2004, Qiu and Jensen, 2004). This section will discuss the techniques used for the testing and training of the neural network for this study. An outline of the process can be seen in Figure 3.5, page 59.

3.6.1 Pre-Signature creation

The processing and creation of signature data was different for the classification when using neural networks. This next section will document the steps and procedures used in the classification of an image.

The ancillary data used with the neural network was derived from a Digital Terrain Model (DTM) of the study site. From this DTM, the aspect and percentage slope (hereafter slope) of the study site was mapped. These new images were added to existing images as additional bands. Additional data was created by creating an NDVI image from the initial image, (Equation 3.1). The NDVI was added with the slope, aspect and DTM as additional bands.

Before these new images could be added, it was necessary to standardise the image that would be used and the new bands that would be added. This was done in three steps, namely **reprojecting, resampling** and **normalising**.

3.6.1.1 Reprojecting

In order for the ancillary data and the satellite image to fit exactly when overlaid, it was necessary to ensure that the two images were at the same geographical projection. The projection of the satellite image is according to ArcGIS at the WGS_1984_Zone 36S using the WGS 1984 Datum. The DTM projection is the ArcGIS GCS_WGS_1984. Using ArcGIS, the projection of the ancillary data was matched.

3.7.3.5 Resampling

While reprojecting of the images was occurring, the images were resampled and the pixel areas changed to fit the SPOT image. The original ancillary data had a pixel area of 0.000204 x 0.000204 decimal degrees, which is approximately 22 m x 22 m. The new pixel resolutions were changed to 10 m. 'Resampling' refers to the process by which a pixel grid is altered to fit another pixel grid; these techniques are applied to all the pixels within the image (Clark Labs, 2000). There are three resampling techniques available in the software packages used for the analysis, namely the nearest neighbour, the bilinear interpolation, and cubic convolution techniques. To alter the position of a given pixel, the neighbouring pixels are taken into account. The final altered pixel can be offset from its original position by half a pixel. This technique is computationally very simplistic and avoids changing the original pixel values. The bilinear interpolation technique uses the surrounding pixel values and the inverse distance weighted averages of the closest four pixels to create a new pixel value for the pixel that is to be altered. The final output image tends to be smoother; however, the grey levels of the pixels within the image will be changed, and thus spectral pattern recognition problems can be experienced. The cubic convolution technique uses 16 pixels around the pixel that is to be altered to determine the pixel value for that pixel. The final output for the image tends to be smoother and more defined than the other two techniques, but the original pixel values are altered (Lillesand *et al.*, 2004).

For this study the nearest neighbour resampling technique was used, for two main reasons. The first is that the technique is computationally simplistic and therefore quicker, the second and the most important reason is that the pixel values within the image are not altered and thus allows the neural network to classify the original pixel values for the image.

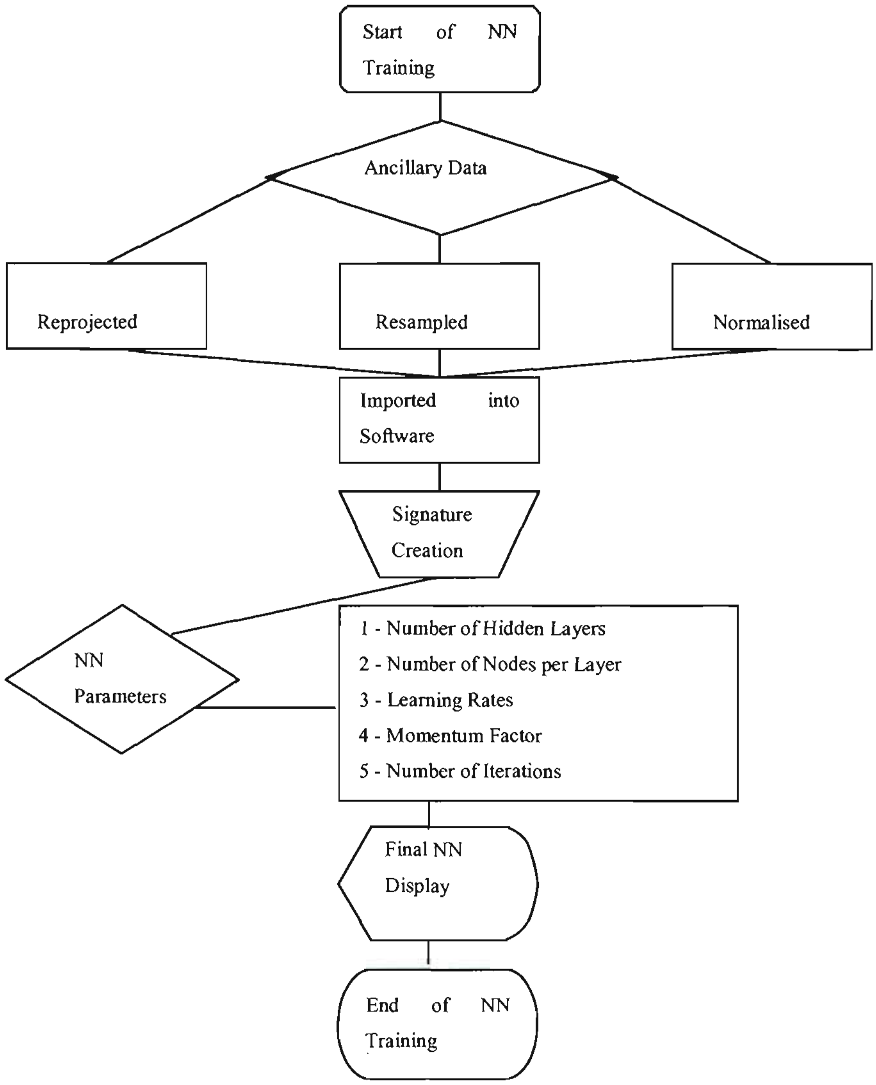

Figure 3.5: An outline of the creation of the neural network.

3.7.3.5 Normalising

For the new bands to be added to the required satellite image, the datasets used must be of the same data type. The satellite data is an unsigned 8-bit image, thus the DTM, aspect, slope, and NDVI image, all of which are continuous data, needed to be converted to the unsigned 8-bit data type. By normalising, or getting the data to within the same range, the speed of convergence to a small error point of the network can thus be increased (Skidmore *et al.,* 1997).

This was accomplished using ERDAS Imagine 8.4. The continuous data were converted to the unsigned 8-bit data type. An 8-bit image contains 256 classes or a numerical range of between 0 and 255 within which the digital numbers of the image can fall.

By standardising the format in which all the data occurs, it was possible to merge the satellite image with the ancillary data together to create an image that contained 8 different bands. This stacked image was used for the creation of signatures within the neural network.

3.6.2 Signature Creation within the Neural Network Software.

The neural network software used for this aspect of the study was IDRISI Andes edition. The creation of signatures within this software is slightly different from the techniques used within ERDAS Imagine 8.4. The principles of creating the signatures to allow the system to discriminate between different spectral classes remains the same, the techniques to create the signature, however, are different.

Using the software, a vector file was created, into which polygons were added. These polygons were created around the defined class vector files that were used during the initial statistical classifications. Each of the classes used within the classification was assigned a code by the user. This code was then used to define a set of polygons, and thus was used in the creation of signatures for the classes. Table 3.5 depicts the classes and codes for the classification within the neural network.

Table 3.5: Tthe user defined codes used for creating the signatures in IDRISI Andes

Signature Code	Class Name
1	Agric
2	Bush
3	Cane
4	Grassland
5	Gum
6	Pine
7	Urban
8	Wattle
9	Wetland
10	Woodland
11	Water

3.7 NEURAL NETWORK DESIGN

The following section will deal with the design of the final neural network to accomplish the creation of an accurate landcover classification which was stated by the objectives.

3.7.1 Structure of the Neural Network in IDRISI Andes

The neural network used within IDRISI Andes, is a Multi-Layered Perception Neural Network that uses a back propagation algorithm (Clark Labs, 2000). The classification has two steps: initially, there is the forward movement of the input data through the nodes within the hidden layers of the network that are connected by weightings. Then secondly there is the backward propagation of the network in order to learn the characteristics of the data (Clark Labs, 2000). The diagram of a neural network can be seen in Chapter two, Figure 2.2, page 29.

An example of the forward movement of a pixel through three layers (i, j, and o) is governed by Equation 3.2 where w_{ij} is the weighting between given nodes i and j, and o_i is the output from node i (Skidmore *et al.,* 1997 and Clark Labs, 2000).

$$net_j = \sum_{i-1}^{m} w_{ij} o_i \qquad \text{Equation 3.2}$$

From Equation 3.2 the output for a given node j can be calculated using Equation 3.3.

$$o_j = f(net_j) \qquad \text{Equation 3.3}$$

Using Equation 3.2 a sigmoidal function f is applied to the sum of the weighted inputs before passing to the next layer. After the forward passes are completed, the expected values for the pixels and thus classes are compared to the actual values. Using this study as an example, there are 11 classes, thus there are 11 output nodes, and the output for class 1 would be 1,0,0,0,0,0,0,0,0,0,0. The output for class 2 would be 0,1,0,0,0,0,0,0,0,0,0; and thus this pattern will continue (Skidmore *et al.,* 1997, Clark Labs, 2000). The network generates a pattern for each of the classes. If the final pattern does not correspond to the input, there is an error in the network. This error is corrected through back propagation through the network and changing of the weightings between the nodes using the delta rule, Equation 3.4, where η is the learning rate and α is the momentum rate with δ as the computed error (Clark Labs, 2000).

$$\Delta w_{ij(t=1)} = \eta \delta_{ij} o_i + \alpha \Delta w_{ij(t)} \qquad \text{Equation 3.4}$$

3.7.2 Basic Options with the MLP

Before any methods can be described within this section of the study, it is best to understand what options are available for the design of a neural network.

1) Band Selection: the number of bands are chosen and selected. This stage of the network design allows for the selection of the number of inputs for the network. The ancillary data are thus added during this stage of the design.

2) Signature Selection: the initial signature files created by the user are inserted into the network.

3) Pixels for testing and training input: this is a user defined selection of how many pixels can be set aside for the testing and training of the neural network. The pixels used are a subset of the number of pixels used in the user created signature file (Clark Labs, 2000). In the present study, the number of pixels used for all of the neural networks created was 40 pixels.

4) Learning Rate Decision: the learning rate is seen to be the most important factor in the design of a neural network. This governs how big and how frequently are the adjustments made, and governs the weighting between nodes within the neural network (Carling, 1992). If the rate is set too small, the network can become overwhelmed and therefore slow; if the rate set too high, the adjustments can become too frequent and too large and thus can create large fluctuations in the accuracy of the network (Skidmore *et al.,* 1997). As has been recommended within the software, the best learning rates are between 0.01 and 0.2 (Clark Labs, 2000).

5) Momentum Factor Decision: is aimed at removing the changes to the RMSE of the surface classification during the training of the network (Clark Labs, 2000).

6) Hidden Layer Selection: allows for a user to define how many hidden layers the neural network can have.

7) Nodes per layer: allows for the user to define how many nodes each layer within the neural network may have.

8) Number of Iterations: allows the user to define how many times the neural network will run until complete. This is one of the 'stopping factors' for the neural network. A 'stopping factor' is the condition under which the network will stop; other factors include accuracy and RMSE, both of which may be defined by the user.

3.7.3 Testing the neural network

In order to ensure the highest accuracy and efficiency for the neural network, it was decided that the parameters would be altered one at a time in order for the establishment of an effective neural network. The next section will describe how each run was conducted. For each of the runs (see Table 3.6, page 64), the testing accuracy and testing Root Mean Square Error (RMSE) was recorded and plotted on a Cartesian plane to allow for graphical interpretation of the changes being made.

An assumption for the design of the neural network was that each increase of the accuracy of classification was a result of the previous changes and thus could be carried forward for the next run and so set of changes.

3.7.3.1 Runs 1 and 2: Testing of Hidden Layers and Nodes per Layer

For Runs 1 and 2, the changes made were very similar. Run 1: the numbers of nodes per layer were changed at a set interval. Run 2: the number of hidden layers was changed to 2, as well as the numbers of nodes per hidden layer. For Run 2, the number of layers was kept constant for each of the hidden layers. Thus, the intervals of change followed numerically from 1 until 10, after which the increments of change were 5 until 50 nodes per layer were reached. So the sequence of change was therefore 1, 2, 3...10, 15, 20...50.

3.7.3.2 Run 3: Testing the Learning Rate

With Run 3, the assumption used for the design of the neural network was used and the best result from Run 2 was used to continue the design. The learning rate of the neural network was to be altered for this run. The number of increment changes per test was 0.001 units. Within the IDRISI Andes training manual, the Learning Rate was identified as being the most important factor for the training of the neural network and therefore, this run was more detailed than the previous runs (Clark Labs, 2000). In total, 31 networks were created to allow for the best accuracy to be calculated.

3.7.3.3 Run 4: Testing the Momentum Factor

Run 4 required the changes within the momentum factors. The rate of increment change was 0.1.

3.7.3.4 Run 5: Testing the Number of Iterations

In run 5, the number of iterations per test was changed. This was an attempt to discover whether or not the process of testing could be more efficiently completed and to discover if a higher accuracy could be attained by letting the processes continue for longer. The increments of change for this run were 1000 until 10 000 iterations were reached. After 10 000 iterations, the amount of increase was changed to 5000, until 50 000 iterations were completed.

3.7.3.5 Run 6: Testing of the Ancillary Data

As stated within the objectives, it is necessary to decide which of the ancillary data incorporated within the image is more important for the accuracy of the classification. Thus, after the highest accuracy had been calculated, the design for the neural network was tested by removing certain bands from the image per test.

Table 3.6 The changes made per run

	Hidden Layers	Nodes Per Layer	Learning Rate	Momentum Factor	Iterations	Number of Bands
Run 1	1	a	0.001	0.5	10 000	8
Run 2	2	a	0.001	0.5	10 000	8
Run 3	2	20	b	0.5	10 000	8
Run 4	2	20	0.16	c	10 000	8
Run 5	2	20	0.16		d	8
Run 6	2	20	0.16			e

a – 18 changes made: 1, 2, 3… 9, 10, 15, 20…50

b – 31 changes made: 0.001, 0.002, 0.003…0.31

c – 10 changes made: 0.1, 0.2, 0.3…1

d – 18 changes made: 1000, 2000, 3000, …10 000, 15 000, 20 000…50 000

e – certain bands removed for each test

3.7.3.6 Run 7: Final Classification

Using the best results from the runs 1 to 6, the parameters for the neural network were set and the network was run. The final output can be found in Chapter 4. It will display the results obtained during the study.

Chapter 4. RESULTS

This chapter will present the results that were acquired during this study. The structure of this chapter will follow the objective outlined in Chapter 1. The effect of scale on the accuracy of the maximum likelihood classification algorithms was studied, as well as the effect that the number of classes available for classification had on the classification accuracy. Different sensors were used to establish which classes were best identified at different spatial resolutions. Finally, a neural network was designed to increase the total accuracy of the land-cover classification including increasing the differentiation between some of the classes.

4.1 MAXIMUM LIKELIHOOD AND RESOLUTION CHANGES

In order to test the role that the spatial resolution of an image plays in the accuracy of a landcover classification, the maximum likelihood classifier was used. Chapter 3 outlined the steps taken to test the effect that spatial resolution has on the accuracy of a classification algorithm. This section will present the results obtained during the process of the testing of spatial scale. The first error matrix shown is used as an example; the rest of the error matrices may be viewed in Appendix I. Table 4.2 displays all of the accuracies and the Kappa Statistics for this section. Figure 4.1 depicts a broad overview of the classification of the SPOT 5 image. Figure 4.2 focuses on a specific area of the landcover classification to display the classification in more detail.

4.1.1 SPOT 5

The first image tested was that of the SPOT 5 sensor with a resolution of 10 m. A total of 11 classes was used and signatures were created. Table 4.1 shows the error matrix for the final classification.

Table 4.1: Accuracy assessment of the SPOT 5 sensor, classified using the Maximum Likelihood algorithm

Classified Data	Agric	Bush	Cane	Grass	Gum	Pine	Urban	Wattle	Woodland	Water	Wetland	Row Total	User Accuracy
Agric	0	0	0	0	0	0	0	0	0	0	0	0	0
Bush	0	2	0	0	0	0	0	0	0	0	0	2	100
Cane	1	0	1	0	0	0	0	0	0	0	0	2	50
Grass	0	0	0	1	0	0	0	0	1	1	0	3	33.33
Gum	0	1	0	0	2	0	0	0	0	0	0	3	66.67
Pine	0	0	0	0	0	1	0	0	0	0	0	1	100
Urban	1	0	0	0	0	0	1	0	0	0	0	2	50
Wattle	0	0	0	0	0	0	0	1	0	0	0	1	100
Woodland	0	1	0	0	0	1	0	0	0	0	0	2	0
Water	0	0	0	0	0	0	0	0	0	4	0	4	100
Wetland	0	0	0	1	0	0	0	0	0	0	1	2	50
Column Total	2	4	1	2	2	2	1	1	1	5	1	22	
Producer's Accuracy	0	50	100	50	100.	50	100	100	0	80	100		

Overall Classification Accuracy = 63.64%

Overall Kappa Statistics = 0.5935

Table 4.1 shows the error matrix for the SPOT sensor with 11 classes. The final accuracy for the image is 63.64%, with a Kappa Statistic of 0.5926. Of all the sensors used during this test, 63.64% was the highest accuracy obtained. In order to attempt to improve the accuracy above, the NDVI band was included to replace the NIR band. The accuracy for this classification was reduced to 54.55%, with a Kappa statistic of 0.4787.

4.1.2 Landsat TM

The error matrix for the Landsat TM image, with a resolution of 30 m, can be seen in Appendix I. The overall accuracy for the Landsat TM test with 11 classes and using the maximum likelihood classifier was 36.36%, and a Kappa Statistic of 0.2837 was obtained. By including the calculated NDVI band in the image, the accuracy was increased by 18.19% to 54.55%, with a Kappa Statistic of 0.4931.

4.1.3 MODIS

The error matrix for the MODIS image, with a resolution of 250 m, can be seen in Appendix I. The overall accuracy for the MODIS test with 11 classes and using the maximum likelihood classifier was 31.82%, with a Kappa Statistic of 0.23058. This was the worst classification accuracy and could be explained by the increased spectral mixing within the pixels of the image.

Table 4.2: Accuracies and Kappa Statistics of the varying sensors using the maximum likelihood classifier

Sensor	Accuracy	Kappa Statistic
SPOT 5 (10 m)	63.64%	0.5926
SPOT 5 with NDVI (10 m)	54.55%	0.4787
Landsat TM (30 m)	36.36%	0.2837
Landsat TM with NDVI (30 m)	54.55%	0.4931
MODIS with NDVI (250 m)	31.82%	0.2308

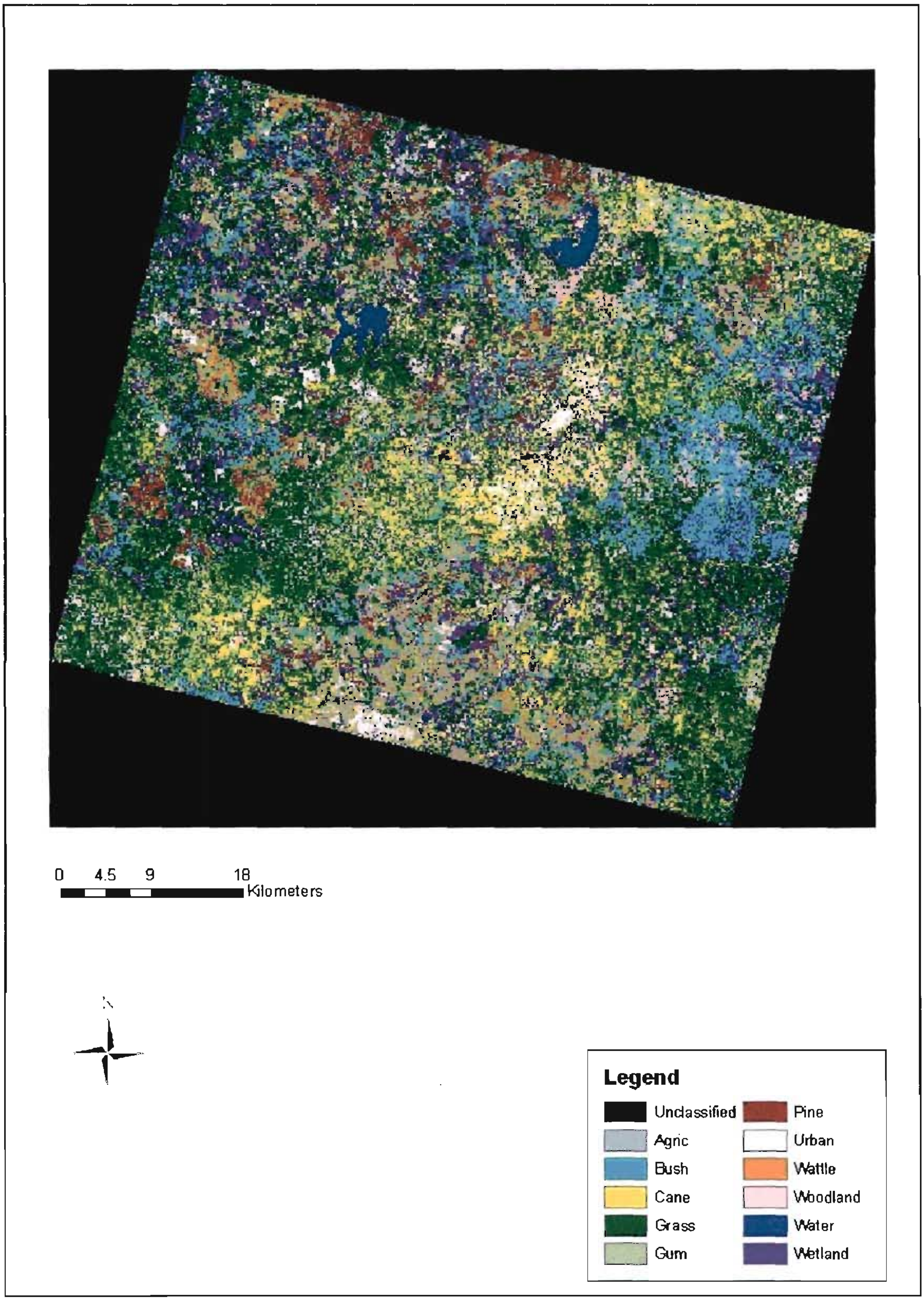

Figure 4.1: The overall classification for the SPOT 5 image, using the maximum likelihood classification algorithm and 11 classes.

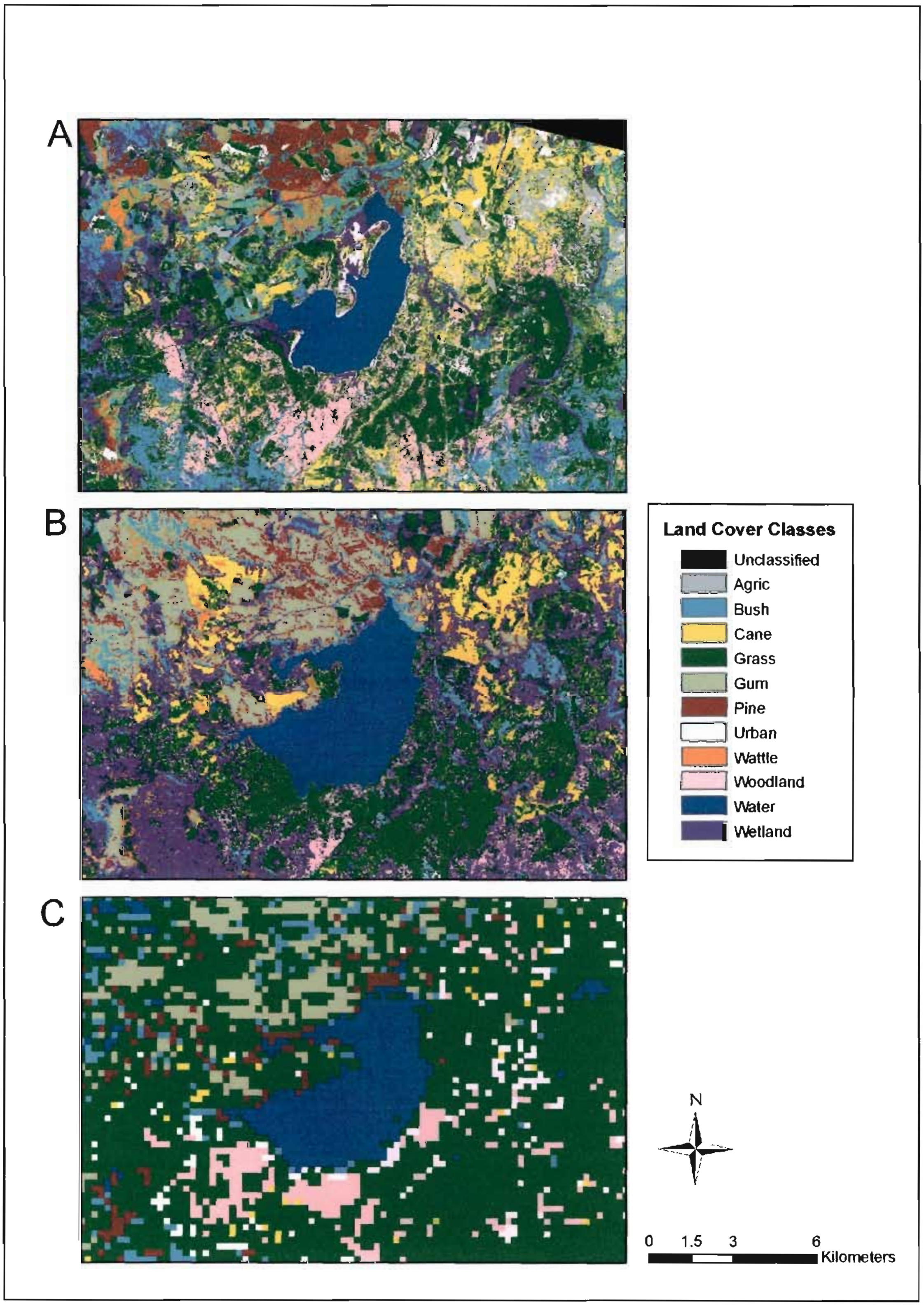

Figure 4.2: Albert Falls dam classified with the maximum likelihood classifier at 3 resolutions with 8 classes, A is SPOT 5, B is Landsat TM, C is MODIS.

Figure 4.1 shows the overall classification of the SPOT image using the maximum likelihood classification algorithm. The classification accuracy for this image was 63.64%. Some of the inaccuracies can be seen around the edge of the Albert Falls dam in Figure 4.2. Which shows more detail of the Albert Falls dam classified using the maximum likelihood classifier. This figure is taken from the overall classifications of the various images used. Figure 4.2 A is the SPOT image and was classified with 63.64% accuracy. Figure 4.2 B is the Landsat TM image with the NDVI band and was classified with 54.55% accuracy. Figure 4.2 C is the MODIS image and was classified with 36.36% accuracy.

4.2 THE EFFECT OF THE NUMBER OF CLASSES ON CLASSIFICATION ACCURACY

Chapter 3 outlined the methods used for testing the effect that changing the number of classes within the classification would have on the final classified accuracy for each of the images used. For each test, the number of classes was reduced to 8 classes and the maximum likelihood algorithm was used. The classes to be merged were chosen according to the similarities of those classes. The Pine, Gum and Wattle classes were merged to form the Plantation class. The Grass and Wetland classes were merged to create the Grassland class. Although containing different diversities of plant species, it was decided that the Wetland and Grassland classes were similar enough for merging. Figure 4.3 shows the spectral profiles for the wetland and grassland classes. As can be seen, the profiles are similar and thus allowed for the merging of these two classes. Table 4.3 is presented as an example of the error matrices used. Table 4.4, page 75, shows the results for all of the sensors. Table 4.5 shows the results of the effect that merging has on each of the specific classes used within the SPOT 5 image.

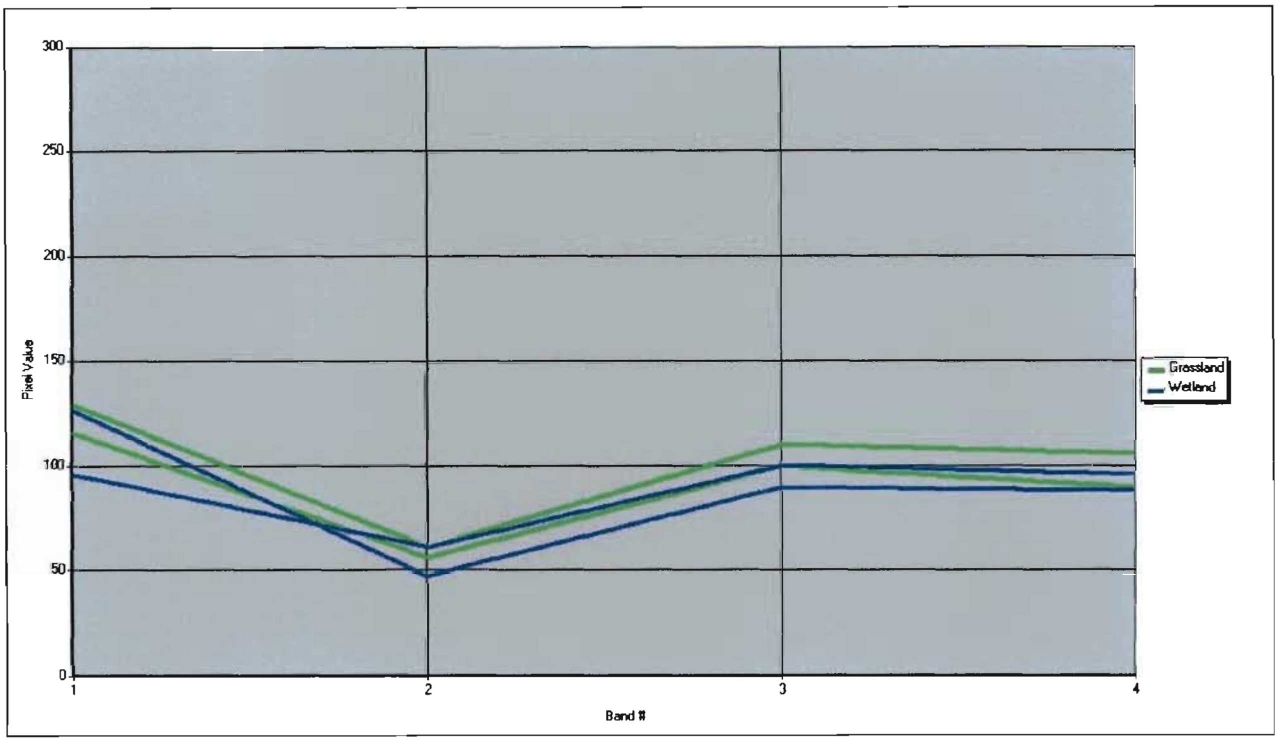

Figure 4.3: Shows the spectral profiles for pixels in the Grassland and Wetland classes

4.2.1 SPOT 5

Initially, the maximum likelihood classification was used on the SPOT 5 image with 11 classes; the number of classes was reduced to 8. The classification with 11 classes produced an accuracy of 63.64%, and a Kappa Statistic of 0.5926. This was the highest accuracy across all the sensors at the 11 class level. The maximum likelihood produced an accuracy of 72.73%, with a Kappa Statistic of 0.6765. Table 4.3, page 74, shows the error matrix for the maximum likelihood classification with 8 classes. In order to attempt to improve upon the accuracy of the broader classes, an NDVI band was added to replace the NIR band. The accuracy obtained from removing the NIR band decreased to 54.55%, with a Kappa statistic of 0.4608, showing that the NIR band is important for the classification.

It can be seen that with 11 classes there was confusion between the Wetland and Grassland classes, the user's accuracy for the Grassland class was 25% and the Wetland class was 50%. Some of the pixels in the Wetland class were incorrectly classified as Grassland. Table 4.5 dis[;ays the results of reducing the number of classes and merging the Grassland and Wetland classes. By reducing the number of classes to 8, and merging the Grassland and Wetland classes, the user's accuracy for the new Grassland class increased to 42.86%.

4.2.2 Landsat TM

The maximum likelihood algorithm was applied to the Landsat TM images, initially with 11 classes and with no NDVI band added, then with the NDVI band used. The Landsat image with no NDVI band at 11 classes produced an accuracy of 36.36%, with a Kappa Statistic of 0.2837. On adding the NDVI band, the accuracy increased to 54.55% and the Kappa Statistic to 0.4931. Using 11 classes the Wetland class was unable to be correctly classified and the Grassland class was classified with a User's accuracy of 33.33%.

On decreasing the number of classes, the accuracies of the maximum likelihood classification increased in the NDVI free and NDVI images. In the NDVI free image, accuracy increased from 36.36% to 59.09%. The NDVI image accuracy increased from 54.55% to 63.64%. By merging the Wetland and Grassland classes the accuracy of the classification of the new grassland class decreased to 30% from 33%. Confusion was created between the new Grassland class and the Woodland and Bush classes.

4.2.3 MODIS

The accuracy of the classifiers for the MODIS image was generally very low. For the fine (11) classes, an accuracy of 31.82% was produced. The Kappa Statistics for the classifier at the fine classes remained steady, with the classifiers producing statistics of a low 0.2. Looking at individual classes, the Grassland class was classified with a user's accuracy of 11.26% and the Wetland class was classified with a user's accuracy of 0%. When the number of classes was decreased to 8, the accuracy increased. The maximum likelihood classifier produced an accuracy of 45.44%. Merging the Wetland and the Grassland classes to create a new Grass class, the user's accuracy increased to 28.57%.

Table 4.3: Error matrix for the SPOT 5 image, with 8 classes and the maximum likelihood classification algorithm applied during the classification process

Classified Data	Agric	Bush	Cane	Plantation	Urban	Grass	Woodland	Water	Row Total	
Agric	0	0	0	0	0	0	0	0	0	0
Bush	0	3	0	0	0	0	0	0	3	100.00%
Cane	0	0	1	0	0	0	0	0	1	100.00%
Plantation	0	1	0	4	0	0	0	0	5	80.00%
Urban	0	0	0	0	1	0	0	0	1	100.00%
Grass	2	0	0	0	0	3	1	1	7	42.86%
Woodland	0	0	0	0	0	0	0	0	0	0.00%
Water	0	0	0	0	0	0	0	4	4	100.00%
Column Total	2	4	1	4	1	3	1	5	21	
Producer Accuracy	0	75.00%	100.00%	100.00%	100.00%	100.00%	0.00%	80.00%		

Overall Classification Accuracy = 72.73%

Overall Kappa Statistics = 0.6765

Table 4.4: The total accuracies and Kappa Statistics for different numbers of classes and classification algorithms

Sensor		**Fine**		**Broad**	
SPOT 5	Classifier	Accuracy	Kappa	Accuracy	Kappa
No NDVI	Max	63.64	0.5926	72.73	0.6765
NDVI	Max	54.55	0.4787	54.55	0.4608
Landsat TM					
No NDVI	Max	36.36	0.2837	59.09	0.5075
NDVI	Max	54.55	0.4931	63.64	0.5676
MODIS					
	Max	31.82	0.2308	45.44	0.3383

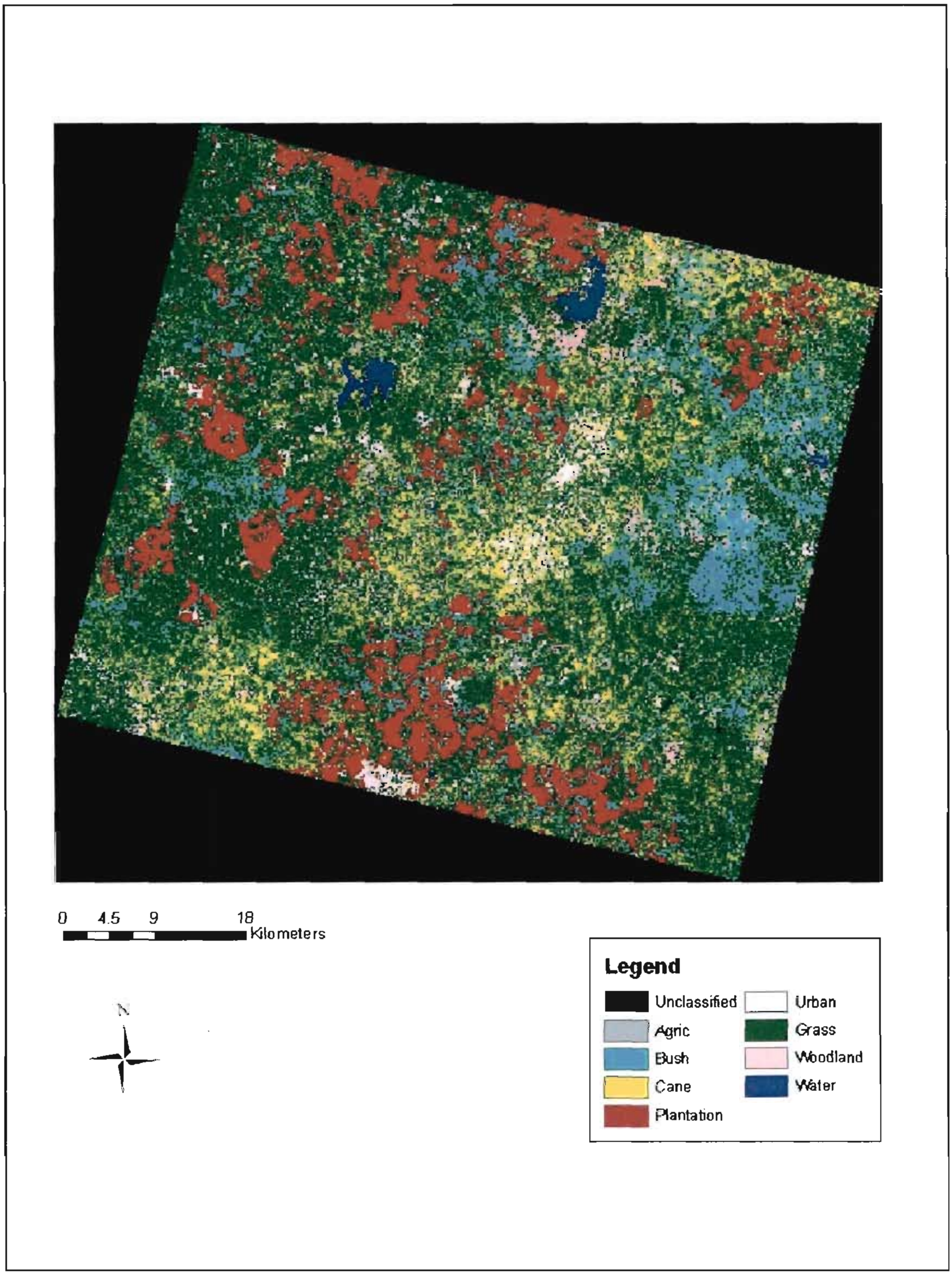

Figure 4.4: The classification of the SPOT 5 image, using the maximum likelihood classification algorithm and 8 classes.

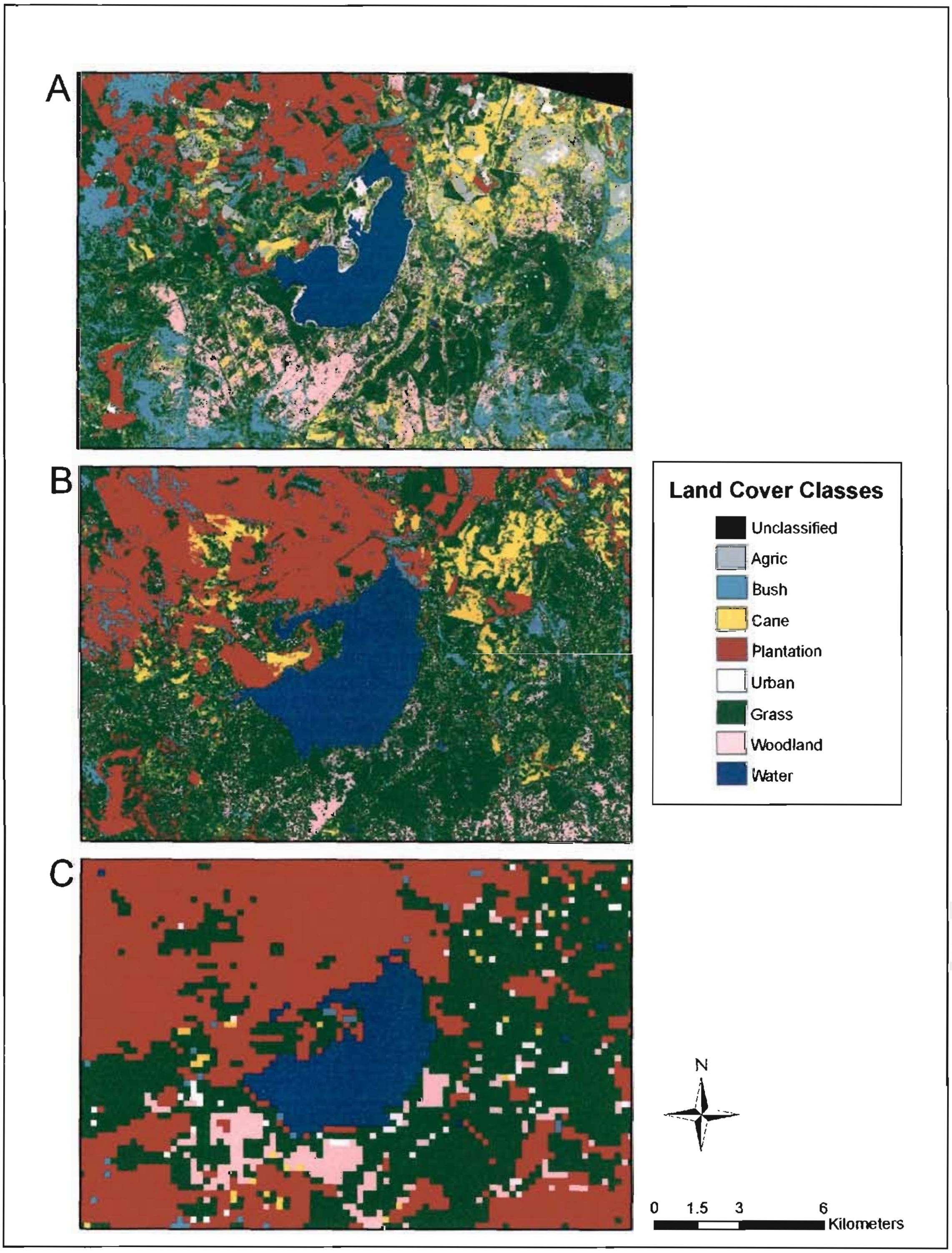

Figure 4.5: Albert Falls dam classified with the maximum likelihood classifier at 3 resolutions with 8 classes. A is SPOT 5, B is Landsat TM, C is MODIS

Figure 4.4 shows an overview of the classification of the SPOT 5 image after the number of classes was reduced to 8. It is now easier to define the plantation stands around the Albert Falls dam. Figure 4.5 shows these results in more detail. Figure 4.5 A shows the SPOT 5 image classified with 8 classes and an accuracy of 72.73%. Figure 4.5 B shows the Landsat image classified with an accuracy of 63.64%, and Figure 4.5 C shows the MODIS image classified with an accuracy of 50%.

Table 4.5: Accuracies of the classes before and after merging

Class	**Before Merge**		**After Merge**
Pine	100.00%	Plantation	80.00%
Gum	67.67%		
Wattle	100.00%		
Grassland	33.33%	Grass	42.86%
Wetland	50.00%		

4.3 Testing the performance of Neural Networks compared with other classification algorithms

As stated in Chapter three, a neural network was designed by testing different parameters and the effect that these changes would have on the final classification accuracy. This section will cover the results obtained through each of the different runs of the neural network to obtain the final product. The final neural network was designed to have both a high accuracy and efficiency and then compared to the other classifiers used on the three images.

As can be seen from the results above, the image that produced the most consistent accuracies is the SPOT 5 image. It was therefore selected to test the effectiveness of the neural network algorithm compared with the other classification algorithms.

4.3.1 Run 1 - Number of Hidden Layers and Nodes per Layer vs. Classification Accuracy

Run 1 tested the effect of one hidden layer being used at 10 000 iterations. Each time the learning rate for the neural network was kept constant at 0.01 and the momentum factor was a constant 0.5. The number of nodes per layer was changed for each test. Table 4.6 and Figure 4.6 present the accuracies and RMSE for each test.

Table 4.6: Number of Nodes per Layer vs. the accuracies and RMSEs of the neural network after testing during Run 1

Hidden Layer(s)	**1**	
Learning Rate	**0.01**	
Momentum Factor	**0.5**	
Iterations	**10 000**	
Number of Nodes	**Accuracy**	**RMSE**
1	**7.7**	**0.002629**
2	**32.45**	**0.00229**
3	**49.24**	**0.001868**
4	**59.09**	**0.001521**
5	**88.26**	**0.001388**
6	**63.76**	**0.001165**
7	**64.14**	**0.001095**
8	**66.92**	**0.000997**
9	**66.29**	**0.000921**
10	**66.67**	**0.000913**
15	**66.29**	**0.000939**
20	**66.54**	**0.000905**
25	**43.56**	**0.001796**
30	**43.81**	**0.001822**
35	**26.14**	**0.002238**
40	**12.21**	**0.002406**
45	**7.7**	**0.002743**
50	**16.79**	**0.002415**

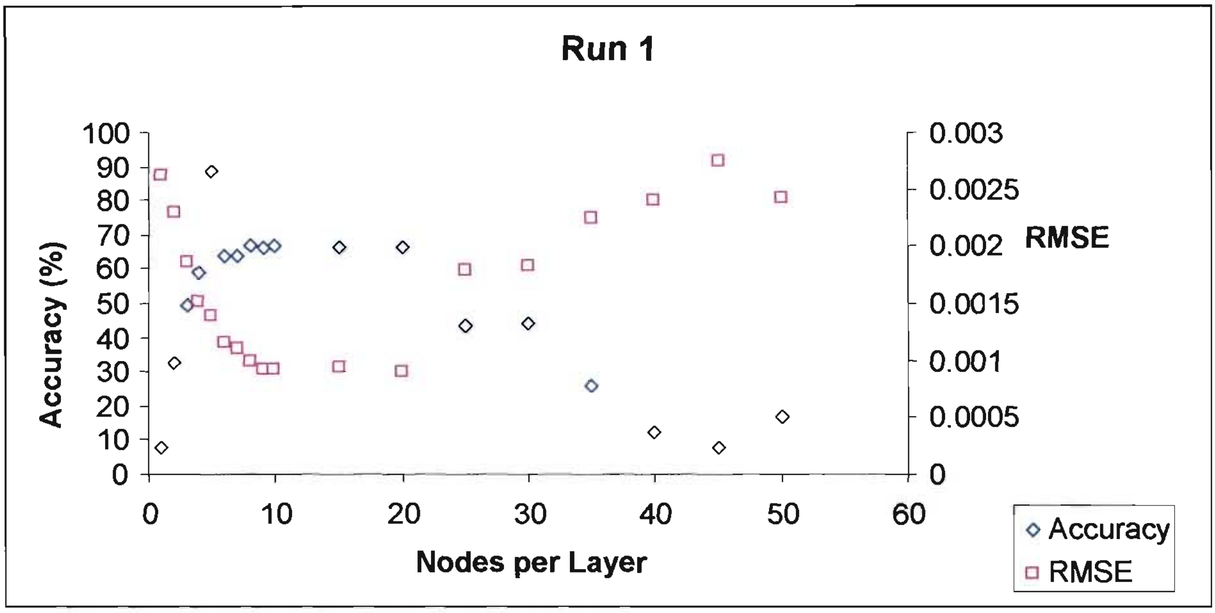

Figure 4.6: The changes in accuracies and RMSEs as the number of nodes changes.

As can be seen, the accuracies for this initial run are higher than the accuracies for the traditional algorithms. It can be seen, however, that the accuracy reaches a critical point from which the accuracies decrease, thus more testing was done.

4.3.2 Run 2 - Number of Hidden Layers and Nodes per Layer vs. Classification Accuracy

Run 2 is very similar to Run 1 in that the change to the testing parameters was a change in the number of nodes per layer; the only change is the change in the number of hidden layers. For this run, the number of hidden layers was increased to 2. Figure 4.7 presents the accuracies and RMSEs for the testing done in this run.

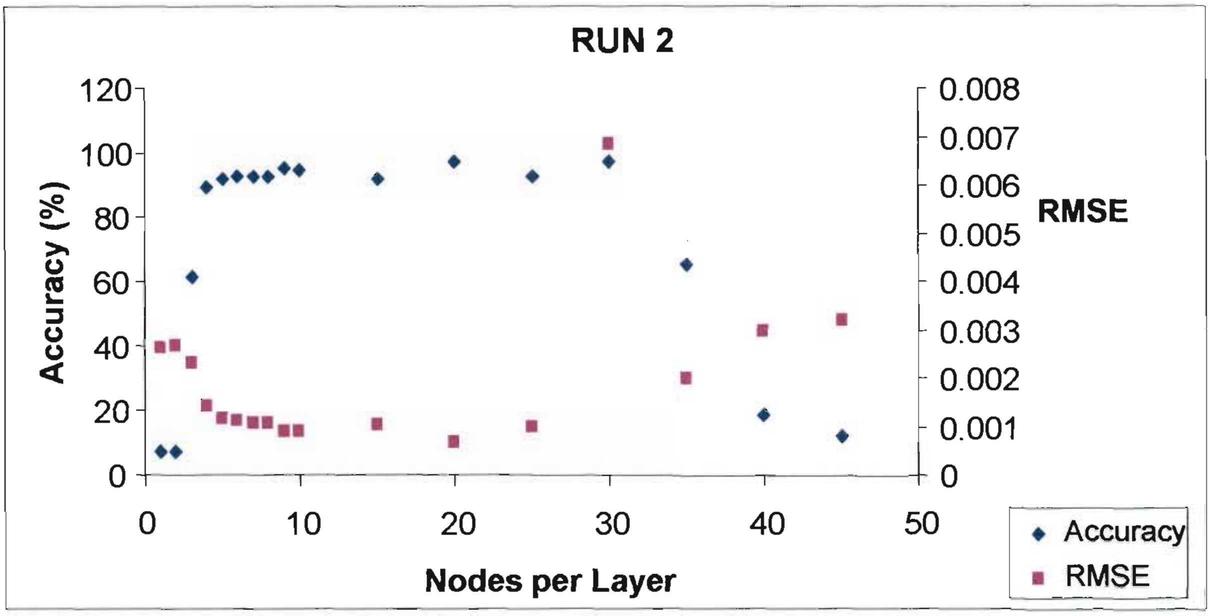

Figure 4.7: The changes in accuracies as the number of nodes per layer is increased.

From Figure 4.7 it can be seen that the highest accuracy is 97.22% at 20 and 30 nodes per layer. At 6 nodes per layer, it can be seen from Figure 4.7 that the accuracy is 92.93% with an RMSE of 0.00109. As has been stated, the objective for the design of this neural network is to create a classification that is both accurate and efficient. It was decided that 6 nodes would be used for the rest of the testing of the neural network for two reasons. Firstly the lower the number of nodes, the more concise the network, and therefore the more efficiently the network will run. Secondly the structure of the network reveals that, there are 8 input nodes and 40 training pixels. By having too many nodes in the hidden layers of the values from the input nodes, are split into many smaller values. This makes the network become less efficient. By choosing 6 nodes per layer as opposed to 20 nodes, the input values are more evenly split up.

4.3.3 Run 3 - Testing for the Learning Rates

Run 3 is identified within the literature (Clarke Labs, 2000), as being the most important factor in creating an accurate classification using neural networks. Therefore more emphasis was placed upon this test, than on the rest of the testing. Using the information from Run 2, the number of nodes was set at 2 and only the learning rate was altered. Figure 4.8 presents the results obtained through the testing.

The learning rate is the rate at which the neural network will change the weightings of the data within the network. The smaller the learning rate, the fewer the changes, and conversely, the greater the learning rate the greater the number of changes within the network. Figure 4.8 shows this: as the learning rate passes 0.2, fluctuations of the RMSE and the accuracy, increase and become erratic. The best rate was seen to be 0.16, which yielded an accuracy of 97.85%, and an RMSE of 0.00623. Literature states (Clarke Labs, 2006) that the best results are obtained between 0.1 and 0.2. This result substantiates what can be seen in Figure 4.8, where once the learning rate exceeds 0.2, the accuracy and RMSE become very erratic.

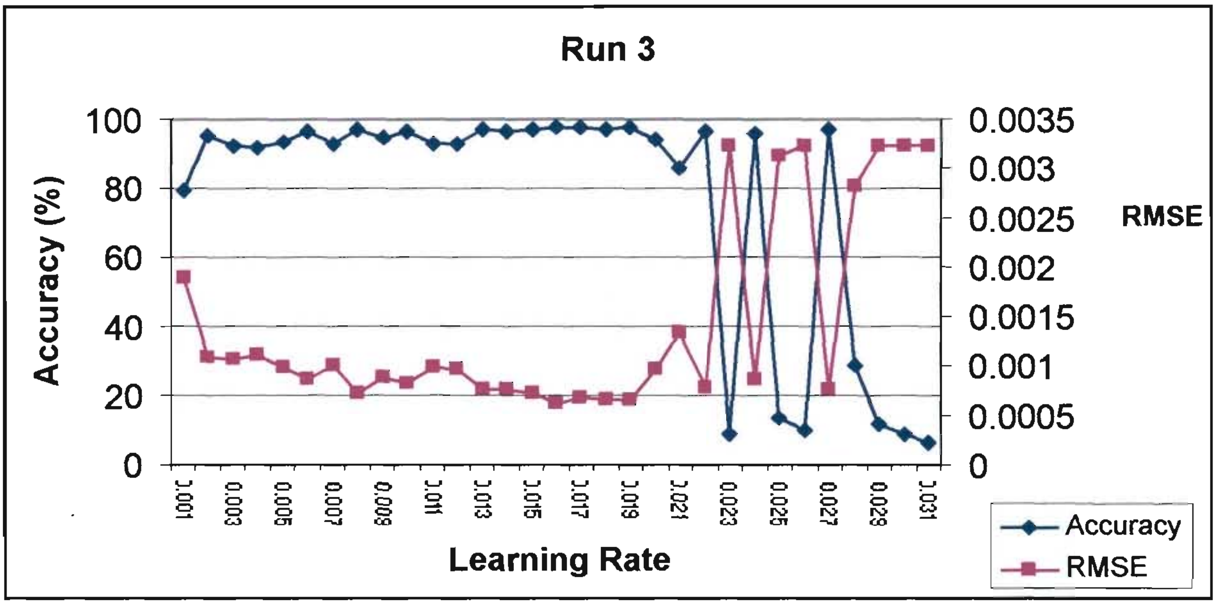

Figure 4.8: The changes in accuracies as the Learning Rate is changed.

4.3.4 Run 4 - Testing the Momentum

The momentum factor is aimed at reducing the RMSE at the surface of the classification and so for Run 4 the momentum factor was changed per test to attempt to attain the highest accuracy and the lowest RMSE. Figure 4.9 presents the results obtained from the tests.

The momentum factor cannot reach 1, hence, when 1 was entered into the neural network, a null error was encountered and so could not be used. The highest accuracy and lowest RMSE can be seen with a momentum factor of 0.3 and so would be used for the rest of the tests.

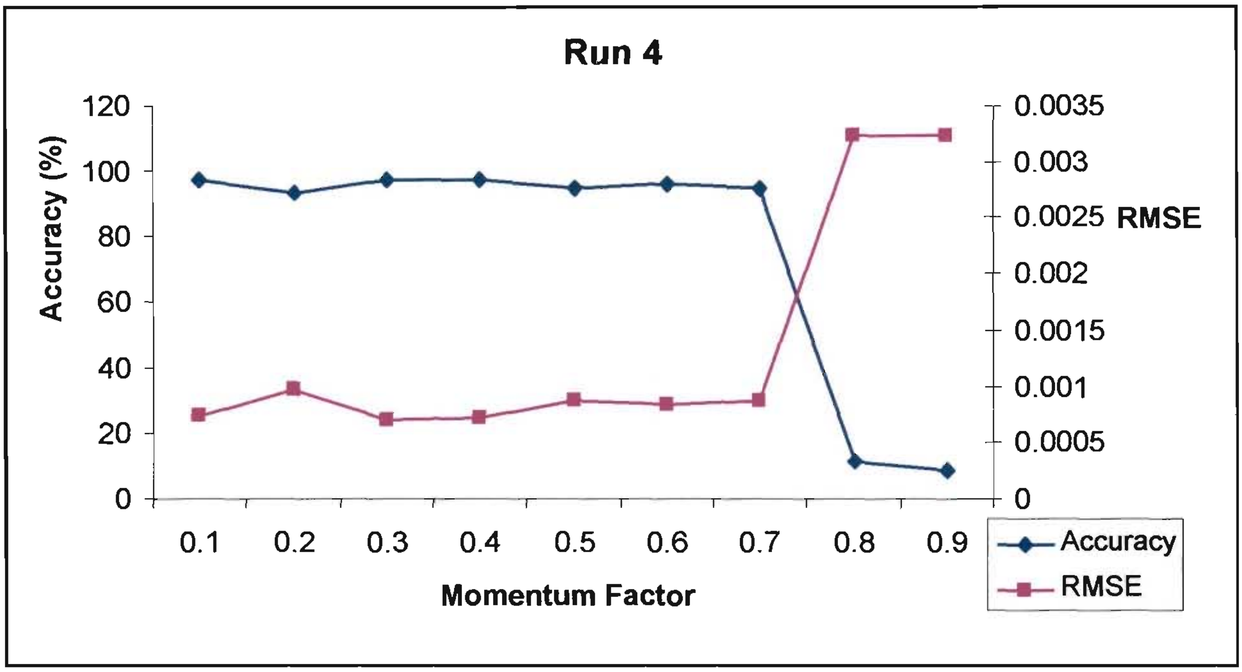

Figure 4.9: The changes in accuracies and RMSEs of the neural network as the momentum factor increases.

4.3.5 Run 5 - Testing the Number of Iterations

This run was aimed at increasing the final efficiency of the neural network. The number of iterations would be altered in an attempt to streamline the classification. By changing the number of times the neural network runs through the processes of classification, it is possible to identify the critical point at which the accuracy is highest and beyond which the neural network becomes redundant in the classifying process. Figure 4.10 shows the accuracies and RMSEs of the neural network as the number of iterations is changed.

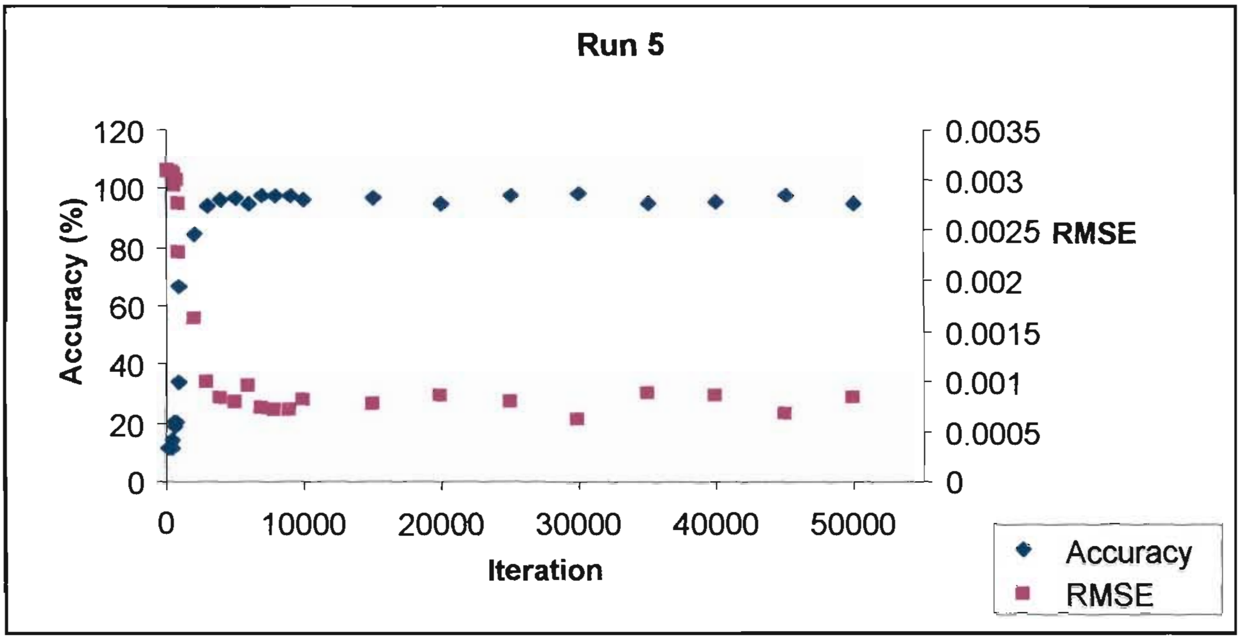

Figure 4.10: The changes in accuracies and RMSEs of the neural network as the number of iterations increases.

The total number of iterations can play a large role in the accuracy of the neural network. However, at a critical point, the accuracy of the classification does not change by any large degree. For this design of the neural network, 9000 iterations allowed for an accuracy of 97.73%, and a RMSE of 0.00706. Hence, the number of iterations to be used in the final classification would be 9000.

4.3.6 Run 6: Testing the number and type of input layers

Run 6 was the final run and for this test, the number of bands and so the number of ancillary layers would be changed in an attempt to allow the neural network to run efficiently. This would be done so that the neural network would not have to use too many input layers and thus would not require as much processing time. Once the network is running, if the accuracy drops after removing a band, then that band is important for the accuracy of the classification. Table 4.7 and Figure 4.11 depict the accuracies and RMSEs for each of the tests.

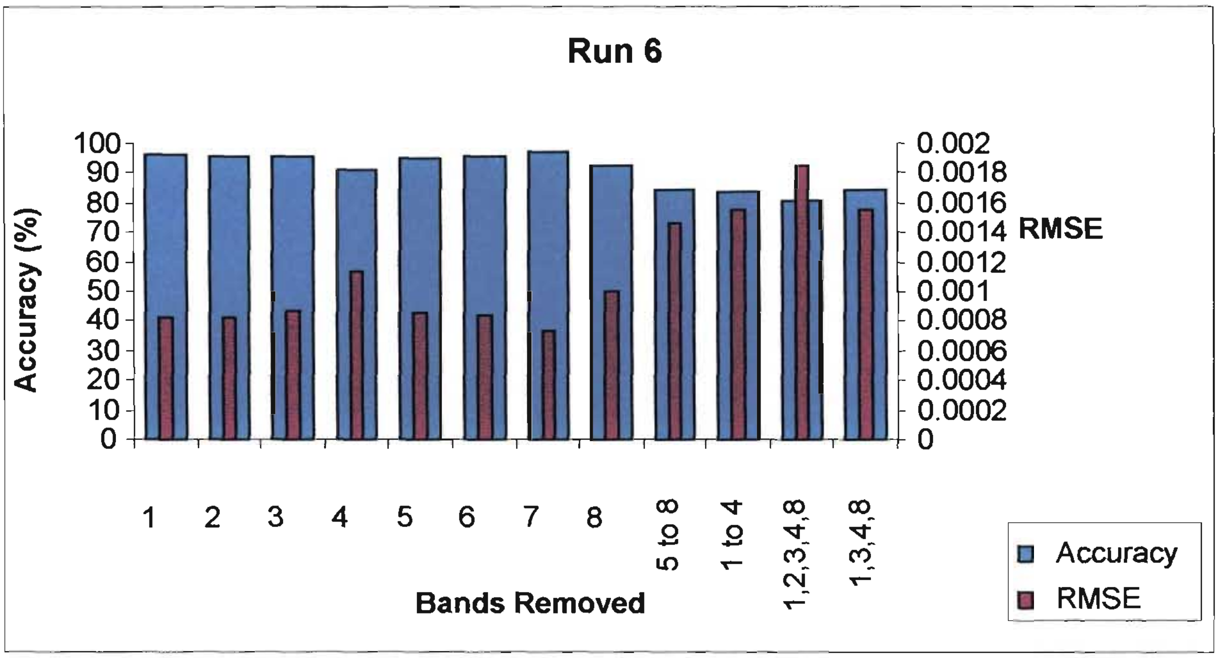

Figure 4.11: The changes in accuracies and RMSEs of the neural network when certain bands are removed.

As can be seen the accuracies of the classifications with set bands missing are roughly the same. There are some minor differences, and these will be discussed in Chapter Five. It must be noted that the accuracy of the SPOT 5 image using the maximum likelihood algorithm with 11 classes was 63.64%. With the use of the neural network using the same bands (from Figure 4.11, bands 5,6,7) the accuracy was 80.81%. It can therefore already be seen that the neural network has outperformed the traditional algorithm.

4.3.7 Final Output

Using the tests devised from Runs 1 to 6, and the assumption described in Chapter 3, it was possible to create the final classification for the SPOT 5 image. The calculated parameters are shown in Table 4.8.

Table 4.8: The final settings for the neural network design

Bands Used:	8
Training Pixels:	40
Testing Pixels:	40
Hidden Layers:	2
Nodes per Layer:	6
Learning rate:	0.016
Momentum Factor:	0.3
Iterations:	9 000
Overall Accuracy:	95.230%
Overall RMSE:	0.000546

Figure 4.12 displays the process of testing and training of the neural network for this study. The final accuracy obtained was 95.22%, with an RMSE of 0.001226. The figure shows the number of input layers, the number of output nodes, hidden layers, learning rates, and momentum factors. The figure shows that the network became unstable between points A and B, but the curve flattens out after B, meaning that the neural network has completed its runs. After this point the neural network may start to overtrain and thus become redundant.

As can be seen, the final product has a very high accuracy. This is in turn substantiated by the final Kappa Statistic that has been calculated at 0.9544: the high Kappa Statistic shows that the classes have a high probability of being correctly classified.

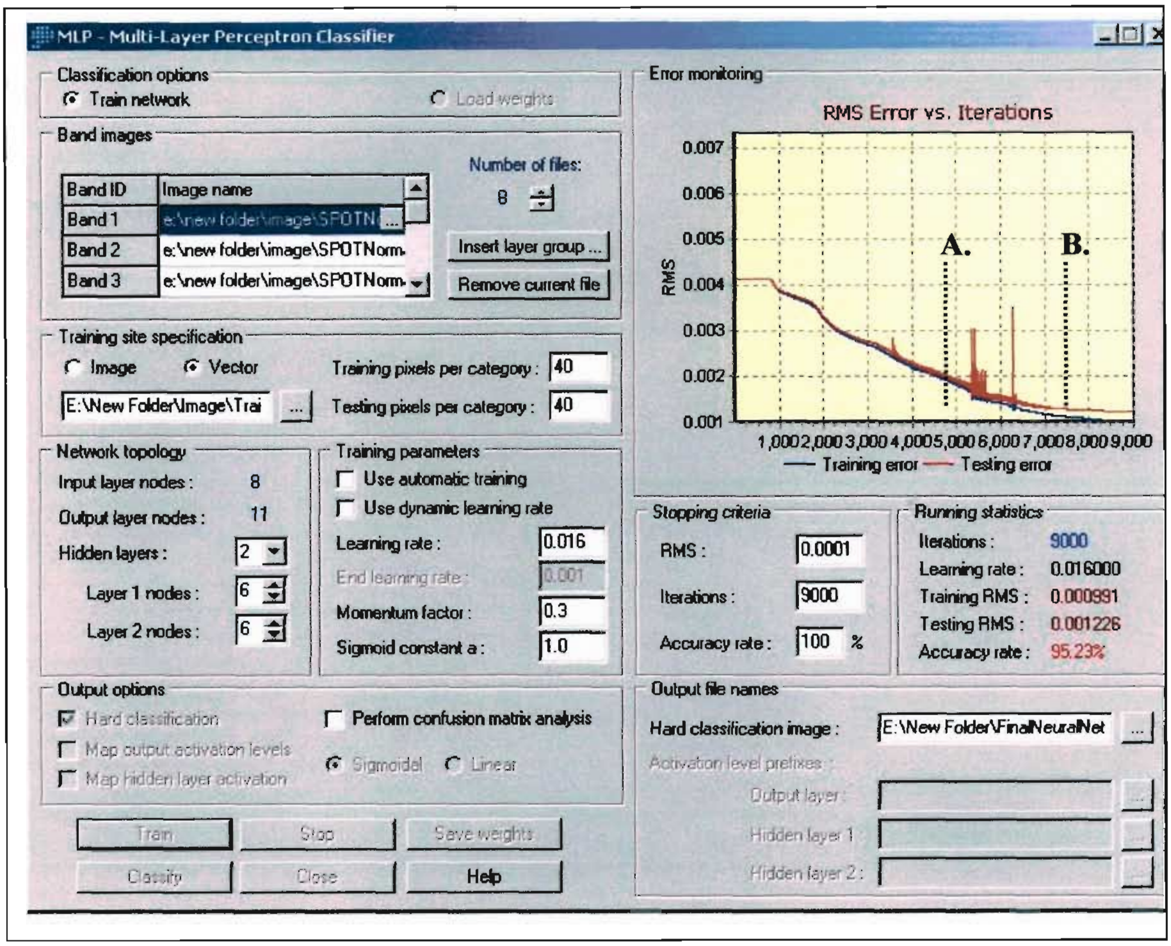

Figure 4.12: The training and testing of the final neural network.

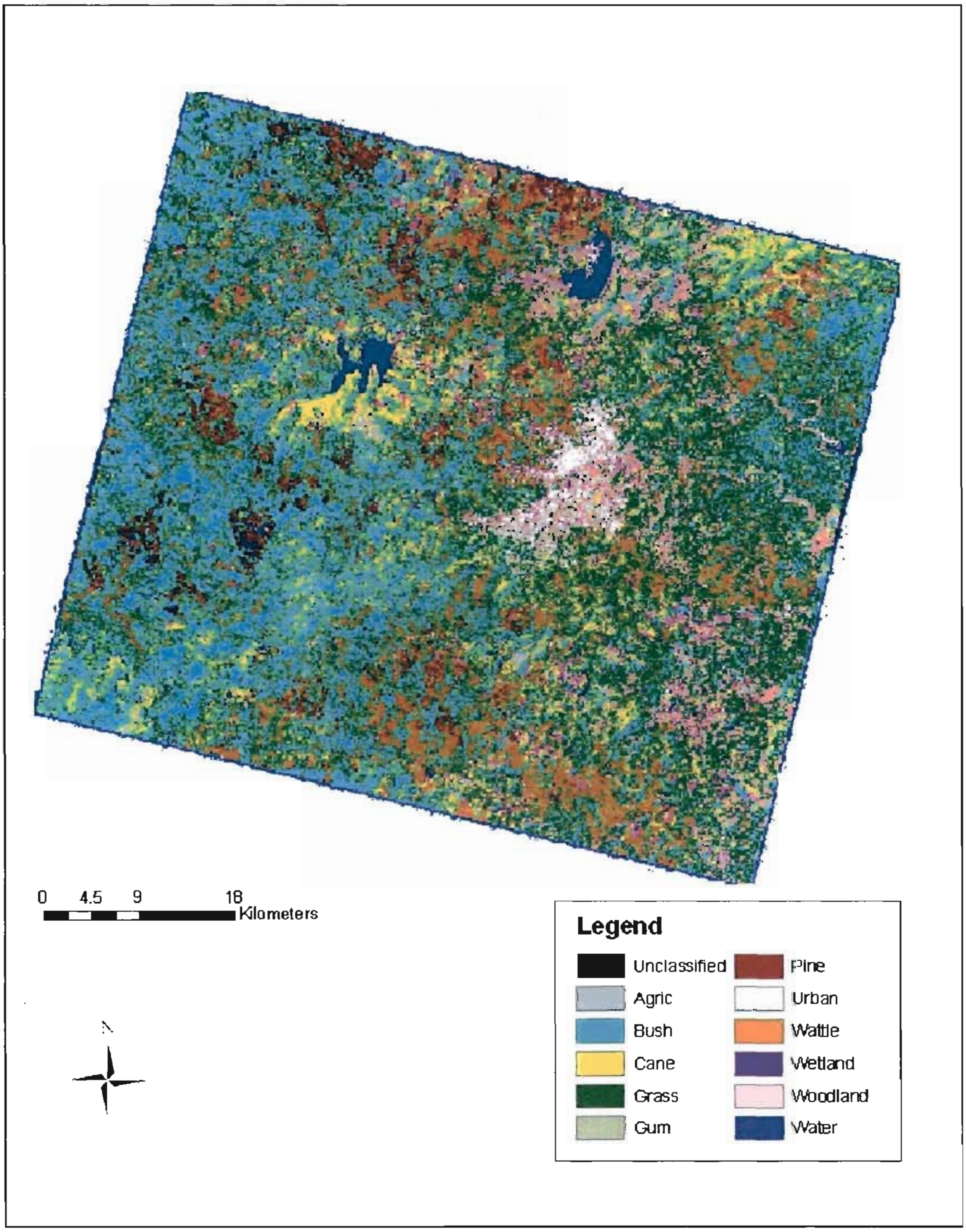

Figure 4.13: The classification of the SPOT 5 image, using the ANN algorithm with 11 classes.

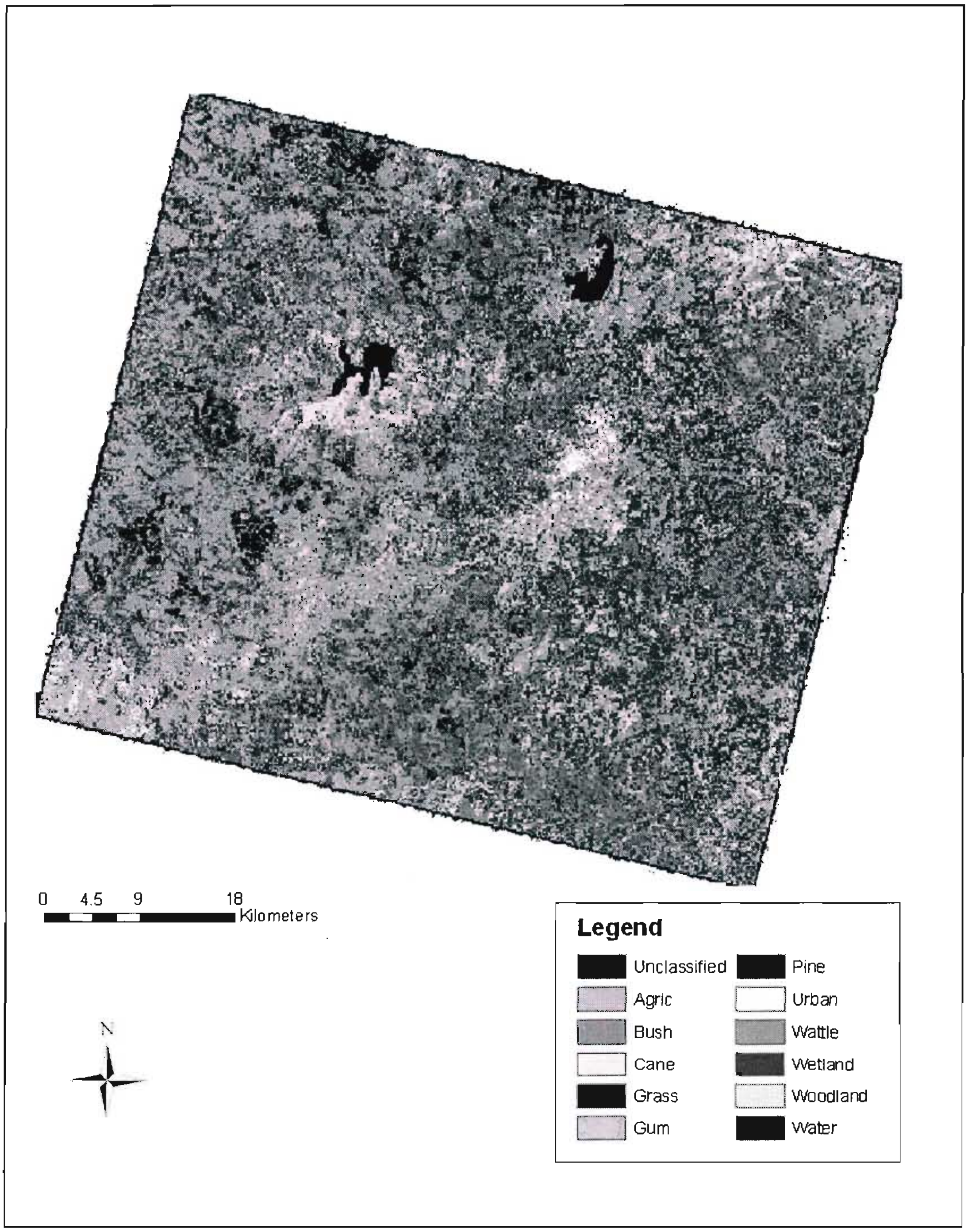

Figure 4.13: The classification of the SPOT 5 image, using the ANN algorithm with 11 classes.

Figure 4.13 shows the classification of the final neural network algorithm. The classification accuracy for this image is 95.23%. Figure 4.14, page 96, shows the comparison between the ANN and the maximum likelihood classification algorithm.

4.4 TRADITIONAL CLASSIFIERS VS. NEURAL NETWORKS

This section will focus on the accuracies of the traditional classifiers compared to those of the neural network. In order for this to be done, the traditional classifiers were run with 11 classes. The accuracies for these classifications were run. If the classifications were not accurate, by using the results from Section 4.2, the number of classes was decreased to improve on accuracies. Table 4.8, page 88, shows all of the results obtained from all of the traditional classifiers.

4.4.1 SPOT 5

Initially, the maximum likelihood classification was used on the SPOT 5 image with 11 classes and then the number of classes was reduced to 8. Overall, the parallel piped algorithm produced the most accurate classification with 11 classes. The accuracy was 68.18%, with Kappa Statistic of 0.6402. The maximum likelihood and the parallel piped classifiers performed identically, each producing an accuracy of 72.73%, with a Kappa Statistic of 0.6765. Table 4.3, page 74, shows the error matrix for the maximum likelihood classification with 8 classes. The minimum distance algorithm produced the least accurate classifications namely, 54.55% and 63.64% for the 11 classes and 8 classes respectively.

In an attempt to increase the accuracy of the various classifiers, an NDVI band was added to the SPOT 5 Image. The three classifiers were run on the images at the different categorical scales. The maximum likelihood classification with 11 classes produced an accuracy of 54.55%, with a Kappa Statistic of 0.4787. By reducing the number of classes to 8, the accuracy of the maximum likelihood classification was 54.55%, and a Kappa Statistic of 0.4608 was obtained. The minimum distance to means produced an accuracy of 59.09%, with a Kappa Statistic of 0.5319. On reducing the numbers of classes to 8 the accuracy was reduced to 54.55%, with a Kappa Statistic of 0.4554. The parallel piped classifier produced an accuracy of 50%, with a Kappa Statistic of 0.4306. On reducing the number of classes to 8, the accuracy was increased to 54.55%, with a Kappa Statistic of 0.4608.

By adding the NDVI band and replacing the NIR band, the accuracies of the image classifications were reduced for all of the classifiers. This proves the importance of the NIR band with the SPOT 5 sensor for landcover classification.

4.4.2 Landsat *TM*

Three classification algorithms were applied to the Landsat TM images, initially with 11 classes and with no NDVI band added, and secondly with the NDVI band used. The increase in the accuracies of the maximum likelihood and parallel piped classifications were large, up to 18% of an increase. The minimum distance classification image performed better without the NDVI band added to the image. The accuracy dropped from 50% accuracy and 0.4346 Kappa Statistic to 40.91% and a 0.3349 Kappa Statistic.

On decreasing the number of classes, the accuracies of the maximum likelihood and parallel piped classification increased with the NDVI free and NDVI images. The accuracy of the NDVI free image increased from 36.36% to 59.09%. The accuracy of the NDVI image increased from 54.55% to 63.64%. The minimum distance classified image for the NDVI free image decreased from 50% to 36.36%. With the NDVI image, the minimum distance classified image increased from 40.91% to 54.55%.

4.4.3 MODIS

The accuracy of the classifiers for the MODIS image was generally very low. For the fine (11) classes all three classifiers produced an accuracy of 31.82%. The Kappa Statistics for the three classifiers at the fine classes remained steady with the classifiers producing Kappa values of 0.2. When the numbers of classes were decreased to 8, the accuracy increased. The maximum likelihood classifier produced an accuracy of 45.44%. The minimum distance classifier produced the most accurate classification of 59.09%, which was the same as the classification of the Landsat TM image with no NDVI band. The parallel piped classifier produced an accuracy of 50%, which is equal to the classification accuracy of the minimum distance classifier using the Landsat TM image with no NDVI.

The closest that the traditional classifier approaches the accuracy of the neural network with 11 classes, is the parallel piped classifier applied to the SPOT 5 image, with 68.18%. By dropping the number of classes, the accuracy is able to be increased to 72.73%. This is still 27% lower than the results obtained by the neural network. The other images are able to have their accuracies increased to obtain accuracies which are relatively close to that of the neural network only by decreasing the classes available to classify.

Table 4.9: The total accuracies and Kappa statistics for different numbers of classes and classification algorithms

Sensor			**Fine**		**Broad**	
SPOT 5		Classifier	Accuracy	Kappa	Accuracy	Kappa
No NDVI		Max	63.64	0.5926	72.73	0.6765
No NDVI		Min	54.55	0.4836	63.64	0.5758
No NDVI		Parallel	68.18	0.6402	72.73	0.6765
SPOT 5 NDVI						
NDVI		Max	54.55	0.4785	54.55	0.4608
NDVI		Min	59.09	0.5319	54.55	0.4554
NDVI		Para	50.00	0.4306	54.55	0.4608
Landsat TM						
No NDVI		Max	36.36	0.2837	59.09	0.5075
No NDVI		Min	50.00	0.4346	36.36	0.2667
No NDVI		Parallel	36.36	0.2837	59.09	0.5050
NDVI		Max	54.55	0.4931	63.64	0.5676
NDVI		Min	40.91	0.3349	54.55	0.4724
NDVI		Parallel	54.55	0.4640	63.64	0.5665
MODIS						
		Max	31.82	0.2308	45.44	0.3383
		Min	31.82	0.2431	59.09	0.5229
		Parallel	31.82	0.2343	50.00	0.9950
SPOT 5		Neural Net	95.23	0.9544	Not Done	Not Done

4.5 ARTIFICIAL NEURAL NETWORK VS. MAXIMUM LIKELIHOOD

In order to fully comprehend the differences between a traditional classifier and the ANN, it is best to compare specific classes from each of the classifications. This section will take 5 classes from each of the classified images and compare how accurate the two algorithms are at identifying the class.

The maximum likelihood algorithm was chosen because it is a popular classifier, yet it performed poorly at identifying specific classes within the classification. The classes used were the Cane, Grass, Gum, Wetland and Woodland classes. These classes were chosen due to the inability for these classes to be correctly identified during the classification using the maximum likelihood algorithm. Table 4.10 shows the comparitive accuracies between the neural network and maximum likelihood algorithm.

Table 4.10: The comparative accuracies between the ANN and maximum likelihood algorithms in classifying specific classes

Class	ANN (Users Accuracy %)	Maximum Likelihood (Users Accuracy %)
Cane	98.65	50.00
Grass	97.64	33.33
Gum	98.73	66.67
Woodland	85.86	0.00
Wetland	62.5	50.00

It can be seen from the table that the ANN outperformed the maximum likelihood classifier by an average of 53% for these classes. Where the maximum likelihood classifier was unable to detect the woodland class, the ANN was able to detect the class with an accuracy 85.86%.

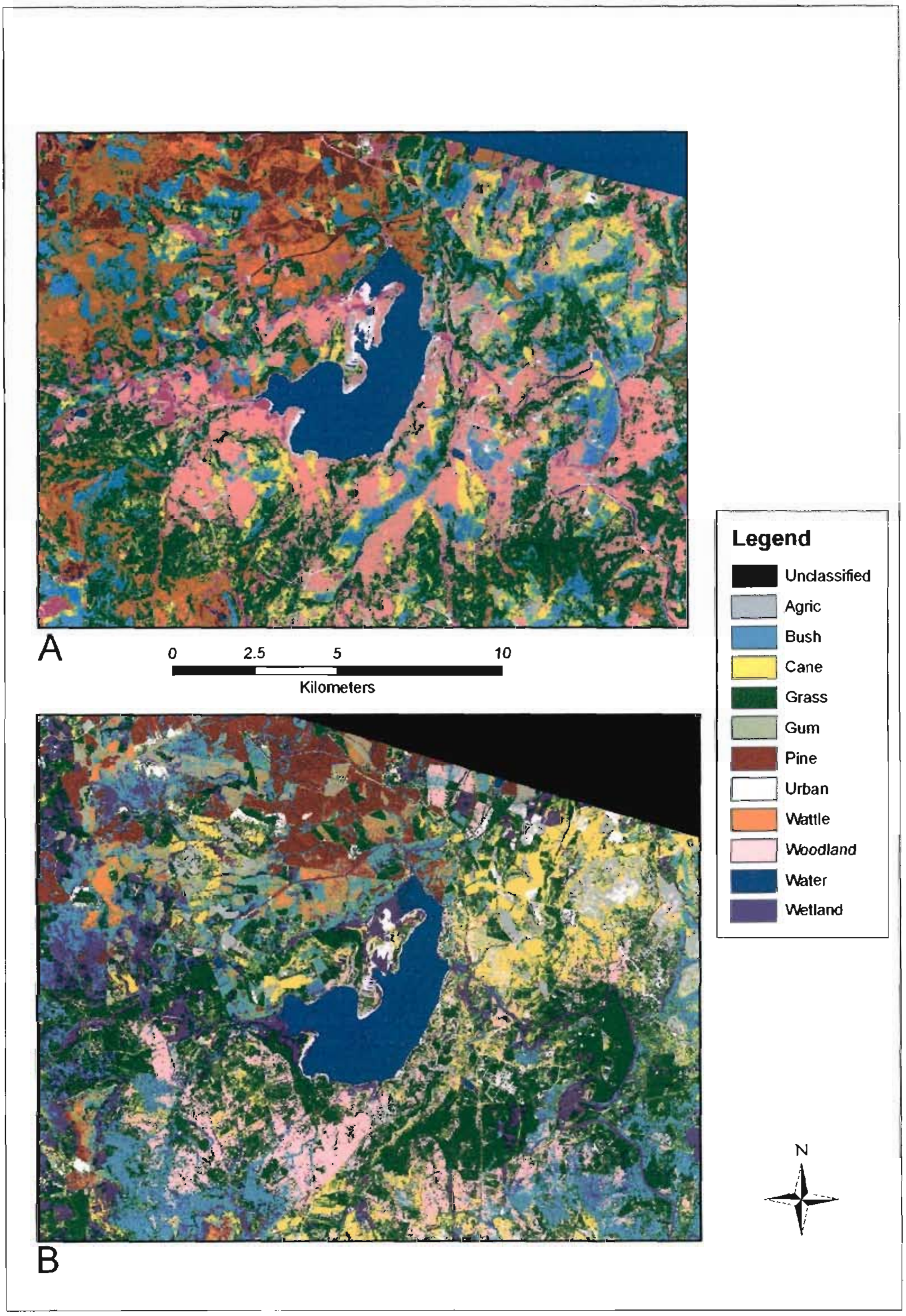

Figure 4.14: A comparison between the Neural Network (A) and the maximum likelihood (B) classification algorithm, for the Albert Falls dam area.

Figure 4.14 shows Albert Falls classified using the Neural Network (A) and the maximum likelihood (B) classification algorithms. It can be seen that the identification of the woodland class around the dam is more pronounced in the neural network classification when compared to the classification of the dam using the maximum likelihood classification.

Chapter 5 will discuss the results obtained within Chapter 4.

Chapter 5. DISCUSSION

This chapter will discuss the results obtained in Chapter 4, focusing on the primary themes described in Chapter 1. These themes are: the effect of resolution, both spatial and categorical, on the accuracy of the landcover classification, the effect of the algorithms used for the landcover classification, and the comparisons between the traditional classifiers and an Artificial Neural Network.

5.1 THE EFFECT OF SPATIAL AND CATEGORICAL RESOLUTIONS ON CLASSIFICATION ACCURACY

The questions asked in this section are aimed at evaluating what role resolution played in the accuracies of the various classification algorithms used. The results presented in Chapter 4 can help in addressing these questions.

In Section 4.4 the different traditional classifiers namely maximum likelihood, minimum distance, and parallel piped were compared with each other as well as a neural network. The neural network will be discussed in another section. The classifiers were run at different resolutions and with different numbers of classes available for classification. Overall, the SPOT 5 images at 10 m resolution produced the most accurate classifications. The MODIS image at 250 m performed the worst classifications with the fine class numbers, but did outperform some of the Landsat TM images at 30 m, in the broad (8 class) class classifications.

5.1.1 The effect of spatial resolution on classification accuracy

In order to test the effect of spatial resolution on the final accuracies of the landcover classifications, three images of differing resolutions were used. This section outlines and discusses the results obtained from the differing resolutions. Each image was classified using different categorical scales of fine classes (11 classes) and broad classes (8 classes).

The algorithms used for these classifications will be discussed in following sections. This Section 5.1.1 focuses primarily on the results obtained at the various spatial resolutions.

Highest Resolution Image: SPOT 5 Image

The SPOT 5 image produced the highest accuracies overall for all of the algorithms used. Using the best statistical algorithm, the best accuracy obtained at the fine class level was 68.18%, and at the broad class level it was 72.73%. Possible reasons for this include the high concentrations of pixels at the boundaries of the different classes due to the resolution of the image. By reducing the spectral mixing at these boundaries the ability of the classifier to discriminate between the various classes is much better than if the spectral mixing were higher.

Moderate Resolution Image: Landsat TM Image

The Landsat TM image with the NDVI band produced the second highest classification accuracies at the fine and broad class levels. Reasons for this include reduction of spectral mixing at the boundaries of the classes. Because of the sizes of some classes (Grassland), these are more easily picked up at the coarser resolutions and so can be classified correctly.

The Landsat TM image without the NDVI band produced low classification accuracies at the fine class level but at the broader class level, managed a final accuracy higher than the accuracies of the Landsat TM image with the NDVI band at the finer class level. This, however, is not relevant because the NDVI band can be created for the image and used thus producing the higher accuracies needed. The NDVI image produced higher accuracies because it enabled there to be more discrimination between the vegetative classes and the non-vegetative classes based upon the amount of reflection at the Red and NIR bands. An example of this can be seen when looking at certain classes within the classification. The Landsat TM with no NDVI band classification error matrix (Appendix II) shows that the Urban and Grassland classes are not correctly classified having a user's accuracy of 0%. In the Landsat TM with the NDVI band classification error matrix (Appendix II), the Urban classes were classified having a user's accuracy which had increased to 100%; and the Grassland class was classified having a user's accuracy which increased to 28.47%.

Lowest Resolution Image: MODIS

The MODIS image performed poorly with all of the classifications at the finer resolutions. The MODIS image has a resolution of 250 m, which results in the boundaries of many of the classes falling within the extent of a single pixel. This is especially true with the smaller classes such as the Bush and Agriculture classes. Thus the ability for the classifier to discriminate between these smaller classes is reduced, resulting in the reduction of the classification accuracy.

By increasing the sizes of the classes being detected, the boundaries between classes can become broader thus increasing the effectiveness of the classifiers to discriminate between those classes. An example of this can be seen in the error matrix of the Fine and Broad error matrices (Appendix I) respectively. The Wattle class is classified having a 20% accuracy, whilst the Gum and Pine classes are not classified correctly having an accuracy of 0%. When these three classes are merged to create one class, namely Plantation, the accuracy increases to 66.67%: as the class areas become larger, so the accuracy of the classification of that class gets larger.

Overall, it can be seen that the higher the spatial resolution of the imagery, the higher the accuracy of the classification produced, regardless of the classification method used. There are exceptions, where a lower resolution of an image can produce classification accuracies very close to the higher resolution of the imagery. Previous research undertaken has shown that the higher the resolution, the more accurate the classification can be (Chen *et al.,* 2004). This is especially true with regards to the classes which occupy a smaller spatial area; an example can be seen when comparing an urban area on a Landsat TM image compared to the same urban area on a SPOT 5 image. The urban area on the Landsat image may look homogenous, whereas in the SPOT image it can be seen that it is in fact made up potentially of vegetation and urban elements (Chen *et al.*, 2004).

Choosing the image to use for the classification depends on what features are needed to be classified. It is evident that the larger the feature that is to be classified the coarser the image can be before the accuracy becomes too low. Features such as large grasslands or plantations areas can be accurately mapped using the coarser imagery; however, areas of smaller features such as small-scale farming or isolated plantation stands will need higher resolution imagery to be accurately mapped. This substantiates opinion in the literature (Franklin and Wulder, 2002) stating that before imagery is chosen for landcover classifications the feature needed to be identified should be known, thus enabling for the correct imagery to be chosen.

5.2 EFFECT OF CATEGORICAL RESOLUTION ON THE FINAL LAND COVER CLASSIFICATION

The questions asked in this section focused on the ability of the classifiers to accurately determine which classes easily differentiates from the others and how the number of classes can play a role in the accurate classification of the imagery. The actual classifiers used will be ignored, because as the primary objective is to discover how the reduction in the number of classes can aid in the final classification accuracy of a) the overall classified image and b) specific classes within the classified image.

The Effect of the number of classes on the overall accuracy of the classification

Overall, it can be said that the fewer the number of classes available for classification, the higher the overall accuracy of the landcover classification map produced. For the SPOT image the highest accuracy obtained for the fine class landcover map was 68.18%. On reducing the number of classes, the accuracy increased to 72.73%. With all of the images this was the trend: when the number of classes was decreased, the accuracy increased.

Which of the classes are easily detected?

One problem with trying to identify features on the earth's surface is detecting classes that are similar in nature. An example of this is the distinction between wetland, grassland (see Figure 4.3 page 71) and cane field area. Although to the naked eye these features can be easily differentiated, each of these classes is very similar spectrally, thus increasing the difficulty for the classifier to detect the spectral difference between these classes. Other issues arise from the resolution of the imagery being used. A wetland can be very large, but most are very small, whereas grassland and cane fields tend to have large spatial areas. If an image has a high resolution, the chances of a wetland falling within the pixels increases. However, with lower resolution imagery the chances of a wetland's signatures mixing in with other larger classes increases.

Taking examples of the highest accuracies for each of the images and the best performing classifiers, problems with resolution and sizes of classes will be discussed. Using the fine and broad classes as an example with the SPOT, Landsat TM with NDVI, and the MODIS images, the Wetland, Grassland and the Cane classes will be compared. As was stated in Chapter 3, the Grassland and Wetland classes were merged due to the problems associated with the inability of the classifier to distinguish between the two.

5.2.1 Classification of the higher resolution image: performance of the SPOT 5 image using 11 and 8 classes

11 Classes

Using the SPOT 5 image, in the classification using the parallel piped classifier with 11 classes, there was confusion between the Wetland and Grassland classes. The user's accuracy for the Grassland class was 25%, with the Woodland and Agric classes being incorrectly classified as the Grassland class. This could be because the Woodland class does have some Grassland type vegetation within the class, thus creating confusion between the two classes. The Wetland class was classified with a user's accuracy of 50%, and confusion being created between it and the Grassland class. Possible reasons could be the similarity between the species of vegetation found within both the Wetland and Grassland classes. The Cane class was classified with an accuracy of 100%.

8 Classes

As was stated in Chapter 3 classes were merged into 8 classes, using the SPOT 5 image and the parallel piped classifier, the classification will be evaluated within this section. The new Grassland class produced a user's accuracy of 42.86%. This is a decrease in the accuracy from the fine class classification. Confusion occurred among the Agric., Woodland and Water classes. Reasons for this could be attributed to some spectral similarities between the Wetland, Grass classes and the Woodland, Agric. and Water classes. These similarities may be caused by the low rainfall period from which this image is taken. Due to the low moisture water levels, it is possible that the spectral reflectances of these water areas may be similar to woodland and agriculture areas. By decreasing the number of classes through merging, some new discrepancies or inabilities to discriminate some classes is increased, this possibly being caused through the compounding of the similarity between the spectral signatures of the Grassland and Woodland classes. There was no confusion between the Cane class and any other class, and the Cane class was classified with 100% accuracy.

5.2.2 Classification of the medium resolution image: performance of the Landsat TM image using 11 and 8 classes

11 Classes

The image that produced the highest accuracy was the Landsat TM image with the NDVI band, using the maximum likelihood classifier. Using 11 classes, the Landsat TM image was unable to correctly classify the Wetland class. The confusion occurred between the Bush and Agriculture classes. This could be the result of the pixel size and errors caused during the training stages of the classification process, whereby pixels from any one of those classes were incorrectly captured as being the Wetland class. Otherwise, the problem may arise from spectral mixing at the borders of the Wetland class, resulting in spectral values equal or similar to those of the Bush and Agric. classes.

The Grass class was classified with a user's accuracy of 33.33%. Confusion between the Bush and Woodland classes reduced the accuracy of the classifier. This may be the result of the pixel size being too large for the detection of breaks within the woodland class, where grass may occur within the woodland class, thus resulting in the mixing of the spectral signatures of these classes. Grasslands can contain woody vegetation. During the training stages of the classification process, it is possible and probable that the woody vegetation was included during the training site delineation. This result could be purely based on the resolution of the image, where in a 30 m x 30 m area the boundary between a woodland and grassland environment can be found. The Cane class was classified with 100% user's accuracy.

8 Classes

The Landsat TM image's classes were merged to create 8 classes. The maximum likelihood created the highest accuracy for the classification. The merged Grassland class had a user's accuracy of 30% which is a decrease of 3% from the unmerged classes. The Bush class was confused with the Grassland class; this could be due to the similarity of the vegetation within the two classes and the inability of the Landsat image's resolution to discriminate between the two classes. The particular Wetland whose class was merged, was very close to a woodland thicket. This proximity could result in the mixing of pixels due to the resolution of the image. The Cane class was correctly classified with 100% user's accuracy

5.2.3 Classification of the medium resolution image: performance of the MODIS image using 11 and 8 classes

11 Classes

The classifier that produced the highest accuracy with the MODIS image was the parallel piped classifier, as it produced the highest kappa statistic of 0.2343. Using 11 classes, the MODIS image was unable to correctly classify the Wetland class. One of the Wetland training pixels was confused with a Grassland class. A probable cause for the confusion between the classes could be the size of the wetland compared to the pixel size of the image. The MODIS sensor has a resolution of 250 m in the visible section of the electromagnetic spectrum. This enables more spectral mixing to occur in the smaller classes and thus can cause problems with the identification of the smaller classes

The Grassland class obtained a user's accuracy of 13.33%. The most confusion between this class and the others occurred with the Bush class. There were, however, other confusions between almost all of the other classes. Possible reasons for the confusion could be that the Grassland class is the largest class within this study, and thus has its boundary alongside many of the other classes. The resolution of 250 m can thus result in the mixing of the Grassland class with the other classes at the boundaries between the classes. Conversely, the error could arise during the training for the creation of the signatures. Due to the size of the pixels within the image, some of the training sites created may have inadvertently included pixels from other classes. An example could be the Wattle class, which is relatively small and has been seen to contain some of the grassland type vegetation near its boundary. Therefore, the chances of some Grassland pixels being included in the Wattle class during the training process is high. The Cane class was not correctly classified in the MODIS image, and was confused with the Grassland class, most likely the result of errors during the training stage of the classification.

8 Classes

The MODIS image's classes were merged to create 8 classes, and the minimum distance to means classifier created the highest accuracy for the classification. The new Grassland class achieved a user's accuracy which increased to 75%, with the Bush class being confused with the Grassland class. This could be due to the Wetland and Grassland classes containing some bush-type vegetation and so confusing the classifier. The Cane class was not correctly classified by the system. Pixels from the Urban class and the Agriculture class were incorrectly classified as part of the cane class.

The MODIS image is an example of how important it is to elect the correct imagery for a specific landcover classification. The smaller classes such as the Cane and Wetland classes could be too small to be correctly detected within the MODIS image, which in turn could lead to the confusion of these classes with other larger classes. Higher resolutions, such as the SPOT 5 image of 10 m can represent the Wetland and Cane classes. It should therefore be noted that the cost of the imagery should be taken into account in conjunction with what will need to be mapped. It can be said, that for the coarser landcover classes, the MODIS image which is freely available, could be used to classify these broader classes in the southern African environment. It has been shown that the choice of the number of classes is vital to the accuracy of the image classification. It must however be noted that the choice of the categorical resolution is dependant on both the spatial scale of the study in question and type of imagery used (Ju *et al.*, 2005).

5.2.4 Lessons learnt from the Analysis of changing the resolutions

From the analysis of the classification accuracy when the spatial and categorical resolutions are changed, it can be seen that these play a role in the accuracy of the final classification.

Firstly, spatial resolution plays a large role in the detection of the smaller classes. It can be seen that the detection of the Wetland class decreases rapidly as the spatial resolution of the image decreases. The large classes, such as the Grassland class, are not drastically affected by the higher and medium resolution images. Within the SPOT 5 image the Grassland class is classified at roughly 43% accuracy but there is a decrease to 33% accuracy using the lower resolution of 30 m from the Landsat TM image.

Secondly, the categorical resolution can also play a role in the overall accuracy of the images. Although a decrease in the resolution does not necessarily mean a better classification of a specific class type, it was seen that decreasing the categorical scale can reduce the accuracy of specific classes. An example can be seen in the accuracy of the Wetland class: on merging with the Grassland class in the SPOT 5 image, the initial accuracy of 50% for the Wetland class decreased to 42.86%. This is, however, not the norm; it is seen as being a general trend, that with the overall classification accuracy for all of the algorithms used, increased with the decrease in the categorical resolution.

Therefore, before a landcover classification is to be done, it is important to decide on the size of the specific landcover types to be determined. This enables the correct resolutions to be determined, resulting in the best possible detection of these classes. It could be stated that determining the resolutions to be worked at should take precedence over the type of classifier that is to be used. (Bian, 1997 and Chen *et al.*, 2004)

5.3 THE PERFORMANCE OF THE TRADITIONAL CLASSIFIERS

Before the comparison of the traditional classifiers with the Artificial Neural Network can be made, it is best to determine how each of the traditional classifiers performed and which of the classifiers performed the best. The neural network was run using 11 classes, thus for this section the classification algorithm accuracies will be looked at with performance using the fine classes.

5.3.1 Maximum Likelihood Classifications

Using the figures from Table 4.9, page 94, it can be seen using the maximum likelihood classification algorithm and fine classes, an accuracy of 63.64% was obtained. After adding the NDVI band to the SPOT 5 image, the accuracy obtained was 54.55%. The Landsat TM image, with the NDVI band was classified with an accuracy of 54.55%. Removing the NDVI band decreased the accuracy of the classification to 36.36%. The MODIS image produced an accuracy of 31.82%.

5.3.2 Minimum Distance Classifications

From table 4.8 the fine classifications for the SPOT 5 image without the NDVI band, produced an accuracy of 54.55%, adding the NDVI band the accuracy increased to 59.09%. The Landsat TM image with the NDVI band produced an accuracy of 40.91% and by removing the NDVI band, the accuracy increased to 50%. The MODIS image produced an accuracy of 31.82%.

5.3.3 Parallel Piped Classifications

As can be seen from Table 4.9, the fine classifications for the SPOT 5 image without the NDVI band, produced an accuracy of 68.18%; by adding the NDVI band decreased the accuracy to 50%. The Landsat TM image with the NDVI band produced an accuracy of 54.55% and by removing the NDVI band, the accuracy decreased to 36.36%. The MODIS image produced an accuracy of 31.82%.

Possible reasons for the decrease in accuracy in the SPOT 5 classifications when the NDVI band was added could be due to the dryness of the area when the image was obtained. It has been stated that the levels of the Albert Falls dam were low when the image was obtained. The Landsat image shows the water level of dam to be much higher than what is shown in the SPOT image. Thus the NDVI values for the SPOT image are lower than those of the Landsat image, due to dryness. This then lends to the spectral confusion of some of the classes and so decreases the overall accuracy of the classification. Whereas the Landsat image is less dry and so the NDVI values are higher allowing for a better spectral separation of the classes allowing for a more accurate image classification.

From the results it can be seen that the parallel piped classifier performed the best using the higher resolution imagery. The parallel piped classifier produced an accuracy of 68.18% with 11 classes. The most probable reason for this is that the boundaries of the different classes are more defined because of how many pixels are able to represent the edge of the classes, thus reducing the spectral mixing of the pixels at these boundaries. With regards to the other images, the parallel piped classifier performed identically to the maximum likelihood classifier.

The maximum likelihood classifier performed well using the other images, producing accuracies higher than the minimum distance classifier did. The minimum distance classifier did, however, outperform both the maximum likelihood and the parallel piped classifiers with the Landsat TM image without the NDVI band. The final accuracy for this classification was 50.00%, whilst for the maximum likelihood and the parallel piped classifiers classified the image at 36.36% accuracy. Although the parallel piped classifier did outperform the maximum likelihood classifier, the latter will be used for the comparison between the traditional classifiers and the ANN, as it is the most widely used classifier.

5.4 PERFORMANCE OF AN ARTIFICIAL NEURAL NETWORK COMPARED WITH THE MAXIMUM LIKELIHOOD CLASSIFIER

Within the specific landcover research questions, the need to increase the accuracy of the classifications is investigated as well as the determining of which neural network properties are the most important in deciding the accuracy of the network.

When compared with the traditional classifiers, the neural network is more complex in nature. This is due to its ability to include ancillary data and its ability to change variables within the network itself. These variables change how specific data within the image relate to themselves and the other data in the network (Qiu and Jensen, 2004). Overall, the neural network with 11 classes performed better when compared to the best traditional classifier with just 8 classes. Studies done in the past follow this trend (Skidmore *et al.,* 1997, Sunar Erbek *et al.*, 2004 and Qui and Jensons, 2004). By using ancillary data (in this case slope, DTM, aspect, and NDVI all of which were added to the 4 bands of the SPOT 5 image) the classification of 11 classes was increased from 68.18% of the parallel piped to 99.80% using the neural network.

It is best to determine which of the parameters within the neural network are the most important to the overall accuracy of the image. The parameters that are possible to alter are: the number of hidden layers, the number of nodes per layers, the learning rate, the momentum factor, the number of iterations, and the number of bands used. It is important to note that there are no set guidelines to follow for setting up a neural network (Qiu and Jensen, 2002). Therefore this section will outline each of these discussing how they affected the final outcome of the classification accuracies.

5.4.1 Hidden Layers and Nodes per Layers

The number of hidden layers and the number of nodes per layers related because they are connected in how they behave. The number of hidden layers refers to the number of layers the input data is put through. The number of nodes per layer refers to the number of smaller nodes that the input data is fed through per hidden layer (Clarke Labs, 2000).
When one layer was used and the number of nodes per layer was increased, the overall accuracy of the image increased to a point (20 nodes). However, the final accuracy was 66.54%, which was lower than that of the highest accuracy of the traditional classifier. After 20 nodes per layer, the overall accuracy of the image decreases and so is ineffective in increasing the accuracy of the final classification.

By using only two layers and increasing the number of nodes per layer, the results obtained were improved. Initially, the accuracy of the image peaked at 6 nodes per layer and the accuracy obtained was 92.93%. The process continued and, at 20 nodes, the two hidden layers peaked at 97.22% accuracy. The accuracy peaked again at 30 nodes per layer. However, the aim is to design a neural network that is both accurate and efficient and so 6 nodes per layer were deemed to be the point at which accuracy peaked. After 30 nodes per layer, the accuracy of the classification dropped sharply. Results obtained by Paola and Schowengerdt, (1997) authenticate this pattern. They found that if the number of nodes per layer is too small, the accuracy of the classification is low; however, if the number is too high, the network takes too long to run and so becomes overfitted and inefficient (Paola and Schowengerdt, 1997).

Examining how quickly the accuracy can rise and fall with the changing of the number of hidden layers and number of nodes per layer, it can be deduced that these factors play a very important role in deciding how efficient and accurate the final classification will be.

5.4.2 Learning Rate

The learning rate of the neural network governs what the weightings for each of the input layers is and how these layers will move through the hidden layers of the network. It is stated in literature (Clarke Labs, 2000) that the learning rate is the most important factor in evaluating the accuracy and the efficiency of the neural network and hence the learning rate was tested the most. Literature states that the best values are between 0.01 and 0.02 (Clarke Labs, 2000).

The accuracy of the neural network, as the learning rate was changed, showed very little change. The overall accuracy of the classification gradually increased, by 2-3% to a point at which the accuracy jumped by 4%, where it became stable. The highest accuracy was recorded at 0.016, where the accuracy was 97.85%. After 0.02, the accuracy became very unstable, which corroborated the literature. Accuracy would change from 96.59% to

9.09% then to 95.96%. The state of the neural network during this portion of the test meant that the values gained would not be useful in the final classification.

On running the neural network; and changing the learning rate it can be seen that the learning rate plays a very large role in final accuracy of the neural network. If the values are too small, the changes in the weighting of the variables will be too small to make any significant changes to the final accuracy. If the learning rate is too large, the changes made to the weighting will become too erratic and large to produce any meaningful classification, as can be seen in the neural network after the learning rate was increased beyond 0.02. After 0.028, the accuracy of the neural network declined steadily to 6.57%.

5.4.3 Momentum Factor

The momentum factor is aimed at decreasing the Root Mean Square Error (RMSE) at the surface of the classification and thus was tested in order to decrease the RMSE whilst increasing the overall accuracy of the image (Clarke Labs, 2000).

The overall change to the accuracy of the image as the momentum factor was changed was minimal. During the initial changes, the accuracy changed by 4% with the highest accuracy being 97.47%, at a momentum factor of 0.3. After 0.3, the accuracy of the classification declined slowly until 0.7, when the accuracy dropped sharply to 8.84%.

From running the tests, it was found that the effect of the momentum factor on the overall accuracy is minimal. Accuracy variations are small as the momentum factor changes. Thus it can be deduced that the momentum factor does play a role in the accuracy of a classification, although it is not the most important factor affecting the neural network.

5.4.4 Number of Iterations

The number of iterations refers to the number of times the neural network will run before it is terminated (Clarke Labs, 2000). This has its advantages because it allows the deciding factors that can increase the accuracy more time to run and so it increases the overall accuracy of the network. This, however, is detrimental to the efficiency of the neural network. The numbers of iterations were increased slowly from 100 to 1000 iterations, at which point the numbers of iterations were increased by 1000.

The accuracy of the neural network remained low during the low iteration tests, but the accuracy sharply increased after 2000 iterations. After 5000 iterations, the accuracy of the neural network stayed in the low 90% accuracy range. The highest accuracies were recorded at 9000 – 97.73% and 30 000 – 97.85%. Due to the very small difference in the accuracy between the two, 9000 iterations were chosen for efficiency.

The numbers of iterations play an important role in the efficiency of the neural network. With too many iterations, the neural network becomes redundant or overtrained: the accuracies will be close to the highest possible but will sacrifice time. This follows the pattern identified by Skidmore *et al.,*(1997), where the network was seen to reach a point where the accuracy of the trained network remained constant, but past a certain point, the network became ovetrained (Skidmore *et al.,* 1997). If the number of iterations is too small, the accuracy of the network will suffer, but it will run quicker. The ideal number of iterations is therefore the number that provides the highest accuracy but in the most efficient manner.

5.4.5 Input Layers

These are the bands that will be used as the input layers that will run through the network. It is possible that some of the bands used might be useless to the overall accuracy of the classification. This is because they may be able to detect some of the classes, although there may be another band that will detect that same class more efficiently.

The base accuracy, to which all other classifications would be compared, was taken using the parameters that had already been chosen. These parameters were obtained from Runs 1 to 5. The initial classification was made using all 8 bands. The accuracy used as the base was therefore 97.73%. The larger the drop was in the accuracy as the band was removed, the more important was the role that band played in the accuracy of the image. The largest drop in accuracy occurred when the 4^{th} band (MIR) was removed: then the accuracy dropped to 92.55%. There was no single band that made a significant impact on the accuracy of the classification; therefore groups of bands were removed.

The classification accuracies were as follows:

- The first group to be removed was that of the bands that are part of the satellite image (Green, Red, NIR and MIR bands). The accuracy fell to 84.47%.
- The second group to be removed consisted of the ancillary data added to the image (Aspect, Slope, NDVI and DTM). The accuracy fell to 83.84%.
- The third group to be removed was that not used in the traditional classification tests done before. Thus the bands used were the Green, Red and NIR. The accuracy for this test was 80.81%.
- The last group to be removed consisted of the bands not traditionally used for landcover mapping, these being the NDVI, Green, Red and NIR bands. The accuracy for this classification was 84.34%.

Conclusions reached regarding this test show the higher are the number of bands or ancillary data the higher is the accuracy of the final classification. By removing the new bands to the image, the accuracy dropped by over 10%. This test showed that the neural network can increase its accuracy even if the bands used are identical to those used by the traditional classification algorithms.

The overall classification using the changes decided upon through testing the neural network produced an accuracy of 95.23%. It was decided that the learning rate is the most important factor within the neural network, followed by the number of hidden layers, then the number of nodes per layer. The number of iterations and bands are also important. The momentum factor plays a role but when compared to the other factors it can be left at the default values of the system.

5.5 Comparison between the traditional classifier and the ANN

The comparison of the neural network against that of the traditional maximum likelihood shows that the identification of individual classes is better in the neural network. Table 4.10 presents the identification of specific classes within both the maximum likelihood classification and the neural network with 11 classes. The Grassland class user's accuracy was detected with 33.33% accuracy; the neural network was able to correctly classify 97.64% of the Grassland class. The Cane class had a user's accuracy of 50.00% with the maximum likelihood classifier; the neural network was able to classify 98.65% of the Cane class correctly. The Wetland class had a user's accuracy of 50.00% with the maximum likelihood classification; the neural network detected the Wetland class the worst from all the classes identified, having a users accuracy of 62.5%. This slight improvement in the accuracy of the Wetland class can aid in the understanding of the complex nature of wetland features. Confusion could have arisen from the proximity of the class to some water bodies as well as the abundance of different types of vegetation within the class, thus creating many different spectral reflectances.

The next chapter will contain discussion on how the objectives to this study have been approached and how the results obtained have met the objectives.

Chapter 6. CONCLUSION

In this chapter, the aims and objectives stated in Chapter 1 will be reviewed, examining how close this study came to reaching the goals set. Some recommendations will be made for future studies within this area of remote sensing.

6.1 AIMS AND OBJECTIVES REVIEWED

6.1.1 Aims

The aim of this study was to evaluate the effect of spatial resolution on the effectiveness or accuracy of a landcover map. A neural network was implemented in an attempt to increase the accuracy of the final classification.

This study has shown that spatial resolution of an image can play a vital role in the process of mapping landcover. By determining the spatial size of the class that is needed to be detected the appropriate resolution can be selected from the appropriate sensor.

The higher the resolution of the imagery is, the higher the concentration of pixels per feature that can be classified will be: this can decrease the amount of spectral mixing both within the feature and at the boundaries between two classes. The lower the resolution is, the more chance there is of features not being detected because of spectral mixing at the boundaries between two classes.

The best algorithm used for a classification is based upon the signatures created for each of the classes as well as the imagery itself. For this study, it was shown that with more classes and at the highest resolution the parallel piped classifier outperformed the maximum likelihood classifier by almost 5%; at the lower resolution, the parallel piped classifier outperformed the maximum likelihood classifier but was surpassed by the minimum distance classifier. The maximum likelihood performed identically with the parallel piped classifier for all of the imagery at each of the fine and broad class levels. The maximum likelihood did perform identically to the parallel piped classifier at the broad class level. The minimum distance classifier performed the best at the lower spatial resolutions. With the Landsat TM with no NDVI band, minimum distance classifier outperformed the other classifiers by almost 14%, and with the MODIS image it outperformed the other classifiers by almost 10%.

6.1.2 Objectives

Four objectives were set in order to meet the aims stated above; in this section, how close the study came to meeting the said objectives will be reviewed.

1. To test the accuracy of Landcover Classification at three different spatial resolutions, each resolution being taken from three remotely sensed images (SPOT 5, Landsat TM and MODIS).

The maximum likelihood classification algorithm was applied to the three images (SPOT 5, Landsat TM and MODIS images) of differing resolutions. The maximum likelihood although used extensively in the literature (Franklin and Wulder, 2002) it however performed on par with the parallel piped classifier.

The results obtained showed a definitive pattern with regards to the performance of the classifier and the spatial resolution of the images. The higher resolution of the SPOT 5 image gave accuracies of 63.64% with the use of 11 classes, and 72.73% with the use of 8 classes. As the resolution of the images became coarser, the accuracies of the classification became lower. The Landsat TM images of 30 m resolution gave an accuracy of 54.55% with 11 classes, and the MODIS image of 250 m resolution gave an accuracy of 31.82% with 11 classes.

Possible reasons for the decrease in the accuracy as the spatial resolution becomes coarser, have been discussed previously and possible causes have been identified as the number of pixels within each of the classes. As the number of pixels decreases within a class, the probability of a specific pixel falling within its specific class decreases. An example can be identified with regards to the Wetland class. The wetland class is a small class, with many small features. Thus the finer the resolution is, the more chance there is that the pixels from a wetland feature will fall within the Wetland class. The coarser the imagery or the coarser the resolution, the more chance that the feature will fall completely within the pixel and so not be classified due to the mixing of other classes in that pixel.

2. To evaluate the effect of the number of classes on the final classification accuracies.

The trend for all the images showed that the accuracy of the image was increased by decreasing the number of classes used.

As has been stated before, this is likely due to the increase in the spatial area of the class and thus the probability of the class falling within the spatial extent of the pixel increases. This, therefore, reduces the proportion of spectral mixing within the class. The most effect was seen on the MODIS image, and this supports the statement made earlier. Some of the classes within the finer class category would be too small to be detected within the 250 m resolution image of the MODIS sensor. By amalgamating these classes into larger classes they can be detected. An example of this can be seen in the detection by the MODIS image of the different plantation type in the study area. The MODIS image did not differentiate among the different trees species accurately. However, by merging the tree species to form a single broad Plantation class, the accuracy was increased.

3. To evaluate the differences between the classification accuracy of an image using fine class definitions and traditional algorithms; and then to compare this to a neural network

This objective was aimed at determining the relative accuracies of a neural network and traditional classifiers. Overall, the traditional classifiers performed poorly when classifying the finer classes. Using the fine definition classifications as a base, the maximum likelihood classified the SPOT 5 image with an accuracy of 63.64%, the minimum distance to means classifier classified the same image with an accuracy of 54.55%, and the parallel piped classifier performed the best and classified the image with an accuracy of 68.18%.

The neural network performed well with the finer classes: even when it was not trained correctly, the average classification was higher than the traditional classifiers.

4. To test the ability of a more computationally intensive Artificial Neural Network to improve the accuracy of the classification.

As has been stated: the traditional classifiers performed poorly and in an attempt to increase the accuracy of the SPOT 5 image with finer classes, a neural network was trained and tested. For the training stages, set parameters were defined and testing was done to streamline the neural network for optimum efficiency and accuracy. The final product outperformed the parallel piped classifier by roughly 28% and the maximum likelihood classifier by 30%.

Generally, the neural network classified specific classes in the image to a higher accuracy than the traditional classifiers were able to. An example is the identification of the Cane class with the maximum likelihood classification: the maximum likelihood was able to produce a user's accuracy of 50% for the classification of the Cane class and the neural network improved upon this classification producing an accuracy of 98.65%. For the same image using the training parameters, the neural network was able to increase the accuracy of the maximum likelihood accuracy to roughly 90.00%, a 40% increase. This shows the ability of the neural network to efficiently classify specific classes on an image. It should be noted that the Wetland class was not classified as accurately as the other classes. The user's accuracy of the Wetland class for the neural network was roughly 62%, this was an improvement by 10% on the maximum likelihood classification, although when compared to the other classes from the neural network this accuracy is the lowest. This points to how complex a wetland system is: the proximity to water allows there to be more diverse vegetation than in other areas and so can result in a complex reflectance pattern, creating difficulties in the classification of the image.

6.2 LIMITATIONS AND RECOMMENDATIONS OF THIS STUDY.

This section will outline a few of the limitations of certain aspects of this study. Where necessary, some recommendations have been made in order to correct these identified problem areas.

6.2.1 Limitations

This study was undertaken as close to accepted practice as possible. However. it must be noted that some improvements can be made to the methodology.

IMAGES

1. Resolutions

   In order to evaluate the true potential of the effect of resolution on the accuracy of the classifications, more images of varying resolutions are needed. The differences between 10 m, 30 m and 250 m can be seen as being too great to show to what extent resolution plays a part in determining the accuracy of the classification of specific landuse types. Some researchers have suggested using techniques of resampling of a higher resolution to a coarser resolution by using roving windows (Chen *et al.,* 2004). These techniques were considered for this study but were not used. Because this study aimed at focusing on the original image resolution for each of the images; by resampling, a pseudo-resolution is created and may not accurately portray the actual reflectance values for the specific classes.

2. Temporal

In order to allow for correct comparison of the classification techniques, it is best to obtain images from similar time periods. The SPOT 5 image, for example, was acquired during a very long dry period and so the Water class was not correctly represented. Albert Falls as an example was at its lowest levels in recent history, thus it exposed the river bed of the dam to the elements. This confused the classification as the bed had a similar spectral signature to the Urban class. Nevertheless, the SPOT 5 image did accurately classify other classes used within the study and so accomplished what was needed to be done to achieve the aims and objectives.

TECHNIQUES

1. Ground Truthing

Although 60 ground control points were collected, more points were needed to be used for the accuracy evaluation. For creating an error matrix that correctly represents the final classification accuracy, 22 points do not seem sufficient.

For the coarser imagery more ground control points could increase the accuracy of the image classification. There were occasions during the training site selection when the landcover class was unclear due to the pixel sizes being too large for accurate representations of the classes.

Regardless of the number of ground truthing points used, adequate results were obtained for the various classifications completed. The results portrayed the effect of the number of classes on the accuracy of the classified image, as well as the effect of resolution on these classifications.

2. Neural Network

The neural network performed extremely well, although it may have suffered the limitation of too few points from which it could evaluate its own performance. As with the limitations stated with the ground truthing, more ground control points could be used to create more training sites from which classifications can be made. The study does, however, show that the neural network does outperform the traditional classifier and thus can be used to improve on the accuracies obtained from the traditional classifiers by including ancillary data for the classification. Care was also taken through experiments to select the optimal neural network parameters, therefore also to increase the efficiency or alternatively to avoid overfitting in the model.

6.2.2 Recommendations

As has been stated, there were limitations to this study, both in the imagery and in the techniques adopted for the study. Some recommendations are discussed to aid in progressing this study to a more scientifically sound conclusion.

1. Images

The differences between the spatial and spectral resolutions of the imagery used can be seen as being too large. Thus, more images need to be used to help make these differences smaller. The ASTER sensor has a resolution of 15 m (Stefanov and Netzband, 2005) and this image can be used between the Landsat TM and the SPOT 5 image. The

Landsat MSS has a resolution of 60 m / 80 m and thus can be used between the Landsat TM and the MODIS images.

2. Techniques

More ground control points are needed to allow for more training sites and points for the error calculations. The coarser the image is the more ground truthing and ground control points are needed to allow features that are not easily identified to be correctly identified.

6.3 CONCLUDING REMARKS

Researchers whose work has been reviewed in the literature rarely advocate the use of the the maximum likelihood classifier alone. There are usually different techniques applied in conjunction with these techniques to improve the accuracy of the images (Yang and Liu, 2005). The present study aimed not to improve the techniques themselves but to evaluate to what extent the resolutions of the different available imagery and the class numbers of the classification play a role in effecting the final out comes of the classification.

This aim was achieved, and the study showed that the lower the resolution of the image is the less accurate the classification algorithm is at detecting differences between the classes required. In itself, the number of classes within the classification can affect the outcome of the classification: by having too many small classes within the classification and too large a pixel size within the imagery, the less accurate the final classification will be.

If improvements to a classification are needed, a neural network is most likely going to provide a more accurate classification when compared to the traditional classifiers. This study demonstrates the power of a neural network to increase the classification accuracy of an image by almost 18%.

In conclusion, this study demonstrates the importance of determining what is needed to be identified in the final product of the classification when choosing an image to use for the classification. Smaller features require high spatial resolutions, whilst the larger features can be identified with lower resolution images. By choosing the correct resolutions, it is possible to avoid costly mistakes of using images that may cost more than those that would give similar results but cost less or are even free.

Neural networks provide a method to increase the accuracy of an image, provided the correct parameters are used and the network is designed correctly. This can be a time-consuming process, and a traditional classifier may be better if time constraints are a problem. Otherwise based on finding of this study, neural networks produce more accurate results.

Chapter 7. REFERENCES

Akbari, M., Mamanpoush, A. R., Gieske, A., Miranzadeh, M., Torabi, M. & Salemi, H. R. (2006) Crop and land cover classification in Iran using Landsat 7 imagery. *International Journal of Remote Sensing,* 27, 4117 - 4135.

Anderson, J. R., Hardy, E. E., Roach, J. T. & Witmer, R. E. (1976) A land use and land cover classification system for the use with remote sensor data. In Usgs (Ed.), Professional Paper 964.

√Atkinson, P. M. (1997) Selecting the spatial resolution of airborne MSS imagery for small-scale agricultural mapping. *International Journal of Remote Sensing,* 18, 1903 - 1917.

Bannari, A., Pacheco, A., Staenz, K., Mcnaim, H. & Omari, K. (2006) Estimating and mapping crop residues cover on agricultural lands using hyperspectral and IKONOS data. *Remote Sensing of Environment,* 104, 447 - 459.

Belluco, E., Camuffo, M., Ferrari, S., Modenese, L., Silvestri, S., Marani, A. & Marani, M. (2006) Mapping salt-marsh vegetation by multispectral and hyperspectral remote sensing. *Remote Sensing of Environment,* 105, 54 - 67.

Beyer, H. L. (2004) *Hawth's Analysis Tools for ArcGIS.* Available at http://www.spatialecology.com/htools.

Bian, L. (1997) Multiscale nature of spatial data in scaling environmental models. In Quattrochi, D.A. & Goodchild, M. F. (Eds) *Scale in remote sensing and GIS.* New York, CRC Press, Inc.

Bolstad, P. V. & Lillesand, T. M. (1992) Improved classification of forest vegetation in northern Wisconsin through a rule-based combination of soils, terrain and Landsat Thematic Mapper data. *Forest Science,* 38, 5 - 20.

Brovkin, V., Sitch, S., Von Bloh, W., Claussen, M., Bauer, E. & Cramer, W. (2004) Role of land cover changes for atmospheric CO_2 increase and climate change for the last 150 years. *Global Change Biology,* 10, 1253 - 1266.

Cao, C. & Lam, N. S.-L. (1997) Understanding the scale and resolution effects in remote sensing and GIS. In Quattrochi, D. A. & Goodchild, M. F. (Eds.) *Scale in Remote Sensing and GIS.* New York, CRC Press, Inc.

Chen, D., Stow, D. A. & P., G. (2004) Examining the effect of spatial resolution and texture window size on classification accuracy: an urban environment case. *International Journal of Remote Sensing,* 25, 2177 - 2192.

√Cihlar, J. (2000) Land cover mapping of large areas from satellite: status and research priorities. *International Journal of Remote Sensing,* 21, 1093 - 1114.

Clark Labs, (2000) IDRISI Andes Help System. *Clark Labs, IDRISI Andes.* Clark University, Worcester, USA.

Claudio, H., Cheng, Y., Fuentes, D. A., Gamon, J. A., Luo, H., Oechel, W., Qiu, H.-L., Rahman, A. F. & Sims, D. A. (2006) Monitoring drought effects on vegetation water content and fluxes in chaparral with the 970 nm water band index. *Remote Sensing of Environment,* 103, 304 - 311.

Csir (2002) The SADC Regional Land Cover Database Project- Project Description *Available at http://www.csir.co.za/plsql/ptl0002/PTL0002_PGE100_LOOSE_CONTENT?LOOSE_PAGE_NO=7020305.*

Dungan, J., Johnson, L., Billow, C., Matson, P., Mazzurco, J., Moen, J. & Vanderbilt, V. (1996) High Spectral Resolution Reflectance Douglas Fir Grown under Different Fertilization Treatments: Experiment and Treatment Effects of Design. *Remote Sensing of Environment,* 55, 17 - 228.

Fairbanks, D. H. K. (2004) Regional land-use impacts affecting avian richness patterns in Southern Africa-insights from historical avian atlas data. *Agriculture, Ecosystems and Environment,* 101, 269 - 288.

Foody, G. M. (2002) Status of land cover classification accuracy assessment. *Remote Sensing of Environment,* 80, 185 - 201.

Foody, G. M. (2004) Supervised image classification by MLP and RBF neural networks with and without exhaustively defined set of classes
International Journal of Remote Sensing, 25, 3091 - 3104.

Foody, G. M. & Arora, M. K. (1997) An evaluation of some factors affecting the accuracy of classification by artificial neural network. *International Journal of Remote Sensing,* 18, 799 - 810.

Franklin, S. E. & Wulder, M. A. (2002) Remote sensing methods in medium spatial resolution satellite data land cover classification of large areas. *Progress in Physical Geography,* 26, 173 - 205.

GAEA Projects (2002) Phase One: Part 3 - -Analysis Report, Report 7: Environmental Planning. uMgungundlovu IDP, 10 December.

Johnson, I. (2005) What should be done the Kyoto Protocol. http://www.thejakartapost.com <Accessed on 18/02/2005>.

Ju, J., Gopal, S. & Kolaczyk, E. D. (2005) On the choice of spatial and categorical scale in remote sensing land cover classification. *Remote Sensing of Environment,* 96, 62 - 77.

Kavzoglu, T. & Mather, P. M. (2003) The use of backpropogating artificial neural networks in land cover classification. *International Journal of Remote Sensing,* 24, 4907 - 4938.

Korontzia, S., Roya, D. P., Justicea, C. O. & Ward, D. E. (2004) Modelling and sensitivity analysis of fire emissions in southern Africa during SAFARI 2000. *Remote Sensing of Environment,* 92, 255 - 275.

Leica Geosystems, (2003) *ERDAS Imagine Tourguides,* Atlanta, Georgia, GIS and Mapping.

le Toan, T., Quegan, S., Woodward, I., Lomas, M., Delbart, N. & Picard, G. (2004) Relating RADAR remote sensing of biomass to modelling of forest Carbon budgets. *Climatic Change,* 67, 379 - 402.

Lillesand, T. M., Kiefer, R. W. & Chipman, J. W. (2004) *Remote Sensing and Image Interpretation (5th Ed.).* , New York, John Wiley and Sons, Inc. .

Linderman, M., Liu, J., Qi, J., An, L., Ouyang, Z., Yang, J. & Tan, Y. (2004) Using artficial neural networks to map spatial distribution of understory bamboo from remote sensing data. *International Journal of Remote Sensing,* 25, 1685 - 1700.

Markham, B. L. & Townshend, J.R.G. (1981) Land cover classification accuracy as a function of sensor spatial resolution. *International Symposium on Remote Sensing of Environment, 15th*, Ann Arbor, MI, USA, 1075 - 1090.

McCabe, M. F. & Wood, E. F. (2006) Scale influences on the remote estimation of evapotranspiration using multiple satellite sensors. *Remote Sensing of Environment,* 105, 271–285.

Munyati, C. (2000) Wetland change detection on the Kafue Flats, Zambia, by classification of a multitemporal remote sensing image dataset. *International Journal of Remote Sensing,* 21, 1787 – 1806.

Murphy, C. S., Raju, P. V. & Badrinath, K. V. S. (2003) Classification of wheat crop with multi-temporal images: performance of maximum likelihood and artificial neural networks. *International Journal of Remote Sensing,* 24, 4871 - 4890.

Mutanga O. & Rugege, D. (2006) Integrating remote sensing and spatial statistics to modle herbaceous biomass distribution in a tropical savanna. *International Journal of Remote Sensing*, 27, 3499 - 3514.

Mutanga, O. & Skidmore, A. K. (2004) Integrating imaging spectroscopy and neural networks to map grass quality in the Kruger National Park, South Africa. *Remote Sensing of Environment,* 90, 104 - 115.

Nabuurs, G. J., Dolman, A. J., Verkaik, P. J., Van Diepen, C. A., Whitmore, A. P., Daamen, W. P., Oenema, O., Kabat, P. & Mohren, G. M. J. (2000) Article 3.3 and 3.4 of the Kyoto Protocol: consequences for industrialised countries' commitment, the monitoring needs, and the possible side effects. *Environmental Science and Policy,* 3, 123 - 134.

Omasa, K., Qiu, G.-Y., Watanuki, K., Yoshimi, K. & Akiyama, Y. (2003) Accurate estimation of froest Carbon stocks by 3-D remote sensing individual trees. *Environmental Science and Technology,* 37, 1198-1201.

Paola, J. D. & Schowengerdt, R. A. (1995) Review Article: A review and analysis of backpropagation neural networks for classification of remotely-sensed multi-spectral imagery. *International Journal of Remote Sensing,* 16, 3033 - 3058.

Pasqaulini, V., Pergent-Martini, C., Pergent, G., Agreil, M., Skoufas, G., Sourbes, L. & Tsirika, A. (2005) Use of SPOT 5 for mapping seagrasses: An application to Posidonia oceanica. *Remote Sensing of Environment,* 94, 39 - 45.

Pearce, F. (2005) European trading in Carbon-emission permits begins. http://www.newscientist.com/article.ns?id=dn6846 <Accessed on 30/01/2005>.

Potter, C., Klooster, S., Myneni, R., Genovese, V., Tan, P.-N. & Kumar, V. (2003) Continental-scale comparisons of terrestrial carbon sinks estimates from satellite data and ecosystem modeling 1982-1998. *Global and Planetary Change,* 39, 201-213.

Powell, R. L., Matzke, N., De Souza Jr., C., Clark, M., Numata, I., Hess, L. L. & Roberts, D. A. (2004) Sources of error in accuracy assessment of thematic land-cover maps in the Brazilian Amazon. *Remote Sensing of Environment,* 90, 221 - 234.

Price, J. C. (2003) Comparing MODIS and ETM+ data for regional and global land classification. *Remote Sensing of Environment,* 86, 491 - 499.

Qiu, F. & Jensen, J. R. (2004) Opening the black box o neural networks for remote sensing image classification. *Internation Journal of Remote Sensing,* 25, 1749 - 1768.

Quattrochi, D. A. & Goodchild, M. F. (1997) Introduction: Scale, Multiscaling, Remote Sensing, and GIS. In Quattrochi, D. A. & Goodchild, M. F. (Eds.) *Scale in Remote Sensing and GIS.* New York, CRC Press, Inc.

Robertson, T. (1998) *Greenpeace: Guide to the Kyoto Protocol,* Amsterdam, Greenpeace International.

Rwetabula, J. & De Smedt, D. E. (2005) Landuse and Land Cover Mapping of the Simiyu Catchment (Tanzania) Using Remote Sensing Techniques. *Pharaohs to Geoinformantics.* Cairo, Egypt.

Sabins, F. (1997) *Remote sensing: Principles and interpretation (3rd Ed.).*W.H. Freeman and Company, USA.

Shoshany, M. (2000) Satellite remote sensing of natural Mediterranean vegetation: a review within an ecological context. *Progress in Physical Geography,* 24, 153 - 178.

Skidmore, A.K., Turner, B.J., Brinkhof, W. & Knowles, E. (1997) Performance of a neural network: Mapping forests using GIS and remotely sensed data. *Photogrammetric Engineering and Remote Sensing,* 63, 5, 501 - 514.

Small, C. (2004) The Landsat ETM+ spectral mixing space. *Remote Sensing of Environment,* 9., 1 - 17.

Song, M., Civco, D. L. & Hurd, J. D. (2005) A competitive pixel-object approach for land cover classification. *International Journal of Remote Sensing,* 22, 4981 - 4997.

Stefanov, W. & Netzband, M. (2005) Assessment of ASTER land cover and MODIS NDVI data at multiple scales for ecological characterization of an arid urban centre *Remote Sensing of Environment,* 99, 31 - 43.

Stuart, N., Barratt, T. & Place, C. (2006) Classifying the Neotropical savannas of Belize using remote sensing and ground survey. *Journal of Biogeography,* 33, 476 - 490.

Sunar Erbek, F., Ozkan, C. & Taberner, M. (2004) Comparison of maximum likelihhod classification method with supervised artificial neural network algorithms for land use activities. *International Journal of Remote Sensing,* 25, 1733 - 1748.

Xiao, X., Boles, S., Frolking, S., Salas, W., Moore Iii, B., Li, C., He, L. & Zhao, R. (2002) Landscape-scale characterization of cropland in China using Vegetation and Landsat TM images. *International Journal of Remote Sensing,* 23, 3579 - 3594.

Yang, X. & Liu, Z. (2005) Using satellite imagery and GIS for land-use and land-cover change maping in an estuarine environment. *International Journal of Remote Sensing,* 23, 5275 - 5296.

Yang, X. & Lo, C. P. (2002) Using a time series of satellite imagery to detect land use and land cover changes in the Atlanta, Georgia metropolitan area. *International Journal of Remote Sensing,* 23, 1775 - 1798.

Yool, S. R. (1998) Land cover classification in rugged areas using simulated moderate-resolution remote sensor data and an artificial neural network. *International Journal of Remote Sensing,* 19, 85 - 96.

Yuan, F., Sawaya, K. E., Loeffelholz, B. C. & Bauer, M. E. (2005) Land cover classification and change analysis of the Twin Cities (Minnesota) Metropolitan Area by multitemporal Landsat remote sensing. *Remote Sensing of Environment,* 98, 317 - 328.

Chapter 8. APPENDIX

Appendix 1

The following pages will display some of error matrices used for the study.

Tables:

1. SPOT 5 Error Matrix - Minimum Distance to Means with Fine Classes
2. SPOT with NDVI Error Matrix - Maximum Likelihood, with Broad Classes
3. Landsat TM with NDVI Error Matrix - Maximum Likelihood, with Fine Classes
4. Landsat TM without NDVI Error Matrix - Minimum Distance to Means, with Fine Classes
5. Landsat TM with NDVI - Maximum Likelihood, with Broad Classes
6. MODIS - Maximum Likelihood, with Fine Classes
7. MODIS - Maximum Likelihood, with Broad Classes

Table 1: SPOT 5 Error Matrix - Minimum Distance to Means with Fine Classes

Classified Data	Unclass.	Agric	Bush	Cane	Grass	Gum	Pine	Urban	Wattle	Woodland	Water	Wetland	Row Total	User's Accuracy
Unclass.	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Agric	0	1	0	0	1	0	0	0	0	0	0	0	2	50.00%
Bush	0	0	2	0	1	0	0	0	0	0	0	1	4	50.00%
Cane	0	0	0	1	0	0	0	0	0	1	1	0	3	33.33%
Grass	0	1	0	0	0	0	0	0	0	0	0	0	1	0.00%
Gum	0	0	0	0	0	1	0	0	0	0	0	0	1	100.00%
Pine	0	0	1	0	0	1	1	0	0	0	0	0	3	33.33%
Urban	0	0	0	0	0	0	0	1	0	0	0	0	1	100.00%
Wattle	0	0	0	0	0	0	0	0	1	0	0	0	1	100.00%
Woodland	0	0	1	0	0	0	1	0	0	0	0	0	2	0.00%
Water	0	0	0	0	0	0	0	0	0	0	4	0	4	100.00%
Wetland	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Column Total	0	2	4	1	2	2	2	1	1	1	5	1	22	
Producer's Accuracy	0.00%	50.00%	50.00%	100.00%	0.00%	50.00%	50.00%	100.00%	100.00%	0.00%	80.00%	0.00%		

Overall Classification Accuracy = 54.55%

Overall Kappa Statistics = 0.4848

Table 2: SPOT with NDVI Band5 Error Matrix - Maximum Likelihood, with Broad Classes

Classified Data	Unclass	Grass	Agric	Plantation	Bush	Cane	Urban	Water	Woodland	Row Total	User's Accuracy
Unclass	0	0	0	0	0	0	0	0	0	0	0.00%
Grass	0	1	0	0	0	0	0	0	1	2	50.00%
Agric	0	0	0	0	0	0	0	0	0	0	0.00%
Plantation	0	0	0	4	2	0	0	0	0	6	66.67%
Bush	0	2	1	0	1	0	0	0	0	4	25.00%
Cane	0	0	0	0	0	1	0	1	0	2	50.00%
Urban	0	0	1	0	0	0	1	0	0	2	50.00%
Water	0	0	0	0	0	0	0	4	0	4	100.00%
Woodland	0	0	0	0	2	0	0	0	0	2	0.00%
Column Total	0	3	2	4	5	1	1	5	1	22	
Producer's Accuracy	0.00%	33.33%	0.00%	100.00%	20.00%	100.00%	100.00%	80.00%	0.00%		

Overall Classification Accuracy = 54.55%
Overall Kappa Statistics = 0.4608

Table 3: Landsat TM with NDVI Error Matrix - Maximum Likelihood, with Fine Classes

Classified Data	Unclass	Agric	Wetland	Cane	Bush	Pine	Wattle	Urban	Gum	Water	Woodland	Grass	Row Total	User's Accuracy
Unclass	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Agric	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Wetland	1	1	0	0	1	0	0	0	0	0	0	0	3	0.00%
Cane	0	0	0	1	0	0	0	0	0	0	0	0	1	100.00%
Bush	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Pine	0	0	0	0	0	1	0	0	0	0	0	0	1	100.00%
Wattle	0	0	0	0	0	0	1	0	1	0	0	0	2	50.00%
Urban	0	0	0	0	0	0	0	1	0	0	0	0	1	100.00%
Gum	0	0	0	0	1	0	0	0	1	0	0	0	2	50.00%
Water	0	0	0	0	0	0	0	0	0	5	0	0	5	100.00%
Woodland	0	0	1	0	0	0	0	0	0	0	0	0	1	0.00%
Grass	0	1	0	0	2	0	0	0	0	0	1	2	6	33.33%
Column Total	1	2	1	1	4	1	1	1	2	5	1	2	22	
Producer's Accuracy	0.00%	0.00%	0.00%	100.00%	0.00%	100.00%	100.00%	100.00%	50.00%	100.00%	0.00%	100.00%		

Overall Classification Accuracy = 54.55%
Overall Kappa Statistics = 0.4931

Table 4: Landsat TM without NDVI Error Matrix - Minimum Distance to Means, with Fine Classes

Cl;assified Data	Unclass	Agric	Bush	Cane	Gum	Urban	Wattle	Wetland	Woodland	Grass	Pine	Water		
Unclass	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Agric	0	0	3	0	0	0	0	0	0	0	0	0	3	0.00%
Bush	0	0	1	0	1	0	0	0	0	0	0	0	2	50.00%
Cane	0	1	1	0	0	0	0	0	0	0	0	0	2	0.00%
Gum	0	0	0	0	1	0	0	0	0	0	0	0	1	100.00%
Urban	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Wattle	0	0	0	1	0	0	1	0	0	0	0	0	2	50.00%
Wetland	0	0	0	0	0	0	0	0	1	0	0	0	1	0.00%
Woodland	0	1	0	0	0	1	0	1	0	0	0	0	3	0.00%
Grass	0	0	0	0	0	0	0	0	0	2	0	0	2	100.00%
Pine	0	0	0	0	0	0	0	0	0	0	1	0	1	100.00%
Water	0	0	0	0	0	0	0	0	0	0	0	5	5	100.00%
Column Total	0	2	5	1	2	1	1	1	1	2	1	5	22	
		0.00%	20.00%	0.00%	50.00%	100.00%	0.00%	0.00%	0.00%	100.00%	100.00%	100.00%		

Overall Classification Accuracy = 50.00%

Overall Kappa Statistics = 0.4346

Table 5: Landsat TM with NDVI - Maximum Likelihood, with Broad Classes

Classified Data	Unclass	Grassland	Plantation	Agric	Cane	Bush	Urban	Water	Woodland	Row Total	User's Accuracy
Unclass	0	0	0	0	0	0	0	0	0	0	
Grassland	0	3	0	2	0	4	0	0	1	10	30.00%
Plantation	0	0	4	0	0	1	0	0	0	5	80.00%
Agric	0	0	0	0	0	0	0	0	0	0	0.00%
Cane	0	0	0	0	1	0	0	0	0	1	100.00%
Bush	0	0	0	0	0	0	0	0	0	0	0.00%
Urban	0	0	0	0	0	0	1	0	0	1	100.00%
Water	0	0	0	0	0	0	0	5	0	5	100.00%
Woodland	0	0	0	0	0	0	0	0	0	0	0.00%
Column Total	0	3	4	2	1	5	1	5	1	22	
Producer's Accuracy	0.00%	100.00%	100.00%	0.00%	100.00%	0.00%	100.00%	100.00%	0.00%		

Overall Classification Accuracy = 63.64%
Overall Kappa Statistics = 0.5676

Table 6: MODIS - Maximum Likelihood, with Fine Classes

Classified Data	Unclass	Wattle	Agric	Bush	Pine	Cane	Gum	Urban	Wetland	Grass	Woodland	Water	Row Total	User's Accuracy
Unclass	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Wattle	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Agric	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Bush	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Pine	0	0	0	0	1	0	0	0	0	0	0	0	1	100.00%
Cane	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Gum	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Urban	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Wetland	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Grass	0	1	2	5	0	1	2	1	1	2	1	1	17	11.76%
Woodland	0	0	0	0	0	0	0	0	0	0	0	0	0	0.00%
Water	0	0	0	0	0	0	0	0	0	0	0	4	4	100.00%
Column Total	0	1	2	5	1	1	2	1	1	2	1	5	22	
Producer's Accuracy	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	100.00%	0.00%	80.00%		

Overall Classification Accuracy = 31.82%
Overall Kappa Statistics = 0.2308

Table 7: MODIS - Maximum Likelihood, with Broad Classes

Classified Data	Unclass	Grass	Agric	Plantation	Bush	Cane	Urban	Woodland	Water	Row Total	User's Accuracy
Unclass	0	0	0	0	0	0	0	0	0	0	0.00%
Grass	0	2	1	0	2	1	1	0	0	7	28.57%
Agric	0	0	0	0	0	0	0	0	0	0	0.00%
Plantation	0	1	1	4	3	0	0	1	1	11	36.36%
Bush	0	0	0	0	0	0	0	0	0	0	0.00%
Cane	0	0	0	0	0	0	0	0	0	0	0.00%
Urban	0	0	0	0	0	0	0	0	0	0	0.00%
Woodland	0	0	0	0	0	0	0	0	0	0	0.00%
Water	0	0	0	0	0	0	0	0	4	4	100.00%
Column Total	0	3	2	4	5	1	1	1	5	22	
Producer's Accuracy	0.00%	66.67%	0.00%	100.00%	0.00%	0.00%	0.00%	0.00%	80.00%		

Overall Classification Accuracy = 45.45%

Overall Kappa Statistics = 0.3383

Appendix II

The following section will display some of the classified maps created for the study.

Figures:

1. SPOT 5 11 classes vs. 8 classes classification – Parallel Piped Classifier
2. Landsat TM NDVI vs. No NDVI classification – Parallel Piped Classifier
3. MODIS 11 classes vs. 8 classes classification – Parallel Piped Classifier

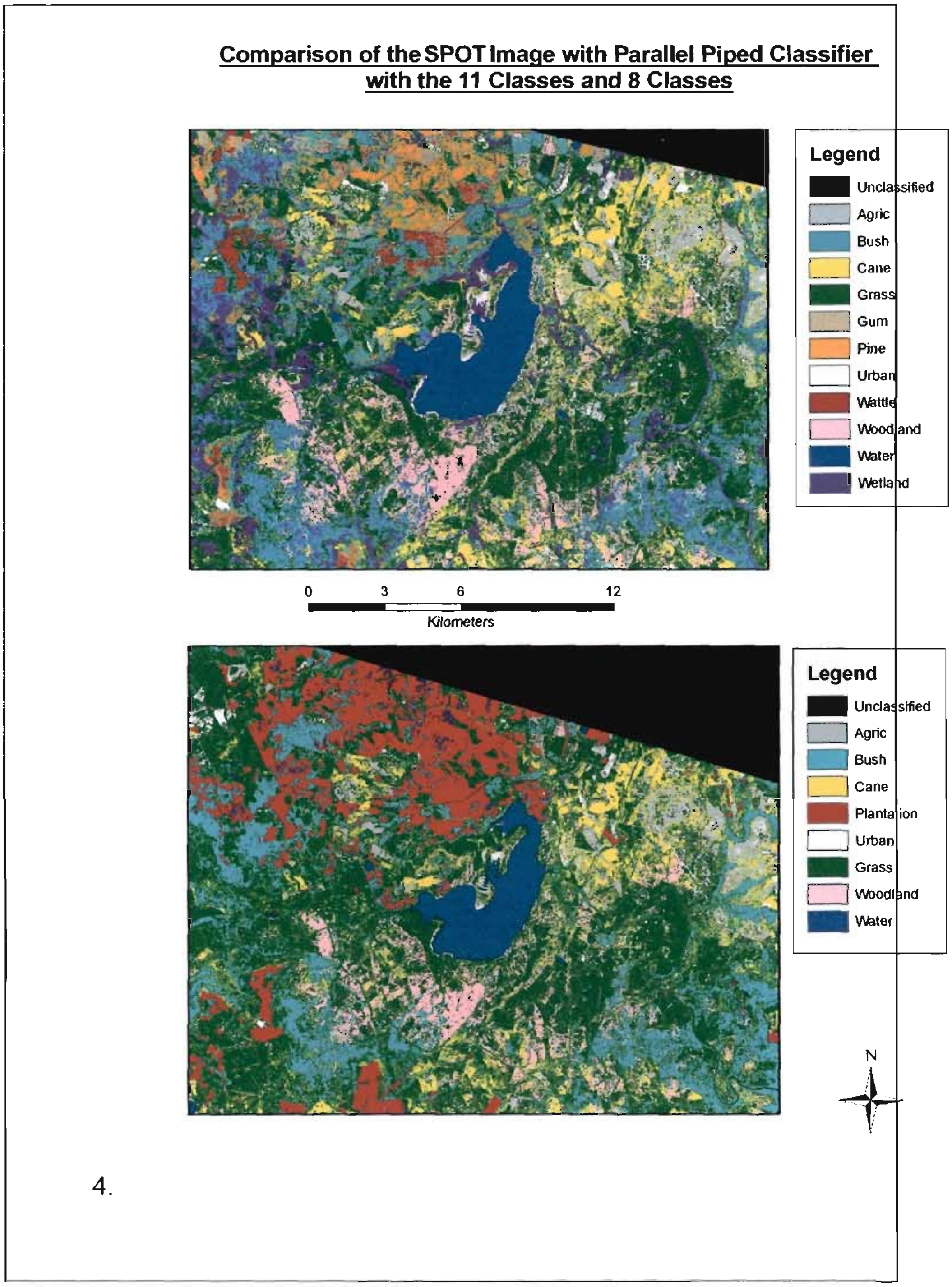

Figure 1: SPOT 5 Parallel Piped, (A) 11 Classes vs. (B) 8 Classes Classification

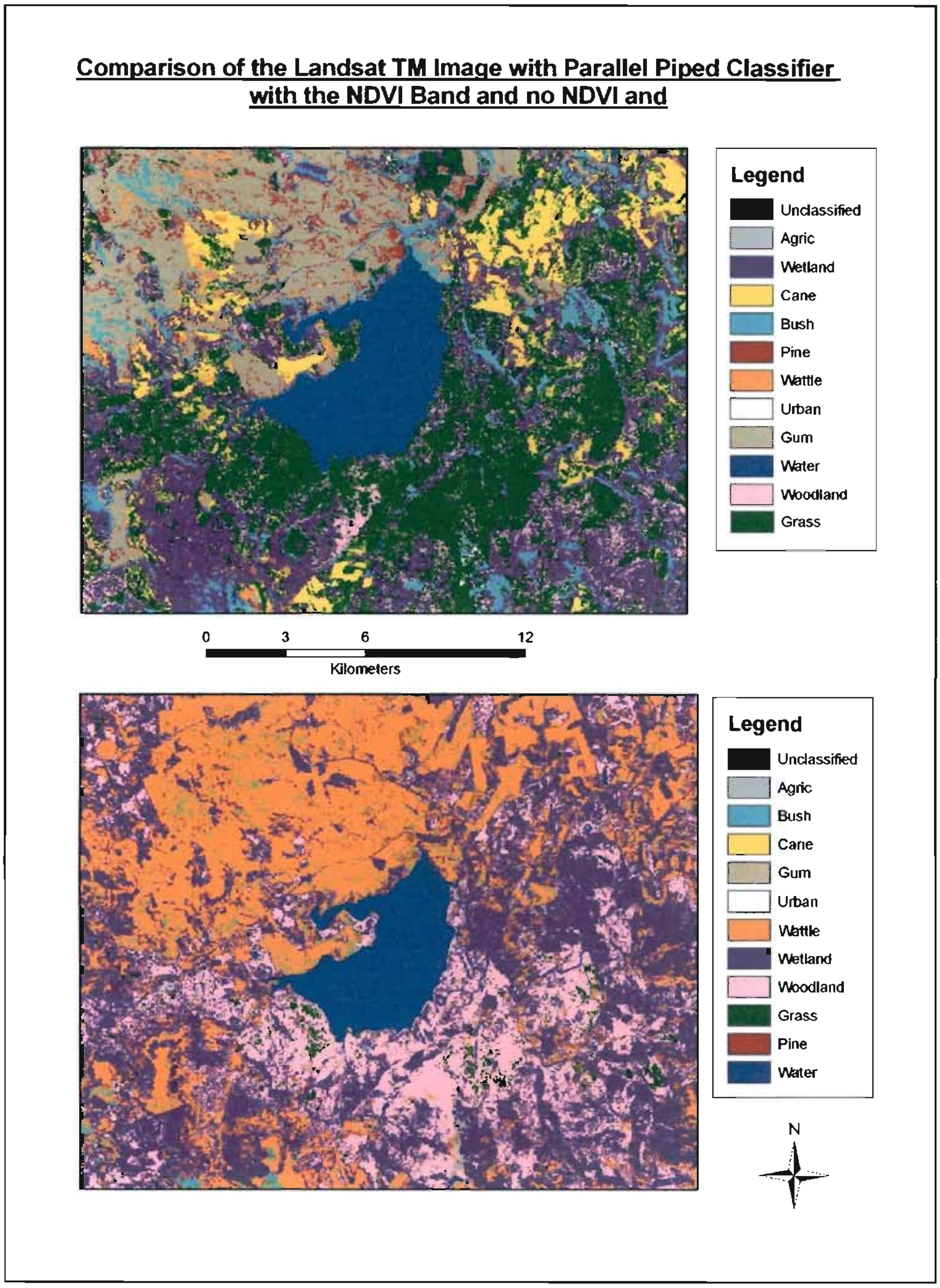

Figure 2: Landsat Parallel Piped, (A) NDVI vs. (B) No NDVI Band Classification

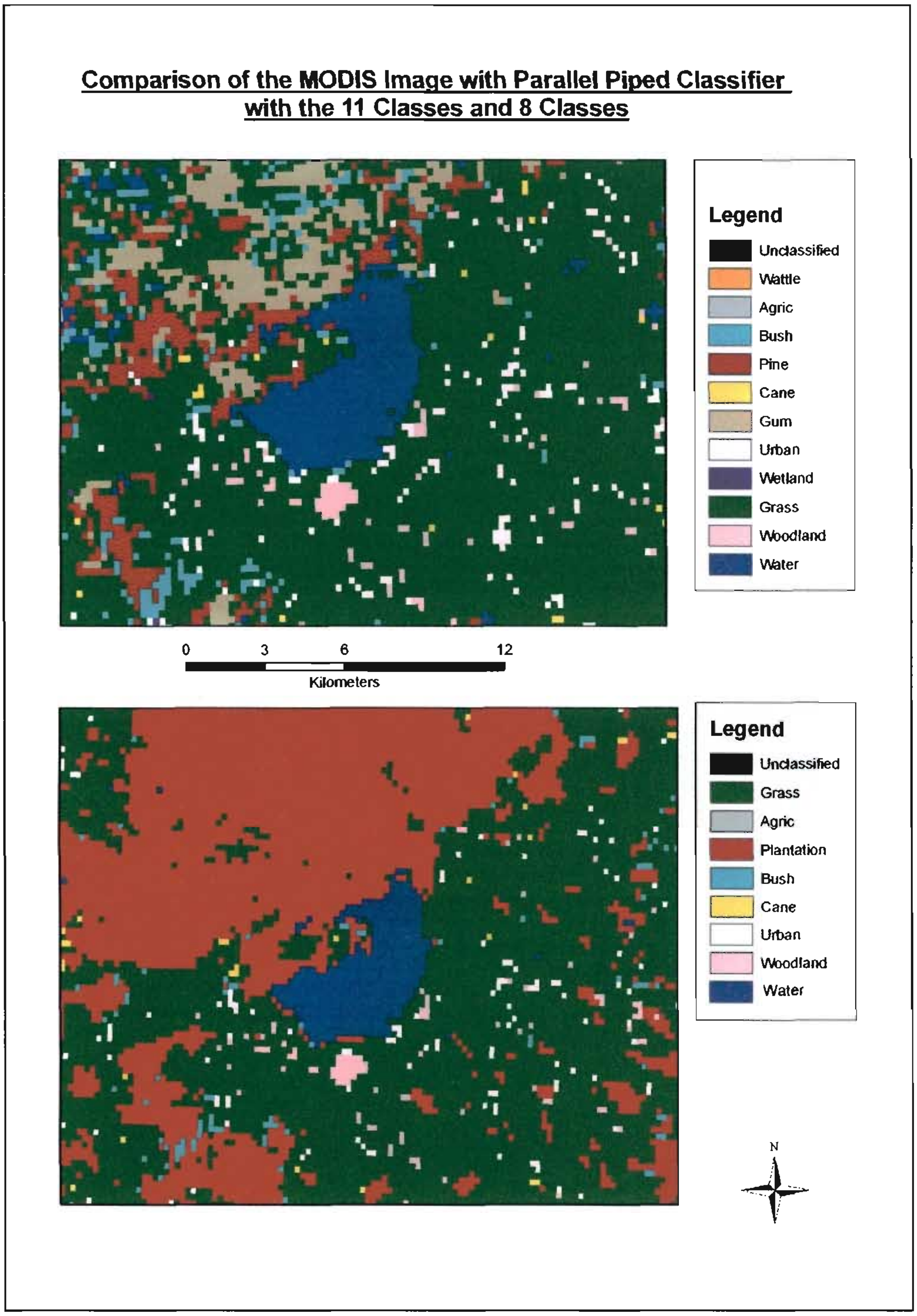

Figure 3: MODIS Parallel Piped, (A) 11 Classes vs. (B) 8 Classes Classification