

**A COMPARISON OF SUPERVISED AND RULE-BASED OBJECT-
ORIENTATED CLASSIFICATION FOR FOREST MAPPING**

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DECLARATION

By submitting this thesis electronically, I declare that the entirety of the work contained therein is my own work, that I am the authorship thereof (unless to the extent explicitly otherwise stated) and that I have not previously in its entirety or in part submitted it for obtaining any qualification.

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SUMMARY

Supervised classifiers are the most popular approach for image classification due to their high accuracies, ease of use and strong theoretical grounding. Their primary disadvantage is the high level of user input required during the creation of the data needed to train the classifier. One alternative to supervised classification is an expert-system rule-based approach where expert knowledge is used to create a set of rules which can be applied to multiple images. This research compared supervised and expert-system rule-based approaches for forest mapping. For this purpose two SPOT 5 images were acquired and atmospherically corrected. Field visits, aerial photography, high resolution imagery and expert forestry knowledge were used for the compilation of the training data and the development of a rule-set. Both approaches were evaluated in an object-orientated environment. It was found that the accuracy of the resulting maps was equivalent, with both techniques returning an overall classification accuracy of 90%. This suggests that cost-effectiveness is the decisive factor for determining which method is superior. Although the development of the rule-set was time-consuming and challenging, it did not require any training data. In contrast, the supervised approach required a large number of training areas for each image classified, which was time-consuming and costly. Significantly more training areas will be required when the technique is applied to large areas, especially when multiple images are used. It was concluded that the rule-set is more cost-effective when applied at regional scale, but it is not viable for mapping small areas.

KEY WORDS

Automation, expert system, forest mapping, rule-base classification, SPOT, supervised classification.

OPSOMMING

Gerigte klassifiseerders is die gewildste benadering tot beeldklassifikasie as gevolg van hulle hoë graad van akkuraatheid, maklike aanwending en kragtige teoretiese fundering. Die primêre nadeel van gerigte klassifikasie is die hoë vlak van gebruikersinsette wat benodig word tydens die skepping van opleidingsdata. 'n Alternatief vir gerigte klassifikasie is 'n deskundige stelsel waarin 'n reëlgebaseerde benadering gevolg word om deskundige kennis aan te wend vir die opstel van 'n stel reëls wat op meervoudige beelde toegepas kan word. Hierdie navorsing het gerigte en deskundige stelsel benaderings toegepas vir bosboukartering om die twee benaderings met mekaar te vergelyk. Vir dié doel is twee SPOT 5 beelde verkry en atmosferies gekorrigeer. Veldbesoek, lugfotografie, hoë-resolusie beelde en deskundige bosboukennis is aangewend om opleidingsdata saam te stel en die stel reëls te ontwikkel. Beide benaderings is in 'n objekgeoriënteerde omgewing beoordeel. Die akkuraatheidsvlakke van die resulterende kaarte was ewe hoog vir beide tegnieke met 'n algehele klassifikasie-akkuraatheid van 90%. Dit wil dus voorkom asof koste-effektiwiteit eerder as akkuraatheid die deurslaggewende faktor is om te bepaal watter metode die beste is. Alhoewel die ontwikkeling van die stel reëls tydwend en uitdagend was, het dit geen opleidingsdata vereis nie. In teenstelling hiermee is 'n groot aantal opleidingsgebiede geskep vir elke beeld wat met gerigte klassifikasie verwerk is – 'n tydwende en duur opsie. Dit is duidelik dat meer opleidingsgebiede benodig sal word wanneer die tegniek op groot gebiede toegepas word, veral omdat meervoudige beelde gebruik sal word. Gevolglik sal die stel reëls meer koste-effektief wees wanneer dit op streekskaal toegepas word. 'n Deskundige stelsel benadering is egter nie lewensvatbaar vir die kartering van klein gebiede nie.

TREFWOORDE

Outomatisasie, deskundige stelsel, bosboukartering, reëlgebaseerde klassifikasie, SPOT, gerigte klassifikasie

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ACRONYMS AND ABBREVIATIONS

AFRI	Aerosol free vegetation index
ARVI	Atmospheric-resistant vegetation index
AI	Artificial intelligence
ANN	Artificial neural network
ASTER	Advanced spaceborne thermal emission and reflection radiometer
ATCOR	Atmospheric and topographic correction
AVHRR	Advanced very high resolution radiometer
CART	Classification and regression tree
CDSM	Chief Director of Surveys and Mapping
CSIR	Council for Scientific and Industrial Research
DEM	Digital elevation model
DWAF	The Department of Water Affairs and Forestry
DN	Digital number
DT	Decision tree
EM	Electromagnetic
ETM+	Enhanced thematic mapper plus
EVI	Enhanced vegetation index
EVI2	Two-band enhanced vegetation index
GCP	Ground control point
GIS	Geographical information system
GLCM	Grey level co-occurrence matrix
GPS	Global positioning system
IR	Infrared
IRS	Indian remote sensing system
KZN	KwaZulu-Natal
MLC	Maximum likelihood classification
MRS	Multiresolution segmentation
MSAVI	Modified soil-adjusted vegetation index
MODIS	Moderate resolution imaging spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalised difference vegetation index
NFI	National forestry inventory

NIR	Near infrared
PCA	Principle components analysis
PC1	The first principal component
PC2	The second principal component
PC3	The third principal component
RGB	Red, green and blue.
SAC	Satellite Application Centre
SAVI	Soil-adjusted vegetation index
SPOT	Satellite Pour l'Observation de la Terre
SWIR	Short-wave infrared
TM	Thematic mapper
UK	United Kingdom

CHAPTER 1: INTRODUCTION

Spatial information is essential when undertaking any form of environmental decision making and for it to be most effective it must be detailed, up to date and accurate (Apan 1996; Benz *et al.* 2004; De Carvalho *et al.* 2004; Lennartz & Congalton 2004). However, collecting such information manually is almost impossible, particularly at large scales and for large areas (Bock *et al.* 2005; Shiba & Itaya 2006). While the advent of aerial photography and satellite imagery has allowed the development of desktop classification of land-cover over much larger areas and in much higher detail than could previously be accomplished, these techniques are not without their disadvantages. High-resolution remotely sensed imagery is expensive (Lennartz & Congalton 2004), computationally demanding (Hay, Niemann & Goodenough 1997) and requires specialised training to use effectively (De Carvalho *et al.* 2004; Gegg, Günther & Riekert 1990; Inglada 2007). This is particularly relevant when an increase in classification accuracy is usually accompanied by an increase in reference data quality, classification method complexity and required image resolution (Blaschke *et al.* 2000; Mather 2004; Moller-Jensen 1997).

1.1 Supervised classification versus rule-set classification

Supervised classification is the most popular digital image classification method for research applications (Brown de Colstoun *et al.* 2003). The attributes favouring its selection over other forms of classification include its strong theoretical base, its ease of use, and its high degree of accuracy. It does, however, suffer a major disadvantage: the expense of identifying and delineating the training areas necessary for the classification procedure. These areas, which are used to ‘train’ the classifier to recognise unknown areas, must be carefully chosen, as the accuracy of the outcome of the classifier is heavily dependent on them. Insufficient, poorly chosen or incorrectly defined training areas will result in lower overall accuracy (Campbell 2006; Mather 2004). In addition, the inherent differences in values among images of different areas often necessitate the reconfiguration of training areas when classifying more than one image (Pax-Lenney *et al.* 2001). This severely limits the degree of classification automation possible over multi-image areas, such as on a regional or national scale.

More recent research has examined classification systems which use a set of expert-informed or autonomously-created rules in logical structures to determine information classes from the different features within remotely-sensed imagery (Brown de Colstoun *et al.* 2003). These rule-based classifiers have two distinct advantages over more conventional methods: the logical,

flexible and transparent manner in which image information is represented within a rule-set; and the modular arrangement of the rule-set, which allows for easy alterations or updates for classifier improvement (Bolstad & Lillesand 1992). The structure of this methodology allows for a more accommodating approach to autonomous classification, where a rule-set can be specifically designed to take into account the inherent differences experienced between images, owing to sensor calibration, time of day of capture, and seasonality.

In addition, both the supervised and rule-set classification approaches have been enhanced by object-orientated methods. Object-orientation image classification involves the delineation and classification of image segments rather than individual pixels, which allows for more meaningful analysis of spectral and textural features. It also introduces the use of geometrical and contextual features, which provide a more intuitive understanding of the relation between image-objects and real-world objects (Benz *et al.* 2004; Bock *et al.* 2005; Hay *et al.* 2005; Mansor, Hong & Shariff 2002; Shiba & Itaya 2006).

1.2 Remote sensing in forestry classification in South Africa

Natural forests, the smallest vegetation unit in South Africa (estimated at 3000km² in size), are difficult to map, as they are both widely distributed and highly fragmented (Geldenhuys & Mucina 2006). However, the efficient management of these natural resources requires constant, up-to-date and accurate inventories on a national scale (Desclée *et al.* 2006). Being responsible for monitoring and managing forests in South Africa, the Department of Water Affairs and Forestry (DWAF) has commissioned several projects to map forests on a regional and national level. The latest project, namely the National Forest Inventory (NFI), was completed in 2002, using supervised classification techniques on Landsat imagery (Wannenburg & Mabena 2002).

Although the NFI provides a good foundation for planning purposes on a national level, its accuracy and scale (1:100 000) are inadequate for monitoring and management on a local level (Van Niekerk 2007). In addition to the low level of detail, the NFI also contains many errors (Mucina *et al.* 2007). Consequently, a more accurate, larger scale (1:10 000) NFI is urgently needed (DWAF 2008). However, to update the NFI using a supervised approach would be prohibitively expensive as it will involve a detailed national survey to collect the required training data. In this regard, an object-orientated rule-based approach may be more cost-effective.

1.3 Overarching aim

The aim of this study is to compare the accuracy and cost-effectiveness of a supervised and rule-based classifier, applied in an object-orientated environment, for mapping forests over large areas.

1.4 Research objectives

To accomplish this aim, the specific research objectives are to:

- 1) Review the relevant literature and related research to better understand the fundamental remote sensing concepts involved;
- 2) Acquire and pre-process the necessary imagery;
- 3) Use a combination of field surveys, recent aerial photography, high-resolution satellite imagery and expert knowledge to develop a reference dataset for rule-set development and training data creation;
- 4) Carry out an object-orientated supervised classification for mapping forests;
- 5) Develop and carry out an object-orientated rule-set classification for mapping forests;
- 6) Compare the accuracies and costs of the two techniques; and
- 7) Interpret the results and make recommendations as to the possible application of each approach for mapping forests over large areas.

1.5 Study area

The techniques were developed and tested in two slightly overlapping 60x60km areas south and north respectively of Richards Bay in the uThungulu Municipal District of KwaZulu-Natal in South Africa, as illustrated in Figure 1.1. The area was chosen for its complexity regarding forest types (i.e. Eastern Scarp Forests, KwaZulu-Natal Coastal Forests, KwaZulu-Natal Dune Forests, Swamp Forests and Mangrove Forests) and other land uses (e.g. agricultural, natural, residential). Natural vegetation accounts for 49.3% of the total land cover in the study area, of which thicket and bushland have the largest proportion (21.4%), followed by unimproved grassland (14.1%) and forest and woodland (13.8%). Agriculture comprises 27.2% of the total land cover, consisting mainly of temporarily semi-commercial or subsistence dryland cultivation (16.6%) and sugarcane (10.9%), the remainder (0.3%) being horticultural crops such as citrus, subtropical fruits and vegetables (KwaZulu-Natal Department of Transport 2008). Other significant land cover types are commercial forestry (10.5%) consisting almost entirely of eucalyptus and pine plantations (Mucina 2008, pers com) and degraded natural vegetation (9.4%). Urban-related land cover is proportionally low (1.2%), with the town of Richards Bay being the commercial and industrial

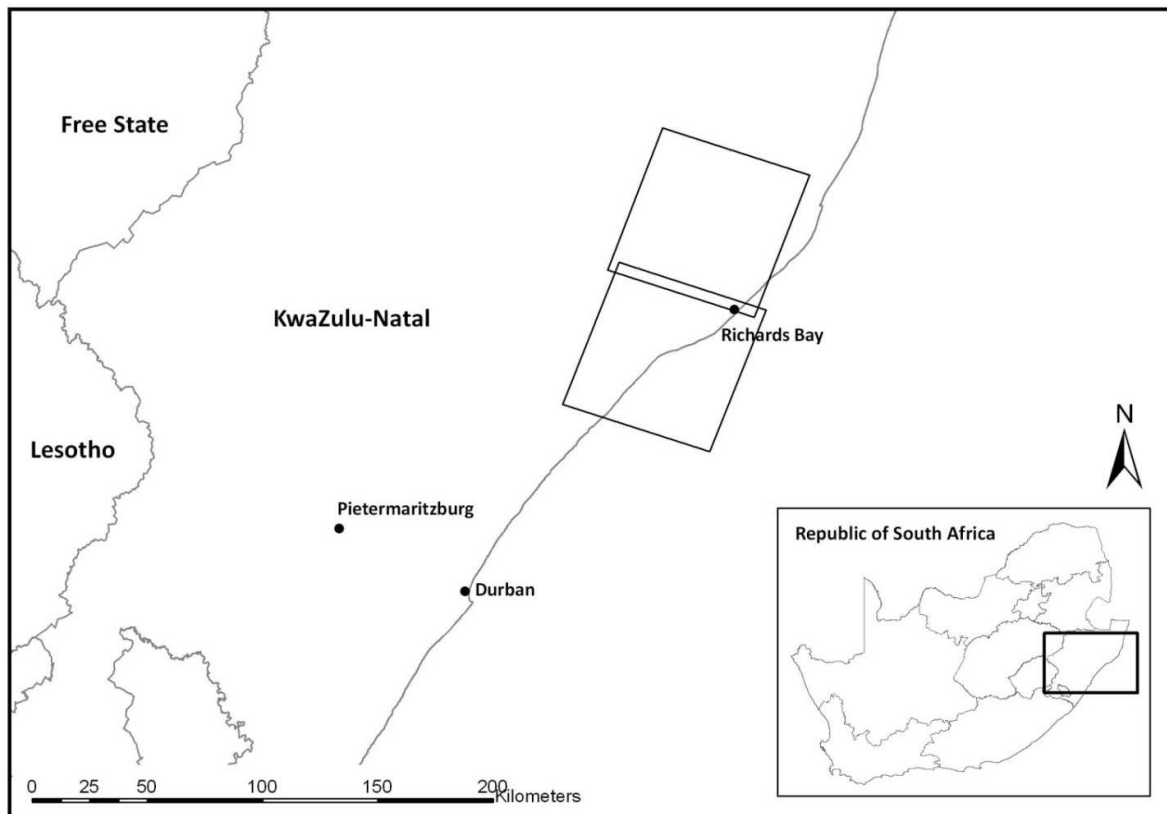


Figure 1.1: Location and extent of the acquired satellite images which demarcate the study area

hub of the area (population 44 852 in 2001). Other notably populated urban areas in the vicinity are Empangeni (population 13 306 in 2001) and the nearby township of Esikhawini (population 32 437 in 2001) (Statistics South Africa 2001). The climate of the area is subtropical, with maximum daily temperatures ranging from 23°C in winter to 29°C in summer. The rainfall average per year is 1228mm (1961-1990) with a concentration during summer (South African Weather Service 2008).

1.6 Research methodology and agenda

The research methodology of a study should be rooted in both the real and everyday world, and in the more abstract world of science and scientific research (Mouton 2004). The relation of this research to the world of scientific enquiry is conceptual: it furthers the knowledge and understanding of the methodologies being tested. The relation of this research to the real world lies in the functional: it applies the conclusions of the research to the undertaking of forestry mapping over a large area. An argument is made that the two classifiers presented, namely a supervised and rule-set classification in an object orientated environment, are the most applicable to the task at hand. The classifiers are then compared in terms of cost-effectiveness and accuracy to determine which should be utilised for national forest mapping.

This research can be categorised as a methodological study, which Mouton (2004:173) describes as a study “...aimed at developing new methods... of data collection and sometimes also validating a newly developed instrument through a pilot study.” Such studies can be non-empirical in nature, deriving conclusions based strongly in established theory. However, while the concepts informing this study were acquired from theory, its conclusions are derived from the evidence of the performance of the compared methodologies, resulting in a distinctly empirical nature. The same precept applies to the nature of the data used: conclusions are based on primary data generated during the course of the study. The specific type of data used is quantitative in nature, comprising numerical, statistical and logical elements, with a high degree of control during methodology comparison.

A layout of the report structure and associated chapters is shown below in Figure 1.2.

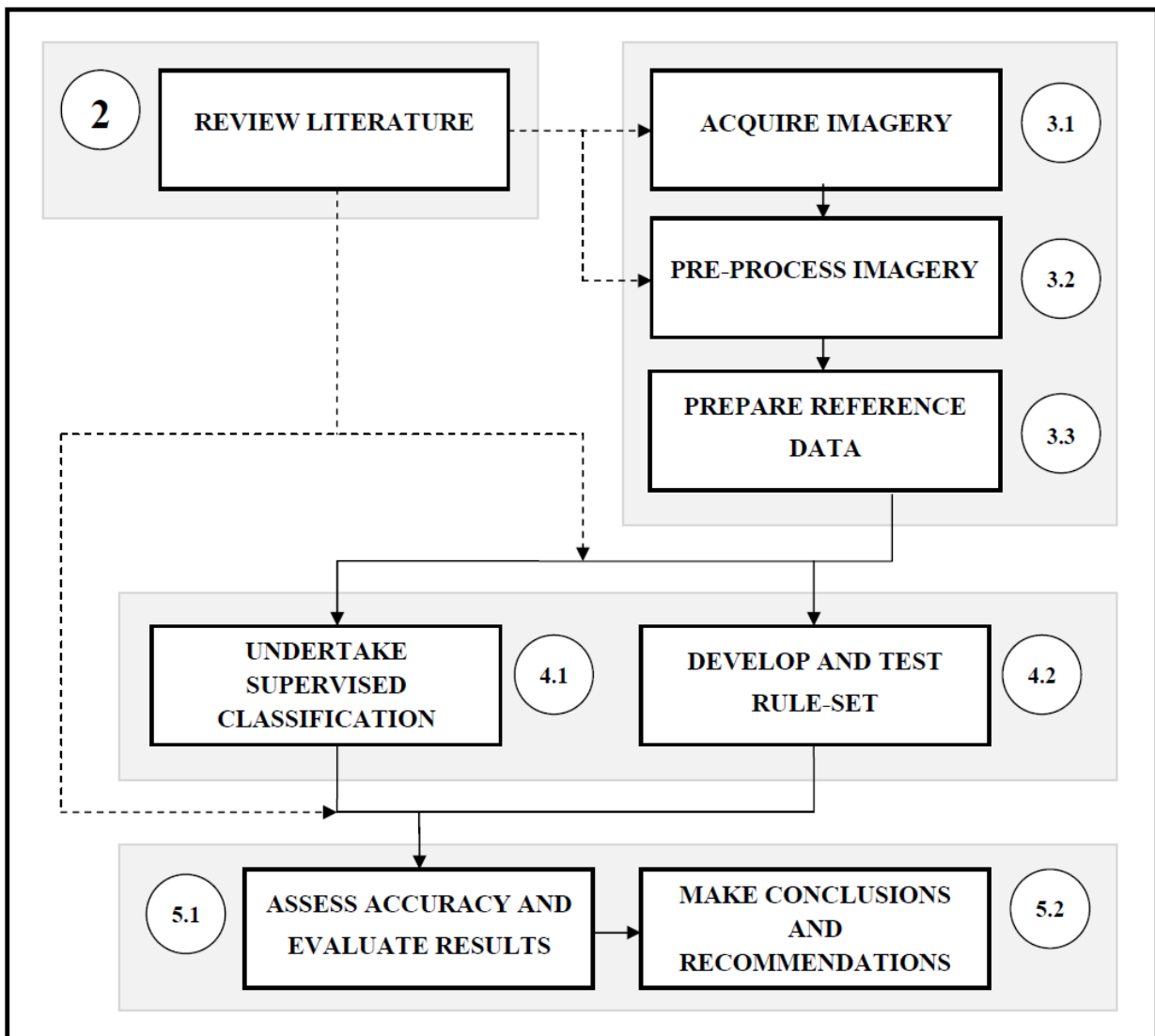


Figure 1.2: Research diagram indicating the chapter structure of the thesis

Chapter 2 provides a comprehensive review of the literature with particular focus on image-classification techniques, object-based classification and segmentation, and image features. The acquisition and pre-processing of the imagery, as well as the creation of the reference data are discussed in Chapter 3. Chapter 4 details the methodology used for the supervised classification and the development of the rule-set. This includes a discussion of training data creation, rule-set design and the subsequent implementation of rules. The research is critically evaluated in Chapter 5, where the accuracy and cost-effectiveness of the supervised approach is compared to the rule-set results. The research is concluded by providing an overview of the findings of the study and placing them in the broader context of a forestry inventory.

CHAPTER 2: IMAGE CLASSIFICATION METHODOLOGIES

Digital image classification methodologies, or image classifiers, involve a set of computer procedures that assign image pixels or objects to classes representing information categories relevant to the user, based on a diverse selection of inherent image features (Campbell 2006). The development of image classifiers has been subject to ongoing research since the introduction of remote sensing, so that there now exists a wide variety of classifier types and forms, each with its own strengths and weaknesses relative to applications to which they may be applied (Lawrence & Wright 2001; Mather 2004). When deciding on a classification method for an application, a user must weigh the importance of several different factors. Efficacy of classification methods is usually judged in the literature according to the statistical accuracies of the final classification. However, the demand for human expertise, the time and expense of preparing and running the classifier, and the degree of automation required are aspects which must be taken into account (Pal & Mather 2003). It should also be noted that the accuracies of different classification methodologies are often specific to the application to which they are put (Liu, Skidmore & Van Oosten 2002). It is therefore important that the user be aware of the different types of classifiers available, to judge which is better suited to the application at hand. This chapter begins with an overview of traditional and alternative pixel-based classification methods, then examines classification methods employed in an object-orientated environment, and concludes with the intrinsic features found in digital images which can be used by classifiers to identify land cover classes.

2.1 General classification in remote sensing

The more conventional methods of classification consist of supervised and unsupervised procedures, which rely strongly on a variety of statistical algorithms employed in geometric space. Although widely used in practical applications, these more traditional classifiers are not without their limitations. The progression of digital image analysis techniques combined with the advancement of computer hardware and software, has led to the development of alternative classifiers which display a greater degree of data mining for image pattern recognition (Tseng *et al.* 2007). This is done by incorporating techniques such as artificial intelligence, logical structures and expert knowledge into the classification procedures (Brown de Colstoun *et al.* 2003; Mather 2004). This subsection expounds on and evaluates both traditional and alternative classifiers.

2.1.1 Traditional classifiers

Traditional classifiers refer to the two classification methodologies with the longest established tradition in remote sensing applications: namely unsupervised and supervised classification.

2.1.1.1 Unsupervised classification

Unsupervised classification is defined by two distinct steps. The first step is the automatic classification of pixels into a user-specified number of image classes according to their spectral properties. The second step is the manual labelling of the classes, usually depicted in images as areas of homogeneity, according to real-world information (Campbell 2006). Although the automated nature of the spectral delineation renders this classification method less user-intensive than others, it cannot be said to be truly unsupervised in nature. It is rather, as Mather (2004:203) puts it, “exploratory”, where repeated unsupervised area delineations with different parameters allow a user to “get a feel” for which real-world classes are spectrally distinct and which are spectrally similar. This understanding of image features can inform the construction of the set of real-world classes to be used in the classification, rendering unsupervised classification extremely useful where a priori information regarding the study area or the classification structure is unavailable or not pre-determined. Conversely, where a real-world class structure is already established it is rare that it will correspond with the automatically delineated spectral classes, resulting in the lowering of the accuracy of the outcome (Campbell 2006). This is especially true for high-resolution imagery where features of interest commonly comprise multiple spectral classes shared by more than one information class (Vanderzanden & Morrison 2002). This is the primary disadvantage of unsupervised classification, and for this reason its use is often limited in practical applications.

2.1.1.2 Supervised classification

Supervised classification is defined by the application of a priori information of real-world classes to determine the identity of unknown image elements. Data for the real-world classes are acquired from an external source and entered into the classifier in the form of designated and labelled polygons termed “training areas” or “training data”. These training areas contain statistical information regarding the spectral properties of each class, which is used by a classification algorithm to identify the class of unknown pixels (Campbell 2006; Lira & Maletti 2002; Mather 2004). Classification algorithms are widely varied, but are all designed to statistically compare the features of each of the classes with those of an unknown pixel in geometric space, and assign a class based on the results of that comparison. The most widely used algorithm is the maximum

likelihood classification (MLC) algorithm, due to its ready accessibility, robustness, strong theoretical foundation, and high accuracies for a wide range of remote sensing applications (Albert 2002; Bolstad & Lillestad 1991; Brown de Colstoun *et al.* 2003; Pal & Mather 2003; Tseng *et al.* 2007). Because of these traits, a number of studies use MLC as the benchmark with which to compare newly developed classification methods (Gumbrecht, McCarthy & Mahlander 1996; Hagnar & Reese 2007; Hepner *et al.* 1990; Liu, Skidmore & Van Oosten 2002; Nangendo, Skidmore & Van Oosten 2007; Neusch & Grussenmeyer 2003; Pal & Mather 2003).

Despite the advantages shown by supervised classification, it does contain a number of drawbacks. First, while accuracies achieved are generally acceptable they are often out-performed by more elaborate classification methods, such as artificial neural networks, expert systems and classification trees (Pal & Mather 2003). The second and third disadvantages pertain to the identification and delineation of training areas. As stated earlier, poorly developed training areas result in weak classification accuracies, and thus training data must be meticulously prepared. This can become expensive in terms of both time and money, especially for projects that span multiple images (Albert 2002). More relevant to this study, however, is the low degree of automation allowable by supervised classification due to training area creation. Again, this is amplified for wider-scale projects, as without rigorous pre-processing new training areas must be developed for each individual image used (Pax-Lenney *et al.* 2001).

2.1.2 Alternative classifiers

Alternative classifiers are classification methodologies that are less used for practical applications due to their complexity and lack of software or they are too recent innovations to have proven credibility (De Carvalho *et al.* 2004). This subsection focuses on the most well-documented alternative methodologies, namely artificial neural networks, supervised rule-sets, and expert systems.

2.1.2.1 Artificial neural networks

One of the older alternative classification methodologies, namely artificial neural network (ANN) classifiers, was among the first to draw from the field of artificial intelligence (AI) in the attempt to improve traditional classification techniques. As with supervised classification, this process requires the input of training data, but whereas supervised classification can be thought of as “forward-propagating” (i.e. the analysis of input data determines the output data), ANNs are “back-propagating” in that the connections between the input and output data are examined and

modified according to the expected and actual classification results. These connections are the links between the “neurons”: elements of the input layer, output layer and one or more hidden intermediate layers which allow for the normalisation, weighting, summation and thresholding of input values in approximating the output values. The adjustment process is the dynamic alteration of the connection weights in the intermediate layer or layers of a network, designed to bring the actual output data closer to the expected output data. Examination and readjustment are performed iteratively until a minimum return threshold is reached or the process become asymptotic. This process is termed “training the network” (Hepner *et al.* 1990; Skidmore *et al.* 1997).

One of the original purposes of the development of ANN classifiers was to overcome the limitations of creating or using a predetermined algorithm for classification. By “learning” a classification procedure according to the training data provided, no a priori knowledge of the area is necessary and the need for specialist assessment and evaluation of the outcome is removed. Additional advantages of back-propagating neural networks include allowance for data of any statistical distribution, higher tolerance of image noise, and the greater ability to recognise unknown patterns which are similar but not identical to the training data (Hepner *et al.* 1990; Mather 2004; Skidmore *et al.* 1997).

However, the development and use of an ANN does contain two significant disadvantages. The first concerns the design specifics of the ANN, as network architecture is determined mostly through trial and error. This is because each application is case-specific, and thus the literature does not provide guidelines on, for example, how many hidden layers to have, how many neurons to have for each layer, what neuron connections are necessary or unnecessary, what the minimum return threshold should be, how many training patterns should be used, and what neuron connection weights should be (Pal & Mather 2003; Tseng *et al.* 2007). Skidmore *et al.* (1997:551) demonstrated that these factors can significantly affect the classification result, leading them to conclude that while the ANN performed as expected, “...the adjustments and fine tuning required of the input parameters would deter many users.” The second disadvantage of ANN classifiers relates directly to that experienced by traditional supervised classification, namely the identification and delineation of training areas. Although findings have indicated that training areas need not be as robust as needed for supervised classifiers (Hepner *et al.* 1990), the principle of inferior training data resulting in an unsatisfactory classification remains valid (Skidmore *et al.* 1997). The time and monetary expenses of training data collection for larger projects is therefore applicable to this classification methodology and this, in conjunction with only modest

improvements to accuracy, a high processing demand (Campbell 2006) and the complex nature of establishing the ANN, have resulted in only modest use of this type of classifier.

2.1.2.2 Supervised rule-sets

Like ANN classifiers, rule-based systems incorporate machine-learning algorithms from the field of AI in attempting to predict digital image classes. While rule-based classifiers can encompass a variety of forms, it is possible to distinguish between those that are developed autonomously from training data input by the user, also termed supervised rule-sets, and those developed manually from external knowledge, which are termed expert classifiers.

One significant difference between ANN and rule-based techniques is the transparency of each classification method. The algorithm created from training an ANN has been termed a “black box” in the literature, because it provides little insight into the relationships between the image classes and image features (Tseng *et al.* 2007). Conversely, a rule-based system is by its very nature discerning in that feature information is used to assign classes by a set of threshold rules of the “If...Then...Else” structure (Bolstad & Lillesand 1992). By scrutinising the rule-set, created either autonomously or manually, users can familiarise themselves with the more discriminating features for each image class.

For autonomously created rule-sets the use of classification trees has, over the past decade and a half, steadily gained in prevalence (Lawrence & Wright 2001). Classification trees, also termed decision trees (DTs) or classification and regression trees (CARTs), are constructed by the recursive division of the training data into increasingly homogenous subsets. An individual node, or split, in the classification tree is a threshold value for the image feature which produces the most deviance in the dataset. Subsequent subsets are subject to further division, perhaps using other features with high heterogeneity, until either a preset subset variance or classification tree level is reached. The result is a hierarchical rule-set used for digital image classification (Hansen, Dubayah & Defries 1996; Lawrence & Wright 2001).

Although classification trees show a relatively high degree of classification accuracy (Bolstad & Lillesand 1992; Brown de Colstoun *et al.* 2003; Hansen, Dubayah & Defries 1996), their major limitation is the same as that of traditional supervised classification and ANNs, that is the need for extensive and accurate training data (Homer *et al.* 2002). Lawrence & Wright (2001) used a CART to classify Landsat imagery of the Greater Yellowstone ecosystem in Idaho, Montana and

Wyoming, and concluded that although classification with CART analysis was effective, the outcome is as sensitive to proper training data selection as the more traditional supervised classifiers. Although no literature could be found where one set of training data has been applied to multiple images for classification tree analysis, it is argued that the statement by Pax-Lenney *et al.* (2001) remains valid, namely that without rigorous pre-processing of different images, new training areas must be developed for each individual image used.

2.1.2.3 Expert systems

The first of the alternative classifiers to overcome the limitations of training data are expert systems. The term "expert system" is used variously in remote sensing and it can represent a number of different techniques. Tsatsoulis (1993) defines the categories of expert systems as user-assistance systems, classifiers, low-level processing systems, data fusion systems, and GIS applications. All pertain to different procedures in remote sensing analysis, but all are defined as "expert" in that they all employ AI inference structures which use expert knowledge (Cohen & Shoshany 2002). For this reason, expert systems are also known in the literature as knowledge-based systems.

For this review, only the classification techniques of expert systems were examined. These comprise a number of rules which use prior expert knowledge to define image classes, and they can be divided into three groups, namely relaxation-systems which apply knowledge in the verification of a classification; pixel-level systems which apply knowledge to determine the identity of a pixel through feature analysis; and domain-level systems where a structural model already exists which can be used for classification (e.g. road types, urban zoning) (Tsatsoulis 1993). Regarding classification accuracy, results have been promising. Nangendo, Skidmore & Van Oosten (2007) demonstrated how the incorporation of expert rules significantly increased the accuracy of East African tropical forest mapping in Uganda. Cohen & Shoshany (2002) found that a knowledge-based classifier returned superior results to unsupervised classification for a number of different satellite images for crop recognition in central Israel. Although Gumbricht, McCarthy & Mahlander (1996) showed that a manually inferred rule-set is superior to a maximum likelihood supervised classifier, they concluded that "...the knowledge representation was the bottleneck, as reported by many other studies" (Gumbricht, McCarthy & Mahlander 1996:278). This remark illustrates the primary disadvantage of expert classification: that the creation of a usable rule-set from expert knowledge is time-consuming (Liu, Skidmore & Van Oosten 2002). Another disadvantage of many rule-based expert systems is the limitation imposed by per-pixel features.

Moller-Jensen (1997) attempted to incorporate texture into a knowledge representation model of an urban environment, and when identifying possible directions for future research suggested a shift to a more object-orientated environment. This is examined in more detail in the following section.

2.2 Segmentation and use of objects

The development of classification methodologies has been enhanced by the advent of object-orientated analysis. Traditional methods of image analysis consider each pixel as an individual unit, with little cognisance of its topological relations to its neighbours or the class structure it represents (Lira & Maletti 2002; Van Coillie, Verbeke & De Wulf 2007). This individuality of pixels renders them susceptible to data noise, atmospheric effects and surface variation (Wicks, Smith & Curran 2002), and limits the usability of spectral, textural and relational information (Lennartz & Congalton 2004; Oruc, Marangoz & Buyuksalih 2004; Rego & Koch 2003). Considering these factors, Blaschke *et al.* (2000) argue that no form of pixel-based classification can really yield reliable, robust and accurate results. In contrast, object-orientated imagery analysis operates on pre-defined areas of the image, derived either from an external pre-defined source or, more commonly, an internal region-partitioning process known as segmentation (Blaschke *et al.* 2000).

2.2.1 Segmentation

Segmentation is usually the first step in object-based classification and involves the delineation of areas of an image into separate objects. Although there are a variety of methods of segmentation, the bottom-up, region-growing method of multiresolution segmentation has been shown to provide good results for a variety of applications and over an array of image types (Baatz & Schäpe 1999). This method starts with objects consisting of single pixels, then repetitively merges adjacent objects until a user-set homogeneity parameter is exceeded. Altering this parameter (termed "scale"), which consists of separate object scale, object size and object form variables, allows the user to define a layer of image objects corresponding to actual geographical objects relative to the scale at which the image is viewed. Repeated segmentations with different scale parameters result in layers of objects of different dimensions which can be structured in a shape-constrained hierarchical object network. Each object in such a network will exhibit both horizontal and vertical spatial awareness, as it is aware of its neighbouring objects in the same object layer, the number of and shared borders of its sub-objects in layers below, and its membership to super-objects in layers above (Benz *et al.* 2004; Karakis, Marangoz & Buyuksalih 2006; Mallinis *et al.* 2007;

Willhauck *et al.* 2000). The result could be termed a multi-scale hierarchy of object-primitives-building blocks defined through a process of repetitive testing which provides optimal information for further segmentations or classifications for the specific application (Mitri & Gitas 2002). It follows that segmentation and classification must be a collaborative process, as defining appropriate segmentation parameters for different scales is challenging and often problematical (Hay *et al.* 2005), and the quality of the segmentation will significantly affect the outcome of the classification (Bauer & Steinnocher 2001; Benz *et al.* 2004; Kermad & Chehdi 2002).

To summarise, the use of multi-scale, object-orientated image analysis offers the following advantages (Benz *et al.* 2004; Bock *et al.* 2005; Hay *et al.* 2005; Mansor, Hong & Shariff 2002; Shiba & Itaya 2006):

- Meaningful statistical calculation of spectral and textural qualities.
- The availability of feature qualities such as shape and object topology.
- The intuitive spatial relations between real-world objects and image objects.
- The ease of integration between GIS and remote sensing environments and flexibility among different software platforms.

A number of researchers have argued that these factors contribute to producing a superior image classification result compared to those provided by pixel-based approaches. Several case studies support this view. Rego & Koch (2003) illustrated the superior accuracy of object-based over pixel-based supervised classifiers in more than 100 image classifications, using IKONOS imagery in Rio de Janeiro City, Brazil. The superiority of object-orientated classification was also shown by Oruc, Marangoz & Buyuksalih (2004) who compared the technique to three different types of pixel-based supervised classification of Landsat-7 enhanced thematic mapper plus (ETM+) imagery in Zonguldak, Turkey. And Benz *et al.* (2004), Blaschke *et al.* (2000) and Willhauck *et al.* (2000) all lauded object-orientation for its superior integration between continuous remote sensing data and a vector-based GIS environment.

2.2.2 Classification techniques in an object-orientated environment

Most pixel-based classifiers can be adapted successfully for an object-orientated environment. Mansor, Hong & Shariff (2002) demonstrated the application of a simple supervised classification of a Landsat TM image for land cover mapping, with an overall accuracy of over 90%. Ali-Akbar, Sharifi & Mulder (2000) incorporated expert knowledge and ancillary data in image segmentation and applied a maximum likelihood classifier to the resulting objects in an attempt to improve the accuracy of deforestation estimates in Chiong Mai Province in Thailand. Their method was used

on Landsat thematic mapper (TM) data, and showed an 8-10% increase in accuracy over previously used methods. Berberoglu *et al.* (2000) compared maximum likelihood and ANN classifiers for a per-field approach to land cover classification of Landsat TM data in the Cukurova Delta in Turkey, obtaining overall accuracies of up to 89% with eight categories.

The family of classification techniques most enhanced by the use of objects is that of rule-based classifiers. As stated earlier, each object-primitive in a hierarchy contains a number of inherent features, as well as relative spatial awareness which is ideally suited to analysis by a rule-set structure. This has been demonstrated by a number of studies. Lewinsky & Bochenek (2008) undertook a land cover-based classification of a SPOT 4 image in the Kujawy region in Poland using feature thresholding in a rule-based decision-tree. Their use of spectral, textural and relational feature thresholds to classify objects attained a satisfactory overall accuracy of 89% with 13 categories. They admitted that although the principle of rule-based classification was sound, modifications were necessary when applying the rule-set to different images. Bock *et al.* (2005) used a hierarchical rule-based classification at multiple scales and at multiple resolutions for habitat mapping in Northern Germany and Wye Downs, UK, and lauded the technique for its potential to incorporate expert knowledge at any stage of the analysis. Mitri & Gitas (2002) developed and tested a hierarchical object membership classifier for Landsat TM images to map burnt areas in two regions in the Mediterranean, with accuracies over 98% for both images. Bauer & Steinnocher (2001) developed a rule-set which used object hierarchy aggregation and allocation to classify urban areas from IKONOS imagery in Venice, Italy, also with favourable results.

In forestry specifically, Mallinis *et al.* (2007) compared a nearest-neighbour classifier to a CART classifier for forest type classification from Quickbird imagery in Thessaloniki in northern Greece. Although the overall accuracies for both classifiers did not exceed 70% for the seven classes, the authors concluded that the rule-based CART outperformed the supervised classification regarding both accuracy and transparency. Shiba & Itaya (2006) used a rule-based classifier in conjunction with a digital elevation model (DEM) in an object-orientated environment to detect forest change in Japan. The classifier was used on IKONOS imagery and the authors concluded that rule-based object-orientated approaches have the ability to greatly improve forest monitoring and management systems for decision-making processes.

More relevant to the aim of this study are expert-system rule-based classifiers, which eliminate the need for training data and thereby increase cost-effectiveness. As stated before, an expert

understanding of the relationships between these objects in the real world, and their intrinsic image features, allows the user to define complex rules for object classification based on spectral, textural and structural qualities, as well as the spatial relationships among the objects (Benz *et al.* 2004; Blaschke *et al.* 2000). Argialas & Harlow (1990:883) put it more elegantly when they state that expert systems “...upgrade the state of image analysis capabilities from brute force mathematical and statistical approaches to analysis techniques based on interpretation logic and heuristics”, but also caution that feature selection relies on the past experience, engineering intuition and domain-specific knowledge of the system designer. It is therefore essential that the variety and composition of image features is fully understood before an expert-system rule-set classifier can be created. This is examined in more detail in the following section.

2.3 Object features

All objects on earth, when struck by the electromagnetic (EM) energy of the sun, absorb and transmit a degree of that energy, and reflect the remainder back into space. The specific manner of the object determines which specific wavelengths of the EM spectrum are absorbed and transmitted, and which are reflected. Remote-sensing instruments are designed to measure and record those reflected portions of the EM spectrum most practical for earth-observation purposes. The most widely used remote-sensing instruments are multispectral scanners, such as used in this study, and these comprise a number of sensors each simultaneously recording different ranges or bands of the EM spectrum (De Jong, Pebesma & Van der Meer 2005). The number of bands and the EM wavelength ranges of each band vary among systems, but the final product is usually a composition of all the bands together in one digital image (Newton 2007). It is the function of the remote-sensing expert to translate, interpret and classify these images.

Traditional image processing was primarily undertaken on a per-pixel basis, with most analysis limited to spectral image properties (De Jong, Pebesma & Van der Meer 2005; Tuominen & Pekkarinen 2005), although there are examples of research which employ pattern recognition of which the work of Haralick, Shanmugam & Dinstein (1973) is the most notable. Contemporary image analyses still make regular use of spectral and textural features, but the advent of object-orientated image analysis has enhanced the manner in which such features can be used. In addition to providing an additional set of feature attributes – that of object geometry – feature analysis can now be undertaken for each object (i.e. locally), within a hierarchical object framework or on all objects (i.e. globally) (Blaschke *et al.* 2000; Definiens 2007). This section examines the object features available for expert-based rule-set classification.

2.3.1 Spectral features

The overview of image classifiers in the previous sections has provided some insight into the use of spectral features for non-object-orientated image analysis. Unsupervised classifiers use spectral properties to classify homogenous areas for manual class labelling, while supervised classifiers match unknown areas of an image to pre-defined training data, primarily using their spectral characteristics. In addition, pixel-based expert systems use prior knowledge of the spectral properties of land cover features in a rule-set to arrive at a classification.

However, in an object-orientated expert system the analysis of spectral features is different. Multiresolution segmentation defines an object network according to the homogeneity of each spectral band selected for the segmentation process. In theory, this creates bordered areas of low variance, which offers a broad range of possibilities for object comparison using statistical measures such as band mean, standard deviation, range, and maximum and minimum values (Definiens 2007). Again, it must be stated that such spectral feature comparisons can be undertaken between objects on the same hierarchical level, on levels above or below, or with the spectral properties of the entire image. For example, for a given object network it may be found that it is possible to differentiate a particular class by comparing the specific object means of a certain band with the global mean of that same band. If the object value is lower than the global value, the object is assigned to that specific class. If it is higher it is left as undefined. The undefined objects might be subject to further segmentation, creating a new object-network below the first, where it may then be found that by comparing the sub-objects' standard deviation of a second band to the standard deviation of their super-object, it is possible to distinguish another, different class. Such an example illustrates the possible use of spectral information for object-orientated image classification. However, in the pursuit for more efficient information extraction techniques, researchers have also developed a number of procedures to enhance spectral data (Mather 2004). These procedures are termed image transforms, and they are examined in more detail in the following section.

2.3.2 Image transforms

An image transform is any operation which re-expresses the information content of an image for the purpose of deriving usable data not immediately apparent from individual bands (Mather 2004). The variety of image transforms is large, ranging from simple arithmetical operations to complex dimensional alteration and compression techniques. Arithmetical transforms are defined by the use of mathematical operators such as addition, subtraction, multiplication and division,

and while these are all used in various areas of remote sensing to some degree, the most widely used and relevant to this research are the family of vegetation ratios or vegetation indices. Of the dimensional transforms, one of the more common is principal components analysis. This section provides a brief overview of vegetation indices and principal components analysis.

2.3.2.1 Vegetation indices

Vegetation indices are arithmetical operations designed to enhance green vegetation in a remotely sensed image (Campbell 2006). To do this, they use the unique spectral properties of green plant material, which is highly absorbent in the red portions of the EM spectrum and highly reflective in the infrared (IR) portions of the EM spectrum. The arithmetical operation most commonly employed between these bands is division, which not only enhances the differences between the red and IR reflectances of vegetation, but also reduces the effects of topographical variation on spectral illumination (Mather 2004).

The simplest vegetation index is the ratio of red and IR bands, which returns an image roughly analogous to the amount of vegetative matter in the image. However, due to the inaccuracies of this simple vegetation indicator, it has been superseded by the more robust normalised difference vegetation index (NDVI), defined as the equation:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red})$$

where NIR is near infrared, a multispectral band in the IR in close proximity to visible red on the EM spectrum and common to a number of remote-sensing systems. The ratio of the sums and differences of the NIR and red bands, rather than the absolute values of the IR:red ratio, render NDVI less affected by atmospheric variation between images, and thus more suitable for multiple image analysis (Mather 2004). This property, as well as the simplicity and relative accuracy of NDVI, have resulted in it becoming the most widely used vegetation index in remote sensing (Karnieli *et al.* 2001). However, NDVI does contain three distinct limitations. First, it does not account for background soil reflectance properties, which are shown to have a strong influence on NDVI values (Huete 1988). Second, the dynamic range of NDVI is prone to saturation at the higher end of the index spectrum, where vegetation canopies are dense and multilayered (Karnieli *et al.* 2001). And third, while it can be said that NDVI is more tolerant of atmospheric conditions, it is by no means completely unaffected by the scattering effects of cloud and aerosols (Mather 2004; Karnieli *et al.* 2001).

The attempts to overcome these limitations have produced two new families of vegetation index, namely those which correct for atmospheric influence and those which correct for soil reflectance. Kaufman & Tanré (1992) developed a vegetation index called the atmospheric-resistant vegetation index (ARVI) which incorporates a blue band to identify and compensate for the red-scattering properties of aerosols in the atmosphere. While moderately successful, the use of a blue band limits the usefulness of this family of indices, as not all remote-sensing systems possess a sensor in the blue portion of the EM spectrum (Jiang *et al.* 2008). To overcome this handicap in part, another “aerosol-free” vegetation index was developed by Karnieli *et al.* (2001), which makes use of a band in the shortwave infrared (SWIR) portion of the EM spectrum. This wavelength is less affected by atmospheric gases and aerosols than the visible spectrum, while also demonstrating a high correlation with a red band regarding vegetation reflectance properties. The vegetation index proposed by Karnieli *et al.* (2001) was termed the aerosol-free vegetation index (AFRI), defined as the equation:

$$\text{AFRI} = (\text{NIR} - 0.66 * \text{SWIR}) / (\text{NIR} + 0.66 * \text{SWIR})$$

where the SWIR band can be either of the 1.6 μm or 2.1 μm atmospheric windows of the EM spectrum, both of which are commonly used bands in most remote-sensing systems. Practical testing of this vegetation index by Karnieli *et al.* (2001) showed AFRI to closely resemble NDVI in clear-sky conditions, while also satisfactorily demonstrating the ability to penetrate atmospheric interferences such as smoke or sulphates.

In an attempt to reduce the influence of soil reflectance on vegetation index calculations, Heute (1988) modelled soil brightness in relation to vegetation canopy to determine a soil-adjustment factor (L) to apply to the formula of NDVI. This new index was named the soil-adjusted vegetation index (SAVI), defined as the equation:

$$\text{SAVI} = (\text{NIR} - \text{Red}) * (1 + \text{L}) / (\text{NIR} + \text{Red} + \text{L})$$

where L is determined manually according to vegetation density. A further improvement on SAVI was presented by Qi *et al.* (1994), where L was represented by a self-adjusting formula designed to determine the optimum value for L for any vegetation density. This index was named the modified soil-adjusted vegetation index (MSAVI), defined by the equation:

$$\text{MSAVI} = [2 * \text{NIR} + 1 - \sqrt{(2*\text{NIR} + 1)^2 - 8*(\text{NIR} - \text{Red})}] / 2.$$

In testing the effectiveness of MSAVI, Qi *et al.* (1994) demonstrated a further improvement in reducing the influence of soil reflectance beyond that shown by SAVI, while still increasing the dynamic range of the index to account for the high-end saturation experienced by NDVI.

The enhanced vegetation index (EVI) was originally developed to monitor climate change through vegetation time-series analyses of images of the moderate resolution imaging spectroradiometer (MODIS) remote-sensing system. As a vegetation index, EVI was created through combining the concepts of both ARVI and SAVI, and as such it was the first vegetation index to overcome all three limitations experienced by NDVI. Although highly successful for use in MODIS imagery, the widespread use of EVI is limited due to the need for a blue band. This limitation was overcome by Jiang *et al.* (2008), who developed a two-band EVI (EVI2), which used only the red and NIR bands. At optimal calibration, as calculated by Jiang *et al.* (2008), EVI2 is defined by the equation:

$$\text{EVI2} = 2.5 * (\text{NIR} - \text{Red}) / (\text{NIR} + 2.4*\text{Red} + 1).$$

EVI2 was shown by Jiang *et al.* (2008) to be highly correlated with the original EVI over a large sample of snow/ice-free land cover types, while still retaining the abilities to overcome aerosol interference, soil-reflectance noise and dense vegetation value saturation. This recommends EVI2 as an appropriate vegetation index for use in multi-area or multi-image studies.

2.3.2.2 Principal components analysis

It is common in multispectral imagery that bands of close proximity show a high degree of correlation and repetition. Principal components analysis (PCA) is a transform procedure which reduces the redundancy of the data by identifying the optimal linear combinations of the original channels and altering the dimensional axes in such a manner that correlation is eliminated. The outcome of PCA is a series of coefficients, or eigenvectors, which align the principal axis along the strongest degree of correlation in dimensional space, and which therefore concentrates the maximum amount of information possible into one band called the first principal component (PC1). The second principal component (PC2) is the second largest axis mutually perpendicular to the first in dimensional space, into which is concentrated the maximum amount of information possible from the information remaining after the creation of PC1. This process is repeated for the

same number of principal components as the original number of bands, resulting in a set of bands of decreasing variability, with the greatest majority of the information contained in the first three component bands (Campbell 2006; Liang 2004; Mather 2004).

The advantages of PCA lie both in data compression and data interpretation. Regarding data compression, because most of the image information is contained within the first three principal components, it is possible to reduce the dimensions of the data by retaining PC1, PC2 and PC3, and discarding the remaining ones. As for data interpretation, multispectral images are usually displayed onscreen by assigning any three of the bands of the multispectral image as red, green and blue (RGB). By rather displaying the first three principal components as RGB, more image information is shown onscreen making it easier to identify spectral differences in land cover, thereby aiding in feature selection for classification (Mather 2004).

The primary disadvantage of PCA is its inability to compare the principal component values between images. This is due to the image-specific characteristics of the inter-band correlation or covariance defined by the transformation, which ultimately restricts the usefulness of PCA in multiple-image comparison (Mather 2004). However, this disadvantage does not extend to the use of textural features on principal components, and as such PCA retains an element of usefulness for this research.

2.3.3 Texture

Although spectral properties are the primary feature for image analysis, there are certain conditions where they are less effective for image classification (Neusch & Grussenmeyer 2003). In their review of pixel-based segmentation and classification, Ali-Akbar, Sharifi & Mulder (2000) state outright that spectral data alone is insufficient for thorough extraction of information from digital images. Berberoglu *et al.* (2000) and Chica-Olmo & Abarca-Hernández (2005) all note that supplementing textural information for classification in an object-orientated environment increases overall accuracy by augmenting the discrimination of classes with similar spectral properties. Tuominen & Pekkarinen (2005) note that for forestry estimation texture features surpass spectral features for imagery with a higher spatial resolution than that of Landsat TM imagery (30x30m). Such comments suggest a need to examine texture as a discriminating feature in more detail.

Image texture has undergone much scrutiny in the literature where it is generally agreed that although it may be intuitively understood to the human eye and brain, it is a difficult concept to measure or even define. Consequently, it has been difficult to incorporate texture into image analysis so that its practical use has been limited (Ferro & Warner 2002; Mather 2004). Haralick, Shanmugam & Dinstein (1973), the first researchers to apply texture measurements to remotely sensed images, defined texture as the spatial statistical distribution of grey-tone variations within a band, and in an attempt to measure texture they introduced a form of second-order statistical analysis measuring the relative frequency distribution of grey values within an image. This statistical measurement, for which fourteen different textural features at four different directions were proposed by Haralick, Shanmugam & Dinstein (1973), gained a degree of popularity and eventually became commonly known as the grey level co-occurrence matrix (GLCM). Although not without disadvantages, the use of GLCM textural features became widely used in remote sensing processing, and image classification in particular (Mather 2004; Tuceryan & Jain 1998). Table 2.1 briefly explains eight of the more commonly used textural features proposed for use on a GLCM by Haralick, Shanmugam & Dinstein (1973).

Table 2.1: Eight commonly used Haralick textural features

Homogeneity	A measure of local homogeneity
Contrast	A measure of local variation, the opposite of homogeneity
Dissimilarity	Similar to contrast, but increasing linearly
Entropy	A measure of GLCM element distribution equality
Angular second moment	A measure of local homogeneity
Mean	An average of the GLCM
Standard deviation	A standard deviation of the GLCM
Correlation	A measure of the grey level linear dependency

Source: Definiens (2007)

An important aspect to consider when using texture features in image analysis is scale. Objects of interest occur at a hierarchy of scales within an image, requiring analysis to be undertaken at a corresponding hierarchy of scales for optimal classification results. With pixel-based analysis the scale of analysis is limited to the spatial resolution of the remote sensor (Ferro & Warner 2002). Object-orientated analysis of high-resolution imagery, on the other hand, allows for the development and analysis of an image on a hierarchical structure of levels of varying scale, as discussed above. This allows for a more in-depth textural analysis, because GLCM textural features can be calculated and compared for every object over a variety of scales.

The literature reviewed in this chapter serves three distinct purposes. The comparison of classifiers in the first section justifies and provides context regarding the research objectives of creating an expert-system rule-based classifier, and comparing it specifically to a supervised classification for evaluation purposes. The overview of segmentation and the use of objects in classification justifies the use of each of the classifiers tested in an object-orientated environment. The last section, an outline of spectral, index and textural object features, provides a basis for feature testing during the creation of the rule-set. However, before rule testing could begin, the imagery had to be acquired and prepared, and reference data established. This is dealt with in the next chapter.

CHAPTER 3: PREPARATORY WORK

This chapter details the preparatory work required before the development of the object-orientated supervised and rule-set approaches could be attempted. It specifically details and justifies the imagery used for the research, the pre-processing that was undertaken both externally and in-house on the imagery, and the creation of the reference data used for accuracy assessment. The chapter is concluded by a brief overview of the possible techniques used in accuracy assessment, which techniques were used in this study, and the factors of bias that may affect returned accuracies due to the specific classification and assessment methodologies used.

3.1.1 Imagery

As one of the major objectives of this research was to maintain cost-effectiveness, the remotely sensed imagery used had to possess a desirable balance between the cost of the data, and the availability, coverage and spatial and spectral resolutions of the data. On the one hand medium-to-very-high resolution imagery such as IRS-P6 Resourcesat-1 (5.8m), FORMOSAT-2 (2m), IKONOS (0.82m), Quickbird (0.61m), Worldview-1 (0.46m) and GeoEye-1 (0.41m) were judged to have too low an image extent, and consequently be too financially expensive to use for mapping over a large area, while on the other hand imagery with higher coverage such as the advanced spaceborne thermal emission and reflection radiometer (ASTER; 15-90m), the moderate resolution imaging spectroradiometer (MODIS; 250-1000m) and the advanced very high resolution radiometer (AVHRR; 1.09km) were considered to have too low a spatial resolution to achieve the desired accuracies of the research (other than perhaps the three 15m near infra-red (NIR) bands of ASTER, which alone would be insufficient for forest classification). Only two remote-sensing systems satisfied the criteria of easy availability, low expense, high coverage per image, and acceptable spatial and spectral resolution, namely Landsat 7 ETM+ and SPOT 5. The spatial and spectral properties of the two systems are set out in Table 3.1.

Band	Landsat 7 ETM+	SPOT 5
Visible blue	0.45-0.52 μ m, 30m per pixel	
Visible green	0.53-0.61 μ m, 30m per pixel	0.50-0.59 μ m, 10m per pixel
Visible red	0.63-0.69 μ m, 30m per pixel	0.61-0.68 μ m, 10m per pixel
NIR	0.78-0.90 μ m, 30m per pixel	0.78-0.89 μ m, 10m per pixel
SWIR	1.55-1.75 μ m, 30m per pixel	1.58-1.75 μ m, 20m per pixel
SWIR	2.09-2.35 μ m, 30m per pixel	
Thermal IR	10.4-12.5 μ m, 60m per pixel	
Panchromatic	0.52-0.90 μ m, 15m per pixel	0.48-0.71 μ m, 2.5m per pixel

Sources: National Aeronautics and Space Administration (NASA) (2008); Spot Image (2005)

National image coverage of South Africa was available at no cost for both systems: Landsat 7 ETM+ imagery is free of charge online, and SPOT imagery is available from the Council for Scientific and Industrial Research's (CSIR) Satellite Applications Centre (SAC), which is tasked with providing a national SPOT 5 mosaic for use in statutory and research institutions (Lück 2007). The decision on which set of imagery to use thus rested on which spectral and spatial properties were better suited to the desired level of precision and accuracy for the research. As evidenced by Table 3.1, Landsat 7 ETM+ imagery possesses a higher spectral resolution with its seven spectral bands to the four for SPOT 5 imagery. Landsat 7 ETM+ imagery also possesses a greater spatial coverage per image, with roughly 180x180km per Landsat 7 ETM+ image compared to 60x60km per SPOT 5 image. However, SPOT 5 imagery has a superior spatial resolution to Landsat 7 ETM+. This was the decisive factor in determining which of the two systems to use. The panchromatic resolution of SPOT 5 (2.5m per pixel) was deemed to be able to significantly increase the level of detail of forestry classification. This assessment is supported by Salajanu & Olson (2001) who suggested that the increased spatial resolution of SPOT data resulted in more accurate forestry classification than the equivalent multispectral bands of Landsat, and by Radoux & Defourney (2007) who suggested the optimal spatial resolution for forest stand delineation is in the range of 2-3m. Consequently, it was decided to use the SPOT 5 national mosaic created by SAC.

3.1.2 Pre-processing

Pre-processing involves any operations which are undertaken on the imagery prior to the primary analysis. These operations can be grouped into radiometric pre-processing, which includes any operation designed to adjust digital values to compensate for atmospheric or sensor calibration differences, or spatial pre-processing, which includes orthorectification, fusion and subsetting (Campbell 2006).

The SPOT 5 imagery offered by SAC was available at three different levels of pre-processing, or rather, three different data products (Lück 2007). The first data product consisted of completely raw, untouched data with no pre-processing undertaken. It was considered that adequate preparation of raw imagery for this research would require a degree of work which was not cost-effective, both in terms of time and money. This was especially true in light of the second data product, which was both orthorectified and pan-sharpened – a fusion technique used to match the spatial resolution of the multispectral bands to that of the panchromatic band. The third data product provided by SAC was a national true-colour mosaic, produced by matching images of the

second data product to a 16-day MODIS colour composite. Although effective in creating a seamless mosaic of South Africa, this colour-matching technique was judged to compromise the spectral information in the image. As a result, it was decided to use the second data product of the SPOT 5 national mosaic, and subsequently two orthorectified and pan-sharpened images were acquired from SAC. The techniques of orthorectification and pan-sharpening used are examined in further detail in subsequent sections, as are the pre-processing techniques of radiometric normalisation, atmospheric correction, and subsetting which were all undertaken in-house on the imagery.

3.1.2.1 Orthorectification

Orthorectification is the process of geometrical correction where images are assigned to the position that represents their “true” location on earth. This is accomplished by resampling a series of points in an unrectified image to corresponding points in a “correct” reference system, which may be data such as pre-projected orthophotos, cadastral information or topographical maps. These associated points are called ground control points (GCPs). Orthorectification also uses a digital elevation model to correct image geometry for distortions caused by terrain. In the case of the SPOT 5 national mosaic, GCPs were collected for the panchromatic band and resampled according to 1:30 000 and 1:50 000 orthophotos and urban cadastral information obtained from the Chief Directorate: Surveys and Mapping (CDSM). The four multispectral bands were then resampled according to the rectified panchromatic band. A spatial assessment using separate GCPs indicated the spatial accuracy of the majority of the images of the KwaZulu-Natal region to be less than 12m at 2 sigma, denoting that any position in an image is within 12m of its “true” position, stated at a 95% confidence interval. In addition, both of the images used for the development of the rule-set had a mean accuracy error of less than 5m (Lück 2007).

3.1.2.2 Pan-sharpening

Pan-sharpening is the term given to the fusion of a higher resolution panchromatic band with a lower-resolution multispectral band, for the purposes of increasing the spatial resolution of the multispectral band. A variety of pan-sharpening techniques exist. Weighted coefficient calculations between the panchromatic and IR bands are common, as are the techniques of principal component substitution, RGB-intensity-hue-saturation, and Brovey’s transformation. It has been noted however, that all of these techniques alter, and therefore compromise, the spectral information of an image to some degree (Cheng *et al.* 2003; Prasad *et al.* 2001). The pan-sharpening fusion used in the SPOT 5 national mosaic is a statistical fusion technique specifically

designed to overcome this problem of colour distortion, retaining the spectral qualities of each band and allowing for meaningful quantitative analysis (Cheng *et al.* 2003). The result is a 2.5m pan-sharpened image consisting of four multispectral bands with very similar spectral properties to those of the raw image (Lück 2007).

3.1.2.3 Radiometric correction

Radiometric correction consists of procedures which correct for sensor calibration differences, called radiometric normalisation, and rectify distortion caused by atmospheric interference. Radiometric normalisation is the procedure of converting DN, a unitless indicator of incoming EM radiation, to at-satellite radiation, the amount of EM radiation recorded by the sensor in $\text{mW}\cdot\text{cm}^{-2}\cdot\text{sr}^{-1}\cdot\mu\text{m}^{-1}$. Between-image differences can be further reduced by converting at-satellite radiation to planetary reflectance, where values are standardised according to the earth-sun distance and solar elevation angle at the time of image capture (Irish 2000). Conversion of DN values to at-satellite radiation is calculated using the following formula (Irish 2000):

$$L\lambda = (gain\lambda * DN\lambda) + bias\lambda$$

Where	$L\lambda$:	At-satellite radiance of band λ
	$DN\lambda$:	digital number of band λ
	$gain\lambda$:	gain value of band λ , read from the image metadata
	$bias\lambda$:	bias for band λ , read from the image metadata.

The dynamic adjustment of SPOT 5 sensors according to the intensity of incoming radiation results in each SPOT 5 image containing a distinct set of gains and bias for each band. These can be read from the metadata file which accompanies each image. Theoretically, images consisting of radiance values can be directly compared, but further normalisation by converting to at-satellite reflectance is recommended (Irish 2000). Conversion of at-satellite radiance to reflectance is calculated using the following formula (Irish 2000):

$$P\rho = (\pi * L\lambda * d^2) / (ESUN\lambda * \cos\theta_s)$$

Where	$P\rho$:	unitless planetary reflectance
	$L\lambda$:	at-satellite radiance
	d :	earth-sun distance

ESUN λ :	mean solar exo-atmospheric irradiances
θ_s :	solar elevation angle.

Exo-atmospheric irradiances and solar elevation angle can be read from the image metadata file, and earth-sun distance can be obtained from astronomy websites. Calculation of at-satellite reflectance ensures the best comparability between images which have not been atmospherically corrected.

Atmospheric particles scatter, absorb and reflect EM radiation to different degrees and over different wavelengths. To compensate for this, a number of atmospheric correction pre-processing techniques have been proposed. These can be classified as either relative or absolute correction models. Relative corrections match atmosphere-affected band histograms to corresponding less-affected band histograms, either in different images or to strongly correlated bands within the same image unaffected by atmospheric distortion. However, these techniques are both difficult to implement and automate (Irish 2000), rendering them unfavourable for this study. Absolute corrections can be either empirical or physical. Empirical models use the knowledge of band-band relationships to correct for distortion. However, such models are often oversimplified and rely on questionable assumptions, which may lead to suspect results. Physical models use the knowledge of the effects of atmospheric gases on different wavelengths of the EM spectrum to compensate for each sensor band accordingly (Lück 2005). However, the required atmospheric information to ensure accurate physical modelling is seldom available for specific images, and thus sensor-specific models for atmospheric correction are often used instead. Despite the generalisation resulting from this technique, physical atmospheric correction is commonly used as it is easily available, straightforward to implement and can be applied to a wide variety of remote-sensing systems (Richter 2004). The physical atmospheric correction model, ATCOR2, which includes radiometric correction, was implemented on the imagery used in this study.

3.1.2.4 Subsetting

Due to the heavy computational demands of remote-sensing operations, it is a generally accepted practice to undertake analyses on smaller sections of an entire image. Four subsets of 15x10km were created from the southern and northern images. The size of the subsets (150km²) was considered to be large enough to contain adequate coverage of the various land-cover types in the area, while not so large to render object segmentation times impracticable. The locations of the subsets were purposefully chosen to include a fair degree of plantation and natural forest, but both

subsets also display significant areas of water, bare ground, non-forest natural vegetation, commercial and subsistence agriculture, and a variety of types of urban settlement. The location and extent of each area is displayed in Figure 3.1.

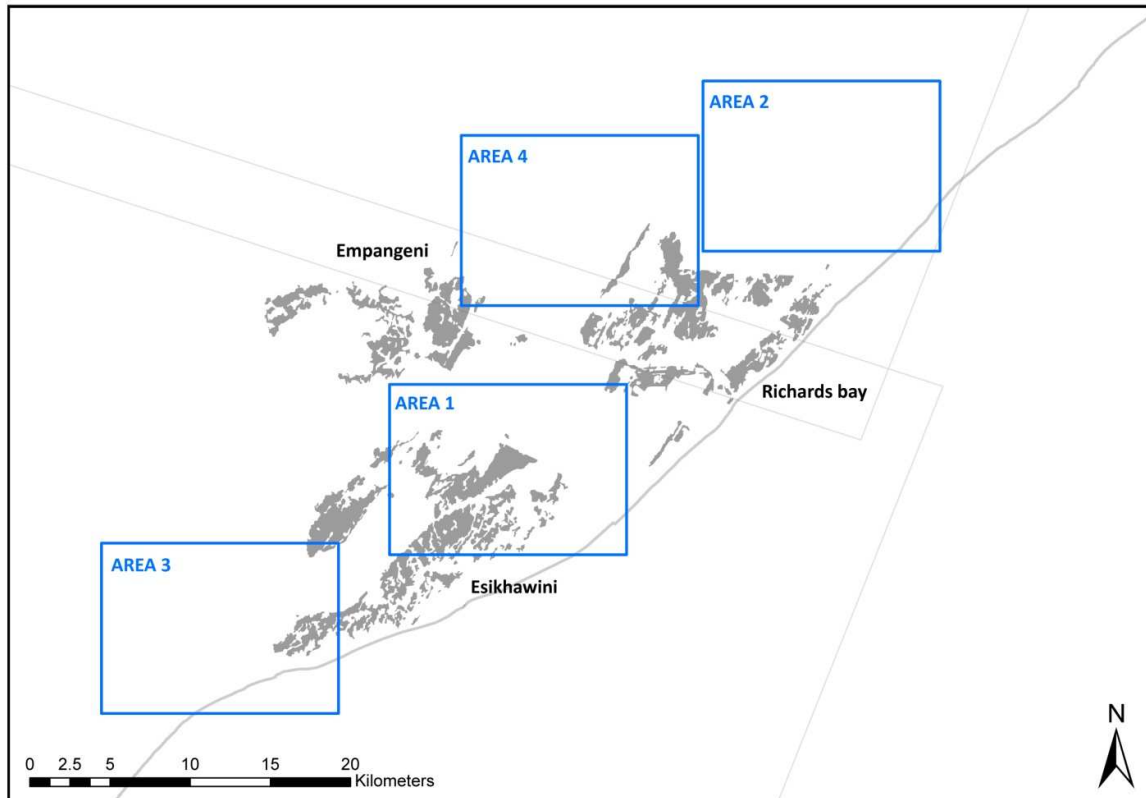


Figure 3.1: The location and extent of the four subsets

3.1.3 Reference data preparation

In order to assess the accuracy of the expert-system rule-set it was necessary to create a dataset consisting of the “correct” data against which to compare rule-set results. For this purpose a reference dataset was created by digitising the classes of *natural forest*, *plantation* and *other* from a set of aerial photographs obtained from the CDSM. Digitising of classes was undertaken at scales of 1:6000 or larger for the 150km² subsets of the northern and southern images using ArcMap 9.2. High-resolution true-colour composite satellite imagery (GoogleEarth) was used as a cross reference where class differentiation was not immediately apparent. Despite the lower resolution, the SPOT 5 images themselves were used as the conclusive class decider where temporal discrepancies between the ancillary data occurred. Further verification was undertaken through field observations undertaken in the study area on 12-14 November 2008. The final reference dataset was verified by a forestry expert with on-site experience of the region who

deemed the data to be accurate enough to be used for comparisons of a minimum mapping unit of one hectare (Mucina 2008, pers com).

3.1.4 Accuracy assessment techniques

The evaluation of each approach required a rigorous method of determining class accuracy. According to Levin (1999), classification accuracy can be assessed in four different ways:

- 1) A field survey of either random or grid-allocated points, compared to corresponding points of the classification.
- 2) A visual estimate of agreement, often by overlaying the reference data with the classification.
- 3) In-depth statistical analysis of numerical data, using techniques such as root mean square error, correlation coefficients, linear or multiple regression analysis and Chi-squared testing.
- 4) Error matrix compilation.

The first two methods lack precision and are prone to subjectivity. Statistical comparison is more thorough, but can become very complex, and is often specific to a particular feature, such as root mean square error calculations for geometric offset determination. Error- or confusion-matrix compilation, which was used in this study, is the most commonly used method for classification accuracy assessment due to its simplicity of implementation and interpretation (Hammond & Verbyla 1996; Verbyla & Hammond 2002). However, a comprehensive understanding of classification accuracy derived from confusion matrices and accompanying statistics is incomplete without first analysing the factors which influence accuracy bias—a factor often lacking in many studies (Hammond & Verbyla 1996).

Bias is any factor which either overstates or understates the returned accuracy figure from a classification accuracy assessment. Overstating an accuracy figure is called optimistic bias, and stems from three main sources: the use of training data in accuracy assessments; the use of reference data with spatial or temporal proximity to training areas; and the restriction of reference data sampling to homogenous areas. Understating an accuracy figure is termed conservative bias, and also stems from three main factors: reference data errors or inaccuracies, positional errors, and generalisation of class delineation in reference data (Verbyla & Hammond 2002). The severity of these factors affecting bias is influenced by the methodology used during classification and accuracy assessment type (Levin 1999).

The expert-system rule-based approach in this study deliberately avoided the use of any form of training data. Consequently, the first two factors causing optimistic bias are negated. However, this is not so with the supervised classification. The third factor, restricting reference data sampling to homogenous areas, is usually observed where reference data sampling is done on the centre of a 3x3 neighbourhood of pixels of the same class, to avoid edge effects and minimise positional uncertainty (Verbyla & Hammond 2002). The accuracy assessments for either classification method conducted in this study are not affected by this factor, as accuracy was calculated on a point basis i.e. the "true" reference class of every point was compared to that of the corresponding point in the classification product. However, as a result of the first two factors which are influenced by the use of training data, the accuracies returned for the rule-set can be confidently interpreted as more understated, and therefore more reliable as that of the supervised classification.

This chapter detailed the reference data creation and pre-processing steps necessary prior to classification. It also provided justification for the specific sensor chosen for the study and expounded on the pre-processing undertaken on the imagery prior to acquisition and further necessary in-house preparation. With the imagery and reference data suitably prepared, the development and application of the supervised and rule-set classifiers could be undertaken. This is dealt with in the following chapter.

CHAPTER 4: METHODOLOGY

This chapter examines the methodology used in the creation and application of the two object-orientated classifications. The first section details the class structure and training data used in the supervised classification, while the second section explains the procedures used in the creation of the rule-set.

4.1 Supervised classification

With the advent of freely-available, high-resolution satellite imagery and object-orientated analysis techniques, the logical alternative to the expert-system rule-based classifier presented in this research would be a supervised classification. Therefore, an object-based nearest-neighbour supervised classification was undertaken on the four test areas, using Definiens Developer 7.0. This was performed in a two-tier hierarchical manner, with training area creation and refinement undertaken iteratively for each class level. The first level was created using a segmentation scale parameter of 80, which returned objects of suitable size and variation for the desired classes. These classes were: *bare ground*, including barren fields, open mines, beaches and very young plantations; *built-up*, including residential, commercial and industrial areas; *vegetation*, including agriculture, natural vegetation and plantations; and *water*. Training classes were created iteratively for each class, where the classification result of each iteration determined the refinement of training classes for the next iteration until a satisfactory classification was obtained. Typically, the features used for a supervised classification are the spectral bands of the sensor, but in this case a textural measure, the standard deviation of band 3 (NIR), was added to improve the final classification.

Once a satisfactory classification had been achieved for the first hierarchical level, the *vegetation* class was further segmented using a scale parameter of 40, resulting in smaller “child” vegetation objects more suitable for specific vegetation distinction. For the classification of objects on this sub-level, training areas were again iteratively created and refined for the following classes: *farmland*, *mangroves*, *natural forest*, *natural vegetation* and *plantation*. Botanically, mangrove forests are classified as natural forests (Geldenhuys & Mucina 2006), but the textural and spectral properties differ so significantly between the information classes of *natural forest* and *mangroves*, that the classification was simplified by assigning mangrove forests an individual class. For the final classification, *mangroves* was merged into *natural forest*, *plantation* was left as its own class, and *natural vegetation*, *farmland*, *built-up*, *bare ground* and *water* were all merged as *other*. To

achieve a suitable final classification, an average of over 80 training area objects was necessary for each class. With nine classes over the four areas, the number of training objects delineated was over 2400 in total.

4.2 Rule-set development

The development of the rule-set classifier was undertaken using Definiens Developer 7, in a two-tier manner. The first tier consisted of the classification of the images into *forest* and *non-forest*, while the second tier consisted of the discrimination of the *forest* class into *natural* and *plantation* (See Appendix A for the complete rule-set). This section explains each tier in more detail.

4.2.1 Tier 1: Forest/non-forest classification

The workflow of Tier 1 is comprised of a number of distinct steps, as illustrated in Figure 4.1.

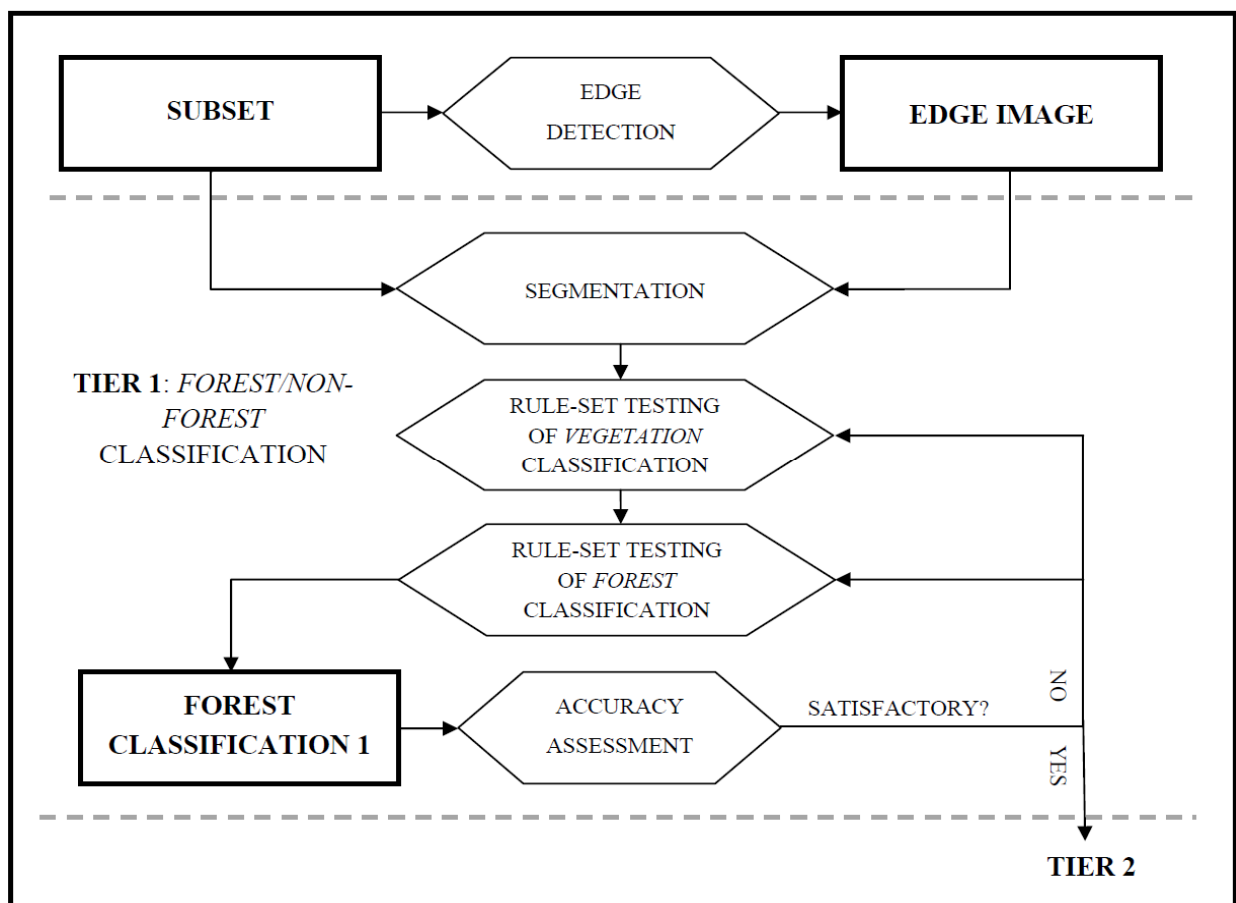


Figure 4.1: The workflow diagram of the first tier of the rule-set–classification of *forest* and *non-forest*

First, an edge mask was created from the target subset, and both the target subset and the edge mask were then entered into a segmentation. Once segmented, two rules were created to classify

the *vegetation* and *forest* class respectively. The creation of rules was iterative, subject to assessment and refinement until a satisfactory classification was created. The following sections explain each of these steps in more detail.

4.2.1.1 Edge masking

The first stage of object-based classification is usually the delineation of the image into homogenous objects using a segmentation algorithm such as multiresolution segmentation (MRS). In this study an additional step was performed before the image was subjected to segmentation. As objects are defined intensely along changes in spectral tone, it was speculated that edge detection would assist the segmentation process. An image was created by applying a 5x5 variance filter on the first principal component of each region. This variance image was subject to a 7x7 median filter and then recoded according to a threshold value of 20. The outcome, an example of which is displayed in Figure 4.3, was a binary mask depicting edge data. A comparison of Figure 4.3 with Figure 4.2 which is a pseudo-colour representation of the same area, shows that both plantation and natural forest (indicated with red and yellow arrows respectively) display a low degree of edge data. Conversely, linear objects, such as roads and field borders, and high-variance areas, such as the residential area of Esikhawini in the south-east of Figure 4.2, are strongly represented in the edge mask image. Edge data were assigned as *no data* before rule-set execution, which assisted in both object creation by inherently delineating object borders, and classification by removing medium- to high-residential areas from the image.

4.2.1.2 Initial segmentation

MRS for object creation requires input parameters for layer weighting, scale and homogeneity (Definiens 2007). Image-layer weighting defines the influence of each layer used in the segmentation process. Theoretically, the layers showing the most difference among the desired classes would be the most suited for use in segmentation. Visual observation showed forests to reflect less of band 1 (green), band 2 (red) and band 4 (SWIR) electromagnetic energy than all other land-cover types excepting water. Consequently testing of segmentation for suitable forest object definition was undertaken on these layers, as well as NDVI and the first principal component of a PCA on the entire subset. Different weight variations were tested among the layers, with the resulting segmentations visually analysed for suitability. Although the results showed little significant variation amongst the layers

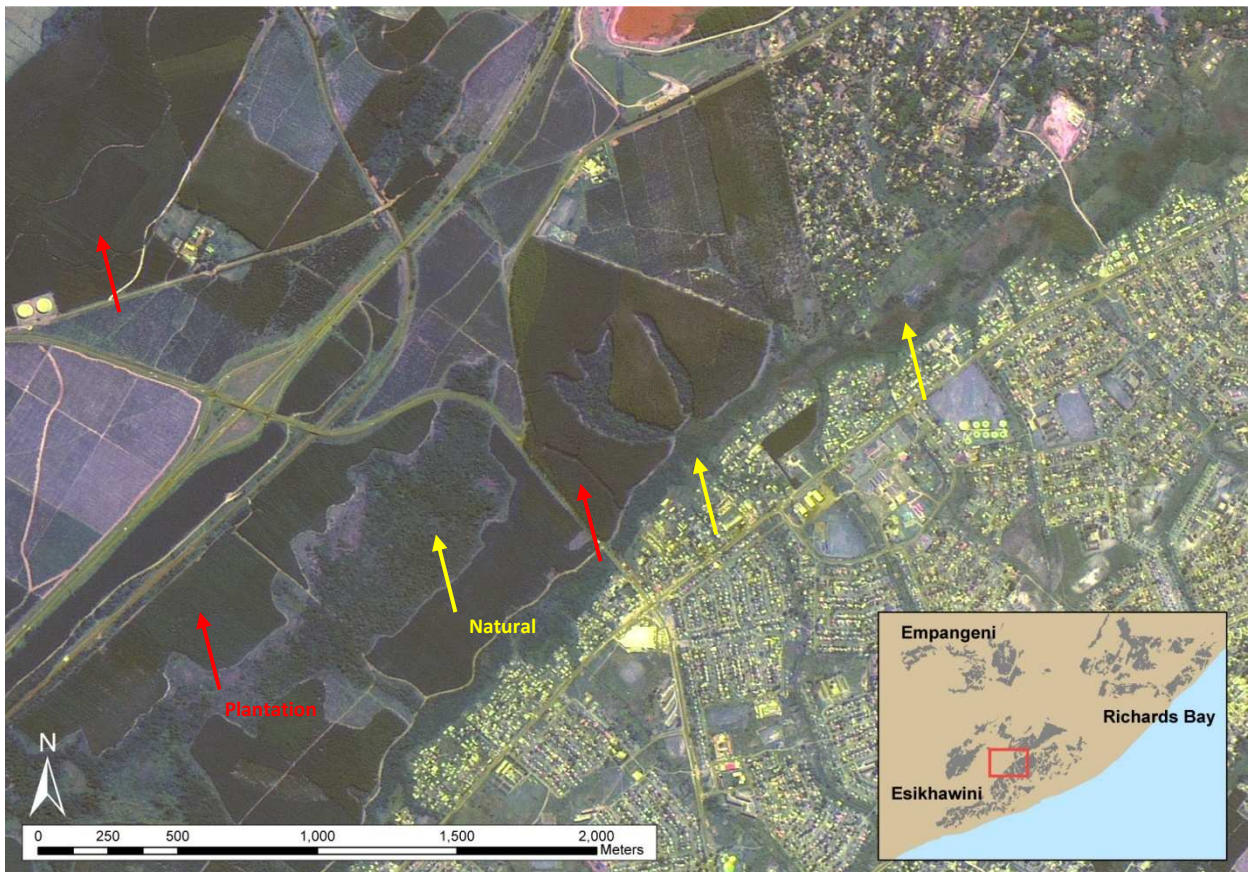


Figure 4.2: A pseudo-colour image of the forests near Esikhawini Township

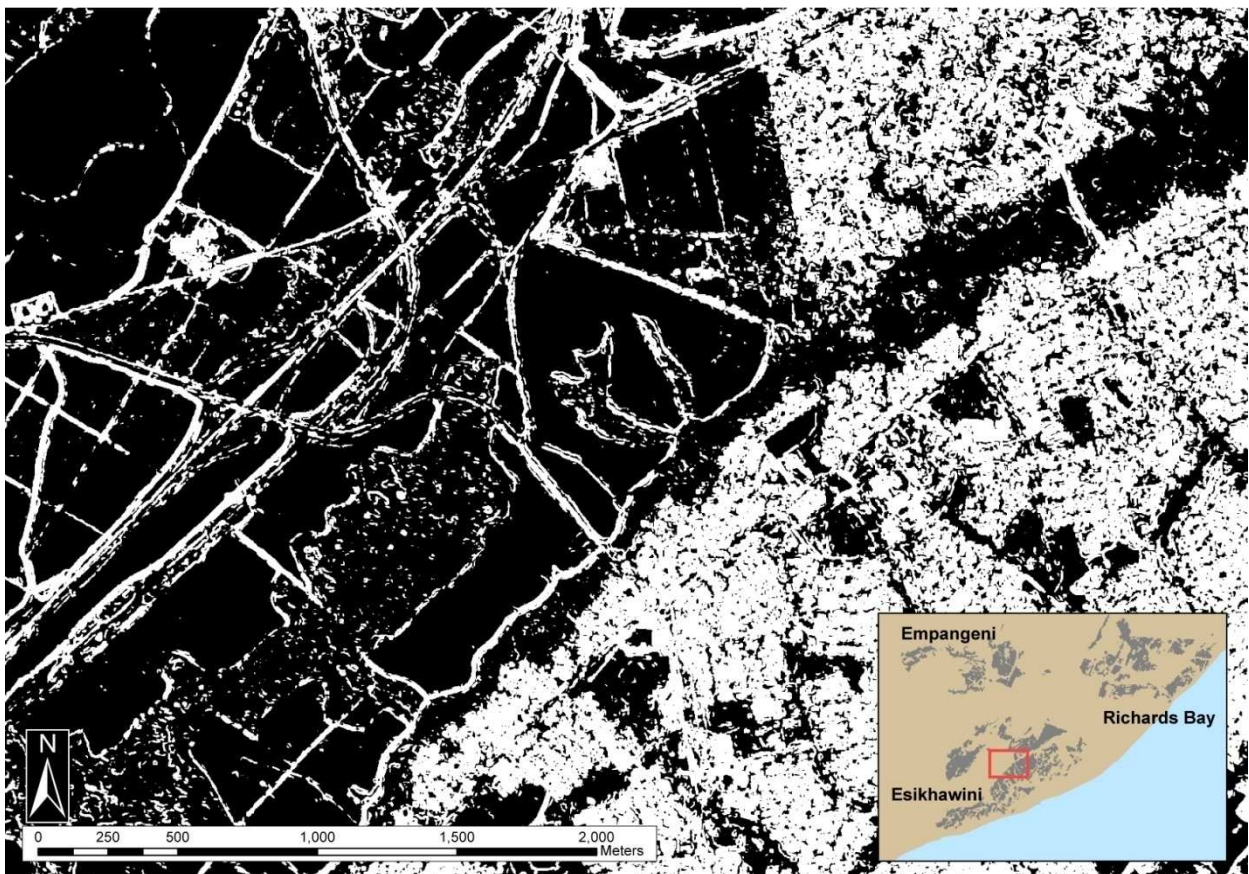


Figure 4.3: Edge mask output

tested for segmentation, the significant influence of the green band during classification promoted the use of a 100% weighting of green for the *forest/non-forest* segmentation.

The second parameter, scale, is a unitless control variable influencing the size of the resulting objects (Definiens 2007). For the purposes of forest classification, it was desirable to create a segmentation that represents forest patches with as few objects as possible. The results of scale parameters ranging from 10 and 250 were sequentially tested and visually assessed. A scale parameter of 25 was determined to be the most suitable for the *forest/non-forest* segmentation, creating objects which comfortably delineated forest land cover without generalisation or unnecessary variation.

The third MRS parameter, homogeneity, comprised a combination of the shape and compactness criteria. The shape criterion specifies the weight that object shape has on the segmentation, with a higher shape value lessening the influence of spectral values on segmentation and returning objects with higher rectangular indices, i.e. more 'blocky'. The compactness criterion is a product of shape, defining the smoothness or compactness of the segmentation (Definiens 2007). Because spectral properties were considered of greater importance than the shape of the resulting objects both the shape and compactness parameters were left as zero.

4.2.1.3 Feature selection for *forest* classification

Feature selection for forest classification began by identifying typical spectral and spatial properties of forest land cover. Information from the literature, reinforced by visual observations, showed forests to have lower values in green, red and SWIR, medium-high vegetation index values, and a homogenous textural structure across all the bands as well as the first principal component (Desclée *et al.* 2006; Huang *et al.* 2008). Vegetation indices, however, displayed a high degree of similarity between agricultural fields and certain types of natural forest, and the same was true for textural features between agriculture and plantations. The individual bands of green, red and SWIR showed the most promise for forest identification, but visual examination showed slightly better results where band values were first subjected to a normalisation process using a generic *vegetation* class. This vegetation class was created by the removal of built-up land cover (e.g. roads and urban areas) during edge masking, and then through the removal of water features and a significant amount of bare ground using a threshold for the scene-adjusted ratio of NIR (the mean value of NIR per object against the mean value of NIR for the entire scene).

Objects were then normalised according to the band means of the vegetation class, according to the following formula:

$$R\lambda = O\lambda / V\lambda$$

Where $R\lambda$: Vegetation-standardised ratio of band λ
 $O\lambda$: Specific object mean of band λ
 $V\lambda$: Vegetation mean of band λ .

The most effective band-ratio for forest classification, determined through experimentation, proved to be the vegetation-standardised ratio of green. The specific values of these two rules, the NIR threshold for *vegetation* classification and the standardised green threshold for *forest* classification were initially developed on Area 1 and then adjusted during the testing of Area 2. The results of this method of rule-set creation are illustrated in Table 4.1, which shows the overall accuracies of each area for each rule. Rule 1 shows a low accuracy in Area 1 (55.6%) and a much higher accuracy in Area 2 (81.4%). This is primarily due to the non-forest vegetation in each image, which strongly affects the accuracy of the *vegetation* class when compared to the reference data of *forest/non-forest*. The vegetation in Area 1 comprised a large amount of agriculture relative to forest. Conversely, the vegetation of Area 2 comprised mostly plantation forests. Overall accuracies for the classification of *forest/non-forest*, were 89% for Area 2 and 98% for Area 1. Noticeable errors in the *forest* classification were predominantly darker agriculture and urban trees (not considered forests in the 2002 NFI). Attempts at correcting these errors resulted in unacceptable omissions of the *forest* classification. Despite this the product was considered acceptable for use in the further classification of *natural forest* and *plantation*. Figure 4.4 provides a graphical illustration of the *vegetation* (light green) and *forests* (dark green) near the Esikhawini Township.

Table 4.1: Tier 1 rule descriptions and accuracies for Area 1 and Area 2

		CLASS	AREA 1	AREA 2
RULE 1:	SCENE-ADJUSTED RATIO BAND 3 <= 0.23	VEGETATION	55.6%	81.4%
RULE 2:	VEGETATION-STANDARD BAND 1 <= 1.1	FOREST	98.0%	89.1%

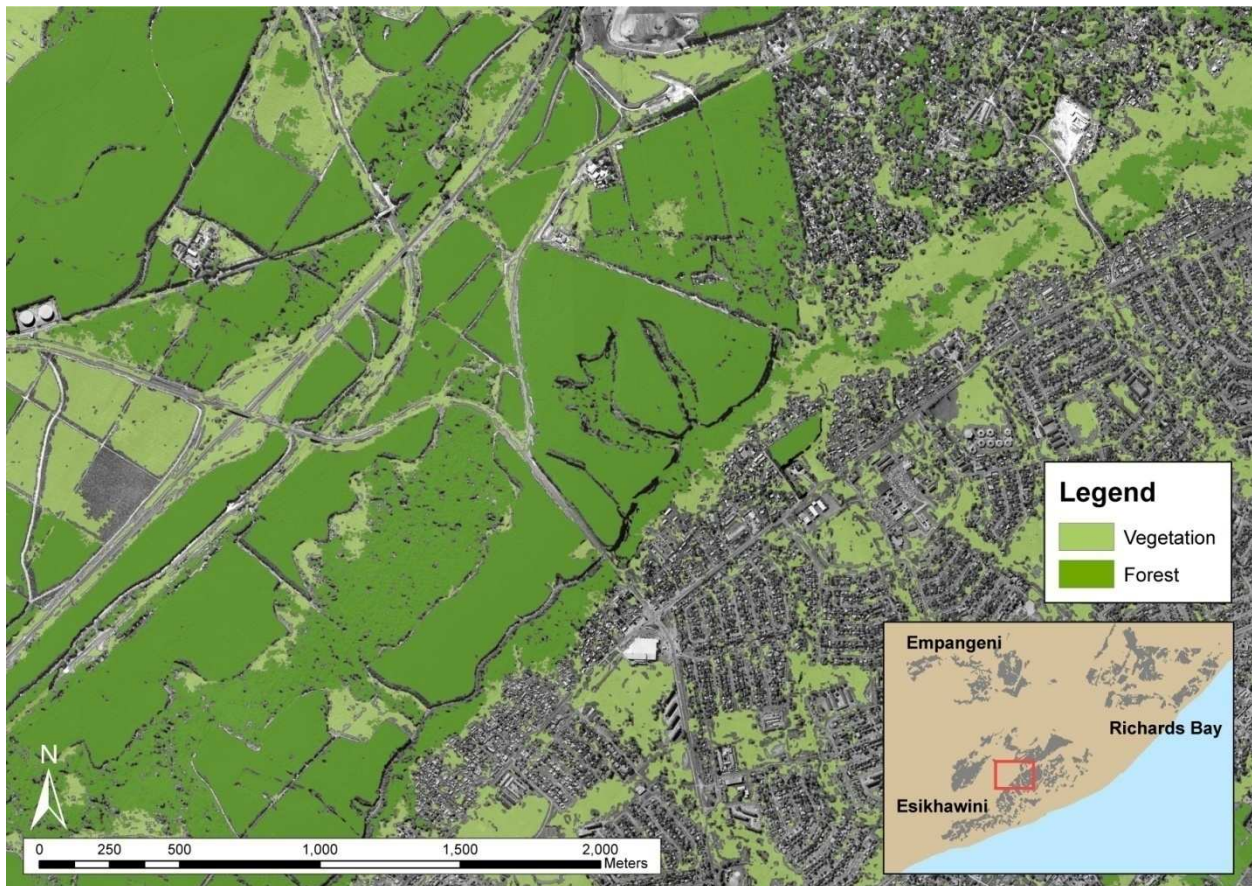


Figure 4.4: The *vegetation* classification result overlaid by the *forest* classification result

4.2.2 Tier 2: Discrimination of *natural forest* and *plantation*

Tier 2 comprised the discrimination of the *forest* class created in Tier 1 into *natural* and *plantation* classes. Figure 4.5 illustrates the steps taken during the creation of this section of the rule-set. The *forest* class was first subject to resegmentation, then tested for suitable rules for the extraction of *plantation*. The remainder of the *forest* class was assigned to *natural*, and the resulting classification was assessed. As with Tier 1, the creation of the rules was an iterative process. These steps are explained in more detail in the following sections.

4.2.2.1 Resegmentation

Due to the unsuitable size of the original objects for this level of the classification, it was found necessary to create a new segmentation below the first one. The aim of the new object level was to create objects in the *forest* category which properly defined the borders of natural forest and plantation while still encompassing as much variation as possible. The *forest* objects were therefore merged and resegmented according to a 100% weighting of NIR, which showed a

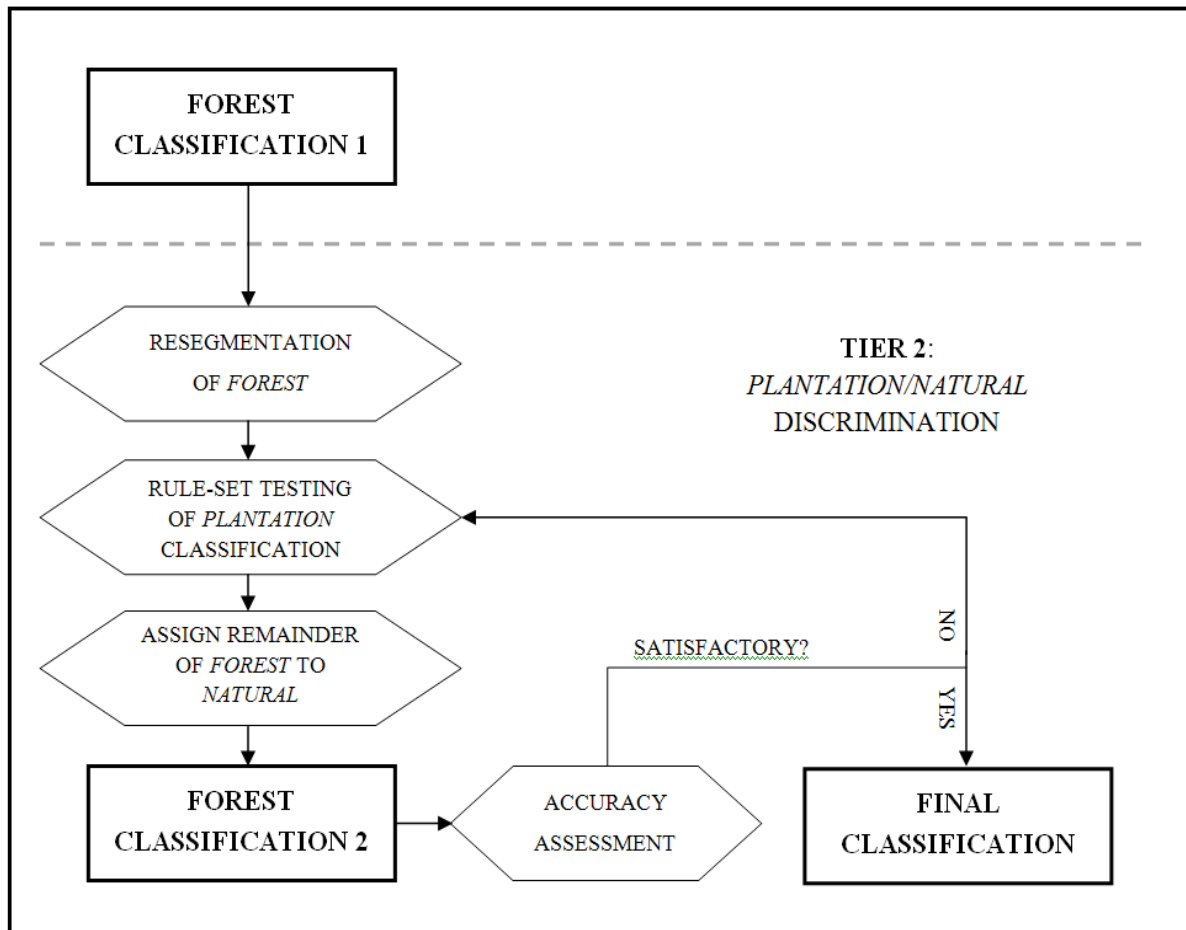


Figure 4.5: The workflow diagram of the second tier of the rule-set–discrimination of *plantation* and *natural*

relatively high degree of contrast between plantation and natural forests, and green. Through experimentation it was found that a scale parameter of 100 was the most suitable, returning objects which accurately delineated borders between adjacent *natural* and *plantation* objects, while also being large enough to allow textural features to be successfully used. Segmentation homogeneity parameters were also introduced, with values of 0.5 for both shape and compactness. These parameters increased the regularity of the objects, which correlated more closely with the less irregular plantation borders.

4.2.2.2 Feature selection for *plantation* and *natural* classification

With a viable segmentation the next step undertaken was an analysis of plantation and natural forest land cover to assess the spectral and spatial differences between the two classes. Through visual observations it was found that plantations appeared to be uniformly darker for every band except NIR, and contained minimal grey-level variation within objects. Conversely, natural forest objects showed wider variation between objects and higher grey-level heterogeneity within

objects. Consequently the following spectral features were tested for *natural/plantation* discrimination: green, red, NIR and SWIR, mean brightness, NDVI, AFRI, MSAVI, EVI2. Standard deviation and the GLCM Haralick textural features of homogeneity, second angular movement and correlation were calculated for all of the spectral bands and the first principal component. Features were initially assessed using density slicing, a procedure which assigns a colour to the brightness of a target layer for enhanced visual analysis. Methodical alterations to the threshold values, while overlaid by the reference data, enabled specific threshold rules to be created and tested for each layer. More promising features were initialised as individual rules and subject to accuracy assessments. This was done by assigning the most suitable threshold value of each feature for *plantation* classification, assigning the remaining *forest* class to *natural* and calculating overall accuracy for the final classification product. These accuracies, which are shown in Table 4.2, provide a more rational indication of the potential usefulness of the features tested in plantation discrimination. As expected, standard deviation, correlation and homogeneity showed high combined accuracies for the classification of the texturally smooth plantation objects. Vegetation indices generally performed poorly in the classification, possibly due to the spectral similarity of natural forests and plantations in the red band, while accuracies of the individual bands of NIR and SWIR showed noteworthy potential as a classification feature. Green, while showing reasonable accuracy for Area 1, was poor for the Area 2, possibly due to the large amount of plantation relative to natural forest in this area.

Table 4.2: Overall accuracies of individual features threshold rules

Features	Area 1 accuracy %	Area 2 accuracy %	Combined accuracies %
NIR standard deviation	79.7	76.9	78.3
PCI correlation	85.2	70.7	78.0
NIR	75.4	76.3	75.8
NIR homogeneity	79.5	70.7	75.1
SWIR	64.5	78.4	71.5
MSAVI	54.4	75.6	65.0
EVI2	76.3	46.7	61.5
NIR correlation	80.8	38.3	59.6
Green	78.7	28.3	53.5
AFRI	73.3	30.9	52.1
Red	55.6	38.7	47.1
NDVI	51.8	38.9	45.4

It is important to note, however, that no one layer showed overall dominance in delineating either the *plantation* or *natural* classes. Because of this the rule-set was constructed in a manner that used a number of different features to sequentially classify as many of the plantations as possible

before assigning the remainder to *natural*. The exception to this methodology was the initial extraction of mangrove swamps, a type of natural forest bordering the Richards Bay Estuary. This land-cover type showed very similar properties to plantation, both being spectrally very dark in the green, red and SWIR bands, as well as texturally homogenous. However, the waterlogged nature of mangrove forests also causes low reflection in the NIR region of the EM spectrum, and as such it was possible to assign mangrove forests as *natural* prior to *plantation* extraction using a threshold value of mean layer brightness. *Plantation* extraction itself was undertaken using threshold values for features in the following order: vegetation-standardised green, ratio-to-scene NIR, and standard deviation of the NIR band. Each feature extracted slightly different areas of plantations and the combination of the features improved the result of the classifier over multiple areas, as can be seen in Table 4.3.

Table 4.3: Tier 2 rule descriptions and accuracies for Area 1 and Area 2

		CLASS	AREA 1	AREA 2
RULE 3:	BRIGHTNESS ≤ 60	<i>NATURAL</i>	n/a	n/a
RULE 4:	VEGETATION-STANDARD BAND 1 ≥ 1.23	<i>PLANTATION</i>	94.4%	79.0%
RULE 5:	RATIO-TO-SCENE BAND 3 ≤ 1.05	<i>PLANTATION</i>	94.6%	87.8%
RULE 6:	STANDARD DEVIATION BAND 3 ≤ 11	<i>PLANTATION</i>	94.3%	90.5%

Due to the lack of *plantation* classification, the calculation of overall accuracy for Rule 3 was not undertaken. Rules 4 and 5 return relatively high overall accuracy for both areas, but with greater accuracy in Area 1. This is due to the method of rule-set design, where the initial rule-set was developed on Area 1 and then tested and tweaked for Area 2. An example of the necessary tweaking is Rule 6, which uses the standard deviation of the NIR band to delineate plantations. Although this rule lowers overall accuracy by 0.3% in Area 1, it increases the accuracy in Area 2 by 2.7%. This slight loss of accuracy in Area 1 was deemed to be outweighed by the increase in accuracy in Area 2.

An area of the final classification is shown in Figure 4.6. A visual comparison of the classification with the reference data revealed a number of noticeable classification errors, the majority of which are plantations classified as *natural*. This occurred due to the spectral differences of younger plantations, the textural heterogeneity of sparsely canopied plantations, and in plantations of smaller area and therefore weaker feature representation. Errors of natural forest classified as *plantation* were much less common, occurring where natural forest objects closely resembled plantations spectrally and texturally.

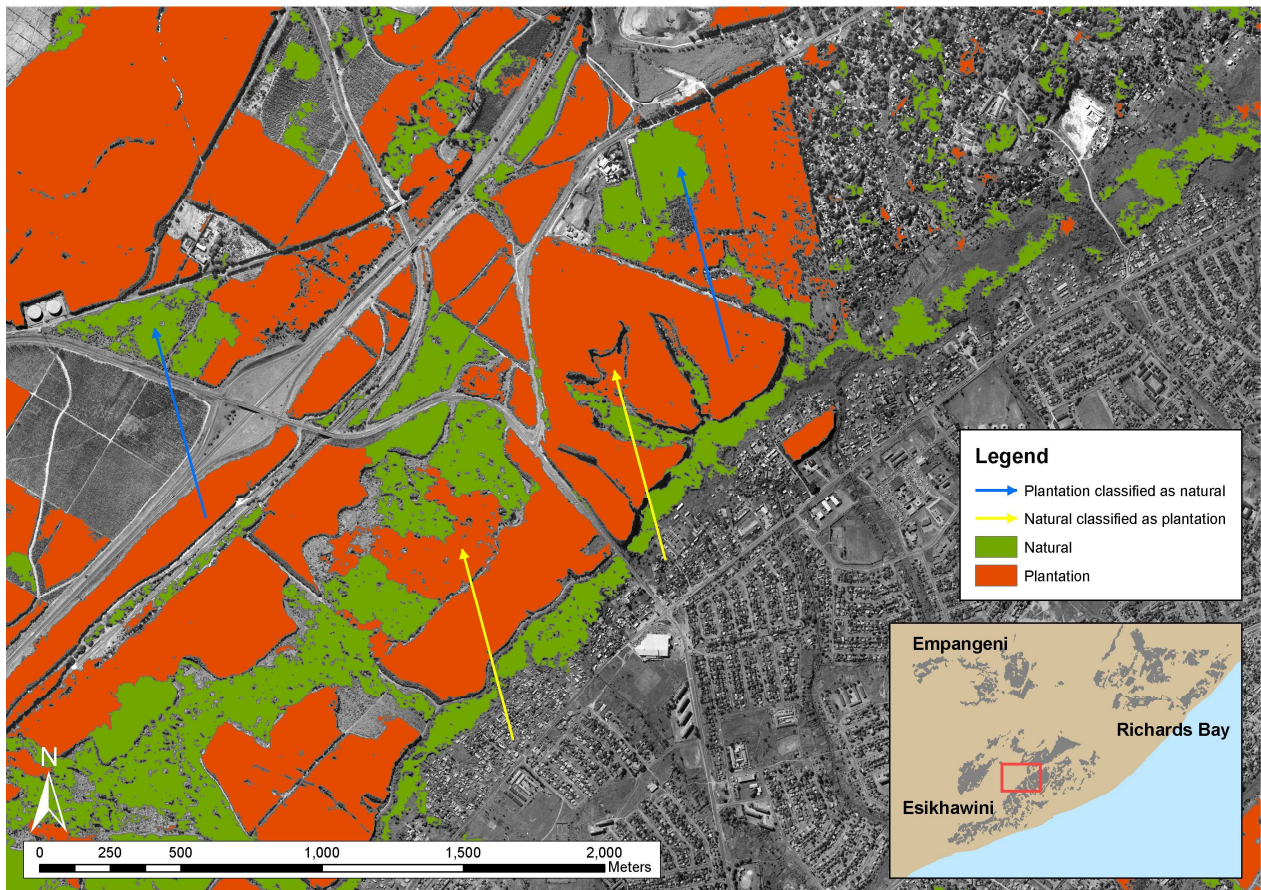


Figure 4.6: The final *natural/plantation* classification product of the area of Esikhawini township

Despite these errors, the overall accuracy of the forest maps of Areas 1 and 2 was deemed sufficient for comparison purposes. The comparison of the rule-set and supervised classification approaches is described and discussed in the next chapter.

CHAPTER 5: EVALUATION AND CONCLUSIONS

This chapter begins by citing the accuracies of the supervised approach, identifying possible reasons for class error and stating the confidence with which accuracies can be interpreted. The second section details the same factors for the rule-set, and the third section compares the two approaches in terms of accuracy and cost-effectiveness. The final section of the chapter provides an overview of the research, the conclusions of the findings and the recommendations for the use of each approach in the context of forest mapping over large areas.

5.1 Expert system versus supervised classification approaches

Although the accuracies of the forest maps of Areas 1 and 2 were tested during both the supervised classification and rule-set creation, a more significant indication of the accuracy of each approach was determined by assessing the accuracies of all four forest maps. The maps generated by the supervised and rule-set classifications were consequently compared using 100 random points for each test area. These points were then combined into one 400 point error matrix for each approach. In theory, error matrixes can be created using either point or polygon data as reference. Although point-based accuracy assessments are less effective than polygon-based assessments in identifying boundary inaccuracies, a point-based approach was chosen for this evaluation because land cover could be unambiguously determined for each reference point using a combination of field visits, aerial photographs, topographical maps and satellite imagery. This approach ensured that the accuracy assessment was a true reflection of the resulting classification quality.

5.1.1 Accuracy assessment of forest maps generated using a supervised classifier

The results of the supervised classifications, given in Table 5.1, show an overall accuracy of 90%. The Kappa index value, an estimate of accuracy which takes into account the possibility of randomly selecting the correct classification, was 0.796, which is generally indicative of a better-than-average classification (Montserud & Leamans 1992; Landis & Koch 1977). The generally higher producer's and user's accuracy of the *other* class suggests that the classifier was more successful in differentiating between *forest* and *non-forest* than separating the different types of forests. This is also indicative of the similarity of the spectral and textural features between *natural forest* and *plantation*.

Table 5.1: The combined error matrix of the supervised classifications undertaken on the four areas

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	
<i>Other</i>	254	6	6	266
<i>Natural</i>	11	73	7	91
<i>Plantation</i>	5	5	33	43
	270	84	46	400
	Producer's Accuracy	User's Accuracy		
<i>Other</i>	95.49	94.07		
<i>Natural</i>	80.22	86.90		
<i>Plantation</i>	76.74	71.74		
Kappa Index	0.796			
Overall Accuracy	90.00			

The primary factor affecting classification accuracy is instances of uncharacteristic plantations and natural forests. Typical plantations are texturally homogenous with low values in green and red, while natural forest has higher grey-level variation, with slightly higher spectral values for every band other than NIR. A number of the occurrences were observed where young or recently burnt plantations were incorrectly classified as *other* or *natural*. Similarly, plantations which display patchy canopy cover, i.e. higher heterogeneity, were classified as *natural*. Conversely, certain sections of natural forest that have homogenous canopies were mistakenly classified as *plantation*. Non-forest riparian vegetation, which has a very similar spectral signature and textural structure to typical plantations was also often incorrectly classified as *plantation*.

5.1.2 Accuracy assessment of forest maps generated using a rule-set classifier

The results of the accuracy assessment carried out on the forest maps generated by the rule-set classifier are summarized in Table 5.2. When compared with Table 5.1 one can see that the accuracies obtained using the rule-set classifier (i.e. 90% and a Kappa Index of 0.788) is virtually the same to that of the maps produced by the supervised classification. Another similarity is the higher producer's and user's accuracy for the *other* class, which is again indicative of the greater separability between the *other* and *forest* classes over the *plantation* and *natural*.

Specific reasons for classification inaccuracies are also comparable to the supervised classification: young, burnt or patchy plantations are incorrectly classified as *other* or *natural forest*, natural vegetation displaying high homogeneity as *plantation*, topography-shadowed agriculture as either *natural forest* or *plantation*, and riparian vegetation as natural forest. However, in addition to these inaccuracies a new type of error is observed, namely edge offsets.

Table 5.2: The combined error matrix of the rule-set classifications undertaken on the four areas

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	
<i>Other</i>	262	4	5	271
<i>Natural</i>	12	65	4	81
<i>Plantation</i>	7	8	33	48
	281	77	42	400
	Producer's Accuracy	Users Accurac'y		
<i>Other</i>	96.68	93.24		
<i>Natural</i>	80.25	84.42		
<i>Plantation</i>	68.75	78.57		
Kappa Index	0.788			
Overall Accuracy	90.00			

Edge offsets are errors which are the result of the discrepancies between the edges defined and removed through edge detection, and the actual borders of plantation and natural forest. Such errors are slight, but tend to be more prone to the delineation of natural forest, as this land-cover type contains a higher degree of heterogeneity. One example of this is the edge detection and removal of the shadow of a visually distinct tree amongst other natural forest. The shadow is erroneously classified as *other*, with the final *natural* classification appearing slightly patchy due to the grey-level variation caused by the heterogeneity of natural forest.

5.1.3 Classifier comparison

It is argued here, that when considering the applicability of the two approaches to forest mapping over large areas, two features are prominent when determining which is superior: accuracy and cost-effectiveness. The accuracies of the two classifiers, as shown in previous sections, are both reasonably high at 90%. This is reinforced by the high kappa indices seen for the classifications: both bordering on 0.8, which indicates a fair amount of confidence with which the classifications can be interpreted. With the accuracies of the two classifiers showing such a high similarity, it can be inferred that a decision on which is the superior classifier must rest with the cost-effectiveness of the technique. This is often directly related to the degree to which the classification process can be automated as one of the main costs of image classification is user input.

The degree of automation of a classification is directly affected by the amount of input required from a user to obtain a classification result. Figure 5.1 illustrates the project workflow used in the supervised classification approach. As can be seen, each of the four areas classified followed the same approach. Training data was created for each area and the areas was classified consecutively.

The results of the classification were assessed and the training data altered accordingly. This process of iterative refinement was repeated until a satisfactory classification was produced.

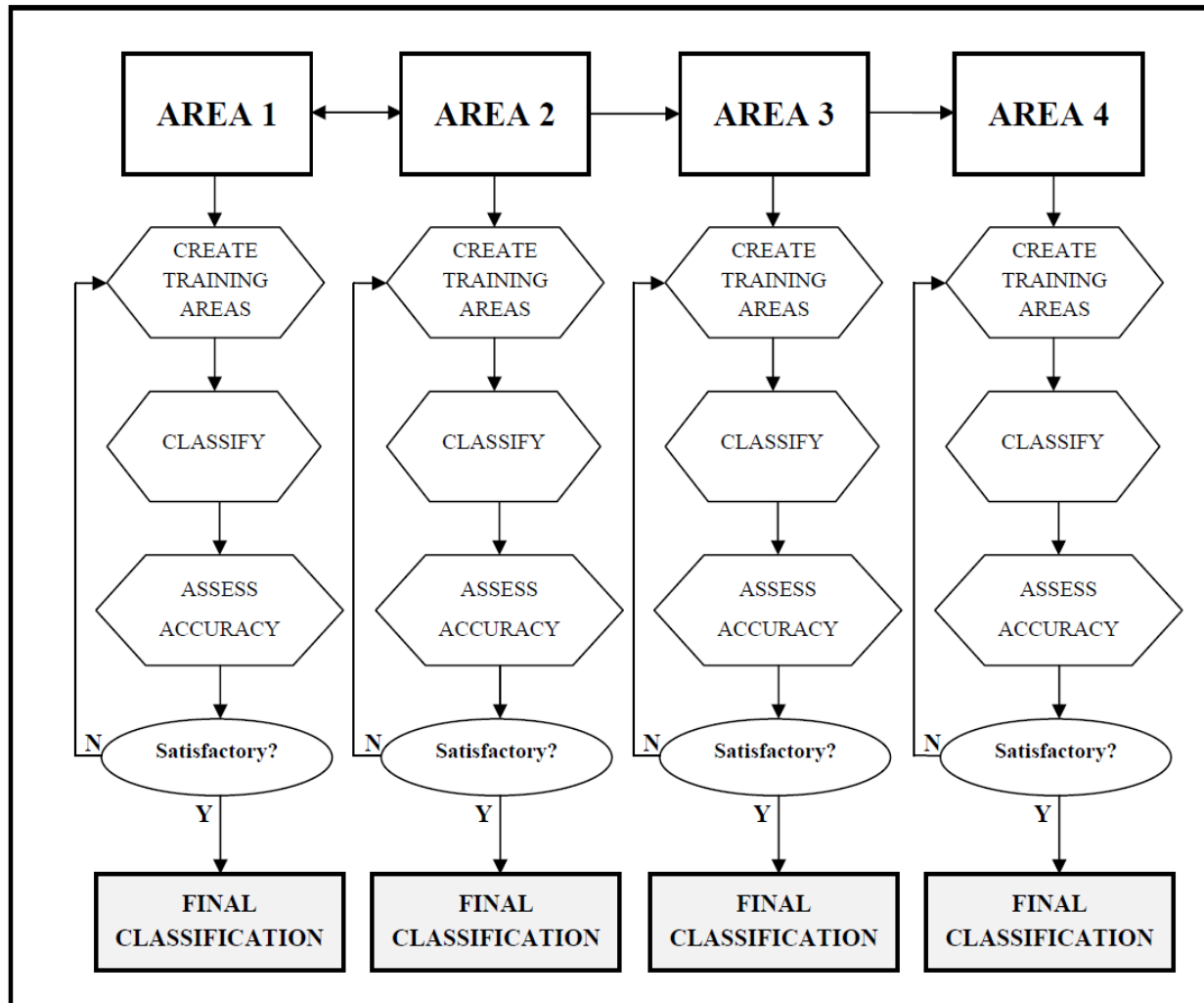


Figure 5.1: The project workflow of the supervised approach

Conversely, the project workflow of the rule-set approach shows a higher degree of automation (i.e. less user input), as illustrated in Figure 5.2. The development of the rule-set was based on Area 1 and modified for Area 2. The rule-set was iteratively adjusted and tested on both Area 1 and 2 until a satisfactory overall classification was obtained. Although the rule-set creation was more user-intensive (i.e. costly) than the creation of training data for one area, the advantage of the rule-set classifier lies in its re-use for Areas 3 and 4 without significant loss of accuracy (see Appendix B for individual error matrices). This result indicates that rule-set classifiers can be applied to different images over a wide area, rendering it more automated and therefore more cost-effective than a supervised classification approach.

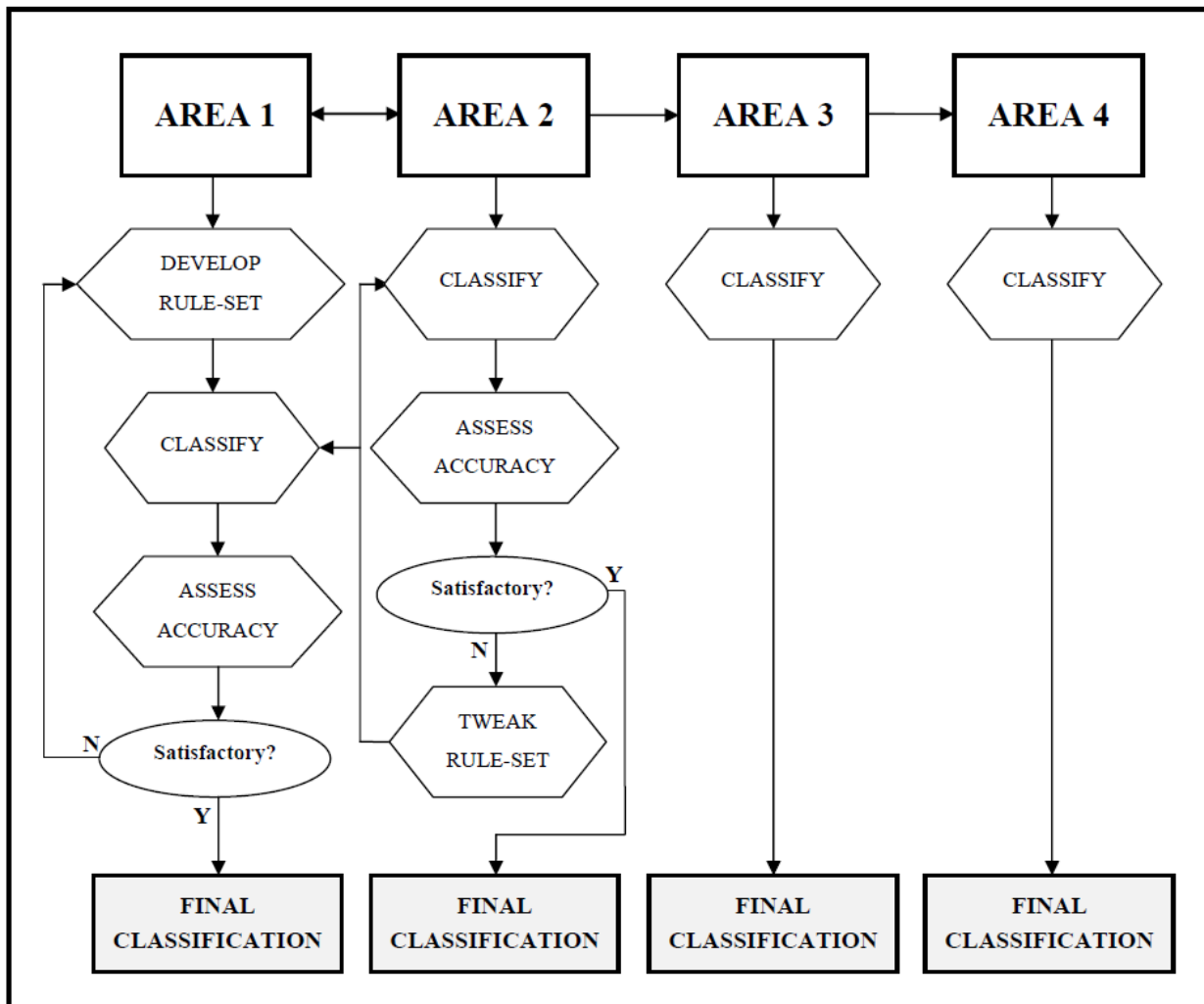


Figure 5.2: The project workflow of the rule-set approach

5.2 Synopsis and conclusions

The aim of this study was to, using object-orientated techniques, compare the accuracy and cost-effectiveness of a supervised and rule-set classification approach for mapping forests on a regional scale. Such a goal prompted a number of questions which needed to be addressed, the first of which was: why select these specific classification approaches? This question was addressed by assessing different methods of image classification in the literature, analysing the advantages and disadvantages of each, and then relating the more suitable methods to the task of a multi-image, large-scale forestry inventory. The review of research in this field made it apparent that, in terms of accuracy, familiarity and ease-of-application, an object-orientated supervised classification was the most suitable for the task at hand. Concerning automation and cost-effectiveness, however, an expert-systems rule-based classification in an object-orientated environment showed significant promise, although the possible accuracies of such a technique were unclear as it had never been attempted for multi-image forestry mapping in South Africa. The crux of this research was then to

develop an expert-system, rule-based classifier, and evaluate its accuracy and cost-effectiveness against a supervised classification for forest mapping on a national scale.

To undertake this, two orthorectified, pan-sharpened SPOT 5 images were acquired from the SAC of the CSIR. Images were further pre-processed using atmospheric correction procedures, and 15x10km image subsets were delineated from each image. Reference data was compiled using ancillary data and field visits, and verified by a forestry expert.

The object-orientated supervised approach was undertaken using a nearest-neighbour algorithm on a nine-class, two-tier hierarchical classification. Training areas were delineated and iteratively refined, using information obtained during a field survey and by using ancillary data. The development of the rule-set was an iterative process, where the accuracies of one classification iteration determined the refinement of individual feature threshold rules used, until a satisfactory classification was returned. When tested on four areas spanning two SPOT5 images, both classifiers returned overall accuracies of 90% with almost identical kappa values of almost 0.8. In terms of automation, the process of training data development for each area rendered the supervised approach more user-intensive, and therefore less cost-effective than the rule-set approach. Adding weight to this argument is the requirement that training data demands the meticulous scrutiny of accurate, large-scale ancillary data, and should be supplemented by field-site verification, which is both time-consuming and financially expensive.

Taking these findings into account, the conclusion of this research is that the greater level of automation shown by the expert-system rule-set approach renders it superior to that of supervised classification for the task at hand. It is therefore suggested that the expert-systems rule-set presented here should be employed for the classification of natural and plantation forests on regional scales. However, more research is needed to determine whether the rule-set classifier can be applied to other areas as it was only tested for the forest types and tree species located in the study area. It is likely that some adjustments will be required to compensate for the spectral and textural variations of other forest types. Thus it is recommended that this rule-set be subjected to further testing in other areas. For a study on a national scale, it may be necessary to modify the rule-base to develop a catalogue of rule-sets for different regions which, at a future date, could be readily applied to any SPOT 5 imagery for monitoring and management purposes.

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PERSONAL COMMUNICATION

- Mucina L 2008. Professor, Department of Botany and Zoology, Stellenbosch University. Email on 15 August 2008 about natural and plantation forest types in the Richards Bay area.

APPENDIX A: RULE-SET DOCUMENTATION

Definiens Developer 7.0 documentation of rule-set *Rules26A.dcp*, the final rule-set used for the classification of *natural, plantation and other*.

Layers:

SPOT Band 1 (green); SPOT Band 2 (red); SPOT Band 3 (NIR); SPOT Band 4 (SWIR); Edge mask.

Classes:

Forest
 Natural
 Other
 Plantation
 Unsure
 Vegetation
 VegetationR

Customized Features:

RatioVegMnL1: [Layer mean of Layer 1, VegetationR]/[Mean Layer 1]

Process: Main:

Forest Extraction

Segmentation

multiresolution segmentation: 25 creating 'Level One'

Classify Vegetation

assign class: with Ratio Layer 3 ≤ 0.23 at Level One: Other

assign class: unclassified at Level One: VegetationR

assign class: Other at Level One: unclassified

Classify Forest

copy image object level: at Level One: copy creating 'Level Two' below

assign class: VegetationR at Level Two: Vegetation

assign class: Vegetation with RatioVegMnL1 ≤ 1.1 at Level Two: Other

assign class: Vegetation at Level Two: Forest

assign class: Other at Level Two: unclassified

Resegmentation

merge region: loop: Forest at Level Two: merge region

merge region: loop: unclassified at Level Two: merge region

multiresolution segmentation: Forest at Level Two: 100 [shape:0.5 compct.:0.5]

copy image object level: at Level Two: copy creating 'Level Three' below

assign class: Forest at Level Three: Unsure

Type Extraction

assign class: Unsure with Brightness ≤ 60 at Level Three: Natural

assign class: Unsure with RatioVegMnL1 ≥ 1.23 at Level Three: Plantation

assign class: Unsure with Ratio to scene Layer 3 ≤ 1.05 at Level Three: Plantation

assign class: Unsure with Standard deviation Layer 3 ≤ 13 at Level Three: Plantation

Cleanup

assign class: Unsure at Level Three: Natural

merge region: loop: Natural at Level Three: merge region

merge region: loop: Plantation at Level Three: merge region

APPENDIX B: INDIVIDUAL ERROR MATRICES

Table B1: Supervised classification error matrix of Area 1

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	78	1	4	83
<i>Natural</i>	0	5	0	5
<i>Plantation</i>	3	1	8	12
Totals	81	7	12	100
Producers Accuracy Users Accuracy				
<i>Other</i>	93.98	96.30		
<i>Natural</i>	100.00	71.43		
<i>Plantation</i>	66.67	66.67		
Kappa Index	0.709			
Overall Accuracy	91.00			

Table B2: Supervised classification error matrix of Area 2

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	66	3	0	69
<i>Natural</i>	4	15	1	20
<i>Plantation</i>	1	0	10	11
Totals	71	18	11	100
Producers Accuracy Users Accuracy				
<i>Other</i>	95.65	92.96		
<i>Natural</i>	75.00	83.33		
<i>Plantation</i>	90.91	90.91		
Kappa Index	0.805			
Overall Accuracy	91.00			

Table B3: Supervised classification error matrix of Area 3

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	76	1	1	78
<i>Natural</i>	3	7	0	10
<i>Plantation</i>	1	1	10	12
Totals	80	9	11	100
Producers Accuracy Users Accuracy				
<i>Other</i>	97.44	95.00		
<i>Natural</i>	70.00	77.78		
<i>Plantation</i>	83.33	90.91		
Kappa Index	0.802			
Overall Accuracy	93.00			

Table B4: Supervised classification error matrix of Area 4

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	34	1	1	36
<i>Natural</i>	4	46	6	56
<i>Plantation</i>	0	3	5	8
Totals	38	50	12	100
Producers Accuracy Users Accuracy				
<i>Other</i>	94.44	89.47		
<i>Natural</i>	82.14	92.00		
<i>Plantation</i>	62.50	41.67		
Kappa Index	0.738			
Overall Accuracy	85.00			

Table B5: Rule-set classification error matrix of Area 1

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	79	0	0	79
<i>Natural</i>	4	8	1	13
<i>Plantation</i>	0	3	5	8
Totals	83	11	6	100
Producers Accuracy Users Accuracy				
<i>Other</i>	100.00	95.18		
<i>Natural</i>	61.54	72.73		
<i>Plantation</i>	62.50	83.33		
Kappa Index	0.754			
Overall Accuracy	92.00			

Table B6: Rule-set classification error matrix of Area 2

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	69	0	2	71
<i>Natural</i>	0	7	1	8
<i>Plantation</i>	3	3	15	21
Totals	72	10	18	100
Producers Accuracy Users Accuracy				
<i>Other</i>	97.18	95.83		
<i>Natural</i>	87.50	70.00		
<i>Plantation</i>	71.43	83.33		
Kappa Index	0.797			
Overall Accuracy	91.00			

Table B7: Rule-set classification error matrix of Area 3

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	72	4	3	79
<i>Natural</i>	2	7	1	10
<i>Plantation</i>	1	1	9	11
Totals	75	12	13	100
Producers Accuracy Users Accuracy				
<i>Other</i>	91.14	96.00		
<i>Natural</i>	70.00	58.33		
<i>Plantation</i>	81.82	69.23		
Kappa Index	0.685			
Overall Accuracy	88.00			

Table B8: Rule-set classification error matrix of Area 4

Reference/Class	<i>Other</i>	<i>Natural</i>	<i>Plantation</i>	Totals
<i>Other</i>	42	0	0	42
<i>Natural</i>	6	43	1	50
<i>Plantation</i>	3	1	4	8
Totals	51	44	5	100
Producers Accuracy Users Accuracy				
<i>Other</i>	100.00	82.35		
<i>Natural</i>	86.00	97.73		
<i>Plantation</i>	50.00	80.00		
Kappa Index	0.804			
Overall Accuracy	89.00			