THE DEVELOPMENT OF A METHOD FOR SEMI-AUTOMATIC CLASSIFICATION OF BUILT-UP AREAS FROM AERIAL IMAGERY

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In fulfilment of requirements for the degree Master of Science in Engineering (Geomatics)

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Plagiarism Declaration

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ABSTRACT

It is essential for geospatial and mapping organisations that changes to the landscape are regularly detected and captured, so that map databases can be updated. The Chief Directorate of National Geospatial Information (CD: NGI), South Africa's national mapping agency, currently relies on manual methods for digitizing features and detecting changes. These methods are time consuming and labour intensive, and rely on the skills and interpretation of the operator. It is therefore necessary to move towards more automated methods in the production process at CD: NGI. The objective of this research is to develop a process for semi-automatic classification of built-up areas from aerial imagery in South Africa. Built-up areas are important as they can grow and change rapidly. Since the South African landscape is varied and climatological conditions differ from one area to another, a general and robust method that can be applied across the country is needed.

This project aims to find the best approach for classifying urban built-up areas from high-resolution aerial imagery by comparing various image classification methods, so that a method that is transferable and applicable in diverse South African scenes may be developed.

Image classification methods were compared and it was found that pixel-based classifiers were unsatisfactory in classifying built-up areas, whereas object-based classifiers had better results. Image segmentation, the first step in an object-based classification, can considerably influence the results of the classification task. It is therefore essential that suitable image segments be generated before the segments are classified.

The proposed methodology involves the use of cadastral data in the image segmentation process and texture measures in the classification of built-up areas within an object-based process. The method can be applied to diverse scenes across South Africa to find built-up areas. This is a generalised approach and can assist the CD: NGI in the process of updating their topographic database by reducing the time that operators spend on identifying and manually digitizing built-up areas.

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List of acronyms

CD: NGI	Chief Directorate of National Geo-spatial Information
CIR	Colour Infrared
CVA	Change Vector Analysis
DMC	Digital Mapping Camera
DSM	Digital Surface Model
GIS	Geographical Information Systems
GLCM	Grey Level Co-occurrence Matrix
GLDV	Grey Level Difference Vector
HSI	Hue, Saturation, Intensity
ISODATA	Self-Organizing Data Analysis Technique
KIA	Kappa Index of Agreement
LIDAR	Light Detection And Ranging
LO	Longitude of Origin
MLC	Maximum Likelihood Classification
NIR	Near Infrared
OBIA	Object Based Image Analysis
PCA	Principal Component Analysis
RGB	Red, Green, Blue
SPOT	Système Pour I'Observation de la Terra
SVDD	Support Vector Data Description
VHSR	Very High Spatial Resolution

1. Introduction

1.1. Background

The Chief Directorate of National Geo-spatial Information (CD: NGI), South Africa's national mapping agency, is responsible for the national topographic mapping, aerial imagery acquisition and control survey network of the country. One of its responsibilities is the capturing and revision of topographical data into the national, integrated database of geo-spatial information. All topographic data is currently manually digitized from aerial imagery, which is a time consuming and labour intensive process and relies on the knowledge and interpretation of the operator.

The CD: NGI aims to detect all changes to the landscape within a year of a change occurring. This highly ambitious goal has yet to be achieved, and current research is focused on finding the most suitable methods of detecting changes to the landscape and updating the CD: NGI national mapping database. Post-classification change detection has been identified as a possible method to assist in achieving the goals of detecting change. The focus of this research is on developing a method for the classification part of this goal, which will be followed up with the change detection part. Keeping in mind the overall goal of CD: NGI, sections of this research are dedicated to change detection, which is a possible application of the results of classification.

1.2. Objective

The objective of this thesis is to develop a process for automatically or semi-automatically classifying built-up areas from aerial imagery in South Africa.

Built-up urban or residential areas are described as areas where people live on a permanent or semi-permanent basis. This includes single story residential units, multi-story units, high rise buildings, as well as low settlement density of rural dwellings (Lück et al., 2010). The CD: NGI define residential land use, or high urban density, as a built-up area where many buildings have been built close together, generally with a spacing of less than 50m between buildings. This definition continues with the explanation that services such as electricity, water and sewage disposal may be available, except in informal settlements. A similar definition is given for low urban density (residential) with the difference being that the buildings are built closely together, but not as closely as in high urban density (Chief Directorate: National Geo-spatial Information, 2013b).

Deciding on the best methodology for the above process is not a trivial task when one considers the large geographical extent of the country, and its varying terrain. The landscape ranges from the dry Karoo, to lush and heavily vegetated regions, to the varying coastal and mountainous regions. There is also the distinction between urban and rural areas and large differences within each of these landscapes, depending on the geographical location. The methodology proposed should be robust and applicable across South Africa, and should require minimal user input or knowledge about the scene being classified.

1.3. Context and scope

The focus of this research is on developing a robust methodology for the classification of built-up areas from aerial imagery. Built-up areas can change rapidly and information about these areas is needed regularly so that the topographic database can be kept up to date. This research is aimed at finding the most suitable method of image classification for detecting built-up areas across South Africa. Once the most appropriate method of image classification is determined, the classified built-up areas can be compared to older, manually captured vector data, so that changes to built-up areas may be identified. Change detection, however, will not be the focus of this research.

The test areas to be used in this study are i) an area in Cape Town, and ii) an area in Johannesburg. These scenes were chosen as they both have large built-up areas that have grown since vector data was last captured for the mapping of these regions. The size of each test area is approximately 5km by 6km and covers one orthorectified aerial image at a resolution of 0.5m, with image bands red, green, blue and near infrared. Cadastral data is also used in this project. Some additional test areas will be used once the method is complete and reliable so that transferability of the method may be proven. Only standard products available to the CD: NGI will be used in this study, and no additional input data will be generated.

1.4. Land cover, land use and topographic mapping

The CD: NGI is responsible for producing high quality land cover, land use and topographic maps for South Africa, and for delivering these maps at predefined intervals. Although land cover, land use and topographic data are different products, they are all related to some extent and have common features or overlap between classes. *Land cover* refers to the physical surface cover, including vegetation, soil, water, and man-made structures. *Land use* refers to the purpose for which the land is dedicated. For example, land cover may consist of '*Graminoids*' (grasses) (see Figure A-1 for the complete land cover legend), and the associated land use may be '*Recreation & Leisure – Sports Facilities*' (see Table A-1 for the complete land cover classification hierarchy).

The relationship between built-up areas within the various classification schemes (land cover, land use and topographic mapping) can be seen in Figure 1-1. Within the 1: 50 000 topographic map structure these features are categorised as '*Residential Landuse*', a subclass of the feature '*Land Cover Land Use (LCLU) – Landuse*'. The structure divides residential areas into two simple categories; high or low urban density, which can be seen in Figure 1-1, and the full topographic data structure is given in the appendices. The 1: 50 000 topographic feature '*Built-up Land*' is currently not compiled for topographic mapping, but the class has been reserved for future mapping purposes. The 1: 250 000 and 1: 500 000 topographic map structures make provision for the class '*Built-up Area*', with subtypes high and low urban density. Within the land cover classification scheme the feature of interest relates to the class '*built-up urban/residential areas*', which is a sub-class of '*Artificial, terrestrial primarily non-vegetated area*'. The associated land use would predominantly be *residential*, but this project's focus is on finding the collective land cover class *built-up areas*, and not sub-classes, or land uses.

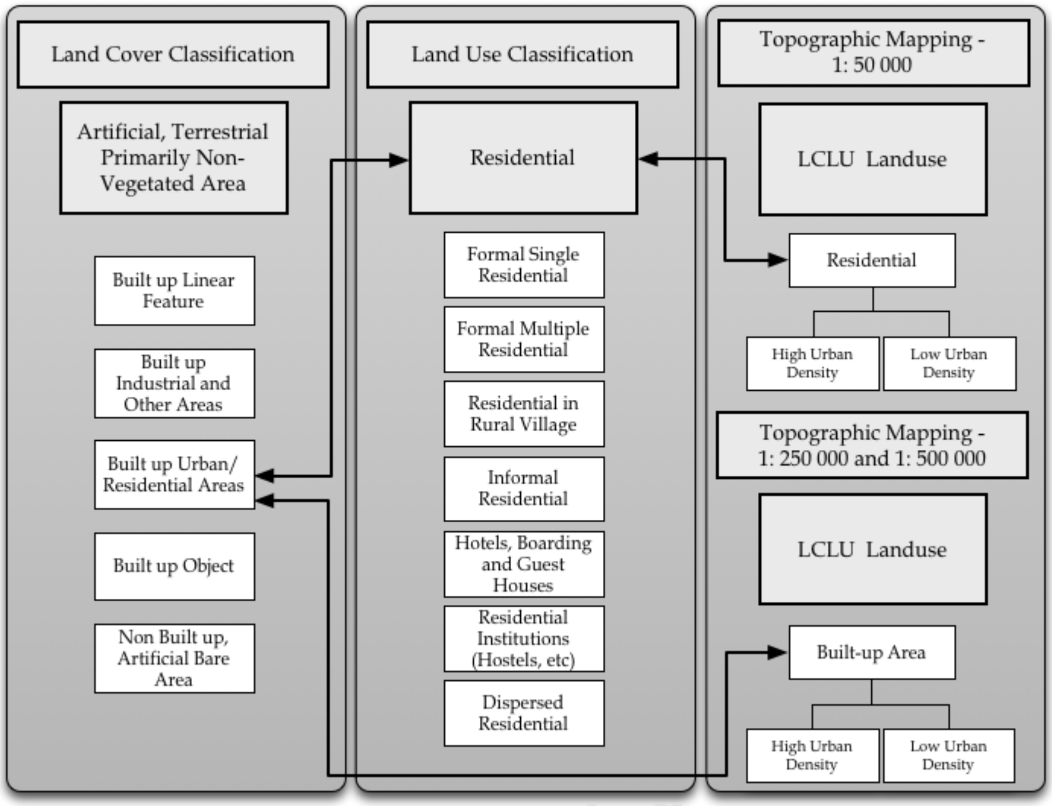


Figure 1-1 Relationship between land cover, land use and topographic mapping

1.5. Key questions

The most important questions relating to this study are as follows:

i. Which is more suitable for classification of built-up areas from very high-resolution aerial imagery: pixel-based or object-based image analysis?

ii. Can thematic data be used reliably to assist in obtaining suitable image segments in object-based classification methods?

iii. Is it possible to develop a method of classification for built-up areas that is robust and transferable across South Africa; and if so, what is it?

1.6. Research approach

The research starts with a comparison of various methods of image classification that includes both pixel and object-based approaches. The per-pixel methods consist of supervised and unsupervised approaches. With the object-based classification method, segmentation is a key factor (Blaschke, 2010) and various techniques are applied in order to find the most suitable method of image segmentation. Image segments should adequately represent features of interest (Smith & Morton, 2008). Since it is possible to generate image segments at various scales, one can create various objects of interest (segments) at different scales for different features (Blaschke & Strobl, 2001; Blaschke, 2010). For example, segments representing general vegetation may be generated at a specific segmentation scale, whereas segments representing a more specific class, such as trees, may be created at a different segmentation scale. It is also possible to include existing vector data in the segmentation approach. Vector data, such as that representing cadastral parcels, may be used to impose boundaries in order to create segments within an image (Smith & Morton, 2008). Cadastral segments can then be further segmented based on spectral, textural or context information (Baatz & Schäpe, 1999). See the image classification research approach in Figure 1-2 for an overview of this experimental methodology.

When urban built-up areas can reliably be classified in the test images, and the accuracy is high (80% or more), the classification algorithm will be tested on additional images in order to prove transferability of the method. If the method does not prove to be transferable, further refinements will need to be made. Once the classification is deemed to be suitable and transferable, classified features can be exported and used for future work within CD: NGI, such as detecting change to built-up areas, updating topographic databases or as input into land cover classifications.

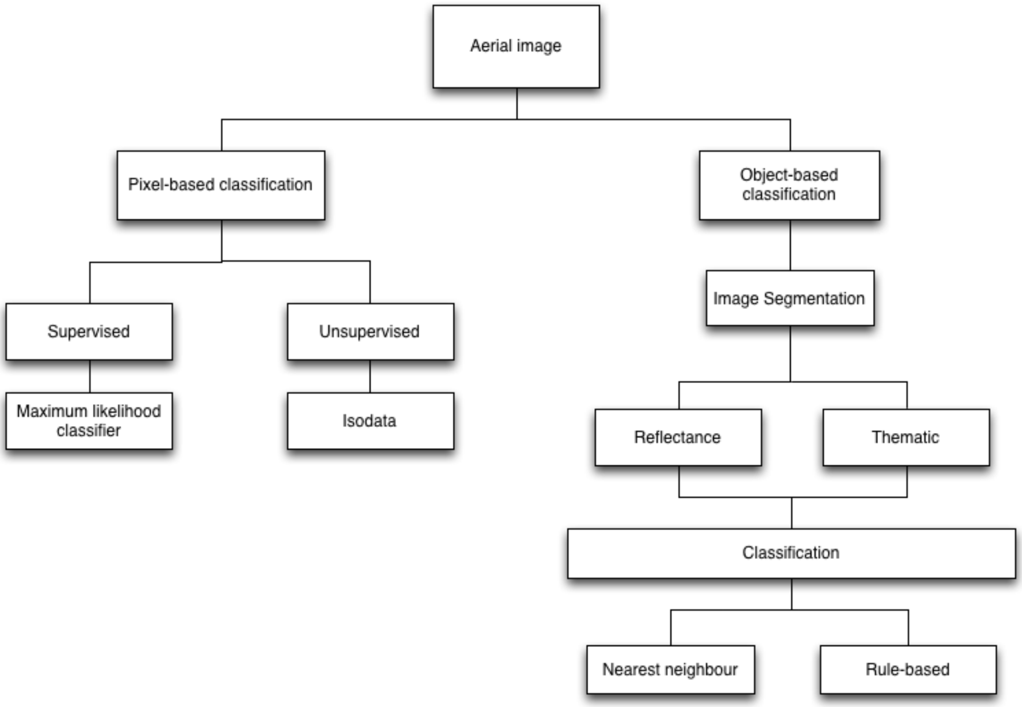


Figure 1-2 Image classification research approach

1.7. Thesis structure

The relevant literature is reviewed and presented in chapter 2. In chapter 3 the proposed image classification methodology is presented, and chapter 4 shows the data used in this study. Chapter 5 presents the results obtained and an analysis of the results. Conclusions are drawn from the results and analysis in chapter 6. Chapter 7 makes recommendations and suggests future work.

2. Literature Review

The literature review starts with the general concept of updating topographic databases and detecting landscape changes. A comparison of different methods of change detection is given and the most promising method is selected - the post-classification method. Relevant literature on high-resolution imagery and image classification is presented, and is followed by studies on classifying the built-environment.

2.1. Updating topographic databases

It is crucial for geospatial and mapping organisations that changes to the landscape are regularly detected and captured so that map databases can be updated. As mentioned in the introduction, the CD: NGI currently relies on time consuming, manual methods of capturing and updating vector data for its topographic database.

Maintenance and revision of topographic map databases can be divided into the following steps: change detection, classification of changes and registration, and updating of the database (Olsen et al., 2002). The focus of this research is on classifying urban built-up areas automatically or semi-automatically so that this data may be used to update topographic databases faster and more efficiently.

2.2. Change detection

Change detection is the process of identifying differences in the state of an object or phenomenon by observing it at different times (Singh, 1989). It involves the comparison of the datasets and consists of the following processes (Armenakis et al., 2002):

- Detection – the discovery of change;
- Recognition – thematic classification of change;
- Identification – description of the feature of the thematic change; and
- Quantification – a measure of the magnitude of change.

Since there are many types of datasets involved in topographic applications, change detection may need to be performed between two images, between an image and vector data, between two sets of vector data, between an image and a map, or between two maps. Change detection between two images acquired at different times can be performed digitally, whereas change detection between other types of data, such as current imagery and old vector data is mostly done visually, with some level of automation having been achieved (Armenakis et al., 2002).

Detecting changes for the purpose of mapping is not a simple task, and although the relatively easy image-to-image comparison may highlight changes in an image, it is generally not suitable due to the natural inter-annual changes that occur within vegetation coverage. These natural variations overshadow the primarily human generated changes that one would want to detect for built-up areas. Change detection must therefore be performed by image-to-vector comparison (Olsen et al., 2002).

Methods for the detection of changes vary between assisted methods and automatic methods, pixel-oriented methods and object-oriented methods, and between spectral characteristics based methods and artificial intelligence based methods (Bouziani et al., 2010).

Two automatic change detection strategies that are identified are: image-to-image comparison and image-to-map comparison. With image-to-image comparison, change detection techniques can be divided into three main classes: techniques based on algebraic operations, techniques based on image transformations and techniques based on classification results. With image-to-map comparison the different methods are: post extraction change detection and map-guided change detection (Bouziani et al., 2010).

The algebra category includes image differencing, image ratioing, image regression, vegetation index differencing, background subtraction, and change vector analysis (CVA). The common characteristic in these methods is the selection of thresholds to find areas that have changed. The difficulty lies in selecting appropriate thresholds to identify changed areas. This is a disadvantage of the algebra category (D. Lu et al., 2004).

Bouziani et al., (2010) propose a method for change detection of buildings in urban environments using very high spatial resolution (VHSR) images and existing digital cartographic data. Firstly, the existing knowledge about the urban objects is modelled and saved in a knowledge base. Then, change detection rules are defined and the image is segmented. The segmented image is analysed using the knowledge base to localize the segments where building changes are likely to occur. The change detection rules are then applied to the segments to identify those segments that represent building changes. The results obtained this object-based method were good and the classes of objects and their relations could be modelled in order to manage the complexity of the urban environment, which would not have been possible with a pixel-based approach. Using the spectral, geometric, contextual knowledge and the use of the rule base considerably improved the change detection of buildings.

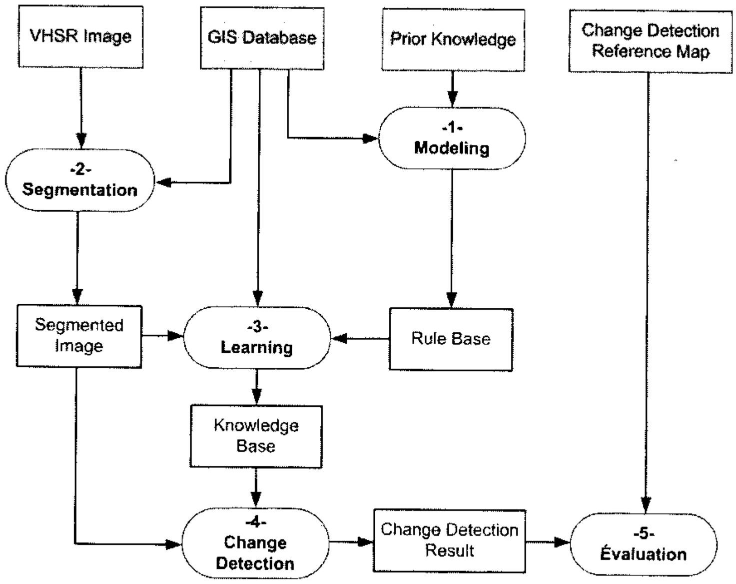


Figure 2-1 Method to detect changes to building (Bouziani et al., 2010)

Changes can be in the form of either spatial or attribute modification. Spatial modification is when the geometry of a feature or its topology changes. Attribute modification is a change in the thematic values of an existing feature. The changes in data patterns are then determined based on the following definitions (Armenakis et al., 2002):

i. Confirmation – when neither the spatial nor the attribute elements of an existing feature has changed.
ii. Addition – when a new feature is added or an existing feature is modified.
iii. Deletion – when a feature or part of it is removed.

Image differencing, principal component analysis (PCA) and post-classification comparison are the most common methods for change detection (D. Lu et al., 2004).

Image differencing, the procedure whereby digital numbers from one image are subtracted from those of a second image, is simple and easy to implement, but results do not show which feature has changed, only that a change exists. “Principal component analysis is a technique that transforms the original remotely sensed dataset into a substantially smaller and easier to interpret set of uncorrelated variables that represents most of the information present in the original dataset” (Jensen, 2005). In a study by Toll et al. (1980) as cited in Singh (1989), it was found that the principal component transformation produced poor results when compared with image differencing for urban change detection. This, however, is a contradiction to Shaoqing & X. Lu, (2008) who found that image differencing is not suitable for change detection in urban areas.

Mas (1999) compared six methods for detecting areas of change to a coastal zone in the State of Campeche, Mexico. The land use in this area is mainly mangrove, evergreen tropical forest, wetlands, pasture and agriculture. The methods compared were image differencing, vegetation index difference, selective principal component analysis, direct multi-date unsupervised classification, post-classification comparison based on supervised classification, and a combination of image enhancement and post-classification comparison. Results indicated that the post-classification comparison based on supervised classification technique was the most accurate procedure and had the advantage of specifying the nature of the changes. It was also found that the selective principal component analysis, when compared to the image differencing method, had a higher accuracy. Contradictory to this, Muchoney & Haack (1994) as cited in D. Lu et al. (2004), when comparing methods for detecting defoliation, found that the classification of principal components and image differencing generally resulted in higher classification accuracies than the spectral/temporal change classification and post-classification comparison. Classification accuracy for image differencing was 69%, and that for PCA was 63%, while spectral/temporal change classification and post-classification comparison both had accuracies of 61%.

Post-classification change detection is the comparison of independently classified images acquired at different times (t_1 and t_2). A change map can be produced by comparing the results of the classification for each image. “Post-classification comparison holds promise because data from two dates are separately classified, thereby minimizing the problem of normalizing for atmospheric and sensor differences between two dates” (Singh, 1989).

Many of the studies that have compared methods of change detection are contradictory. This is discussed in a study on change detection accuracy and image properties using simulated data by Almutairi & Warner (2010). They found that the accuracy of change detection methods varied with changes in image properties. Their results indicated that in most cases direct classification and post-classification comparison were the least sensitive to changes in image properties of class separability, radiometric normalization error and band correlation. Moreover, direct classification and post-classification comparison methods consistently had the highest accuracy while the accuracies of the principal component analysis, change vector analysis, and image differencing methods were highly variable.

The question as to which is the most suitable method of change detection for a specific study is one that remains unanswered. Different change detection algorithms each have their own advantages. It can be concluded that no single method is appropriate for all cases (D. Lu et al., 2004; Blaschke, 2005).

2.3. High resolution imagery and classification

High-resolution imagery is very well suited to mapping urban environments, and presents improvements in the level of detail mapped. However, this also introduces new types of misclassifications (Thomas et al., 2003). In their study using high-resolution imagery and a maximum likelihood pixel-based classification, Walter & Fritsch (1998) found that forests are recognised as homogenous and are well detected, while agricultural areas are also well detected, but show inconsistencies due to their planting structure. Larger streets are recognised without problems, but sometimes there is confusion between pixels from the street class and pixels representing roofs of houses due to their similar spectral characteristics. Pixels are only recognised as settlement areas if they represent house roofs, while other pixels in the settlement class are classified as features such as forest or agricultural areas, due to the high resolution of the imagery. When tested with lower resolution imagery, settlements are recognised as uniform but the accuracy of the results deteriorates.

With high-resolution imagery, it is very likely that neighbouring pixels belong to the same land cover class as the pixel under consideration (Blaschke & Strobl, 2001), but pixel-based classifications using high-resolution imagery often results in the 'salt and pepper effect' (Blaschke et al., 2000). Pixel-based approaches are also recognised as having the following limitations (Hay & Castilla, 2006):

- Pixels are not true geographical objects.
- Pixel topology is limited.
- Pixel-based classifiers largely neglect the spatial photointerpretive elements such as texture, context and shape.
- Increased variability implicit within high resolution imagery confuses pixel-based classifiers resulting in lower classification accuracy.

The relationship between an object under consideration and the spatial resolution of an image is demonstrated in Figure 2-2, where the size of an object is compared to a low resolution (20m) image pixel, a medium resolution (5m) image pixel and a high resolution (1,25m) image pixel. With low-resolution imagery, sub-pixel methods are needed. For medium resolution images, pixels and objects are of a similar size, and pixel-based techniques are therefore appropriate. With high-resolution imagery, pixels are significantly smaller than objects, and therefore object-based classification is needed (Blaschke, 2010).

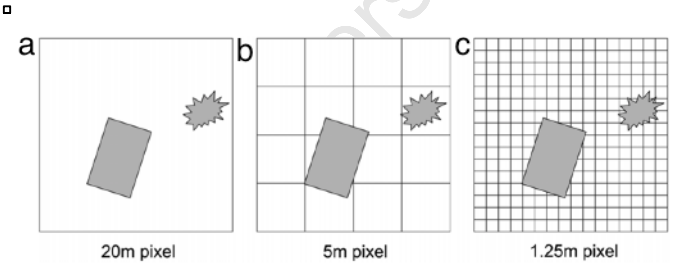


Figure 2-2 The relationship between an object under consideration and the spatial resolution of an image (Blaschke, 2010)

Successful mapping from high-resolution imagery can be found by integrating spectral response with elements such as shape, texture and context (Thomas et al., 2003). The increasing availability of imagery demands automatic and fast methodologies for information extraction. Object-based and knowledge-based classification approaches are the most beneficial choices for high spatial resolution image analysis. Object and knowledge based systems have the possibility of (Novack & Kux, 2010):

- having segments rather than pixels as elementary analysis units, which allows for the exploration of spectral, geometrical, textural and contextual features for the class descriptions;
- using data from different sources and spatial resolutions, ancillary data and customized layers in the analysis;
- creating class descriptions with any number of features, and associating a fuzzy membership function or a simple crisp selection for every feature;
- arranging hierarchically the aggregation of membership values, calculated for every feature of a given class description, using different aggregation operators; and
- representing human knowledge as hierarchical and semantic nets.

The limitation of the pixel in tackling issues of location, scale, neighbourhood and distance has caused a shift towards object-based classification (De Dapper et al., 2006). Even though traditional pixel-based classifiers are well developed and there are sophisticated variations, they do not make use of available spatial concepts (Blaschke et al. 2000; Blaschke & Strobl 2001). The need for context-based algorithms and object-oriented image processing is increasing and it is hypothesized that object-based image analysis will initiate new developments towards integrating GIS and remote sensing functions (Blaschke et al., 2000).

Object-based image classification is often used for the analysis of high-resolution imagery. Taubenböck et al., (2010) proposed an object-based, multilevel, hierarchical classification framework using shape, spectral, contextual and hierarchical information to extract urban features from high-resolution satellite imagery, and achieved an overall accuracy of greater than 81%. Zhou et al., (2008) used high-resolution aerial imagery and Light Detection and Ranging (LIDAR) data in an object-based classification of urban land cover. The approach proved to be successful with an overall accuracy of over 92%.

2.4. Classifying the built environment

In many instances object-oriented classification has proven to be superior over per-pixel methods in classifying complex environments like built-up areas and patterned landscapes (Blaschke & Strobl, 2001). Hurskainen & Pellikka (2004) found that the pixel-based approach is not justifiable for classifying complex urban environments with very high-resolution remote sensing data. The reasons for this are as follows (Hurskainen & Pellikka, 2004):

- Pixels do not sample the urban environment at the spatial scale to be mapped.
- Buildings are represented by groups of pixels that should be treated as individual objects.
- Buildings produce a wide range of spectral signatures.
- Many features in the urban environment appear spectrally similar.

These reasons support the use of object-based classification for identifying built-up areas in high-resolution imagery. This is backed up in the study by Flanders et al. (2003), in which urban features were classified with significantly higher accuracy in an object-based classification compared to a pixel-based maximum likelihood classification. However, a drawback of object-based classification is that the user needs to be aware of the spatial and spectral behaviour of the objects of interest, understand the underlying processing and have good ground information in order to choose the best parameters to identify and classify these objects (Flanders et al., 2003).

Holland et al. (2008) confirm the success of object-based classification over the decision tree classifier and Support Vector Data Description (SVDD) methods. However, in all three methods the main problem was that grey-tiled and asphalt rooftops were confused with tar and concrete ground surfaces. The object-based classification had the highest accuracy (76.0%), followed by the decision tree classifier (73.0%), and lastly the Support Vector Data Description (SVDD) (70.0%). The results were improved by including a digital surface model (DSM) and the following accuracies were achieved: object-based classifier (91.0%), decision tree (90.0%) and SVDD (85.0%). Even with the addition of the DSM certain areas of the image were still misclassified and the types of errors differed between pixel-based and object-based classifications. With the pixel-based classification methods, above ground 'clutter' such as vehicles and shipping containers were frequently misclassified as buildings, and there was still a problem of misclassification of rooftops and tar with concrete ground surfaces, in areas where terrain was not flat. With the object-based approach there was also the problem of ground clutter being misclassified. Rooftops and man-made surfaces were however successfully distinguished from one another. The remaining errors occurred because objects such as low-rise buildings (e.g. sheds and garages) failed to meet the height and area thresholds within the rule-set, and were misclassified as buildings. This was expected, since the rule-set was created to exclude small buildings. The authors stated that it would be possible to create a rule-set that would detect small buildings, but this would result in misclassification of objects of a similar size and height.

Another example of how object-based image analysis can be used to successfully extract information from remotely sensed imagery to update geo-information was seen in the study by Benz et al. (2004). The input into this example was 0.5m resolution RGB aerial imagery and vector data showing building footprints. The vector data was to be updated and polygons added for impervious areas. The classification strategy consisted of iterative segmentation and classification. The results were a classification map and a reliability map (Figure 2-3), statistics with relation to certain classes and to single objects, and an updated and extended shape file (vector data). The authors found that the method reduces the amount of manual interactions substantially, as only objects flagged as having a low reliability have to be manually assigned after inspection. A product with high classification accuracy and reliability can be provided, and the process is time efficient.

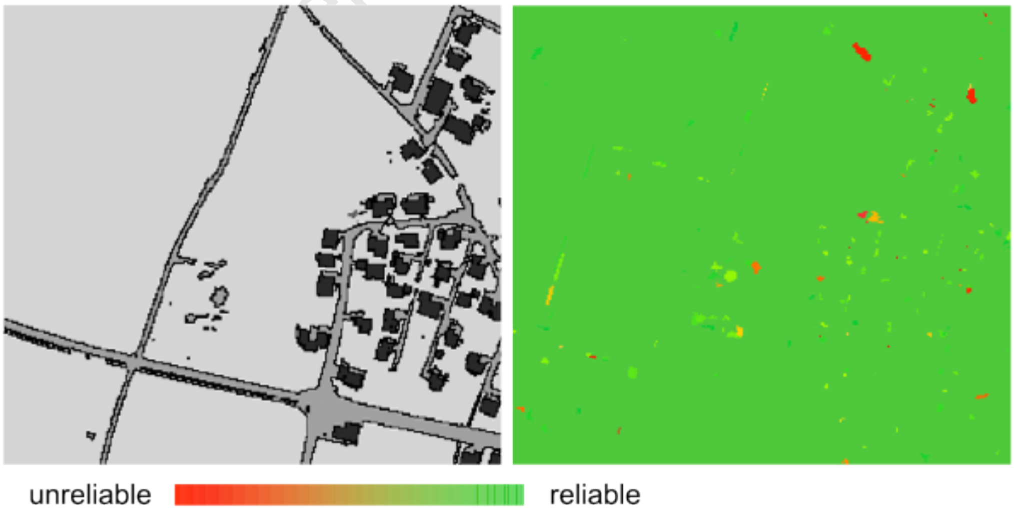


Figure 2-3 Left: classified map of buildings, other impervious areas & non-impervious areas; right: reliability map (Benz et al., 2004)

With the increase in spatial resolution of imagery, between-class spectral confusion, and within-class spectral variation has increased for land cover or land use studies (Haack et al., 1987; Barnsley & Barr, 1996) as cited in Q. Zhang et al., (2003). Spectral information alone is not sufficient to map urban land cover or land use from medium to high-resolution imagery (Q. Zhang et al., 2003). Studies show that textural approaches based on the co-occurrence matrix statistical measures, derived from the work of Haralick and others, has been used in the classification of remotely sensed imagery with significant improvement over the traditional radiometric approach (Pesaresi, 2000). Pesaresi et al. (2008) present a method for deriving built-up areas using image texture. The method is based on the calculation of texture measures derived from the GLCM and takes into account different directional components of the textural measure and produces a "built-up-presence" index. Pesaresi et al. (2008) introduced this method as an alternative to the traditional radiometric approach, which was unsatisfactory in recognition of scattered or heterogeneous settlements, and especially where settlements were composed of varying materials. It is difficult to differentiate between building roofs, roads and open spaces of settlements from other non-vegetated surfaces using radiometric criteria alone, as the spectral reflectance signatures produced are indistinguishable from one another (Pesaresi et al., 2008). In a study by Zhang et al. (2003), supervised classifications were performed using texture features produced from SPOT panchromatic imagery to detect urban spatial patterns. They found that single texture features generally performed poorly, and classification accuracy increased by increasing the number of texture features, until three or four texture features were combined. Zhang et al. (2003) also found that fewer texture features were needed for more homogenous areas.

Puissant et al. (2005) confirmed that the inclusion of texture analysis in the classification of built-up areas in very high-resolution images was beneficial and improved classification accuracy. They selected the following four Haralick texture measures because of their applicability in urban areas: homogeneity, dissimilarity, entropy and angular second moment. The four texture indices with six window sizes were tested on images and it was found that the optimal index for improving the classification was the homogeneity measure with a 7 x 7 window size.

In a study by Su et al. (2008), it was concluded that textural and spatial information can be used to improve object-based classification of urban areas using very high resolution imagery. Texture analysis was based on two levels: segmented image objects, and moving windows across an entire image. In the texture analysis over image objects, the angular second moment at a 45° angle, was found to be better than any other direction at depicting building patterns. The texture analysis based on moving windows was carried out using the following four GLCM textural features: homogeneity, contrast, angular second moment and entropy at window sizes ranging from 3 x 3 to 13 x 13. The GLCM contrast feature with a 7 x 7 window size improved classification results by up to 6%.

3. Image Classification Methodology

This chapter starts with an introduction on image classification methods (3.1), which follows on to the various methods that were tested. The proposed research explores various approaches to image classification with the focus on classifying built-up areas from aerial imagery. The research starts with an investigation into pixel-based methods (3.2), which includes both the supervised and unsupervised methods, and is followed by the object-based classification methodology (3.3).

The object-based classification methodology is split into two general approaches based on the segmentation technique used. These include segmentation based on image reflectance values and segmentation based on thematic data. Classification of segments is conducted by fuzzy logic and may be carried out using the nearest neighbour method, or a rule-based approach to classification.

Figure 3-1 illustrates the approaches to image classification that are tested in this research.

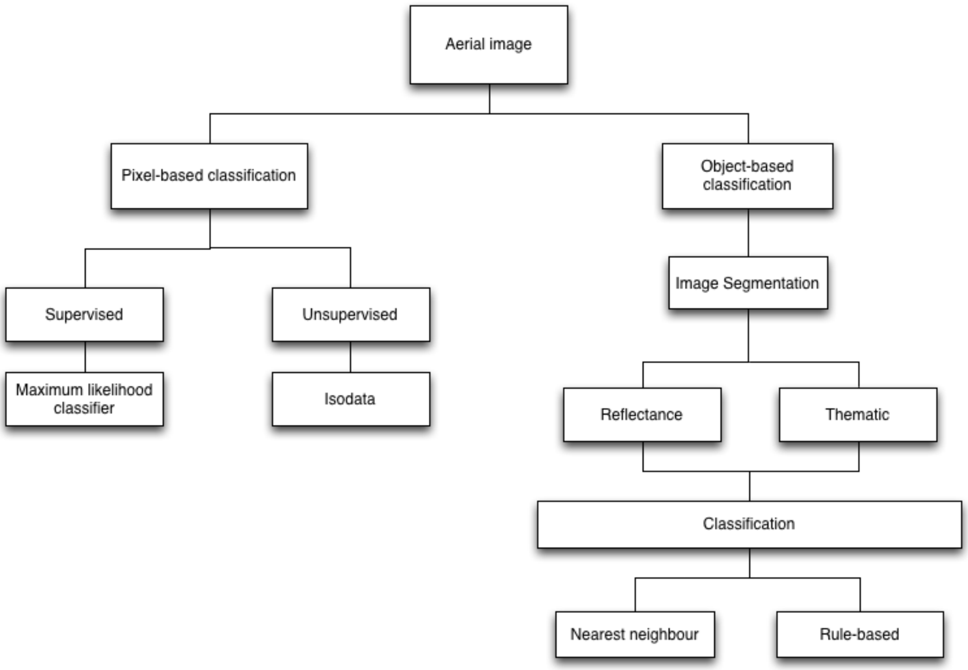


Figure 3-1 Image classification methodology

3.1. Introduction

Image classification is the process of categorizing all pixels in an image into land cover classes or themes. In the framework of remote sensing, the purpose of pattern recognition, or image classification, is to link each object or pixel in a study area to one or more elements of a user defined label set, so that the radiometric information contained in the image can be converted to thematic information, such as vegetation type (Tso & Mather, 2009). The concept of the classifier as the link between an image and a set of labels is illustrated by Tso & Mather (2009) in Figure 3-2.

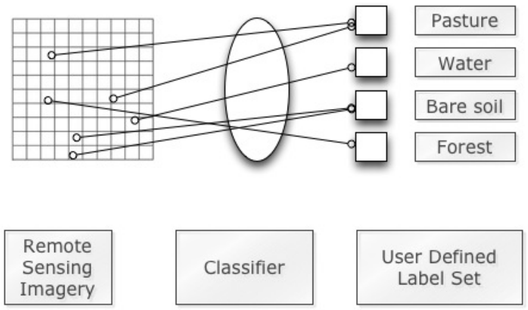


Figure 3-2 The concept of the classifier as the link between the image and a set of labels (Tso & Mather 2009)

There are various methods of multispectral image classification, including (Jensen, 2005):

- algorithms based on parametric and nonparametric statistics, as well as nonmetric methods;
- supervised or unsupervised classification logic;
- hard or fuzzy set classification logic; and
- per-pixel or object-oriented classification logic.

3.1.1. Parametric, nonparametric and nonmetric methods

The maximum likelihood classification method and unsupervised clustering method are examples of parametric methods. They assume normally distributed remote sensing data, and knowledge about the forms of the underlying class density functions (Jensen, 2005).

Nearest-neighbour classifiers, fuzzy classifiers, and neural networks are nonparametric methods and may be applied to remote sensing data that is not normally distributed. With these methods, there is no assumption that the forms of the underlying densities are known. The rule-based decision tree classifier is a nonmetric method and can operate on both real valued data, such as reflectance values ranging from 0 to 100%, and on nominal scaled data, for example, class 1 = forest; class 2 = agriculture (Jensen, 2005).

3.1.2.Supervised and unsupervised methods

With supervised classification, land cover classes are known a priori, and the analyst identifies samples of the known land cover classes as training sites. The spectral characteristics of these training sites are used to train the algorithm for classifying the remainder of the image. With unsupervised classification, land cover classes are not known a priori. Pixels with similar spectral characteristics are grouped into clusters and the analyst then labels and combines clusters into useful classes (Jensen, 2005).

3.1.3.Hard or fuzzy set classification logic

Supervised and unsupervised classification algorithms typically use hard classification logic to produce classification maps that consist of hard, discrete categories (e.g., forest, agriculture), but it is also possible to use fuzzy set classification logic, which takes into account the “heterogeneous and imprecise nature of the real world” (Jensen, 2005). With fuzzy classification a pixel is not assigned to a single class out of *m* possible classes, but rather each pixel has *m* membership values that describe the proportion of the *m* land cover types within the pixel. Figure 3-3 illustrates the concept of the fuzzy classifier. This figure is explained in more detail in the section 3.3.4 below.

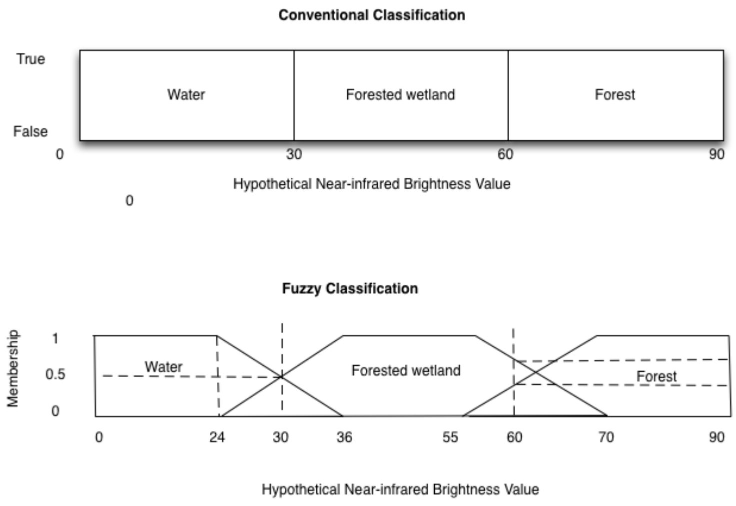


Figure 3-3 Conventional classification compared to fuzzy classification logic (Jensen, 2005)

3.1.4.Per-pixel or object-oriented classification logic

Traditionally, most image classification was based on classifying an entire image, pixel by pixel. With object-based image classification, the image is segmented into homogeneous image objects (Baatz & Schäpe, 2000). The image objects are then subjected to traditional statistical or fuzzy classification logic (Jensen, 2005). These two methods are presented in further detail in 3.2 and 3.3.

3.2. Pixel-based classification

In this study, both supervised and unsupervised classification algorithms were assessed. Since the supervised approach generally gives more accurate class definitions and higher accuracy than the unsupervised approach, it is the preferred method of classification, even though selecting training data may be tedious (Tso & Mather, 2009).

For this study, the maximum likelihood classifier was chosen for the supervised classification method and the Iterative Self-Organizing Data Analysis Technique (ISODATA) was used for unsupervised classification.

Pixel-based classifiers are commonly used for land-cover classification, but there are notable limitations with these classifiers. One such limitation often resulting from pixel-based classifications, especially when using high to very high resolution data, is the salt and pepper effect (Blaschke et al., 2000). Object-based classifiers overcome this problem by segmenting an image into homogenous segments that consist of groups of pixels, which can then be classified based on properties such as shape, spectral properties, texture and relation to other segments.

3.2.1.Supervised Maximum Likelihood Classification

The maximum likelihood classifier, which is based on probability, is widely used for supervised classification (Song et al., 2005). The probability of a pixel belonging to each of a predefined set of classes is calculated, and the pixel is assigned to the class that has the highest probability. Assuming that the data has a Gaussian distribution, and that class signatures are well selected, the maximum likelihood method usually provides high classification accuracies. This method is illustrated in Figure 3-4, where the unknown measurement vector X associated with a single pixel in a two-band dataset would be assigned to forest, because the probability density of its measurement vector X is greater for forest than for agriculture (Jensen, 2005).

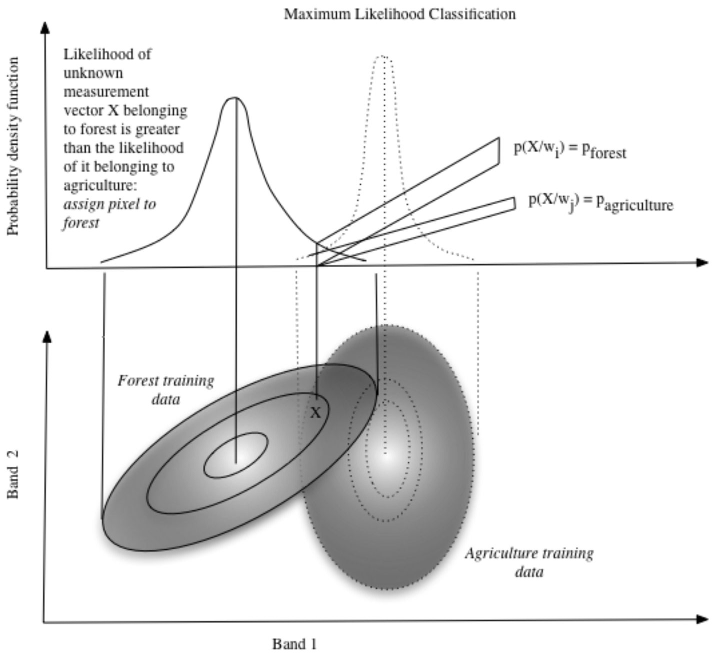


Figure 3-4 Example of the maximum likelihood classification (Jensen, 2005)

3.2.2. Unsupervised classification – ISODATA method

In unsupervised classification, pixel values within a certain land cover type should be close together in the measurement space, whereas data in different classes should be reasonably well separated. The classes that result from unsupervised classification are spectral classes (Lillesand et al., 2004).

The unsupervised ISODATA method is popular in the classification of heterogeneous high resolution images as it is very successful in finding the spectral clusters that are inherent in images (Y. Zhang, 2001). Unsupervised classification may address some of the shortcomings of applying supervised classification for land use or land cover classification where classes have a high degree of spectral variability. Where there is a high degree of spectral variability, suitable training sites for relevant land use or land cover classes will always be difficult to achieve. The unsupervised method is simple to use and no training data or samples are needed, thus making it much faster to implement than the supervised approach. Another advantage is that the unsupervised classifier identifies the different spectral classes present in an image, which might not be obvious to an analyst applying a supervised classifier. Similarly, there may be so many spectral classes in a scene that it would be difficult to train on all of them. Since unsupervised classification is the identification of spectrally distinct classes in an image, the analyst must still use reference data to associate spectral classes with the land cover types of interest. The spectral classes identified may not be uniquely associated with a land cover type, and one may have several spectral classes representing a single feature class (Lillesand et al., 2004).

3.3. Object-Based Image Analysis (OBIA)

It is generally agreed that OBIA builds on older segmentation, edge detection and classification concepts that have been used in remote sensing image analysis for decades (Benz et al., 2004; Blaschke et al., 2008; Blaschke et al., 2000; Flanders et al., 2003; Blaschke, 2010). The main objective of OBIA is to develop automated or semi automated methods and tools that can mimic human interpretation of remotely sensed imagery, and result in an increase in repeatability and production, and a decrease in subjectivity, labour and time costs (Hay & Castilla, 2006). The concept of OBIA gained widespread interest with the advent of the first commercial software for what was then called 'object-oriented image analysis' (Blaschke et al., 2008).

The first step in object-based image classification is the generation of homogeneous image objects or segments. The segments are comprised of groups of pixels that are the basic input for further classification. Image segments (objects) can then be classified based on spectral, shape and texture properties (Benz et al., 2004; Hofmann, 2001a). Blaschke (2010) explains how the amount of literature on OBIA has rapidly increased to such an extent that there are sub-topics within OBIA. These include specific OBIA hierarchy and scale concepts, segmentation, OBIA change detection and OBIA accuracy assessment. There is also the trend for OBIA methods to become part of dedicated workflows and join with GIS applications (Blaschke, 2010).

3.3.1.Image segmentation

Image segmentation is one of the most important steps in object-based classification (Marpu et al., 2010), but the selection of suitable segmentation parameters is not a simple task. Hofmann (2001b) makes the point that as the results of the image segmentation strongly depend on the image data and the assessment of the segmentation results depends on the classification task, and it is almost impossible to suggest well-suited segmentation parameters in general.

Smith & Morton (2010) describe segmentation as a "black art" due to the dependence of the results on the image data and the limited, and often vaguely specified, control parameters available to the user. Suitable segmentation parameters are often chosen by trial and error and resulting segments reflect the spectral structure of the image rather than the true structure of the landscape. Results of image segmentation therefore represent the sensor's view of the surface rather than the user's (Smith & Morton, 2010).

Selecting suitable segmentation parameters is difficult and requires the knowledge and experience of operators (Hofmann, 2001b; Flanders et al., 2003; Smith & Morton, 2010). Skilled operators need to have significant knowledge of the objects of interest and they should be aware of the spatial and spectral behaviour of the objects. They should also understand the underlying processing and have good ground information (Flanders et al., 2003). A significant amount of exploratory work is required to define appropriate segmentation levels and solutions are not fully operational and transferable across scenes without major corrections (Hay et al., 2003).

One approach to image segmentation is the multiresolution segmentation technique, which is a bottom-up strategy to image segmentation. This image segmentation technique starts with each pixel forming one image object. At each step a pair of image objects is merged into one larger object until a specific threshold is reached. The merging decision is based on local homogeneity criteria which describes the similarity of adjacent image objects (Baatz & Schäpe, 2000). The multiresolution segmentation approach is illustrated in Figure 3-5. Figure 3-6 shows an image that was segmented using the multiresolution segmentation approach. The segments shown may be used as they are, or they can be used as input into another segmentation process to create new segments.

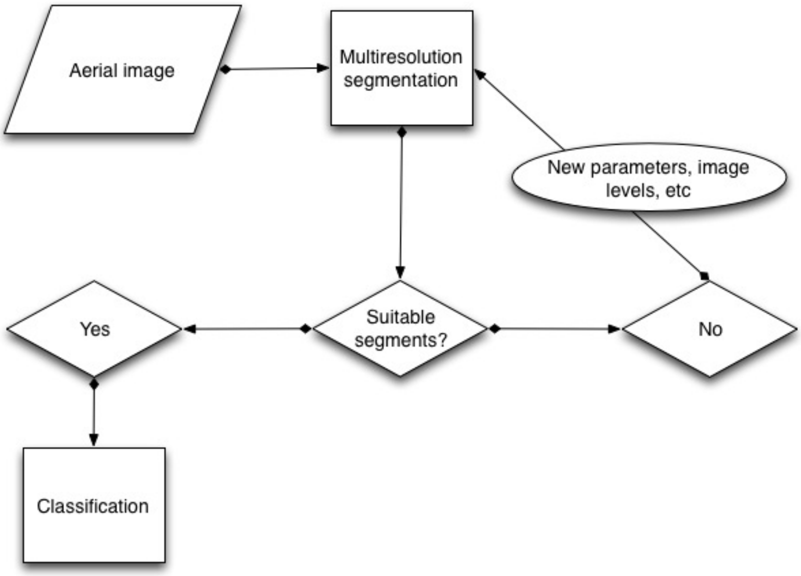


Figure 3-5 Multiresolution segmentation approach

Figure 3-6 Multiresolution segmentation (level 1, scale parameter: 20)

The region merging and region growing process was designed with a view to meeting the following design goals (Baatz & Schäpe, 2000):

- Image-object primitives should be homogenous.
- Segments should be adaptable to different scales.
- Segments should be of a similar size for a chosen scale.
- Segmentation results should be reproducible.
- The region merging and region growing process should be applicable to a variety of data types.
- Performance should be reasonably fast, even on large image data sets.

Another example of the multiresolution segmentation approach is illustrated in Figure 3-7, where trees and meadows have similar spectral values, but are separated because of the difference in their spectral homogeneity (Baatz & Schäpe, 2000).

Figure 3-7 Mulitresolution segmentation of trees (Baatz & Schäpe, 2000)

The shape of image segments is determined by the following parameters (Hofmann, 2001b):

- *Weight of image channels:* specify the weight of each spectral band in the segmentation. Channels with higher weights have a greater influence on object generation.
- *Scale parameter:* controls the average object (segment) size. This parameter determines the maximum allowed heterogeneity of the objects. The larger the scale parameter, the larger the objects become.

- *Colour/Shape:* the influence of colour vs. shape can be adjusted. The higher the shape value, the less spectral homogeneity influences the object generation.
- *Smoothness/Compactness:* these are attributes of the shape criterion. If the shape criterion is larger than 0, the user can determine whether objects shall be more compact or smoother.
- *Level:* a newly generated image level can either overwrite a current level, or the generated objects can contain sub- or super-objects of an existing level. The order of generating the levels affects the objects' shape (top-down vs. bottom-up segmentation*).*

Since the selection of suitable segmentation parameters for a multiresolution segmentation is difficult (Hofmann, 2001b; Flanders et al., 2003; Smith & Morton, 2010; Drăguţ et al., 2010), an alternative method is to start the segmentation process using thematic data and a chessboard segmentation. The chessboard segmentation follows a top-down approach and works by cutting the image or image objects into smaller objects. With the chessboard segmentation algorithm, existing vector data can be used to create initial segments (as seen in Figure 3-10) that can later be segmented based on image reflectance properties such shape, colour, texture, etc. The inclusion of thematic data for image segmentation is discussed in more detail in 3.3.3.

3.3.2. Object scale and hierarchy

Different image objects require different scales of segmentation. As mentioned above, the scale controls the average object size, and it determines how heterogeneous segments may be. A smaller scale parameter will mean that there is less variability within segments and therefore smaller segments are created. A segmentation scale at one particular scale may, for example, be suitable for defining buildings, but may not be appropriate for built-up areas, roads or vegetation. The segmentation approach in object-based image classification allows users to generate image objects at various scales. A hierarchical network of image objects (see Figure 3-8) can be generated in which high resolution objects are sub-objects of super-objects, and each object knows its context, its neighbouring objects and its sub-objects (Baatz & Schäpe, 1999).

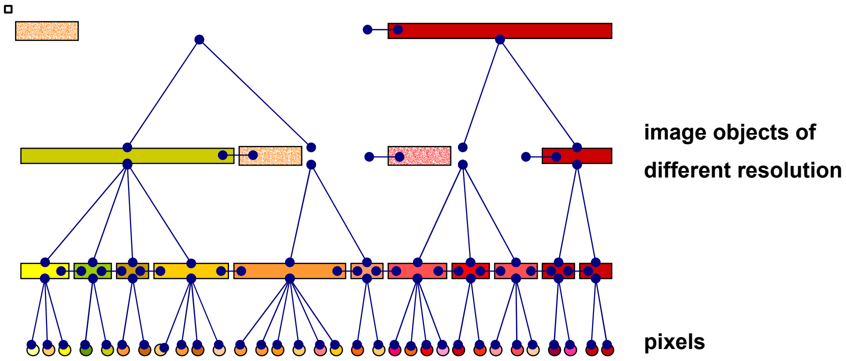


Figure 3-8 Hierarchical network of image objects (Baatz & Schäpe, 1999)

3.3.3. The use of thematic data in image segmentation

Image segmentation is generally described as the first stage in any OBIA process, but Smith & Morton (2010) suggest that the first step should rather be more broadly defined as “obtaining a set of meaningful land parcel objects which represent the features of interest to the user in the landscape, whether or not they have spectral distinction in the image”, and that real world feature datasets be used as the starting point for OBIA before segmentation is considered. Objects should be meaningful and relate to real world objects and the use of image segmentation should be appropriate and effective. Smith and Morton (2010) have indicated that much of the literature that has come out to develop the theory for OBIA has failed to identify sources for image objects other than segmentation, and they have pointed out that where high quality large scale cartographic mapping exists, this data can be used in the OBIA process.

Of the various approaches to image segmentation, one method is to use the reflectance values of image bands such as the values for red, green, blue and near infrared to create segments, while another is to use thematic (cadastral) data to segment an image. The rationale for using cadastral data is that built-up areas will typically have cadastral data identifying land parcels and ownership, and this information can be used as a starting point for image segmentation. Land parcels may have varying land cover features within them, and should not necessarily be segmented based on their spectral properties alone, as this may result in multiple image objects that may need to be preserved as one object. Segments represented by cadastral boundaries can be further segmented based on image reflectance, shape, texture and context within the land parcels, if necessary.

The methodology proposed in this research is to segment an image using cadastral land parcels (using a chessboard segmentation) and then to create new segments within those boundaries using the multiresolution segmentation technique that relies on image reflectance values (see Figure 3-9). Once suitable image segments have been generated, they can then be classified. The classification of image objects is described in the following section 3.3.4.

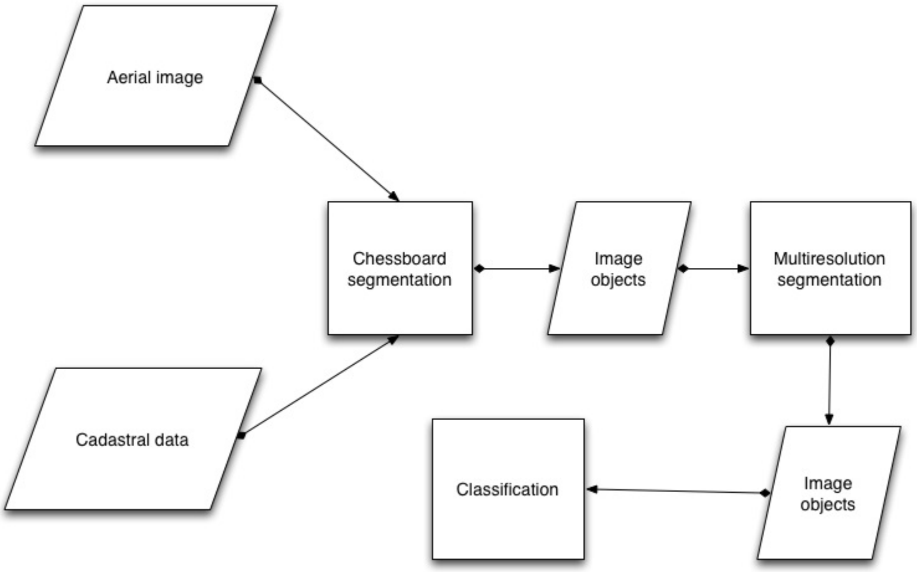


Figure 3-9 Proposed image segmentation process

Figure 3-10 Chessboard segmentation using cadastral boundaries

3.3.4. Classification of image objects

After an image has been segmented into suitable image objects, the image objects can be classified by assigning each image segment to a class based on features and criteria decided on by the user. A feature in OBIA is an algorithm that measures various characteristics such as shape, colour, texture and size of image objects. Image objects can be assigned to a specific class based on the value of certain features (Baatz & Schäpe, 1999; Baatz & Schäpe, 2000; Blaschke, 2010).

In this study, classification is conducted using fuzzy logic. The classification process is based on either a nearest neighbour classifier on a fuzzy logic basis, or through a rule-based approach that uses fuzzy functions defined for selected features, calculated for each segment. Fuzzy classification provides not only the assignment of an image object to a class, but the degree of membership of all objects to classes under consideration. The rule-based approach is given preference over the nearest neighbour method, as it allows more control over the classification process and can be easily adapted to fit new data (Kressler et al., 2005).

The difference between crisp and fuzzy sets is in the membership function. Fuzzy classification allows for greater flexibility over crisp classification because with crisp classification a pixel or data element of the set can only belong to one information class for which it has a membership of one. With fuzzy classification a data element may concurrently hold several non-zero membership grades for different information classes (Tso & Mather, 2009). Figure 3-3 illustrates the concept of the fuzzy classifier in comparison to a conventional classifier. With the conventional hard classifier, classification rules are applied to discriminate between discrete classes. The logic of the fuzzy classifier in this illustrated example is that a pixel with a brightness value of less than 24 would have a membership value of 1.0 in water, and 0 in both forested wetland and forest, but a pixel with a brightness value of 30 would have a membership of 0.5 in water and 0.5 in forested wetland, and 0 in forest. Thus a pixel, or an image object, can have membership to more than one class.

The nearest neighbour classifier uses a set of training samples of different classes to assign membership values. With this method, image objects are classified based on their nearest sample neighbours. The nearest neighbour classifier returns a membership value of between zero and one, based on the image object's feature space distance to its nearest neighbour. In Figure 3-11 the basic concept of the nearest neighbour classifier is illustrated. The distance between the unknown pixel X and training samples A, B and C are computed, and the unknown pixel is assigned to the class with the shortest distance.

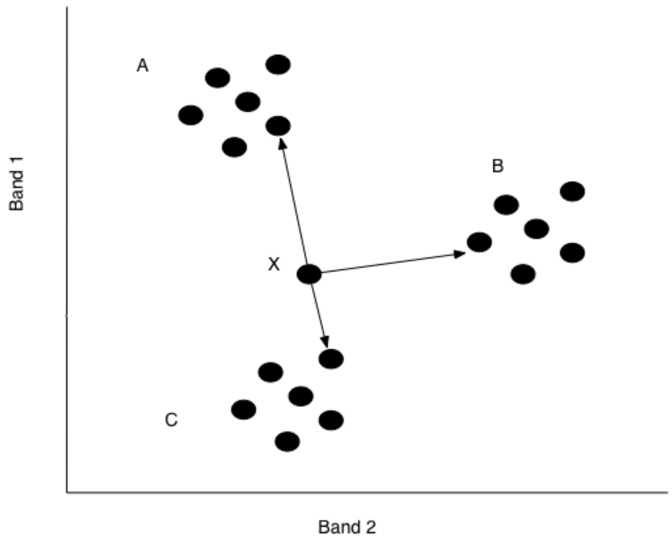


Figure 3-11 Nearest neighbour classification

The rule-based approach to classification is also based on fuzzy logic and features describing various characteristics of image objects such as size, shape, colour, texture, etc., as described above, but with this approach images segments are classified using a decision tree method. Figure 3-12 illustrates the methodology that uses a rule-based approach to classification of image objects. Image objects are first split into the classes *"water"* and *"not water"*, based on certain characteristics of the objects. The non-water segments can be evaluated and further split into additional classes, based on other user specified criteria or feature values. The process of classifying and splitting continues until all desired classes have been found.

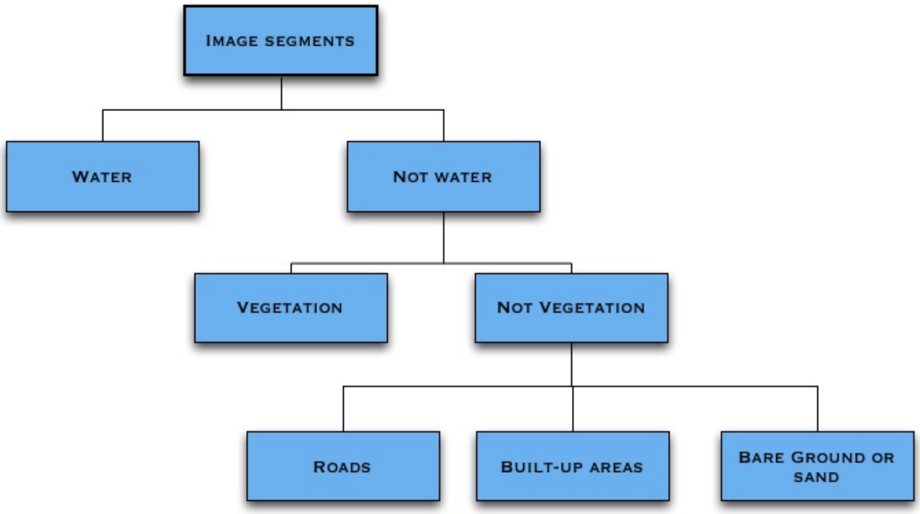


Figure 3-12 Rule-based classifier (decision tree)

3.3.5.Features for classifying image objects

As mentioned in 3.3.4 above, features in OBIA can be used to measure various characteristics of image objects. Some common features used for classifying image objects are (Benz et al., 2004; Hofmann, 2001a; Laliberte et al., 2010; Blaschke, 2010; Taubenböck et al., 2010):

- *Spectral statistics*: e.g. mean or standard deviation of image reflectance bands, mean brightness, and vegetation indices such as NDVI.
- *Shape and size*: e.g. area, length, length to width ratio, and compactness.
- *Texture*: e.g. GLCM and GLDV.

3.3.5.1. *Image texture*

The three fundamental pattern elements used in photointerpretation are spectral, textural and contextual features (Haralick et al., 1973). “Spectral features describe the average tonal variations in various bands of the visible and/or infrared portion of an electromagnetic spectrum, whereas textural features contain information about the spatial distribution of tonal variations within a band” (Haralick et al., 1973). Discrete tonal features are connected sets of pixels that all have the same, or almost the same, grey shades or brightness values. When a small area of the image (e.g. a 3 x 3 pixel area) has little variation of discrete tonal features, the dominant property of that area is a grey shade, and when a small area has a wide variation, the dominant property of that area is texture (Jensen, 2005).

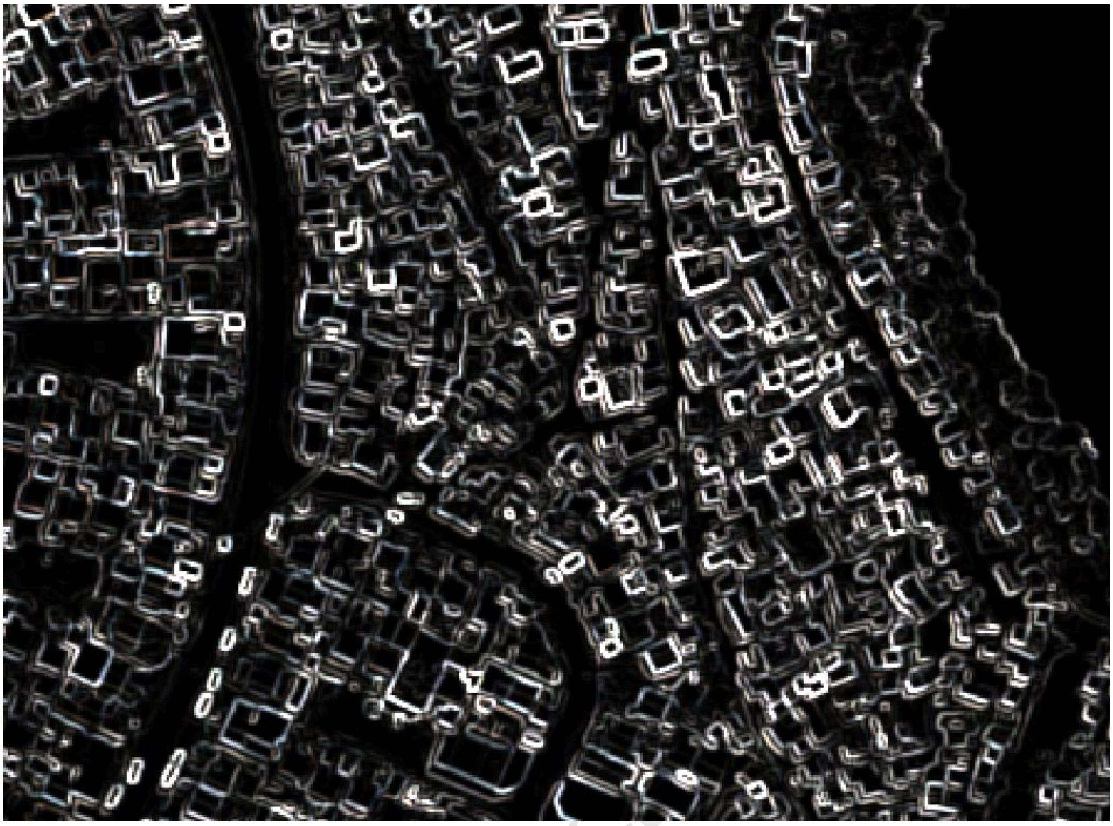


Figure 3-13 Example of texture analysis: variance using a 3x3 window in an urban built-up scene

A popular texture feature extraction technique is based on the grey level co-occurrence matrix (GLCM). The concept of GLCM is that texture information contained in an image is defined by the adjacency relationships that the grey tones in an image have to one another (Tso & Mather, 2009). GLCM is a tabulation of how often different combinations of pixel grey levels occur in an image (GLCM texture: a tutorial 2007). Haralick et al. (1973) developed a set of texture features based on the GLCM. The inclusion of texture features have been found to increase classification accuracies (Franklin & Peddle, 1990).

Another method to measure texture is to use the grey level difference vector (GLDV), which is the sum of the diagonals of the GLCM. With object-based classification, texture features calculated for image objects are based on the pixels that make up the object.

Since built-up areas have significant texture from their encompassed buildings and roads, texture should be used in the classification process.

3.3.5.2. *Vegetation and water indices*

Vegetation indices are dimensionless, radiometric measures that indicate relative abundance and activity of green vegetation, including leaf area index, percentage of green cover, chlorophyll content, green biomass and absorbed photosynthetically active radiation (Jensen, 2005). There are many vegetation indices available, and many of them use the inverse relationship between the red and near-infrared reflectance, which is associated with healthy vegetation.

The Normalised Difference Vegetation Index (NDVI) is a simple and very effective technique to quickly identify vegetated areas and the health of such areas. NDVI uses the near-infrared (NIR) radiation and red (R) reflected radiation in the following equation:

$$\text{NDVI} = \frac{NIR - R}{NIR + R} \qquad \text{(Jensen, 2005)}$$

Derived using similar principles to the NDVI is the Normalised Difference Water Index (NDWI). NDWI makes use of the reflected near-infrared (NIR) and green (G) bands to enhance the presence of water features (McFeeters, 1996). NDWI is calculated using the following equation:

$$\text{NDWI} = \frac{G - NIR}{G + NIR} \qquad \text{(McFeeters, 1996)}$$

Since the above indices are useful in classifying vegetation and water, they should be included in the classification process.

3.4. Accuracy assessment

Accuracy assessment is an important part of any classification and is done in an effort to understand how well a classifier performed. The accuracy assessment is undertaken by comparing the classification with reference data. Sources of reference data may include ground truth data, maps, etc. The reference data used for the accuracy assessment should be independent from any training data used in the classification process.

Results of the accuracy assessment are summarised in the confusion matrix. The confusion matrix may also be called the error matrix.

3.4.1. Confusion matrices

The confusion matrix compares reference data to the classified data, and is presented in a square array of numbers set out in rows and columns. The columns are usually assumed to be correct and represent the reference data, and the rows are usually used to represent the classified data. See example of confusion matrix in Table 3-1.

In the confusion matrix, the individual accuracy of each class is described along with the errors of inclusion (commission errors) and errors of exclusion (omission errors) present in the classification or classified map. A commission error occurs when an area is included in an incorrect category, and an omission error occurs when an area is excluded from its true category. Every error in the classification is an omission from the correct category and a commission to an incorrect category (Congalton & Green, 2009).

Table 3-1 Example of confusion matrix (Story & Congalton, 1986)

		Reference data			Row total
		X	Y	Z	
Classified data	X	15	2	4	21
	Y	3	12	2	17
	Z	1	3	14	18
Column total		19	17	20	56

3.4.2. Overall accuracy

The overall accuracy can be derived from the confusion matrix. It is the sum of the diagonal values (correctly classified sample units) divided by the total number of sample units in the confusion matrix. In the example given above, the overall accuracy would be (15+12+14)/56 (i.e. 73%). This may be useful, but does not indicate how well individual classes performed. Individual category accuracies are needed. The user and producer accuracies are widely used to measure individual class accuracy.

3.4.3. User and producer accuracy

Individual category accuracies can be assessed by calculating the producer and user accuracies for each class. These accuracies are computed from the confusion matrix.

The producer accuracy is calculated by dividing the number of correctly classified samples of category X (see Table 3-1) by the total number of reference samples of category X (column total). The resulting percentage accuracy (producer accuracy) indicates the probability that a reference sample will be correctly classified. This method measures the errors of omission, which means that samples that have not been correctly classified as category X have been omitted from the correct category. The user accuracy is calculated by dividing the number of correctly classified samples of category X by the total number of sample that were classified in category X (row total). The user accuracy refers to the probability that a sample from the classified image actually represents that category on the ground. The user accuracy is a measure of the errors of commission and signifies the reliability of the classification (Story & Congalton, 1986).

3.4.4.Kappa

Kappa analysis is another technique used in accuracy assessment (Congalton, 1991). This kappa statistic (k), or kappa agreement, reflects the difference between actual agreement in the confusion matrix and the agreement expected by chance (Congalton & Green, 2009). Since the kappa statistic takes into consideration the agreement occurring by chance, it is considered to be a more reliable measure than the overall accuracy. A kappa statistic of 1 would indicate perfect agreement, while that of 0 would indicate agreement equal to that occurring by chance. Conceptually, the kappa agreement can be defined as (Lillesand et al., 2004):

$$\hat{\mathrm{k}} = \frac{observed\ accuracy - chance\ agreement}{1 - chance\ agreement}$$

The kappa agreement is computed as (Lillesand et al., 2004):

$$\hat{\mathrm{k}} = \frac{N\sum_{i=1}^{r} x_{ii} \ - \ \sum_{i=1}^{r}(x_{i+}\ .\ x_{+i})}{N^2 - \ \sum_{i=1}^{r}(x_{i+}\ .\ x_{+i})}$$

where

r = number of rows in the error matrix;

x_{ii} = number of observations in row i and column i (on the major diagonal);

x_{i+} = total of observations in row i (shown as marginal total to right of the matrix);

x_{+i} = total of observations in column i (shown as marginal total to the bottom of the matrix); and

N = total number of observations included in the matrix.

Using the example in Table 3-1, kappa would be calculated as follows:

$$\sum_{i=1}^{r} x_{ii} = 15 + 12 + 14 = 41$$

$$\sum_{i=1}^{r} (x_{i+} x_{+i}) = (21 \times 19) + (17 \times 17) + (18 \times 20) = 1048$$

$$N = 56$$

$$\hat{k} = \frac{56\,(41) - 1048}{56^2 - 1048}$$

$$\hat{k} = 0.60$$

Note the kappa value of 60% differs from the overall accuracy of 73% that was calculated in 3.4.2.

4. Data

The aerial imagery used in the study was captured at 0.5m resolution using an Integraph Digital Mapping Camera (DMC). Both RGB and CIR orthorectified imagery was used for each test area. The size of an orthorectified image, which is the size of a single test scene, is approximately 5km by 6km. Two test areas were used for all methods of classification examined. All aerial imagery used in this study was obtained from the CD: NGI. The first test scene was an area in Table View, Cape Town (Figure 4-1). This area has grown rapidly since the last topographic map for this area was compiled in 2000 (Figure 4-1). The latest imagery for the Cape Town scene was captured early in March 2010, i.e. in the dry summer season. This scene in Cape Town was chosen as it covers a variety of built-up areas. There is the older suburb of Table View in the Southwest of the image, and the new suburb of Parklands in the Northwest of the image. In the Northeastern side of the image there is a large informal settlement called Dunoon, and adjacent to this is the light industrial area of Killarney Gardens, both of which have grown.

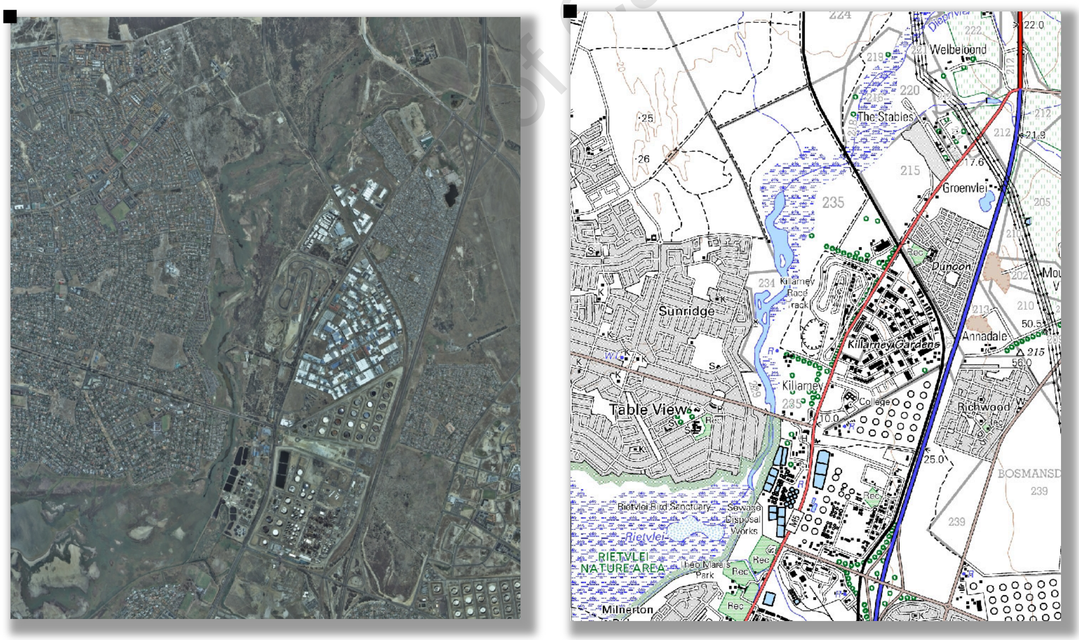


Figure 4-1 Test area 1 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2000)

The second test area is an area called Tembisa in Johannesburg. Tembisa is a large built-up area that has also expanded in size since the last topographic map of it was compiled in the year 2002 (Figure 4-2). Tembisa is predominantly comprised of built-up areas and both formal residential and informal settlements can be seen in the image covering this area. The imagery used for the Johannesburg scene was captured towards the end of July 2010, i.e. in the dry winter season.

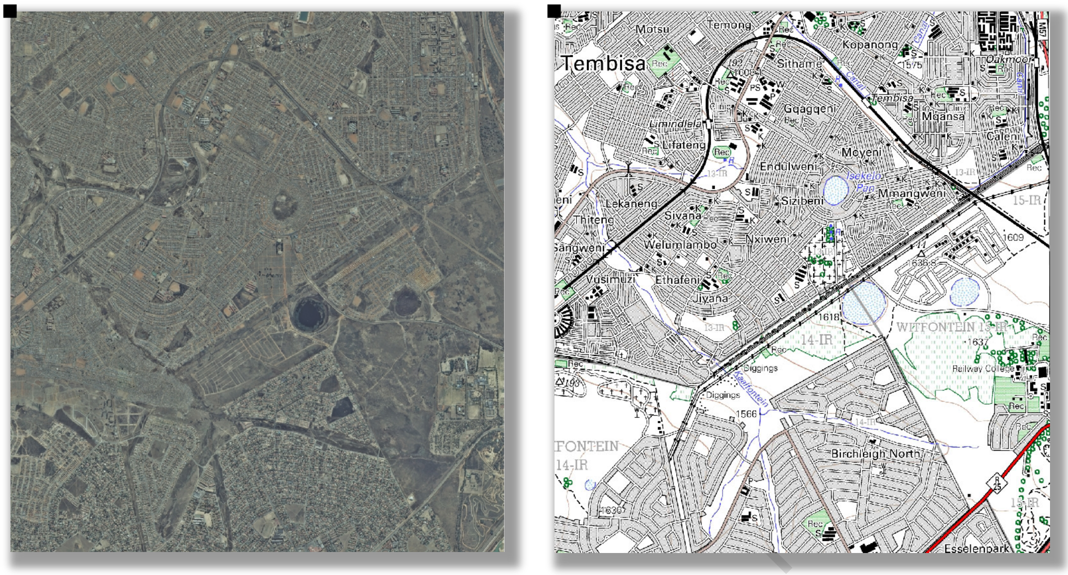


Figure 4-2 Test area 2 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2002)

For the final proposed method of object-based classification two additional scenes were selected to prove transferability of the method. These scenes were areas from Stellenbosch (Figure 4-3) and Atlantis (Figure 4-4) near Cape Town. As with the other test scenes, both the RGB and CIR orthorectified aerial imagery was used. These images were acquired in late February and early March 2010, i.e. the summer season, as part of the Cape Town imagery data set.

The CD: NGI typically acquire all their aerial imagery in the dry season of the region being flown, to avoid cloud cover. Cape Town experiences winter rainfall and therefore imagery was captured in summer, and Johannesburg has summer rainfall and imagery was captured in winter.

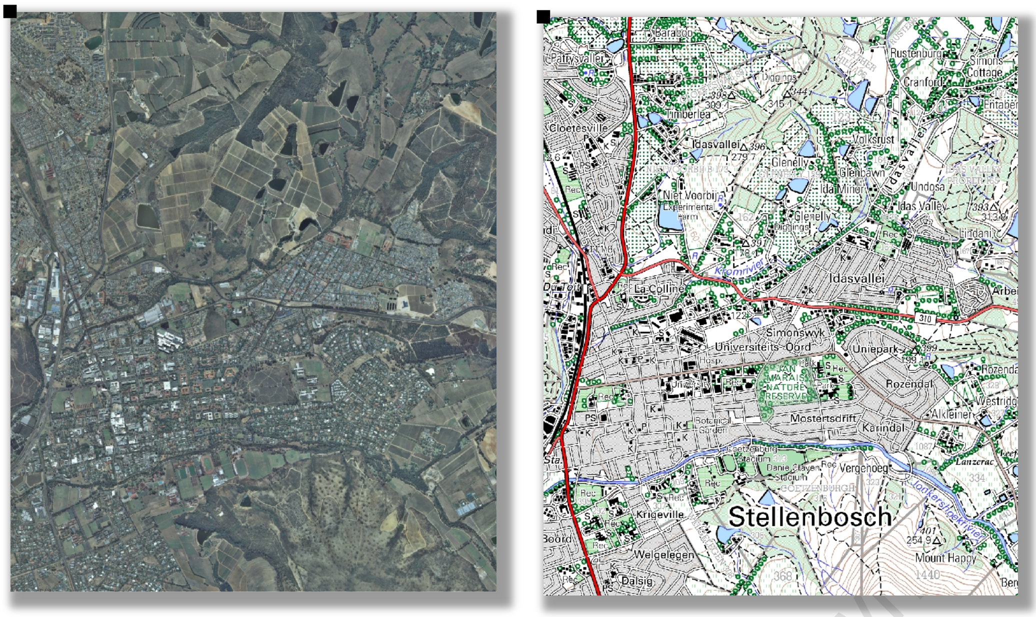


Figure 4-3 Test area 3 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2000)

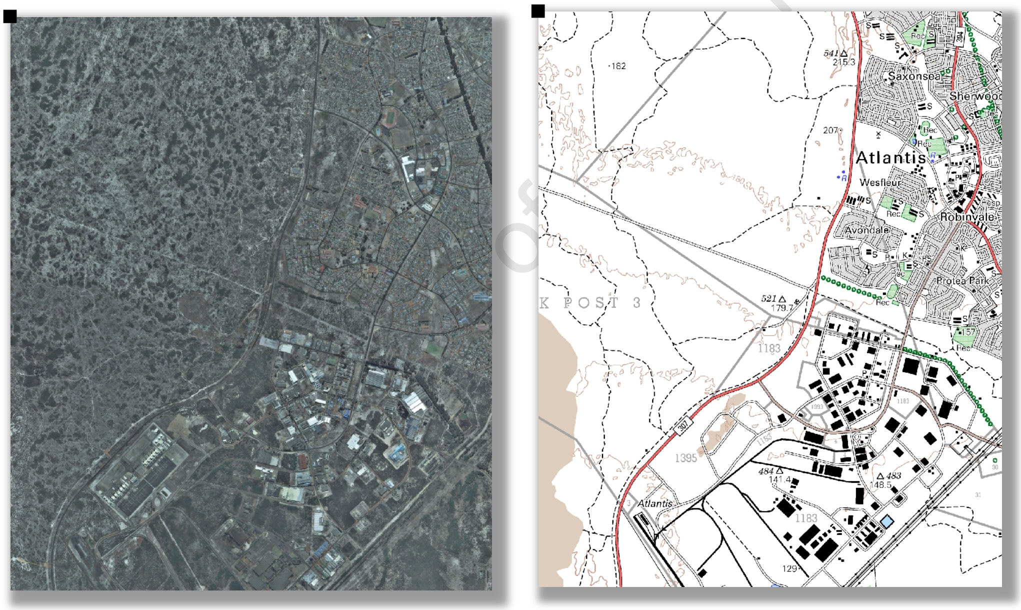


Figure 4-4 Test area 4 – left: aerial image (2010); right - portion of 1:50 000 topographic map (2000)

4.1. Supervised and unsupervised pixel-based classification

Orthorectified images covering the areas of i) Table View, Cape Town and ii) Tembisa, Johannesburg were used. The input data for each scene was an orthorectified 8-bit RGB image and an orthorectified 8-bit colour infrared (CIR) image. The red, green and blue bands from the RGB image were combined with the near infrared band from the colour infrared image to make one four-band image for each test area. Each four band image was created using the layer stack function in ERDAS Imagine 2011.

4.2. Object-based classification

All object-based approaches were carried out using eCognition Developer 8. For the first method that relied on only the reflectance properties of the image bands for image segmentation, the RGB image and near infrared band from the CIR image were used as input for each test scene.

For all subsequent object-based methods, in addition to the four image bands being used, thematic data was also included. Thematic data representing cadastral boundaries covering each area of interest was included in the image segmentation process. The cadastral data (vector data) that was used was comprised of erven and farm portions that were stored in shapefile format. Cadastral data is maintained and supplied by the Office of the Surveyor-General in South Africa. Data for all Cape Town scenes was dated at 2012, and Johannesburg data was from 2010.

The Surveyor-General's Office is responsible for examining and approving all cadastral surveys for the registration of property ownership and land rights, as well as the examination, approval and safe-keeping of all survey records relating to diagrams, general plans and draft sectional plans for registration purposes. This office keeps a complete record of all cadastral surveys, and ensures that there is almost no possibility of properties overlapping, and once properties are registered, there is little chance of conflicting claims to ownership (Functions).

The relationship of all land parcels and administrative boundaries, as well as land rights such as servitudes and leases in South Africa, is stored in a digital map that is maintained by the Surveyor-General's Office (Functions). Erven and farm portions that were used in this study were obtained from this dataset.

5. Results and analysis

The following sections cover the various methods that were tested and the results and analysis for each method.

5.1. Pixel-based supervised classification

With supervised classification, classes must be decided on beforehand, and adequate samples that represent the classes must be collected. Sufficient samples should be collected for each class. Due to the spectral variation within a class, one sample may differ substantially from another sample, but both may be part of the same class. Therefore, sufficient samples of a class should be collected and merged to make the final class. A further challenge lies in the fact that a class may consist of various land cover types that are spectrally diverse, but need to be grouped together. Such an example is the urban built-up class that may consist of buildings, gardens (vegetation), swimming pools and bare ground. One may consider classifying buildings separately, but this decision is influenced by the purpose of the classification, and in this case the built-up area was required. Even individual buildings can have a multitude of different land cover types and colours; for example, roof tiles, thatch, metal sheeting, etc., which are spectrally diverse.

In this example the maximum likelihood classification method was tested using four-band multispectral aerial imagery. The software ERDAS Imagine was used for this method. Since this was a supervised method of classification, it was necessary to collect adequate training samples for each land cover class in the image. Once sufficient training samples for each class were collected, they were merged into five final classes that consisted of water, vegetation, road, built-up areas and bare ground or sand. Training samples were stored in a signature file that was used in the supervised maximum likelihood classification.

The accuracy of the supervised classification was assessed using a confusion matrix that was generated through a random sampling of reference points. Fifty points were used in accuracy assessment and their distribution was equalized randomly, so that each class had an equal number of random points generated. This was done to ensure that there were sufficient reference points for each class, and to prevent any class from having no reference points in the accuracy assessment.

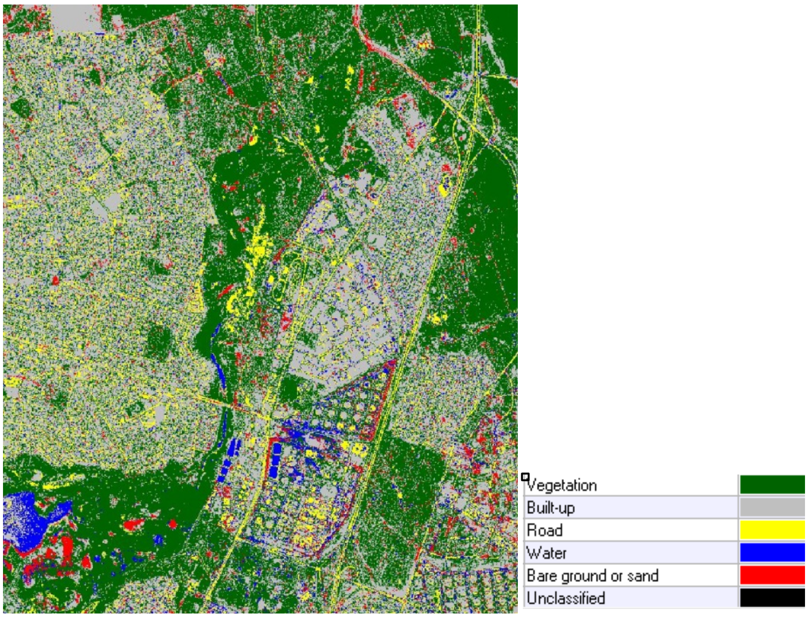


Figure 5-1 MLC – test area 1: classified image

Figure 5-1 shows the resulting classification for test area 1 (full image). From the results it is clear that there is confusion between some classes, and this is illustrated in Figure 5-2, where a large water body has been incorrectly classified as part of the road class. It should be noted that samples were taken from this water body and used as part of the training data for the classification, which explains why some of the pixels have been classified as water, but the remainder and majority of pixels are incorrectly classified as road. From the zoomed in image of the classified wetland in Figure 5-3, one can see that some pixels representing water were incorrectly classified as built-up areas and roads.

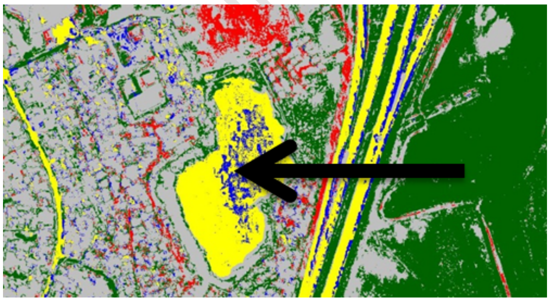


Figure 5-2 MLC – test area 1: dam incorrectly classified as road

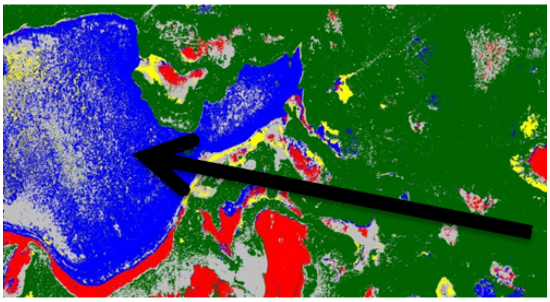


Figure 5-3 MLC – test area 1: wetland

The accuracy assessment of the supervised classification was based on random samples (see Figure 5-4). From the accuracy assessment in Table 5-1, it can be seen that the overall accuracy for test area 1 was 60% and the kappa index of agreement (KIA) was 50%. The built-up class, which is of foremost interest in this study, had a producer and user accuracy of 36% and 40% respectively, indicating that 36% of the built-up class is identified correctly, and 40% of built-up features are actually in this class. The accuracy assessment is discussed in more detail below.

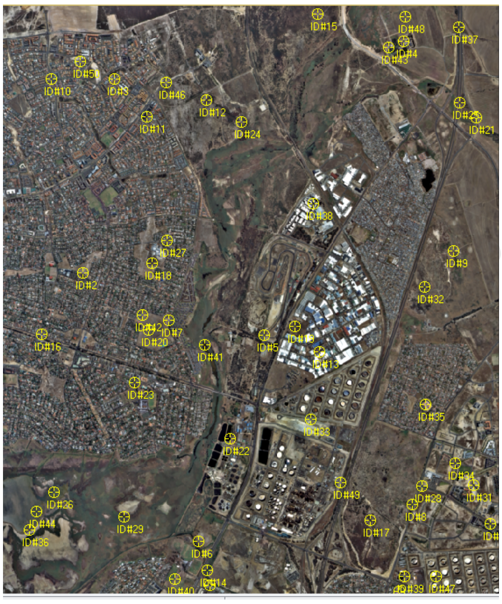


Figure 5-4 Random points for accuracy assessment: test area 1

Table 5-1 Accuracy assessment and kappa statistics for supervised pixel-based MLC: test area 1

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.36	0.40	0.23
Bare ground or sand	0.69	0.90	0.86
Vegetation	0.62	0.80	0.73
Water	0.80	0.40	0.33
Road	0.63	0.50	0.40
Overall accuracy	**0.60**		
KIA	**0.50**		

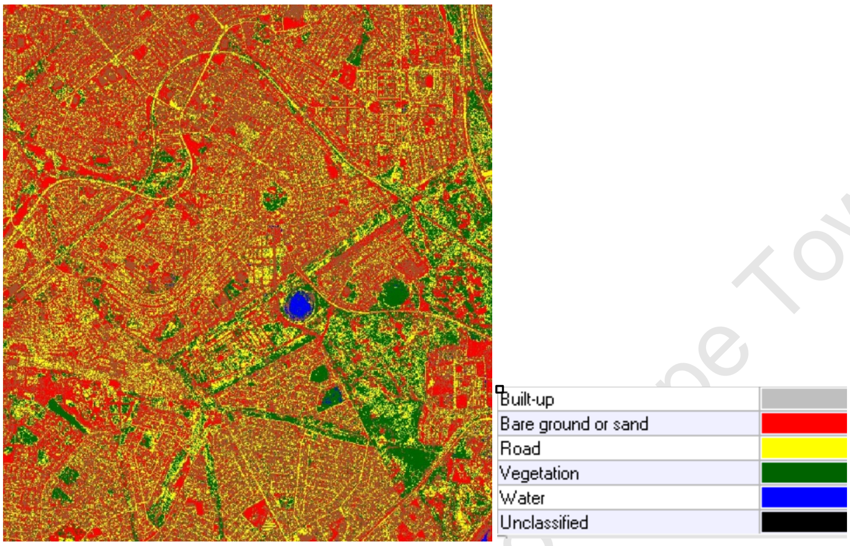


Figure 5-5 MLC – test area 2: classified image

From the resulting classification, it is clear that there is confusion between certain classes. The difficulty in discriminating between the classes built-up area and road can be seen in Figure 5-6 (top left of image), where an urban built-up area is incorrectly classified as road (yellow).

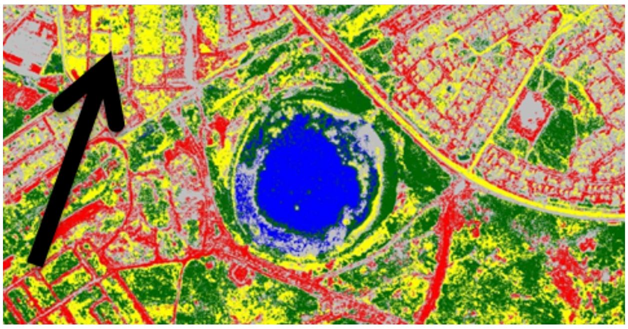


Figure 5-6 MLC – test area 2: built-up area incorrectly classified as road

The accuracy assessment was based on random samples (see Figure 5-7). From the accuracy assessment in Table 5-2, it can be seen that the overall accuracy for test area

2 was 60% and the kappa index of agreement (KIA) was 50%, as was the case for test area 1. The built-up class, the main class of interest, produced a producer and user accuracy of 43% and 60% respectively, indicating that 43% of the built-up class is identified correctly, and 60% of built-up features are actually in this class.

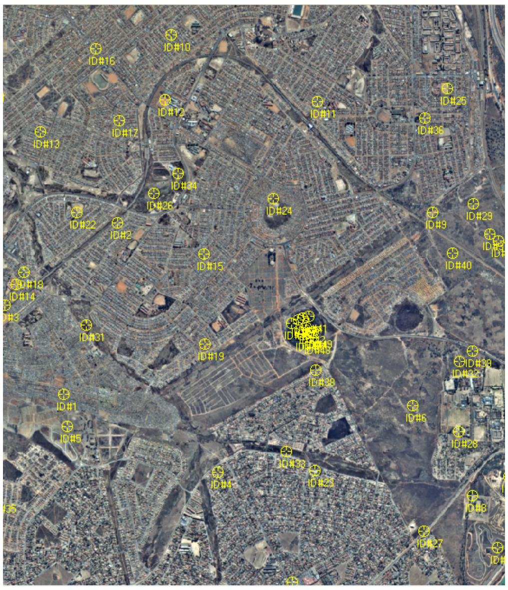


Figure 5-7 Random points for accuracy assessment: test area 2

Table 5-2 Accuracy assessment and kappa statistics for the supervised pixel-based MLC: test area 2

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.43	0.60	0.44
Bare ground or sand	0.55	0.60	0.49
Vegetation	0.60	0.90	0.86
Water	1.00	0.90	0.88
Road	0.00	0.00	-0.02
Overall accuracy	0.60		
KIA	0.50		

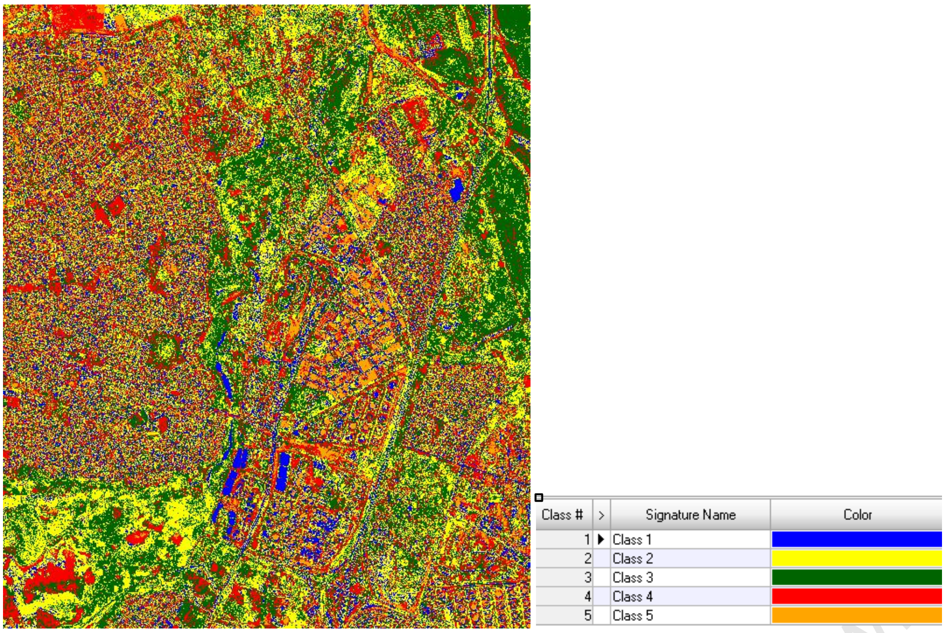
The accuracy assessment and kappa statistics for the supervised method of classification for each of the test areas can be seen in Table 5-1 and Table 5-2. The overall accuracy was 60% and the kappa index of agreement (KIA) was 50% for both scenes. These results are not very encouraging, and the user and producer accuracy of the built-up class were also very low. KIA per class for built-up areas was poor in both test areas. The user and producer accuracies, as well as the KIA per class for built-up areas, were significantly lower for test area 1 compared to test area 2. Test area 2 was comprised of significantly more built-up areas than test area 1, and the built-up areas in the second test area were very similar in appearance, whereas in the first test area there was more variation within the type of built-up areas. User and producer accuracies for the remaining classes differed substantially between scenes, excepting for results for vegetation, which were similar. The accuracy of the road class in the second test area was particularly poor, with both user and producer accuracy equal to 0.00, and KIA of -0.02, indicating that the agreement is slightly worse than that expected by chance. Overall, the unsupervised maximum likelihood classification resulted in unsatisfactory results.

5.2. Pixel-based unsupervised classification

In this example the ISODATA method was tested using five and twelve classes respectively. Five classes were chosen for comparison with the supervised classification in which road, water, vegetation and bare ground were classified in addition to the built-up class. The unsupervised classification was also carried out using twelve classes for comparison to the five-class classification. Deciding on the number of classes was done by trial and error, and having a greater number of classes would not have added any value, as they would have to be reduced to the original five topographic classes that were needed to be identified. The unsupervised classifications were carried out using the software ERDAS Imagine 2011.

With the unsupervised approach, pixels with similar spectral properties are grouped together to represent a single class. The number of classes must be decided on beforehand, but the classes are usually unknown a priori. Once the image has been classified, the analyst can then label the classes and combine classes where necessary.

Since there is so much overlap between classes with this method of classification, meaningful names, e.g. road or water, cannot be given to classes.



Class #	>	Signature Name	Color
1	▶	Class 1	🟦
2		Class 2	🟨
3		Class 3	🟩
4		Class 4	🟥
5		Class 5	🟧

Figure 5-8 ISODATA – test area 1 (5 classes): classified image

From the classified images (see Figure 5-8 and Figure 5-9), it can be seen that there are many mixed classes. Even though water appears to be classified reasonably well (see dam in Figure 5-9) and represented by class 1, there are pixels that are not water but are also classified as class 1. This is evident from parts of the road and built-up areas that are incorrectly classified as class 1 (blue) in Figure 5-9. Other water features, such as the wetland in the bottom left of Figure 5-8, was classified as mostly class 4 (red) and not in the same class as the dam. There also appears to be overlap between what should be the built-up class and the bare ground class. The road class cannot be isolated and seems to be represented by various classes. Vegetation seems mostly to be split across two classes, but there is too much overlap between classes to confirm exactly which classes represent any one particular feature.

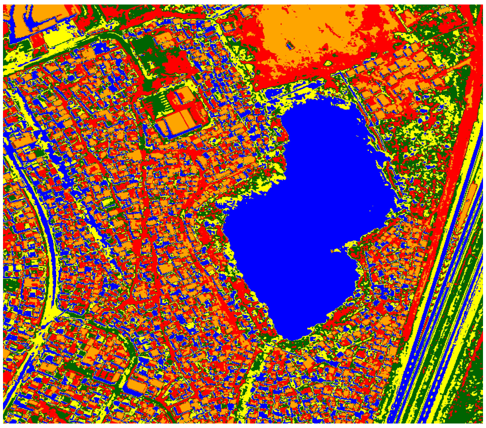
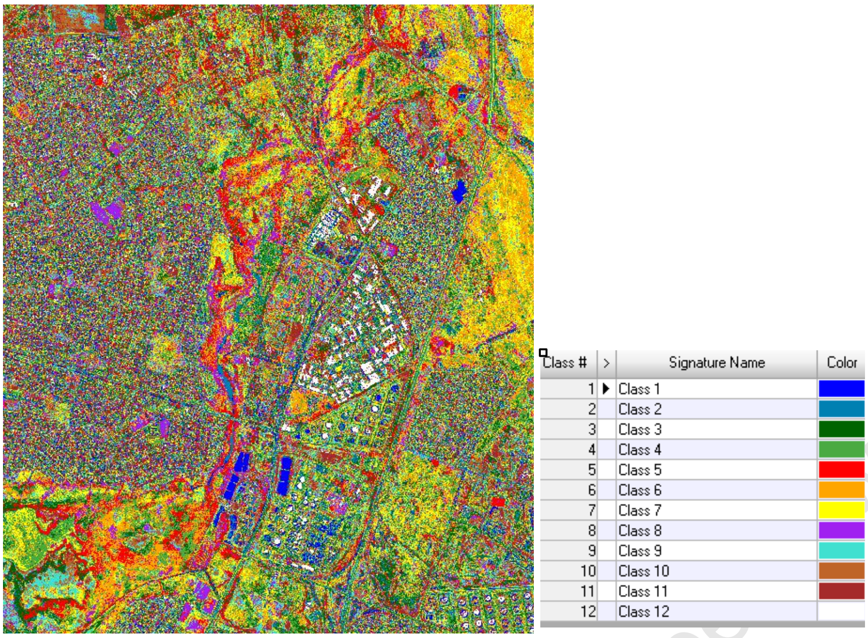


Figure 5-9 ISODATA – test area 1 (5 classes): dam classified as single class

The twelve class classification (Figure 5-10) may have isolated certain classes better than the five class classifier, but these classes would ideally need to be reduced to the five desired topographic classes mentioned previously.



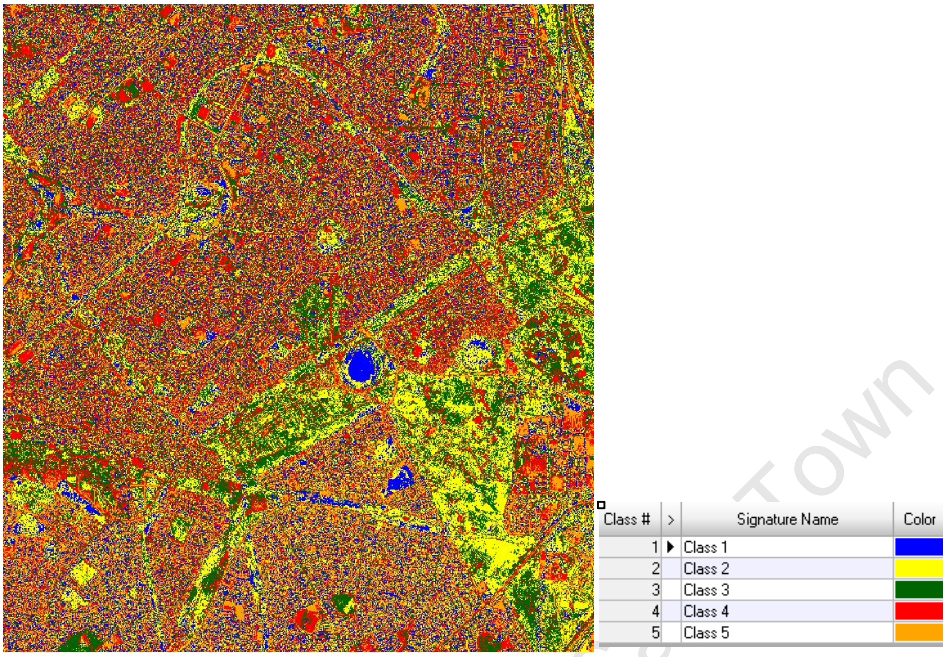
Class #	>	Signature Name	Color
1	▶	Class 1	🟦
2		Class 2	🟦
3		Class 3	🟩
4		Class 4	🟩
5		Class 5	🟥
6		Class 6	🟧
7		Class 7	🟨
8		Class 8	🟪
9		Class 9	🟦
10		Class 10	🟫
11		Class 11	🟫
12		Class 12	

Figure 5-10 ISODATA – test area 1 (12 classes): classified image

As with the five class classification, the twelve class unsupervised method classified many water bodies as class 1 (blue), but once again there were also non water pixels that were incorrectly classified as part of class 1 (see Figure 5-11). The wetland area (bottom left of Figure 5-10) was classified as many classes, but not the same class as the dam (class 1).

Figure 5-11 ISODATA – test area 1 (12 classes): classified dam

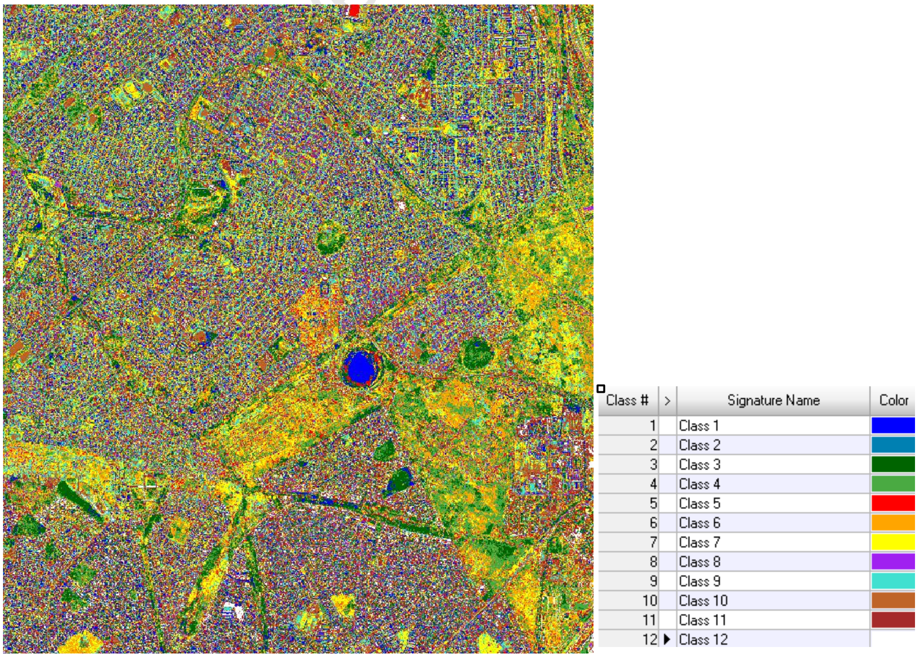
As was the case with the first test area, classes could not be differentiated easily in the second test area. Figure 5-12 and Figure 5-13 represent the five and twelve class unsupervised classifications respectively.



Class #	>	Signature Name	Color
1	▶	Class 1	🟦
2		Class 2	🟨
3		Class 3	🟩
4		Class 4	🟥
5		Class 5	🟧

Figure 5-12 ISODATA – test area 2 (5 classes): classified image

The results for both the five and twelve class unsupervised classifications were not satisfactory and classes were not easily separated, due to the large variability among classes. The accuracy of the unsupervised method was based on a visual inspection.



Class #	>	Signature Name	Color
1		Class 1	🟦
2		Class 2	🟦
3		Class 3	🟩
4		Class 4	🟩
5		Class 5	🟥
6		Class 6	🟧
7		Class 7	🟨
8		Class 8	🟪
9		Class 9	🟦
10		Class 10	🟫
11		Class 11	🟫
12	▶	Class 12	

Figure 5-13 ISODATA – test area 2 (12 classes): classified image

There are advantages and disadvantages to using both the supervised and unsupervised classification methods. With supervised methods the user must decide on the number of classes, the name of each class and collect samples for each class in order to train the classifier. The unsupervised method is almost user independent, and with this method only the number of classes must be decided on by the user and the classifier assigns pixels to classes based on their statistical properties. Where there is a high degree of spectral variability, unsupervised classification may have an advantage over supervised classification, since appropriate training sites may be difficult to attain. Collecting samples for a supervised classification can be labour intensive, but the advantage of this method is that it usually has more accurate class definitions and higher accuracy than unsupervised methods (Tso & Mather, 2009).

It is difficult to compare the supervised and unsupervised results because the classifications do not have exactly the same classes. The unsupervised classes were left as numbered classes, as no single class could be clearly identified as one of the target classes. Another problem with the unsupervised classifications was that where there are many classes, there is the problem of a class being split into more than one class due to the spectral differences within a class. Where there are only a few classes, there is the problem of unrelated classes being classified as the same class.

5.3. Object-based classification – Segmentation using reflectance values and a nearest neighbour classification

The software that was used for the object-based classifications was eCognition Developer. The red, green, blue and near infrared image bands were imported into eCognition, and these bands were used with equal weighing in the segmentation process. The multiresolution segmentation algorithm was used for segmentation, starting with small segments that had a scale parameter of 20. Small segments were used to create larger segments using the multiresolution segmentation method. The approach of starting with small segments and using them to make larger segments resulted in obtaining more homogeneous segments, when compared to the alternative approach of starting with large scale segments. The size of segments was decided on by trial and error. Smaller segments were merged to create larger segments that consisted of built-up areas as opposed to individual buildings. These built-up areas consisted of residential buildings, gardens, small roads, etc.

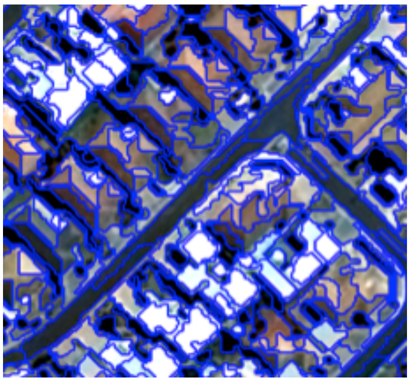


Figure 5-14 Small segments (level 1)

The smaller the scale parameter, the smaller and more homogeneous the image segments will be. Pixels are used as the input to the initial segmentation process, and once the initial image objects (segments) have been created (level 1), the segments can be used as input into further segmentations. With the segmentation process, a hierarchical network of image objects is created. Segmentation parameters can be seen in Table 5-3.

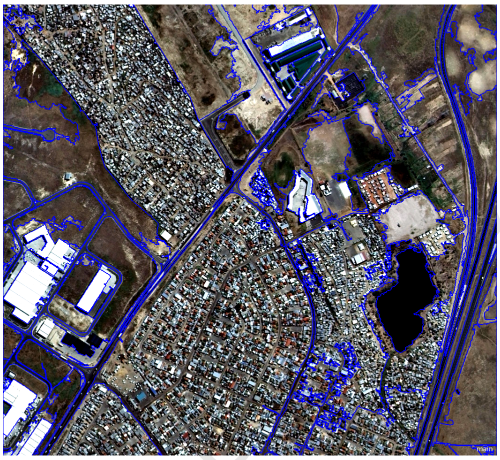


Figure 5-15 Large segments (level 4)

Once the segmentation was completed, a class hierarchy was created that included the following classes: built-up, bare ground or sand, vegetation, water, and road (for identifying the larger roads that were not included in the built-up area). Samples were collected for each of these classes and classification was performed on large segments (level 4) using the nearest neighbour method. A large scale parameter (segmentation level 4) was chosen for classifying the image in order to adequately delineate the large built-up areas.

Table 5-3 Segmentation parameters used for both test areas

Level	1	2	3	4
Segmentation	Multiresolution	Multiresolution	Multiresolution	Multiresolution
Scale parameter	20	100	200	500
Shape: Colour	0.1: 0.9	0.1: 0.9	0.1: 0.9	0.1: 0.9
Compactness:	0.5: 0.5	0.5: 0.5	0.5: 0.5	0.5: 0.5

The features used in the classification were the mean values for red, green, blue and near infrared, brightness, maximum difference, HSI transformation - hue, length, length/width, compactness, NDVI, GLCM mean (quick 8/11)(all directions) and GLDV Angular 2nd moment (quick 8/11)(all directions). These features were included in the classification as they cover a range of spectral, shape and textural features. Spectral values of segments are the simplest features that can be used in a classification and are useful for detecting segments that are spectrally similar. Spectral information is the most basic information in multispectral imagery and is therefore important to include. Shape features, such as length and more specifically, length over width, are useful in identifying elongated segments, such as roads. NDVI was included to assist in classifying vegetation, and the texture measures are useful in discriminating built-up areas from non built-up areas. Each Haralick texture feature has a performance optimized version that works on 8 and 11 bit data, and is thus named ‘quick 8/11’.

From the resulting classification for the two test areas as seen in Figure 5-16 and Figure 5-17, it is evident that built-up areas are generally classified well, and this is supported by the results for user and producer accuracy, as well as KIA per class. The other classes in the classification generally were not classified very well, which may be because in some instances certain segments did not perfectly represent a class of interest and contained pixels from more than one class. Although there were not many unclassified segments, there was one large segment representing a built-up area that was not classified in the first test area (see Figure 5-16). This unclassified segment formed part of an informal settlement, and it is likely that the large spectral variations within this segment was the reason for it not matching one of the predefined classes, and therefore being unclassified. The accuracy assessments for the two test areas are presented in Table 5-4 and Table 5-5.

Figure 5-16 Object-based classification – test area 1: classified image

Table 5-4 Accuracy assessment and kappa statistics – test area 1

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.83	0.83	0.78
Vegetation	0.64	0.54	0.52
Water	0.67	0.57	0.62
Road	0.55	0.86	0.48
Bare ground or sand	0.77	0.91	0.71
Overall accuracy	**0.70**		
KIA	**0.62**		

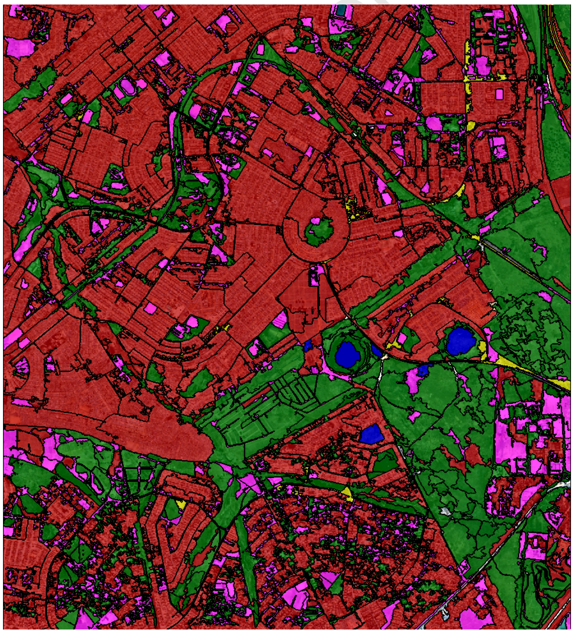


Figure 5-17 Object-based classification – test area 2: classified image

Table 5-5 Accuracy assessment and kappa statistics – test area 2

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.92	1.00	0.89
Bare ground or sand	1.00	0.85	1.00
Vegetation	0.82	0.75	0.75
Road	0.33	1.00	0.30
Water	0.40	0.50	0.34
Overall accuracy	**0.78**		
KIA	**0.72**		

The accuracy assessment was performed in eCognition using the fuzzy classification tools, classification stability and best classification result, as well as an error matrix based on samples, as presented in Table 5-4 and Table 5-5. "Classification stability evaluates the differences in degrees of membership between the best and the second best class assignments of each object. The smaller the value of an object/class, the more ambiguous its classification is. Best classification result assesses how the objects of a class fulfil the class description" (Drăguţ & Blaschke, 2008). It is arguable whether the classification stability and best classification result actually fall under accuracy assessment, since they do not use independent data sets like the error matrix, which is based on independent samples. It is perhaps more correct to call the classification stability and best classification result "consistency checks" (Drăguţ & Blaschke, 2008) and these are therefore not presented here, but can be found in the appendices.

The overall accuracy and KIA, as well as the user and producer accuracy for the object-based method was significantly higher than that of the pixel-based method. Accuracies were slightly higher for the second test area compared to the first with the object-based approach, but overall the classifier performed well. The user and producer accuracy for the built-up area for the first test area were both 83%, and the KIA for this class was 78%. For the second test area the results were 92% for the producer accuracy, 100% for the user accuracy, and 89% for the KIA per class for the built-up area. See Table 5-4 and Table 5-5 for the complete accuracy assessment for each of the test areas.

5.4. Object-based classification – Segmentation using thematic data and a nearest neighbour classification

With this example, thematic data was included in the segmentation process to assist in obtaining suitable image objects.

For each test scene, cadastral boundaries comprising erven and farm portions that fell within the area of interest were extracted from the larger dataset that contained data for the relevant province. The extracted erven and farm portions were then merged to create a single thematic layer representing parcels. This was done for each scene. The resulting parcel layer was then projected onto the relevant longitude of origin (LO19 for the first test area and LO29 for second) so that it matched the orthorectified image of the same area. This is illustrated in Figure 5-18. ArcGIS was used for extracting, merging and projecting the vector data.

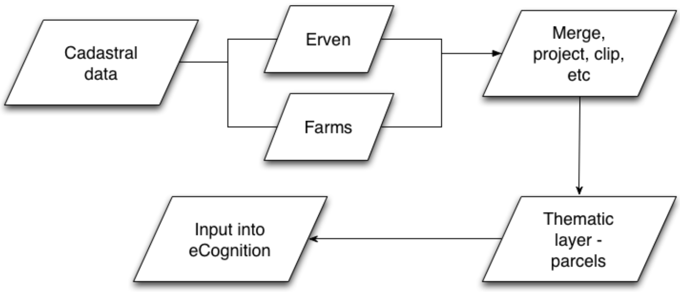


Figure 5-18 Exporting cadastral data for use in the image segmentation process

The red, blue, green and near-infrared image bands as well as the thematic data representing erven and farm portions were then imported into eCognition. The thematic data was used for the initial image segmentation process in order to avoid the problem of having unsuitable segments, such as those that spanned across roads, or contained mixed classes. The initial segmentation was performed using a chessboard segmentation that used the thematic layer to create segments at the cadastral layer level.

In Figure 5-19 it can be seen how a segment may include various unrelated features and how the inclusion of thematic data can be used to fragment the image into suitable blocks that can then be further segmented.

Figure 5-19 Left - segmentation based on shape and spectral properties; right - segmentation based on cadastral parcels (test area 1)

After the initial segmentation, a second segmentation was performed within the boundaries of the cadastral segments. This second segmentation was done using the multiresolution segmentation algorithm with a scale parameter of 300. It was not necessary to segment within small residential erven, but there were erven that needed to be segmented due to the varying land cover classes that existed within these boundaries. Such an example can be seen in Figure 5-20, where the highlighted segment contains bare ground, a built-up area (part of the informal settlement) and a water body (a dam).

The scale parameter was decided on by trial and error, and it was found that a scale parameter of 300 would create smaller segments (as seen in Figure 5-21) within the existing larger segments (as seen in Figure 5-20), without altering the already suitable smaller segments. Image layers were all equally weighted so that each image channel had an equal influence on object generation.

Table 5-6 Segmentation parameters used for both test areas

Image object domain	Pixel level	Image object level
Level	1	2
Algorithm	Chessboard	Multiresolution
Thematic layer usage	Yes	Yes
Scale parameter		300
Shape: Colour	-	0.1: 0.9
Compactness: Smoothness	-	0.5: 0.5

A high degree of colour means that segments will be more spectrally homogenous. Since spectral data is the main information contained in imagery, it was decided to set the shape to colour ratio at 0.1: 0.9. The smoothness and compactness attributes of the shape criterion were equally weighted.

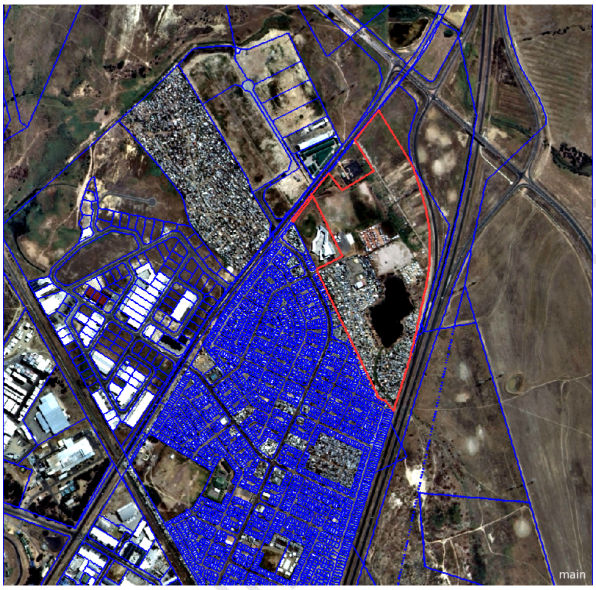


Figure 5-20 Image segmentation using thematic data (level 1) – test area 1

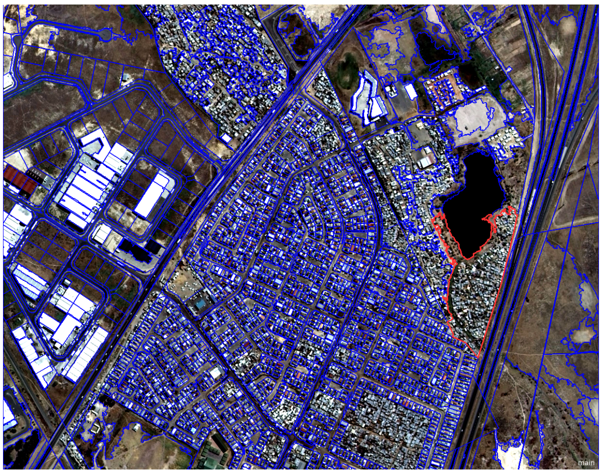


Figure 5-21 Image segmentation (level 2, scale parameter: 300) – test area 1

The next step was to create the following classes: built-up, bare ground or sand, vegetation, road and water. These classes were defined in a class hierarchy in eCognition and suitable samples of each were identified and used as training data in the nearest neighbour classification. For consistency, the same features that were used in the previous object-based classification were also used here. See 5.3 above for details on features used. The classification was performed on level 2 segments for all classes.

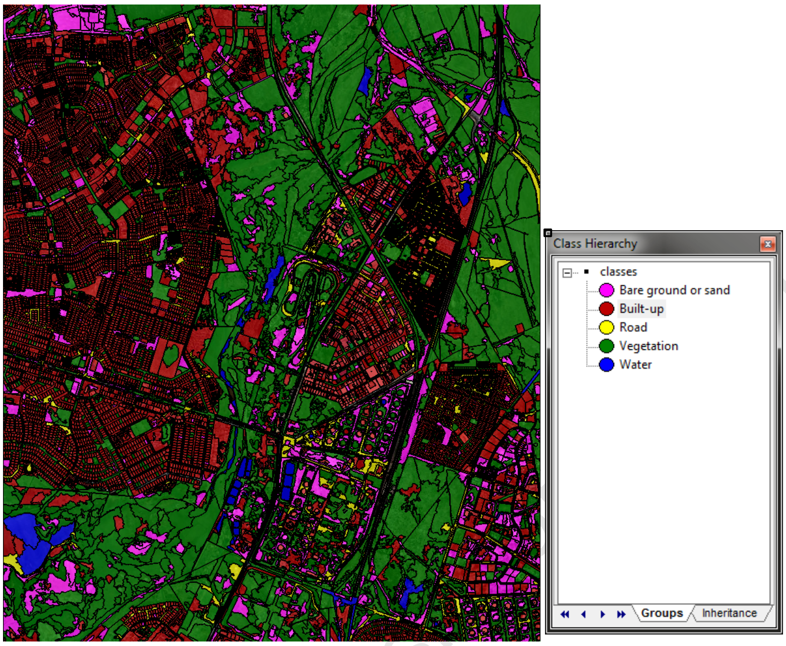


Figure 5-22 Object-based classification (segmentation using cadastral data) – test area 1

Table 5-7 Accuracy assessment and kappa statistics – test area 1

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.95	0.92	0.90
Bare ground or sand	0.90	0.83	0.89
Road	0.41	0.90	0.37
Vegetation	0.88	0.72	0.85
Water	0.64	1.00	0.62
Overall accuracy	**0.83**		
KIA	**0.76**		

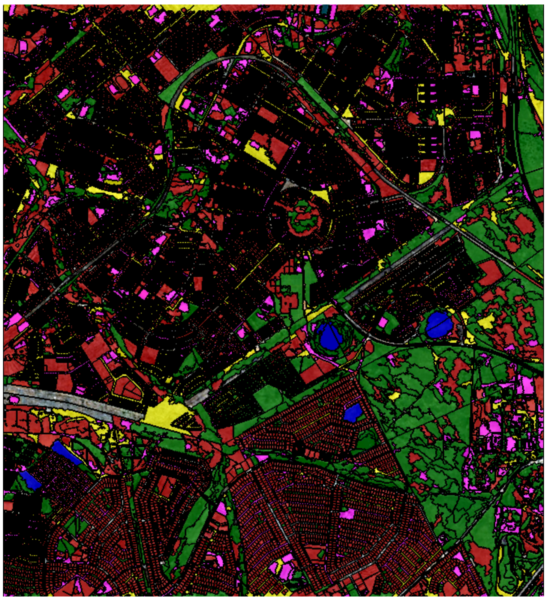


Figure 5-23 Object-based classification (segmentation using cadastral data) – test area 2

Table 5-8 Accuracy assessment and kappa statistics – test area 2

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.93	0.84	0.85
Bare ground or sand	0.72	0.95	0.68
Road	0.18	0.60	0.15
Vegetation	0.80	0.78	0.74
Water	0.50	0.75	0.49
Overall accuracy	**0.77**		
KIA	**0.67**		

The main difference with this approach, compared to the previous object-based method, was the method of segmentation and the size of the final segments used. From a visual perspective most classes appear to be classified reasonably well, and are distinguishable from one another.

The accuracy assessment and kappa statistics for the object-based nearest neighbour method of classification for both the test scenes can be seen in Table 5-7 and Table 5-8. The overall accuracy and KIA was better for the first test area than it was for the second. When compared to the pixel-based supervised method, this object-based method resulted in a better classification for both test areas.

The producer and user accuracies of the built-up class, as well as the KIA per class, for this method were better than the previous method (5.3) for the first test area, and very similar to the results for the second area. The classification of the road class was poor, especially in the second scene. This may be because there were many roads that were not tarred or sealed, and were comprised of bare ground as seen in Figure 5-24, which may have caused confusion between these classes. Although the user accuracy for water was better than in the previous method, overall this class wasn't classified well.

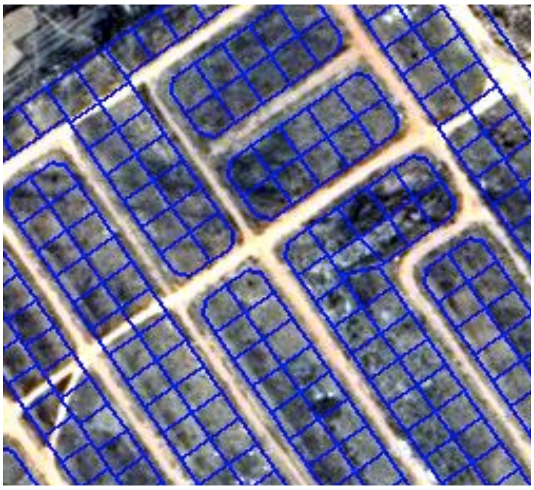


Figure 5-24 Untarred roads

Table 5-9 Comparison of accuracy assessment and kappa statistics for object-based classifications 5.3 and 5.4, where the method of segmentation differed, but the classification method was the same

	Object-based classification – segmentation using image reflectance values (see 5.3)		**Object-based classification – segmentation using thematic data (see 5.4)**	
Test area	Overall accuracy	KIA	Overall accuracy	KIA
1	0.70	0.62	0.83	0.76
2	0.78	0.72	0.77	0.67

The use of thematic data for segmentation is useful for constraining the image segmentation. In this example the cadastral data layer was used to segment an image into parcels that could then be further segmented. Using thematic data to impose segment boundaries has an advantage over using only image properties for image segmentation. When only shape and spectral information are used in the image segmentation process, segments may be homogenous, but may not represent logical boundaries. The use of cadastral data can effectively be used to constrain the segmentation process by creating logical segments with cadastral boundaries. These segments can be further segmented if necessary. Using cadastral data for image segmentation is a robust method and can be applied to many different images and scenes across South Africa.

5.5. Object-based classification – Segmentation using thematic data and classification based on shape and spectral properties of segments – a rule-based approach

The approach to segmentation was the same as in 5.4 above.

Table 5-10 Segmentation parameters

Level	1	2
Segmentation algorithm	Chessboard	Multiresolution
Thematic layer usage	Yes	Yes
Scale parameter	-	300
Shape: Colour	-	0.1: 0.9
Compactness: Smoothness	-	0.5: 0.5

Once suitable segments were created, i.e. the segments represented objects of interest, then the segments could be classified. Since built-up areas were difficult to classify at first, the idea with this method was to first classify the objects that were easy to detect, and from the remaining segments, it would be easier to classify built-up areas.

The first class to be classified was the road class. It was noticed that roads segments had a considerably higher value for the feature *compactness* compared to other segments. *Compactness* was used to classify roads, but not all road segments were classified using this feature. Remaining road segments were classified based on their value for *length over width*, since this attribute was significantly higher for these road segments when compared to other segments in the image (see Figure 5-25). The next class, vegetation, was classified based on a high *NDVI* value as well as an *area* threshold in order to only classify large areas of vegetation and not small residential parcels that may contain lawns and trees, which would increase the average *NDVI* value of the segment. Following this, water was classified using the *Normalised Differential Water Index (NDWI)*. Most segments representing the water class had a value of greater than 0.1 for *NDWI*. Threshold values were found by trial and error.

Table 5-11 Parameters used in classification – test area 1

Class	Feature	Threshold
Road	Compactness Length/width	≥ 7 ≥ 8
Vegetation	NDVI	> 0.07
Water	NDWI	> 0.1

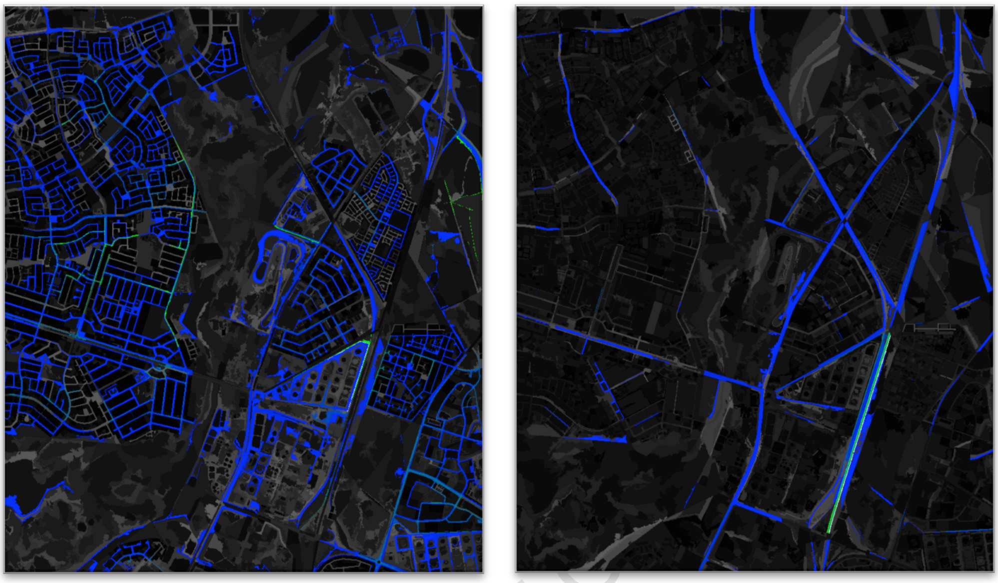


Figure 5-25 Left: highlighted roads have a value for length over width of 8 or greater; right: highlighted roads have a value for compactness of 7 or greater

Most of the roads in the first test area were classified using the features *compactness* and *length over width*. There were some segments that were incorrectly classified as road because they exhibited similar shape and size characteristics. This can be seen in Figure 5-27 where a vegetation segment is incorrectly classified as road. Overall though, based on visual inspection, roads appeared to be classified reasonably well. From the classified image it can be seen that there are segments that represent vegetation that were not classified as such. This is because their *NDVI* value is lower than the minimum threshold value for vegetation. If the minimum threshold value for *NDVI* was set lower, then too many non-vegetation segments would be classified as vegetation. There were not many water bodies in this scene, but most of the water segments were correctly classified. An exception to this is the wetland area in Figure 5-27 that was not classified.

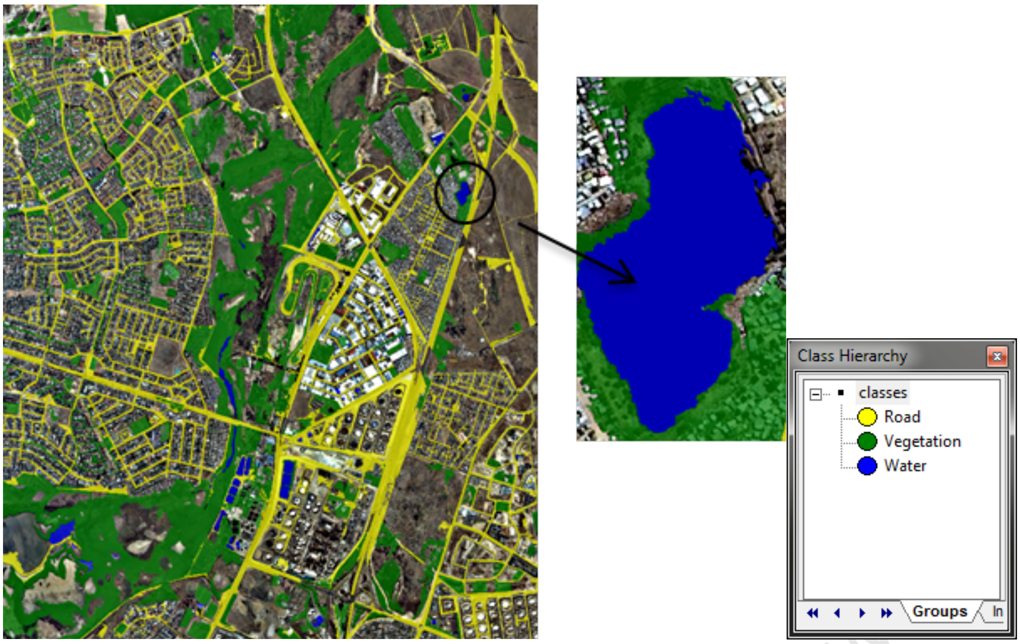


Figure 5-26 Object-based classification (segmentation using cadastral data) – test area 1: rule-based classification of roads, vegetation and water

There were remaining segments representing most classes, as can be seen in Figure 5-26, and it was difficult to extract built-up segments from these unclassified segments.

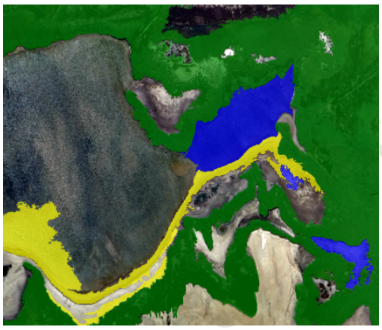


Figure 5-27 Vegetation segment incorrectly classified as road (yellow) due to its shape properties that are similar to road segments; large part of wetland area is not classified

The same method was applied to the second test area. The threshold values were not altered, and the same sequence of classification was followed. Road segments were classified first, and they were classified reasonably well. This was followed by vegetation and then water. The rule to classify vegetation only highlighted a few vegetation segments, as many of these segments had negative values for *NDVI* in this scene.

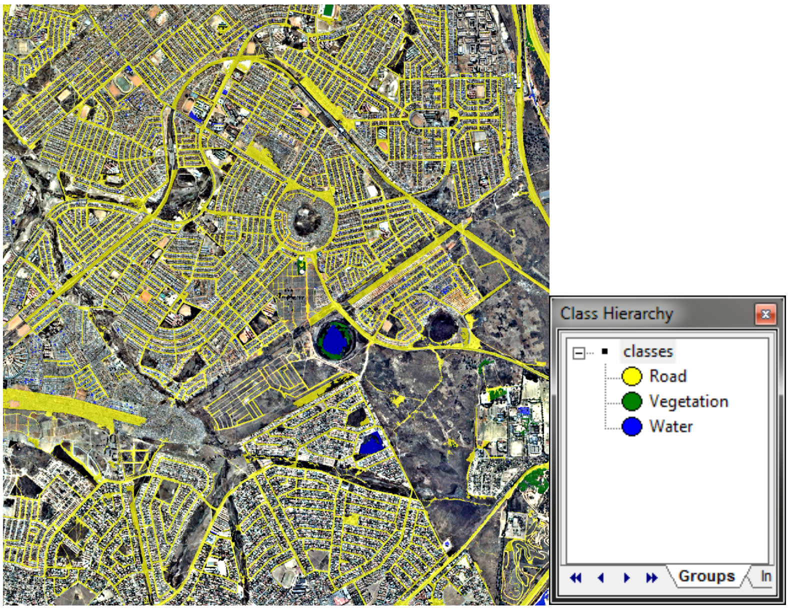


Figure 5-28 Object-based classification (segmentation using cadastral data) – test area 2: rule-based classification of roads, vegetation and water

Figure 5-29 Example of vegetation segment that was not classified due to its very low value for NDVI (test area 2)

This method was not developed further, as it relied on positive *NDVI* to classify vegetation, and when applied to the second test scene, it proved not to be transferrable because of the large difference in vegetation between the two scenes. The varied landscape and climatological conditions in South Africa make it impractical to generalise the classification of vegetation. It was also difficult to differentiate between remaining classes in both test scenes. There was therefore no accuracy assessment done for this method as it was incomplete and did not classify the built-up class, which was the main class of interest.

5.6. Object-based classification – Segmentation using thematic data and a rule-based approach to classification using texture

The method of segmentation was the same as in 5.4 and 5.5 above.

The aim of this method was to focus on classifying built-up areas in each scene. A class hierarchy was created with the classes *built-up* and *not built-up*. It was necessary to have at least two classes so that an accuracy assessment of the classification could be performed.

Various features were examined in an attempt to find a feature, or features, that isolated built-up areas from other classes. Texture measures such as *GLCM mean*, *GLCM homogeneity* and *GLCM contrast* were evaluated and it was found that *GLCM contrast (quick 8/11) (all directions)* could be used to discern between *built-up* and *not built-up* image segments most effectively. Numerous values were tested, but generally segments that had a value of more than 200 for *GLCM contrast* represented built-up areas. This is because built-up areas are highly textured in comparison to other features, such as vegetation and water.

The built-up class was classified using the threshold condition for *GLCM contrast*. Any segments with a value higher than the specified threshold for *GLCM contrast* were classified as *built-up* and all other segments were classified as *not built-up*.

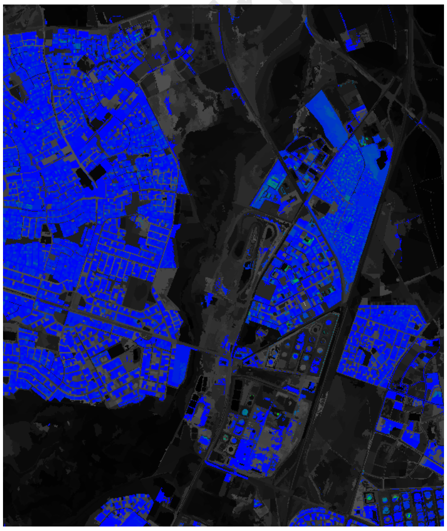


Figure 5-30 Image objects with a value of greater than 200 for GLCM contrast are displayed in colour and all objects below this are displayed in shades of grey – test area 1

The resulting classified image and accuracy assessment for test area 1 can be seen in Figure 5-31 and Table 5-12.

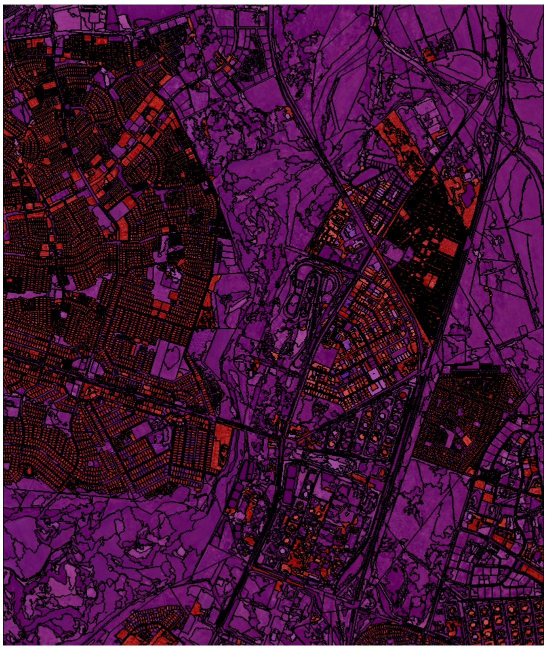


Figure 5-31 Object-based classification (segmentation using cadastral data) – test area 1: rule-based classification of built-up (red) and not built-up (purple) segments

Table 5-12 Accuracy assessment and kappa statistics for object-based classification using thematic data for segmentation and texture for classification – test area 1

Class name	**Producer accuracy**	**User accuracy**	**KIA per class**
Built-up	0.90	0.98	0.72
Not built-up	0.95	0.81	0.93
Overall accuracy	**0.92**		
KIA	**0.81**		

Figure 5-32 Object-based classification (segmentation using cadastral data) – test area 1: rule-based classification of built-up segments (red): left – informal residential; right – formal residential and school area

The same method was followed for the second test area, but with this scene a threshold of 200 for GLCM contrast did not sufficiently classify all of the built-up areas. As can be seen in Figure 5-33, many built-up segments are highlighted using a threshold value of 200, but there are clearly built-up segments that fall below this threshold. It was found that a threshold of 120 for GLCM contrast for the second test area was very effective in classifying built-up areas. This suggests that the method can be transferred from one scene to the next without changing the process, and only editing the threshold value to be better suited to the specific scene.

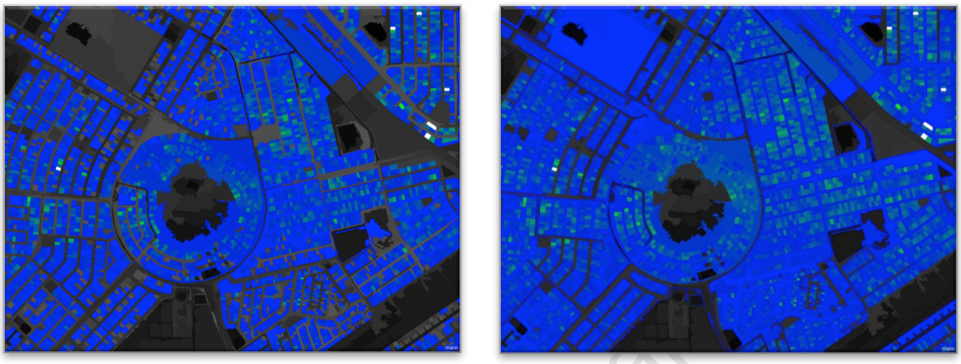


Figure 5-33 Test area 2: left - highlighted image segments have a value for GLCM contrast that is greater than 200; right - highlighted image segments have a value for GLCM contrast that is greater than 120

The classified segments for the second test area can be seen in Figure 5-34.

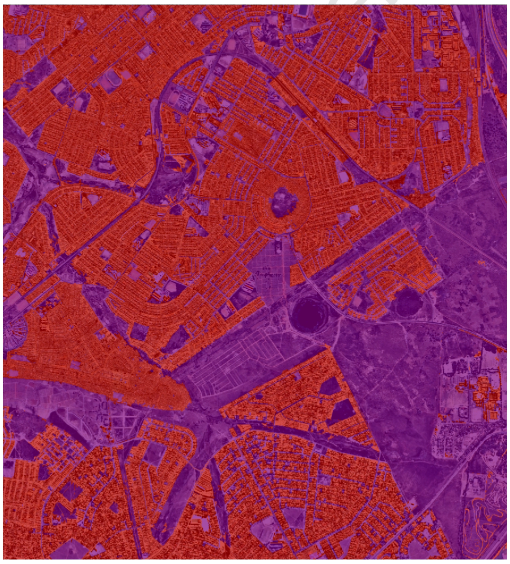


Figure 5-34 Object-based classification (segmentation using cadastral data) – test area 2: rule-based classification of built-up (red) and not built-up (purple) segments

Table 5-13 Accuracy assessment and kappa statistics for object-based classification using thematic data for segmentation and texture for classification – test area 2

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.97	0.96	0.91
Not built-up	0.92	0.94	0.88
Overall accuracy	**0.95**		
KIA	**0.89**		

The same method was applied to a third test scene. This scene was in Stellenbosch near Cape Town and contained many farms as well as residential areas. Many of the residential areas contained large trees, as can be seen in Figure 5-35. When applying the feature *GLCM contrast* to the image to highlight built-up areas, it was noticed that certain crops were highlighted due to their highly textured appearance, which can be seen clearly in Figure 5-36. This problem may be overcome by including *NDVI* in these instances, but as mentioned previously, the solution presented needs to be generalised so that it is applicable across South Africa's diverse landscape. If the threshold value for *GLCM contrast* was increased to exclude textured vegetation, then too many built-up areas were also excluded. It was decided to keep the *GLCM contrast* threshold value at 200, and classify all segments with a value of over 200 as built-up, and all other remaining segments as not built-up, as was done previously. The aim of this example was not to find a perfect solution for individual scenes, but rather to test the transferability of the generalised method of classifying built-up areas in diverse regions in South Africa.

Figure 5-35 Portion of test area 3 showing a residential area with many trees

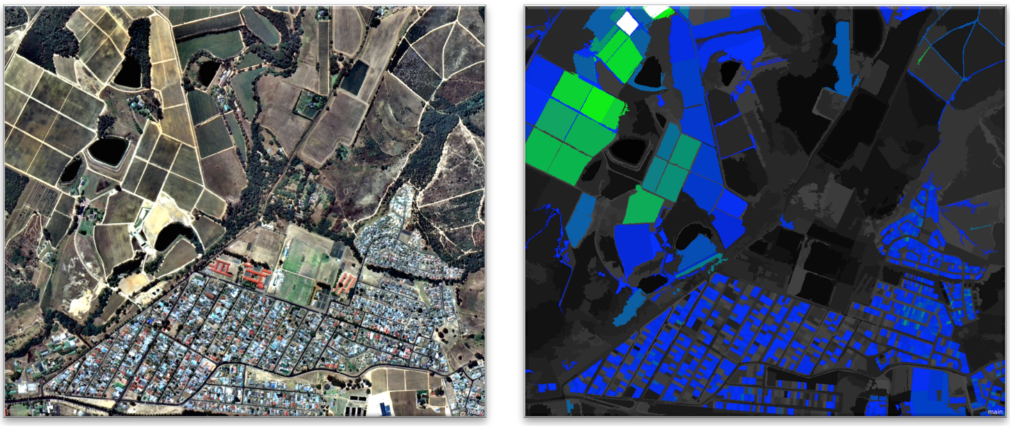


Figure 5-36 Test area 3: left – residential and farms; right - highlighted image segments have a value for GLCM contrast that is greater than 200

The resulting classified image and accuracy assessment for test area 3 can be seen in Figure 5-37 and Table 5-14.

Figure 5-37 Object-based classification (segmentation using cadastral data) – test area 3: rule-based classification of built-up (red) and not built-up (purple) segments

Table 5-14 Accuracy assessment and kappa statistics for object-based classification using thematic data for segmentation and texture for classification – test area 3

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.77	0.93	0.49
Not built-up	0.88	0.66	0.78
Overall accuracy	**0.81**		
KIA	**0.60**		

As with the previous test areas, the same method was applied and only the threshold value for *GLCM contrast* was tested to find an optimal value in the fourth test area. As with both other Cape Town scenes, a threshold value of 200 resulted in highlighting most of the built-up areas in this scene (see Figure 5-38). There was, however, the same problem as with the third test area, where some highly textured vegetation was also highlighted with the threshold value used. As mentioned previously, including additional features to exclude vegetation could possibly solve this, but since this scene was only used to prove transferability and repeatability of the main method, additional classification rules were not included.

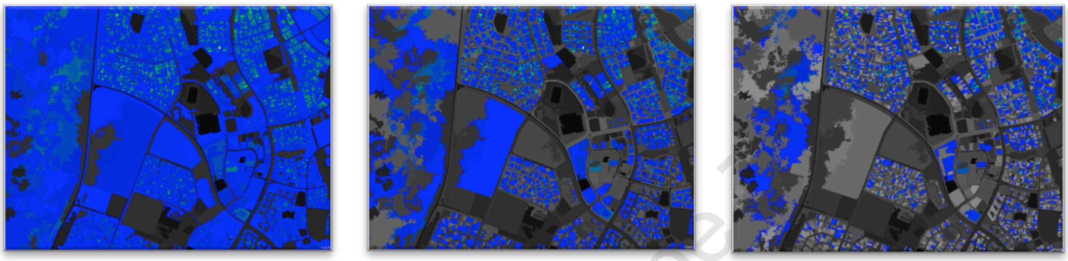


Figure 5-38 Highlighted segments in test area 4 – value for GLCM contrast: left – greater than 100; middle – greater than 200; right – greater than 300

The resulting classified image and accuracy assessment for test area 3 can be seen in Figure 5-39 and Table 5-15.

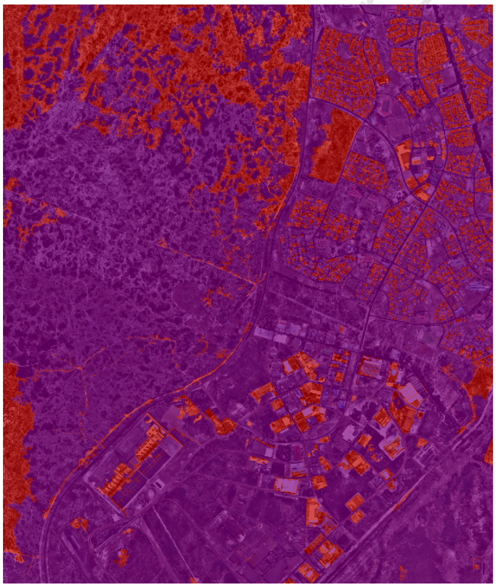


Figure 5-39 Object-based classification (segmentation using cadastral data) – test area 4: rule-based classification of built-up (red) and not built-up (purple) segments

Table 5-15 Accuracy assessment and kappa statistics for object-based classification using thematic data for segmentation and texture for classification (test area 4)

Class name	Producer accuracy	User accuracy	KIA per class
Built-up	0.80	0.85	0.57
Not built-up	0.82	0.76	0.66
Overall accuracy	**0.81**		
KIA	**0.61**		

The use of the texture measure *GLCM contrast* proved to be very effective in differentiating built-up areas from non-built-up areas when included in the process of an object-oriented classification methodology. The overall accuracy and KIA were 92% and 81% respectively for the first test area, and 95% and 89% for the second area. The producer and user accuracies for the built-up area for both test areas 1 and 2 were 90% or greater. This classification resulted in the highest accuracies of all the methods tested.

Overall accuracy and KIA for the additional test areas, test area 3 and test area 4, were lower than that of test area 1 and 2, but still better than the pixel based results. Test area 3 had an overall accuracy of 81% and a KIA of 60%. For test area 4, results were similar with 81% for overall accuracy and 61% for KIA. There were some highly textured vegetation segments in test area 3 and 4 that had a value for *GLCM contrast* that was similar to that of the built-up area segments and thus caused those vegetation segments to be incorrectly classified. Making the threshold value for *GLCM contrast* low enough to exclude the textured vegetation resulted in the exclusion of too many built up areas.

6. Conclusions

The objective of this study was to develop a process for automatic or semi-automatic classification of built-up areas from aerial imagery in South Africa. The methodology proposed should be robust and applicable across South Africa, and should require minimal user input or knowledge about the scene being classified. A generalized method is needed, as South Africa is a country with highly varied landscape and climatological conditions, and therefore it is unreasonable to expect that a perfect solution may be found.

Various methods of image classification were compared and their results analysed in the previous chapter. Pertinent conclusions drawn from each method are presented below. From the different approaches tested, the methodology that is finally proposed is an object-based, or object-oriented approach that uses cadastral data in the initial image segmentation process, and a rule-based approach to classify image objects. Image texture is of key importance in the classification of built-up areas in the proposed methodology. The proposed methodology can be applied reliably to a variety of scenes in South Africa to give a generalized solution to finding built-up areas. This methodology can assist the CD: NGI in their goal to speed up the process of updating their topographic database by reducing the time that operators spend on identifying built-up areas and manually digitizing them. The workflow for the final proposed method is presented in Figure 6-1.

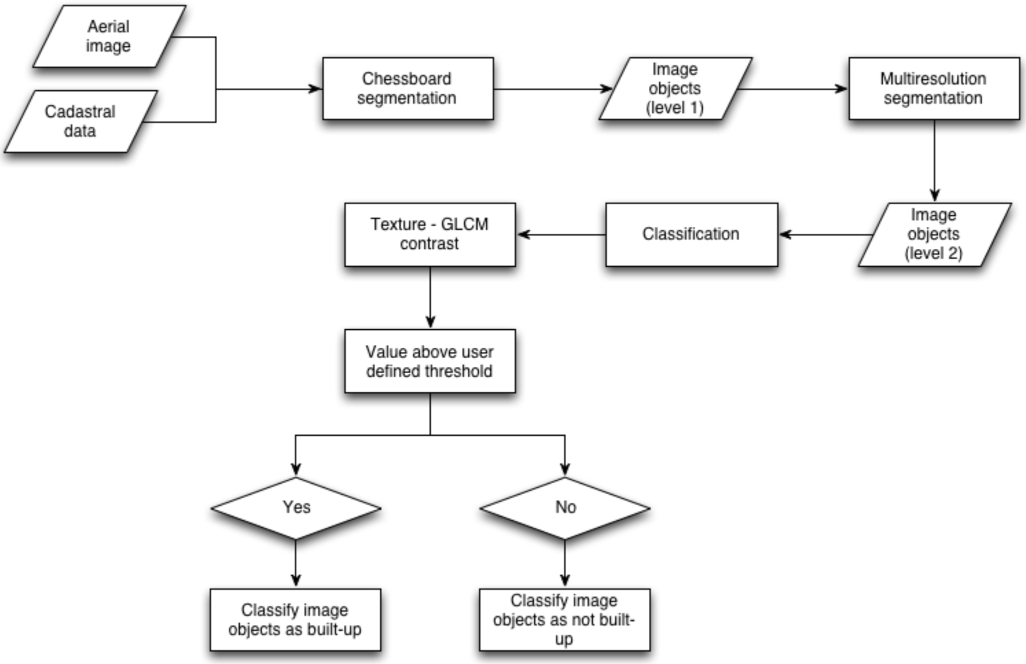


Figure 6-1 Workflow for final proposed method – a simple approach to classifying built-up areas using object-based classification

6.1. Pixel-based classification

Generally, the supervised and unsupervised pixel-based classifiers did not perform very well. The overall accuracy and KIA of the pixel-based supervised methods were lower than any of the object-based classification results. The assessment of the pixel-based unsupervised ISODATA method was done by visual inspection and found to be unsatisfactory.

The results for the supervised maximum likelihood classification were unreliable, since the overall accuracy and KIA were 60% and 50% respectively, for both test areas. The producer and user accuracies for built-up areas were 36% and 40% for the first test area, and 43% and 60% for the second. These accuracies indicate that the classifier performed poorly in identifying built-up areas, and that the probability of a sample being correctly classified is very low.

Although the classification of vegetation was not the main class of interest in this study, it is interesting to note that the user and producer accuracies for this class were higher than those of built-up areas. The result for user accuracy was 80% for the first test area and 90% for the second, while the producer accuracy was 62% and 60% respectively.

There were inconsistent results for the classification of roads, but generally results were very poor. In the first test area, producer and user accuracies were 63% and 50%, while in the second test area they were both 0%, indicating that the classification is no better than that expected by chance.

The classification of manmade features, such as built-up areas and roads, using the pixel-based maximum likelihood classification method, is unsatisfactory. This can be due to large spectral variations within these classes, as opposed to natural features, which tend to be more homogeneous.

6.2. Object-based classification

The success rate of classifying built-up features was much higher with the object-based methods compared to the pixel-based methods. With the first object-based approach, the nearest neighbour method of classification was used and segmentation was based on image reflectance properties. This object-based method demonstrated an improvement over the pixel-based maximum likelihood classification. The results for the KIA for this object-based method were 62% (test area 1) and 72% (test area 2) compared to 50% that was achieved with the pixel-based method for both test areas. The user and producer accuracies were significantly better with the object-based approach, where these values are all greater than 80%.

The improvement in accuracy with the object-based methods is due to the classification of homogeneous segments as opposed to individual pixels. Groups of pixels represent classes of interest more accurately than individual pixels.

Subsequent object-based classification methods, which relied on the use of thematic data for image segmentation, resulted in even better success rates of classifying built-up areas (see 6.3 and 6.4 below). Therefore, object-based classification can be used successfully to classify built-up areas from aerial imagery.

6.3. The use of thematic data for image segmentation in object-based classification

Segmentation using image reflectance values works, but may not generalize well. Typically segments representing features of interest will need to be created through an iterative process of segmentation that may rely on various image and segment properties. Depending on the features of interest and the spectral characteristics of the image, this process can vary substantially from one scene to the next. Following on from the previous object-based classification method, subsequent methods included thematic data for image segmentation. Thematic data is useful in constraining image segmentation. The use of thematic data for image segmentation proved to be beneficial in achieving suitable image objects or segments, that could then be classified. Using thematic data provides a robust method of image segmentation. The second object-based classification method used cadastral data in the image segmentation process, and classification was based on the nearest neighbour method. The results for producer and user accuracy for this classification method were generally better than the previous object-based approach, but the KIA results for the two classifications were quite similar. In the previous object-based method, the user accuracy for the second test area was 100%, which would have increased overall accuracies for this method. A reason for the high user accuracy for this method may be due to the fact that the second test area was predominantly comprised of built-up areas that were very similar in appearance, whereas the first test area had much more diversity within the built-up class.

With the third object-based classification method, segments were created using thematic data, but instead of using the nearest neighbour method of classification as in the previous methods, a rule-based approach was carried out. The classes vegetation, water and road were classified based on shape and reflectance properties of image segments, but it was found that this method did not generalize well, and rules that worked on one test area did not yield the same results in a second test area. With this method, the aim was first to classify features that were thought to be simpler to extract, and from the remaining segments the built-up class would be easier to find. This method was based on the assumption that the vegetation index, NDVI, would assist in classifying vegetation; which was true for the first test area, but not for the second. When the rule to classify vegetation was applied to the second test area, very few vegetation segments were classified as such. Even though imagery for both areas was captured in months that receive little or no rainfall, vegetation health differed in the two scenes. Only in the first scene did the spectral characteristics of the vegetation allow for it to be reliably detected using NDVI. This method was not transferable between different scenes, and was therefore not developed further. Since this method was not complete, accuracy was assessed based on visual inspection only. This method guided the focus of the final method and the object-oriented methodology in general.

6.4. The use of texture for classifying built-up areas

In the final object-based classification method, thematic data was used for image segmentation and classification was carried out using a rule-based approach. Texture was used to classify built-up areas and it yielded very encouraging results. The particular texture measure used was *Texture after Haralick – GLCM contrast*. The threshold value for *GLCM contrast* is scene dependent, and must be found by fine-tuning the value to find the optimal solution for the area of interest.

The producer and user accuracies of built-up areas for the first test area were 90% and 98%, and for the second area they were 97% and 96%. These results were better than any of the previous methods, and the high values achieved demonstrate the ability of the classifier to identify built-up areas successfully in aerial imagery. The overall accuracies and KIA results were also better than those of any the previous classifications. For the first test area the overall accuracy was 92% and KIA was 81%, and for the second test area results were 95% and 89%. These results show that the texture measure *GLCM contrast* can be used to classify successfully built-up areas from aerial imagery when included in the process of an object-oriented classification methodology. However, highly textured vegetation causes a problem when classifying built-up features using only *GLCM contrast*, as was seen in the additional two scenes – test areas 3 and 4, which were used to demonstrate transferability of the method. Even though there were some segments representing vegetation that were incorrectly classified as built-up areas, the producer and user accuracies for built-up areas was still high with results of 77% and 93% for the third test area, and 80% and 85% for the fourth area. Results for all test areas using this object-oriented method of classification are significantly better than the pixel-based results and prove that the proposed method is successful in classifying built-up areas from aerial imagery.

The proposed method achieves the objective of developing a process for semi-automatic classification of built-up areas from aerial imagery in South Africa. The method is robust, requires little user input, and is generalized so as to be applicable across South Africa.

7. Recommendations and future work

The objective of this dissertation is to develop a semi-automatic method to classify built-up areas from aerial imagery. The method needs to be generalized so that it is applicable across South Africa's varied landscapes and wide-ranging climatological conditions. The process needs to be fast and reliable, and should assist the CD: NGI in updating their topographic map database more efficiently. The method proposed for classifying built-up areas relies on cadastral thematic data for image segmentation and the use of texture (GLCM contrast) for classification of built-up segments within an object-oriented classification process. Although the accuracy of this method was high, with an overall accuracy of over 90% in the two main test areas, and over 80% in the additional two areas, even greater accuracies could possibly be achieved by including additional measures, such as context, shape, size, spectral properties, etc. Additional measures may be used to exclude other features from the built-up class. These may be based on spectral reflectance and shape properties of segments and may assist in classifying textured vegetation, for example, which could then be removed. Context and relationships of segments with other segments may also be useful in classifying additional classes of interest, or in isolating built-up areas. There were some vegetation segments in certain scenes where the texture value for *GLCM contrast* was very similar to those segments of the built-up area. As was seen in the results and analysis chapter, vegetation indices such as *NDVI* may be useful in classifying vegetation in some scenes, but not in others, due to the varied landscape and climatological conditions that exist in South Africa, and therefore *NDVI* alone cannot be used to successfully classify vegetation in the proposed project. It is recommended that context and relational information, in addition to texture, shape and spectral properties of images, be considered for future work.

Future research in the following areas is considered:

- The robustness of the methodology should be further evaluated by increasing the number of test sites.

- Study areas were limited in size due to the processing power requirements of the software, eCognition developer, and it is recommended that for future work, additional computing resources be allocated to the software. Testing was conducted on a mobile system with an Intel Core i5 processor and 8GB of

RAM, which was barely sufficient for the test areas under discussion. Larger datasets consisting of more than one aerial image per scene should be tested. The size of future test areas should be comparable to those typically captured in the manual process of digitizing features for topographic mapping, i.e. a minimum mapping area of 2500 km^2.

- The methodology should also be tested using satellite data such as SPOT 5 or SPOT 6 imagery. Image bands are similar to CD: NGI's aerial imagery, with the exception of the blue band, which is not available in SPOT 5 imagery. It does, however, have a short-wave infrared band, which may be useful for future image classification. The large geographical extent covered by a single SPOT image may be advantageous in detecting large built-up areas, and for large areas the lower resolution of the satellite imagery, compared to that of aerial imagery, would not be a limitation.

- Only standard products available to CD: NGI were used in this study, but for future work one may consider including a digital surface model in the image classification process.

- The purpose of this investigation was not to distinguish between different types of built-up areas, but rather to find a collective 'built-up' land cover class. However, for future work, one may wish to distinguish between different types of built-up areas; for example, residential, commercial and industrial areas. The inclusion of size and shape parameters may assist in differentiating between different types of built-up areas. Commercial and industrial areas will typically be characterised by buildings that are considerably larger than those found in residential areas. The presence of large parking areas may also indicate commercial or industrial use, while vegetation presence, such as gardens, may indicate residential use.

- The classified built-up areas can be exported to vector data and used for comparison to existing, manually captured vector data, so that changes to built-up areas may be detected. It is recommended that this task be carried out and the accuracy of changed areas be assessed. Future work should be in editing areas identified as changed built-up areas so that they are compatible with the CD: NGI topographic database.

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A. Appendices

Land cover classification

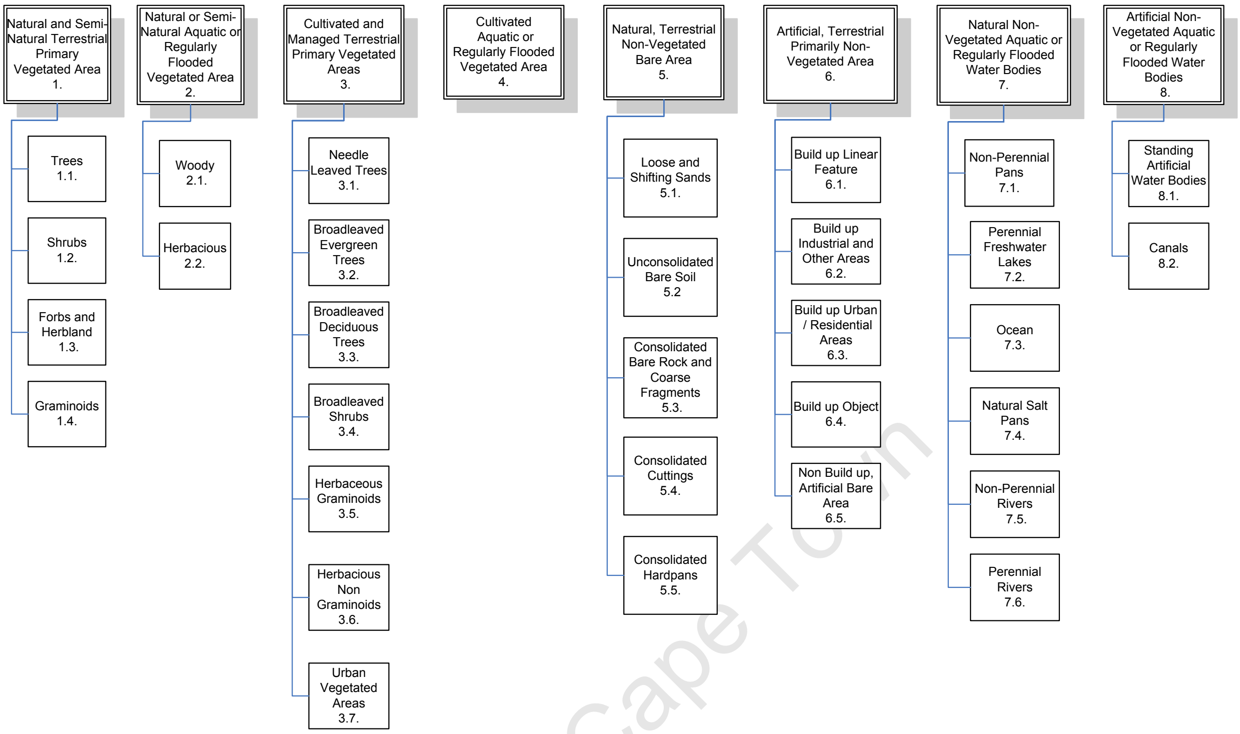

Figure A-1 The South African Land Cover Legend showing the 8 super classes and 32 subclasses (Lück et al., 2010)

Land use classification

Table A-1 The South African Land Use Classification Hierarchy (Chief Directorate: National Geo-spatial Information, 2009)

Notation	Main Class	Notation	Sub-class
1	**Agriculture & Fisheries**	1.1	Commercial Agriculture
		1.2	Subsistence Agriculture
		1.3	Small Scale Agriculture
		1.4	Grazing
		1.5	Fisheries
2	**Forestry**	2.1	Managed Forest Plantation
		2.2	Managed Natural (Indigenous) Forest
		2.3	Unmanaged Forest Plantation
		2.4	Unmanaged Natural (Indigenous) Forest
3	**Conservation**	3.1	National Parks
		3.2	Nature Reserves
		3.3	Conservation Areas
4	**Mining**	4.1	Mineral Workings & Quarries
5	**Transport**	5.1	Transport Tracks & Ways
		5.2	Transport Terminals and Interchanges
		5.3	Car Parks
		5.4	Other Vehicle Storage
		5.5	Goods & Freight Handling
		5.7	Waterways
6	**Utilities & Infrastructure**	6.1	Energy Production & Distribution
		6.2	Water Storage & Treatment
		6.3	Sewerage Treatment Plants
		6.4	Refuse Disposal
		6.5	Cemeteries & Crematoria
		6.6	Post & Telecommunications
		6.7	Bulk Pipeline Networks
7	**Residential**	7.1	Formal Single Residential
		7.2	Formal Multiple Residential
		7.2	Residential in Rural Village
		7.3	Informal Residential
		7.4	Hotels, Boarding & Guest Houses
		7.5	Residential Institutions (hostels, etc.)
		7.6	Dispersed Residential
8	**Community Services**	8.1	Health Care Facilities
		8.2	Places of Worship
		8.3	Education
		8.4	Community Facilities
		8.5	Administrative Facilities

9	**Commercial**	9.1	Retail
		9.2	Financial Institutions
		9.3	Restaurants & Cafes
		9.4	Bars, Taverns & Night Clubs
		9.5	Offices
		9.6	Informal Trading
10	**Industrial & Storage**	10.1	Light Industries
		10.2	Heavy Industries
		10.3	Storage
		10.4	Wholesale Distribution
11	**Recreation & Leisure**	11.1	Open Spaces
		11.2	Amusement & Show Places
		11.3	Libraries, Museums, Art Galleries
		11.4	Sports Facilities
		11.5	Resorts
12	**Protection Services**	12.1	Defense
		12.2	Police
		12.3	Emergency Services
		12.4	Correctional Services
13	**Undeveloped Land**	13.1	Undeveloped Land
14	**Water**	14.1	Surface water used for storage
		14.2	Surface water used for recreation
		14.3	Surface water used for irrigation

Topographic data structure

Table A-2 List of CD: NGI topographic features – x: mandatory features to be captured; xx: features that require additional subtypes; xxx: features that require additional operational status (Chief Directorate: National Geo-spatial Information, 2013a)

Attribute	Domain/Description
	ADMN_BOUNDARIES:
	1 Any Other Administrative Boundary
	2 Country
	3 District Municipality
	4 Environmentally Protected Area
	5 Forest Reserve
	6 Game Reserve
	7 Magisterial District
	8 Marine Reserve
	9 Category A Municipality
	10 Military Area
	11 Municipality
	12 National Park
	13 Nature Reserve
	14 Province
	15 Ramsar Site
	16 Reserve Area
	17 Suburb
	18 Township
	19 World Heritage Site
	435 Health District
	436 Health Region
	437 Voting District
	438 Electoral Ward
	439 Precinct
	440 Police Area
	441 Tribal Authority
	469 School District
	ADMN_CENSUS_BOUNDARIES:
	24 Enumeration
	25 Populated Place
	ADMN_GEONAMES:
	26 Geographical Name
	ADMN_HISTORICALBOUNDARIES:
	27 Any Other Historical Administrative Area
	28 Census District
	29 Divisional Council
	30 Group Area
	31 Joint Services Board
	32 Pre 1994 Province
	33 Regional Services Council
	34 Self Governing Territory
	35 TBVC State
	AERO_AREAS:
	36 ATA
	37 FIR
	38 CTA
	39 TMA
	40 ATZ
	41 CTR
	42 UTA
	43 FAD
	44 FAP
	45 FAR
	46 Advisory Area
	47 All Purpose Area
	48 Special Rules Area
	49 UIR
	50 Region
	AERO_BEACONS:
	51 NDB
	52 VOR
	53 DME
	54 Marine Light
	55 MNDB
	56 Reporting Point Compulsory
	57 Reporting Point Non Compulsory
	58 TACAN
	59 VORTAC
	AERO_FACILITIES:
	60 Aerodrome Civil
	61 Aerodrome Civil And Military
	62 Aerodrome Military
	63 Aerodrome Unlicensed

	64 Aerodrome Emergency
	65 Aerodrome Customs
	66 Heliport
	67 Heliport Military
	68 Helistop
	AERO_LINES:
	69 ATS Air Traffic Services
	70 ATS Lower Air Traffic Services
	71 ATS Upper Air Traffic Services
	72 ATS Sectorisations
	73 AWY
	74 Advisory Route
	75 FISR
	76 RNAV Route
	77 Advisory Route Center Line
	78 All Purpose Line
	79 Airpassage
	AERO_OBSTRUCTIONS:
	80 All Purpose Obstruction Point
	81 Danger Point
	CULT_BARRIERS:
x	82 Anti Erosion Wall
	83 Any Other Barrier
x	84 Avenue
x	85 Breakwater
x	86 Cutline
x	87 Dam Wall
x	88 Fence
x	89 Fire Break
x	90 Wall
x	91 Weir
	92 Windbreak
	CULT_EDUCATIONAL:
	93 Abet Centre
	94 Any Other Educational Facility
	95 Classroom
x	96 College
	97 Multiple Educational Facility
	98 Research Facility
x	99 School
x	100 University of Technology
	101 Training Area
x	102 University
	CULT_INDUSTRIAL:
x	103 Factory

	104 Refinery
x	105 Sawmill
x	106 Conveyor Belt
x	107 Saltworks
x	108 Silo
	173 Any Other Pipe
x	194 Any Other Reservoir
x	199 Fish Farm
	442 Gas Pipe
	443 Oil Pipe
	444 Fuel Storage Tank
	445 Chemical Storage Tank
	CULT_PUBLIC:
	109 Any Other Heritage Site
	110 Any Other Observation Structure
	111 Any Other Public Structure
	112 Any Other Religious Place
	113 Archeological Site
x	114 Border Post
x	115 Botanical Garden
x	116 Cemetery
x	117 Correctional Facility
x	118 Clinic
x	119 Community Hall
x	120 Court
	121 Cultural Site
x	122 Ground Sign
	123 Historical Area
x	124 Ruin
x	125 Hospital
	126 Hostel
x	127 Hotel
x	128 House
	129 Hut
x	130 Legislative Building
x	131 Library
	132 Market
x	133 Military Base
x	134 Mission
x	135 Monument
x	136 Museum
	137 National Heritage Site
	138 Place of Pilgrimage
x	139 Place of Worship
	140 Planetarium

x	141 Police Station
x	142 Post Office
x	143 Refuse Dump
x	144 Retail Outlet
x	145 Shipwreck
x	146 Shopping Centre
	147 Tall Structure
x	148 Town Hall
x	149 Tree
x	150 Building
	151 Warehouse
x	152 Watchtower
x	153 Zoological Facility
x	476 Grave
x	479 Bird sanctuary
	CULT_RECREATIONAL:
x	154 Amusement Park
x	155 Any Other Recreational Facility
x	156 Caravan Park
x	157 Cinema
x	158 Clubhouse
x	159 Gambling Facility
x	160 Golf Course
x	161 Holiday Resort
	162 Indoor Sport Centre
x	163 Urban Park
x	164 Scale Model Facility
x	165 Shooting Range
x	166 Sports Field
x	167 Stadium
x	168 Swimming Pool
	169 Theatre
	170 Water Sport Facility
x	171 Horse-race course
x	172 Motor sport track
x	392 Hiking Trail
	446 Tennis Court
	447 Race Route
x	477 Golf driving range
x	478 Garden
	CULT_UTILITIES:
x	1003 Substation
	174 Power Line
x	175 Telecommunication Tower
x	176 Any Other Power Station

x	177 Nuclear Power Station
x	178 Solar Panel Array
x	179 Wind Farm
x	207 Sewage Works
x	210 Water Treatment Plant
	233 Sewer
x	242 Cooling Tower
	449 Sewage Bridge
x	450 Sewerage Pipe
x	451 Coal-fired Power Station
x	452 Combustion Engine Power Station
x	453 Combustion Turbine Power Station
	454 Fuel Cell
x	455 Hydroelectrical Power Station
	456 Septic Tank
	457 Cellular Telephone Base Station
	458 Microwave Tower
	459 Radio Antenna Site
x	460 Satellite Antenna
	461 TV Antenna Site
x	1000 Any Other Utility Pipe
	HYDR_AREAS:
	195 Bog
x	196 Dam
x	197 Dry Pan
x	198 Dry Water Course
x	200 Flood Bank Area
x	201 Lake
x	202 Marsh
x	203 Mudflat
	205 Unknown River
	206 Salt Pan
x	208 Vlei
x	209 Water Tank
x	462 Closed Reservoir
x	463 Open Reservoir
x	464 Natural Pool
x	465 Perennial Pan
x	474 Non-Perennial River
x	475 Perennial River
x	481 Non-perennial pan
	HYDR_COASTAL_AREAS:
	1001 Bay
x	1002 Channel
x	218 Coastline

	219 High Water Mark
	220 Low Water Mark
	HYDR_LINES:
	221 Any Other Channel
x	222 Aqueduct
	223 Culvert
x	224 Drainage Canal
x	225 Dry Water Course
x	226 Furrow
x	227 Irrigation Canal
x	228 Irrigation Tunnel
x	229 Navigable Canal
x	232 Rapid
x	234 Siphon
	235 Spring Line
	236 Unknown River
	237 Water Pipe
x	238 Waterfall
x	472 Non-Perennial River
x	473 Perennial River
	HYDR_POINTS:
	240 Any Other Spring
	241 Artesian Well
x	243 Hot Spring
	244 Seep
x	245 Spring
x	246 Water Pump
x	247 Water Tower
x	248 Well
x	249 Wind Pump
x	466 Water Reservoir
x	1004 Water Point
	HYPS_ELEVATION_LINES:
x	250 Contour
x	251 Depression Contour
	252 Breakline
	253 Ridge Line
	HYPS_ELEVATION_POINTS:
	254 Digital Elevation Model Point
x	255 Spot Height
	LCLU_LANDCOVER:
x	263 Forest and Woodlands
	264 Thicket, Bushland, Bush Clumps and ShrubForest
	265 Scrubland

	266 Herbland
	267 Grassland
	268 Forest Plantations (288)
	269 Waterbodies
	270 Wetlands
x	271 Barren Lands
x	272 Cultivated Land
	273 Built-up Land
	274 Mines and Quarries
x	1005 Tunnel Farming
	LCLU_LANDUSE:
	275 Unknown
	276 Undeveloped Land
	277 Unclassified Urban Area
xx	278 Residential Landuse
	279 Commercial Landuse
	280 Agricultural Landuse
	281 Public Service Landuse
	282 Transportation Landuse
	283 Industrial Landuse
	284 Cultural Landuse
	285 Recreational Landuse
	286 Informal Landuse
x	287 Orchard / Vineyard
x	288 Plantation
	PHYS_LANDFORM_ARTIFICIAL:
x	289 Cutting
	290 Deep Level Mine
x	291 Embankment
x	292 Excavation
x	293 Mine Dum
	294 Mine Dump Top (Use :298)
x	295 Open Cast Mine
	296 Quarry
x	297 Slimes Dam
x	298 Artificial terrain crest
x	299 Mine Head Gear
x	471 Digging
	PHYS_LANDFORM_NATURAL:
	300 Alluvial Fan
x	301 Any Other Island
x	302 Beach
x	303 Boulder
x	304 Cave
	305 Cliff

	306 Crag
	307 Donga
xx	308 Dune
x	309 Eroded Area
	310 Gorge
	311 Hill
	312 Island in Inland Water
	313 Mountain
	314 Mountain Range
	315 Nek
	316 Plain
	317 Reef
	318 Rock
x	319 Rocky Outcrop
x	320 Sandbank
	321 Sea Island
	322 Sheet Erosion
x	323 Sinkhole
	324 Slope
	467 Mountain Peak
	TRAN_CROSSINGS:
x	339 Any Other Bridge
x	340 Any Other Tunnel
	341 Level Crossing
	342 Low-level Bridge
x	343 Pedestrian Bridge
x	344 Pont
x	345 Rail Bridge
x	346 Rail Tunnel
x	347 Road Bridge
x	348 Road Tunnel
x	349 Tunnel Entrance
	TRAN_FACILITIES:
xxx	350 Aerodrome
xxx	351 Airfield
xxx	352 Airport
	353 Any Other Harbour Facility
	354 Any Other Transport Node
	355 Basin
	356 Bus Station
x	357 Cable Car Station
x	358 Depot
	359 Electronic Navigation Beacon
x	360 Harbour
xxx	361 Helipad

x	362 Jetty
xxx	363 Landing Strip
	364 Land Mark
xx	365 Marine Navigation Beacon
	366 Parking Lot
x	367 Pier
xxx	368 Railway Station
x	369 Taxi Rank
x	370 Toll Gate
xxx	468 Runway
	TRAN_LINE_OTHERS:
	371 Air Route
x	372 Cableway
	373 Combination Route
x	374 Dock
x	375 Dry Dock
	378 Other Route
	379 Pass
x	381 Quay
	382 Rail Route
	383 Road Route
	384 Sea Route
x	480 Wharf
	TRAN_RAILWAY_LINES:
xxx	385 Marshalling Yard
xxx	386 Narrow Gauge Railway Line
xxx	387 Standard Gauge Railway Line
xxx	388 Other Railway Line
	389 Railway Siding
x	1006 Old Rail Route
	TRAN_ROADS:
xxx	390 Arterial Road
x	391 Footpath
xxx	393 Interchange
xxx	394 Main Road
xxx	395 National Freeway
xxx	396 National Road
xxx	397 On/Off Ramp
xxx	398 Other Road
xxx	399 Secondary Road
x	400 Slipway
xxx	401 Street
x	402 Track

Classification stability and best classification results for 5.3 and 5.4

Table A-3 Statistics of classification stability and best classification result for 5.3 (test area 1)

Test area: Cape Town		**Classification stability**		**Best classification result**	
Class	**Objects**	**Mean**	**StdDev**	**Mean**	**StdDev**
Built-up	261	0.146	0.104	0.875	0.108
Vegetation	386	0.231	0.235	0.801	0.149
Water	71	0.241	0.296	0.666	0.259
Road	43	0.288	0.266	0.718	0.249
Bare ground or sand	389	0.269	0.184	0.691	0.195

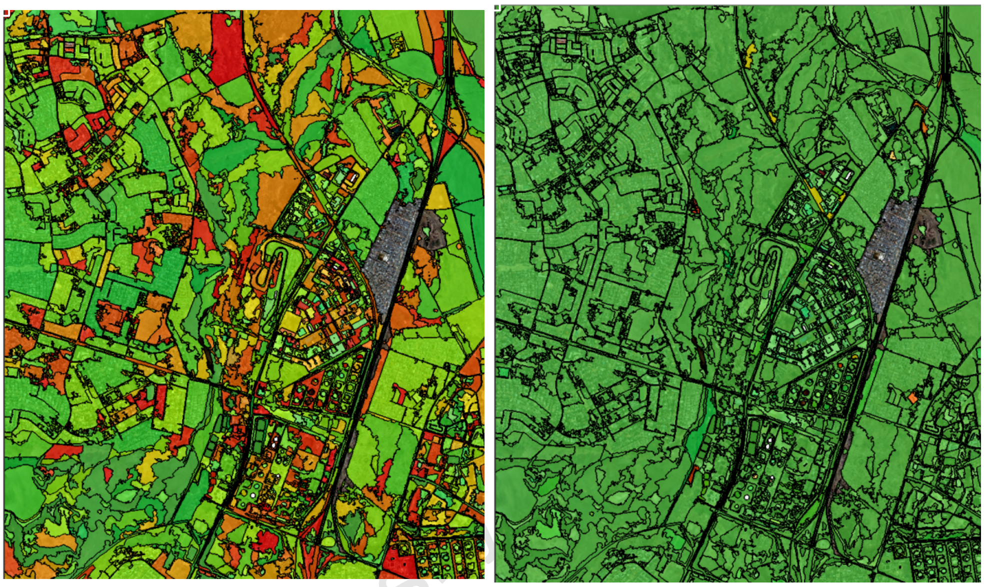

Figure A-2 Classification stability (left) and best classification result (right) for 5.3 (test area 1)

Table A-4 Statistics of classification stability and best classification result for 5.3 (test area 2)

Test area: Johannesburg		**Classification stability**		**Best classification result**	
Class	**Objects**	**Mean**	**StdDev**	**Mean**	**StdDev**
Built-up	399	0.203	0.137	0.813	0.146
Vegetation	311	0.240	0.168	0.768	0.154
Water	6	0.242	0.352	0.879	0.099
Road	11	0.506	0.395	0.560	0.343
Bare ground or sand	258	0.335	0.260	0.740	0.173

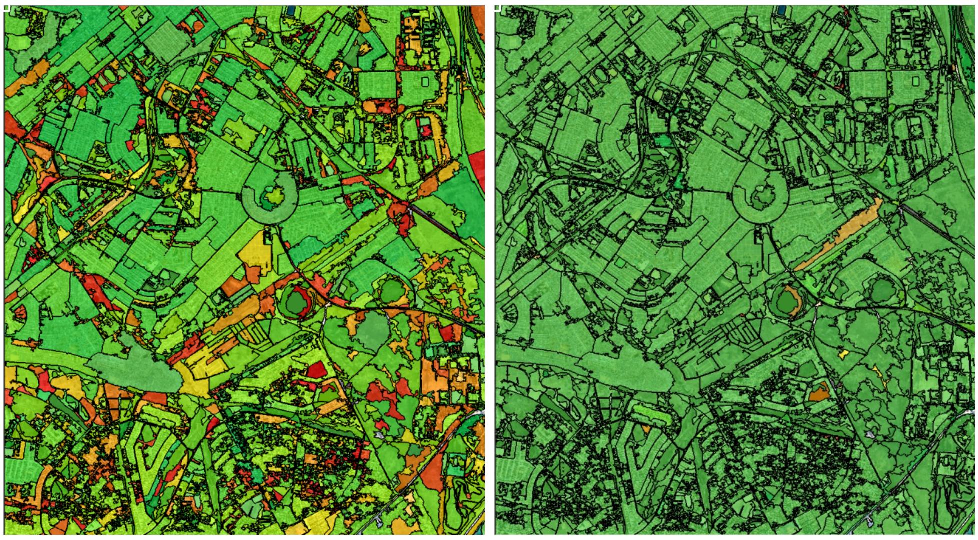

Figure A-3 Classification stability (left) and best classification result (right) for 5.3 (test area 2)

Table A-5 Statistics of classification stability and best classification results for 5.4 (test area 1)

Test area 1		**Classification stability**		**Best classification result**	
Class	**Objects**	**Mean**	**StdDev**	**Mean**	**StdDev**
Built-up	20136	0.172	0.131	0.874	0.150
Bare ground or sand	1919	0.145	0.147	0.742	0.188
Road	204	0.247	0.254	0.557	0.228
Vegetation	6058	0.131	0.134	0.627	0.227
Water	90	0.269	0.251	0.389	0.256

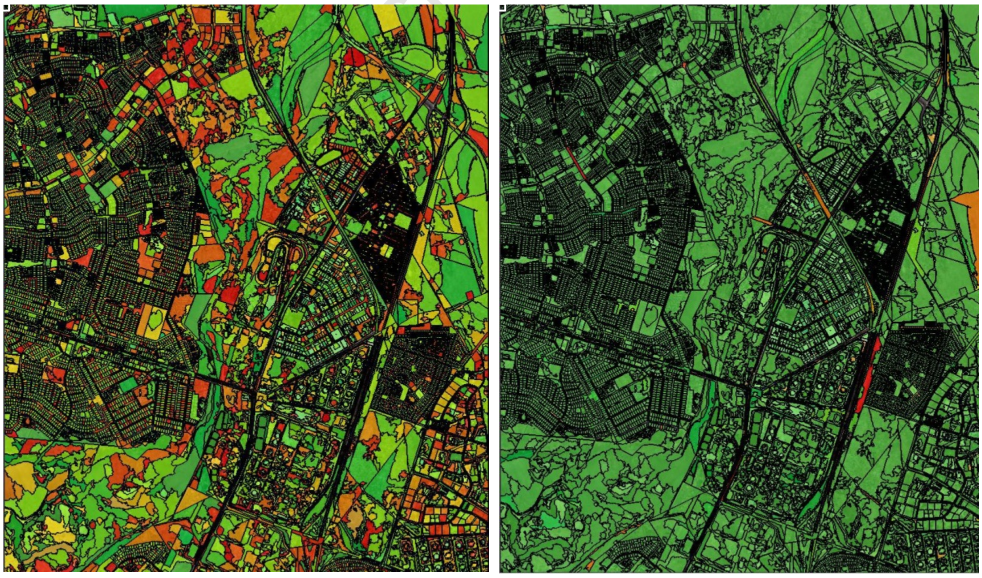

Figure A-4 Classification stability (left) and best classification result (right) for 5.4 (test area 1)

Table A-6 Statistics of classification stability and best classification results for 5.4 (test area 2)

Test area 2		**Classification stability**		**Best classification result**	
Class	**Objects**	**Mean**	**StdDev**	**Mean**	**StdDev**
Built-up	43756	0.170	0.094	0.866	0.208
Bare ground or sand	2497	0.145	0.127	0.553	0.231
Road	214	0.233	0.222	0.570	0.257
Vegetation	9149	0.123	0.092	0.608	0.263
Water	8	0.261	0.326	0.861	0.149

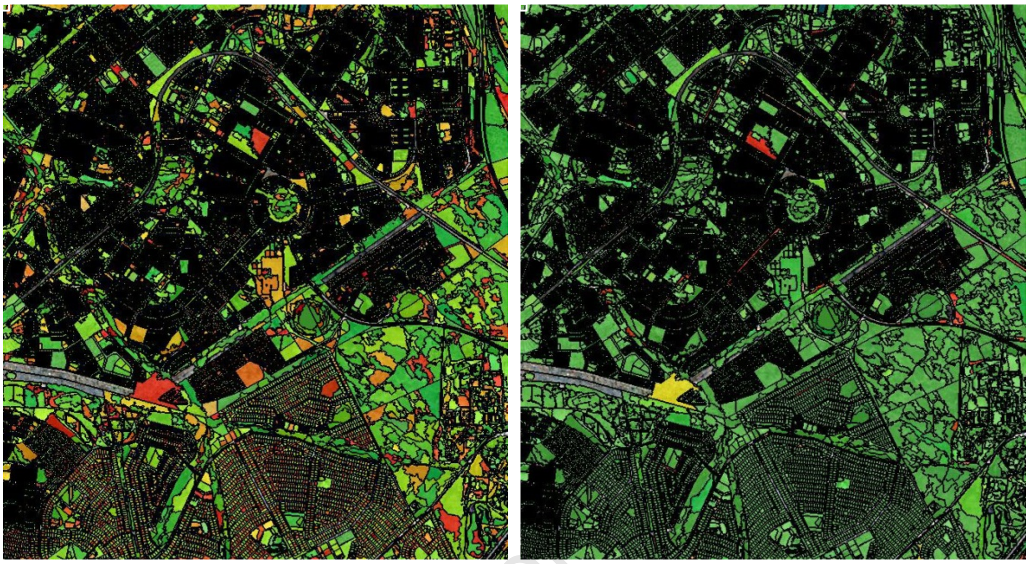

Figure A-5 Classification stability (left) and best classification result (right) for 5.4 (test area 2)

The difference in degree of membership between the best and second best class assignment of each object resulted in a large mean value for each class, indicating that the classification is stable and reliable, and that objects mostly have the highest degree of membership to the correct class.