Fuzzy Land Cover Change Detection and Validation: A Comparison of Fuzzy and Boolean analyses in Tripoli City, Libya

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Abstract

This research extends fuzzy methods to consider the fuzzy validation of fuzzy land cover data at the sub-pixel level. The study analyses the relationships between fuzzy memberships generated by field survey and those generated from the classification of remotely sensed data. In so doing it examines the variations in the relationship between observed and predicted fuzzy land cover classes. This research applies three land cover classification techniques: Fuzzy sets, Fuzzy c-means and Boolean classification, and develops three models to determine fuzzy land cover change. The first model is dependent on fuzzy object change. The second model depends on the sub-pixel change through a fuzzy change matrix, for both fuzzy sets and fuzzy c-means, to compute the fuzzy change, fuzzy loss and fuzzy gain. The third model is a Boolean change model which evaluates change on a pixel-by-pixel basis.

The results show that using a fuzzy change analysis presents a subtle way of mapping a heterogeneous area with common mixed pixels. Furthermore, the results show that the fuzzy change matrix gives more detail and information about land cover change and is more appropriate than fuzzy object change because it deals with sub-pixel change. Finally the research has found that a fuzzy error matrix is more suitable than an error matrix for soft classification validation because it can compare the membership from the field with the classified image.

From this research there arise some important points:

- Fuzzy methodologies have the ability to define the uncertainties associated with describing the phenomenon itself and the ability to take into consideration the effect of mixed pixels.
- This research compared fuzzy sets and fuzzy c-means, and found the fuzzy set is more suitable than fuzzy c-means, because the latter suffers from some disadvantages, chiefly that the sum of membership values of a data point in all the clusters must be one, so the algorithm has difficulty in handling outlying points.
- This research validates fuzzy classifications by determining the fuzzy memberships in the field and comparing them with the memberships derived from the classified image.

Keywords: Fuzzy set, Fuzzy c-means, Fuzzy change and Fuzzy validation.

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List of Abbreviations

ATM: Airborne Thematic Mapper

BD: Bounded Difference

CI: Confusion Index

CROSSTAB: Cross Tabulation

EM: Error Matrix

ETM: Enhanced Thematic Mapper

FCM: Fuzzy c-means

FEM: Fuzzy Error Matrix

GIS: Geographic Information System

GPS: Global Positioning System

LARC: Libyan Agricultural Research Center

LRSC: Libyan Remote Sensing Center

LSD: Libyan Survey Department

LULC: land use and land cover

MC: Magnitude of Change

MFs: Membership Functions

MLC: Maximum Likelihood Classification

MSS: Multi - Spectral Scanner

RS: Remote Sensing

SPOT: Système Pour l'Observation de la Terre

TM: Thematic Mapper

List of Publications

Conference Proceedings

Khmag, A., Fisher, P. and Comber A., (2009). Fuzzy change detection in Tripoli city, Libya. In Tansey (ed) Proceedings of Remote Sensing and Photogrammetry Society Annual Conference 2009, New Dimensions in Earth Observation, 8th -11th September 2009 Leicester.

Khmag, A., Comber A. and Fisher P., (2010). Accuracy Assessment for Boolean and Fuzzy Classification in Tripoli, Libya.Pp401-404 in N Tate and P Fisher (eds.), Proceeding of the 9th International Symposium on Spatial Accuracy Assessment in Natural Resources and Environmental Sciences, 20th - 23rd July 2010, University of Leicester, Leicester.

Khmag, A., Comber A. and Fisher P., (2011). Accuracy Assessment for Fuzzy Classification in Tripoli, Libya. In Proceedings of the 11th International Conference on Geo-Computation, eds. Tao Cheng Paul Longley Claire Ellul Andy Chow), University College London, 20th – 22nd July 2011.

Chapter1: Introduction

1.1 Overview

Land cover is the physical material at the surface of the earth; it includes trees, grass, woodland, water, and bare areas. Land cover classes are usually defined by their biophysical properties, such as bio-geographic location and landscape context (Comber et al., 2005). Land resources are gradually becoming scarce as the increase in population places pressure on these natural resources. Changes in land use and land cover have been recognized as a consequence of human activity which may lead to global change (Roy and Tomar, 2001) and endanger ecosystem performance and biological diversity (Foley et al., 2005; Sala et al., 2000). Read et al. (2002) stated that in order to understand the relationship between land use and land cover changes and the global earth system, information is required on what changes happen, when and where they happen, the rates of change and the driving forces. Human activities and population growth are the main driving forces for change that have led to a widespread transition from natural to developed land, which today represents about 3 per cent of earth's land area (Imhoff et al., 2004). As human populations continue to grow, urban areas are expected to increase (Alberti et al., 2003; Grimm et al., 2000; Houghton, 1994; Jeffrey et al., 2008 Meyer et al., 1992). Depending on economics, social preference, and land use policy, specific types of land cover and use changes can result in significant losses of agricultural and natural lands that used to maintain social systems and cultural diversity along with natural systems and biodiversity (Alberti, 2008; Foley et al., 2005), although the specific directions of changes will vary from location to location.

The rapid increases in population, urbanization and demand for food are considered to be among the most important factors responsible for land cover and land use change in developing countries, mainly in areas where agricultural production is limited by water scarcity, urbanization and desertification. Changes include clearing woodland expansion of agriculture, building new houses, erecting industrial buildings and encroachment on agricultural areas. Because of these factors, methods of change detection in developing countries are needed to develop a model for predicting land cover and land use changes over time to help in planning. This is because the applications of new spatial techniques in change detection in developing countries are very limited (Nwer, 2005). However, the technique for understanding these changes requires the use of readily available information, such as topographic data, land use data, soil and geological maps and remote sensing data. These can be integrated using novel techniques for more efficient and informative output.

In recent times, GIS and remote sensing have been widely used in detecting land cover and land use change. Remotely sensed data from satellites are used to describe and map environmental situations at one particular time; the accessibility of multi-temporal information allows an understanding of land cover and land use processes (Roy and Tomar, 2001). Change detection analysis by using GIS and remote sensing software is increasingly providing the required information for land cover and land use such as urban expansion, forestry and agriculture (Guild, 2004).

Fuzzy classification has been used on natural phenomena that are distributed regularly and continuously over space without hard boundaries (Roberts et al., 2001), which makes it more suitable for representing reality (Cheng et al., 2001) or uncertainty in the mapped reality. Fuzzy set theory has been applied both for dealing with uncertainty in land cover mapping (Fisher and Pathirana, 1989) and for evaluating the accuracy of classified maps (Gopal and Woodcock, 1994). Many studies have demonstrated that fuzzy classification approaches allow researchers to take into account problems which derive from a Boolean classification, since habitats are expected to vary continuously within a landscape (Fisher, 2000b; Rocchini, 2010). Zhang and Foody (2001) applied fuzzy classification techniques for land cover mapping and found that they were more accurate than Boolean classifications. Okeke and Karnieli (2006) used a fuzzy classification for land cover change and compared the results with a Boolean classification. Their results showed fuzzy classification to be more suitable for land cover change.

Traditional crisp or Boolean classifications have one mainly hindrance, their inability to properly represent continuous phenomena (Foody, 1995; Wang, 1990; Woodcock et al., 2000; Zhang et al., 2001; Zhu et al., 1996). Land cover is usually only poorly represented by discrete classes for two main reasons, (1) pixels are often mixed – representing areas on the ground which have multiple land cover types heterogeneous and (2) land cover classes often intergrade due to the continuous nature of vegetative land cover (Zhang et al., 1997; Zhang et al., 2001). Mixed pixels or 'mixels' occur because the pixel size may not be fine enough to capture detail on the ground necessary for specific applications or where the ground properties, such as vegetation, vary continuously, as almost everywhere.

Comber et al., 2005 argue that analyzing complex ecosystems where land cover types are heterogeneous or are poorly represented by large pixels, fuzzy classification may be more appropriate than another classification.

Change detection techniques have been applied in developed and a few developing countries using remote sensing, GIS and uncertainty methods (Baja et al. 2006). Fuzzy set theory, as a method for including some of the uncertainty associated with land classification, accepts that multiple classes or sets can be present at one place or at one time, and expresses the possibility to which each class or set is present as a membership value (Brown, 1998). Fuzzy classifications that assign multiple class memberships to a pixel may be appropriate for images dominated by mixed pixels; fuzzy sets can define the sub-pixel very well (Groenemans et al., 1997; Van Ranst et al., 1996; Wilma, 2008). The use of fuzzy sets in GIS in land management and land use planning has a number of advantages. Firstly, 1) uncertainty / fuzzy in extent 2) uncertainty / fuzzy in definition 3) uncertain / fuzzy representations 4) uncertain / fuzzy change (Zoran et al., 2004). Fisher et al. (2006) presented the logic of fuzzy change detection techniques in land cover and land use changes and landscape mapping. (Zhang and Foody, 1998) and Foody (1999) used fuzzy classification techniques to classify sub-urban land cover categories by using GIS and remote sensing data. Secondly, the use of fuzzy set theory is able to identify a vague environment. Finally, Fuzzy sets are able to describe the integrated between ecological land cover phenomena.

Against this background, this project compares different fuzzy approaches for classify land cover form remotely sensed data and compares them to standard Boolean (maximum likelihood) approaches for detecting land cover and land use change in Tripoli and surrounding regions of Libya, covering a period of about thirty years (1976-2009). In the typical nature of a growing city, the area is characterized by rapid changes in land cover and land use due to the increase in population. These changes increase the complexity of the land cover in the area as a result of spatial intermixing; creating a need for change analysis that would provide information for the planners to avoid exacerbating the problem.

1.2 Research aim and objectives

The aim of this study is to detect fuzzy changes and to undertake fuzzy validation in the built-up areas, woodland and vegetation land. The change detection analysis used remote sensing data from 1976 to 2009 to analyse land cover changes in Tripoli, Libya. This study will:

1. Detect spatial changes over time in land use and land cover in the study area;
2. Use fuzzy classification (fuzzy sets and fuzzy c-means) and Boolean classification (maximum likelihood) to establish the proportion of land use and land cover change;
3. Develop a prototype framework for change detection in Tripoli;
4. Assess the accuracy and suitability of fuzzy and Boolean classification in the study area.

1.3 Research questions

In order to address the research aim and to analyse the changes that have occurred over time in land cover and use in Tripoli, the following research questions have been developed:

1. What are the magnitude, rate and limits of fuzzy land cover changes that have taken place in the growing city of Tripoli from 1976 to 2009?
2. To understand this magnitude of change, which change model is most suitable in detecting these changes and accommodating the uncertainty, considering the developing nature of the city?

3. What are the advantages and differences of a fuzzy supervised classification in change detection, compared to Boolean classification, in the context of a developing country like Libya?
4. What is the most suitable model for mapping the extent of fuzzy land cover at different times (1976, 1989, 2005 and 2009)?

1.4 Thesis structure

The thesis is divided into ten chapters, from an introduction to the conceptual background, followed by methodological issues, then results, through to the conclusion on the appropriateness of the methodologies in detecting change in Tripoli. The research aims to compare fuzzy methods for describing land use and land cover and for detecting change. Chapter 1 serves as the introduction to the thesis and provides a brief summary of background to the study from which the research aims and objectives are drawn. The chapter also encompasses the research questions, and thesis structure.

Chapter 2 presents a review of fuzzy set theory and its application in image processing in remote sensing. Fuzzy sets, membership functions, its application to remote sensing classifications and to handling uncertainty in the process of classification are explained. The chapter goes on to demonstrate the use of fuzzy sets in GIS land management and land use planning. The chapter finally describes the use of the fuzzy c-means classifier to establish the methodological stance of the thesis. Chapter 3 provides a detailed justification for the methods used by the researcher in this study, such as mosaicing, image enhancement and geometric correction, fuzzy sets and fuzzy c-means, and maximum likelihood classification. Also contained in this chapter is a description of the six-stage approach adopted in collecting data and analysing land use change and land cover transformation in the study area. Chapter 4 specifically concentrates on a detailed analysis of the approaches used for Boolean and fuzzy classification. Chapter 5 presents digital detection techniques for Boolean and fuzzy change. The method for calculating the magnitude of change and the principles behind it are also contained in this chapter. Chapter 6 covers data collection and field survey. The aim of this chapter is to collect the information about the research and determine the membership from the field to be used in validation. Chapter 7 evaluates the various methods used in the study for data collection and analysis. The chapter discusses the accuracy of classification of kappa co-efficient and confusion matrix for Boolean classification and fuzzy error matrix, fuzzy kappa and cross tabulation for fuzzy accuracy. Chapters 4, 5, and 7 all include methods, description, results and discussion of the results. Chapter 8 summarises the results arising from the different approaches described in Chapters 4 and 5. The chapter highlights fuzzy classification, fuzzy change and fuzzy validation, compares them, and assesses the best model. Discussion of the results from the previous chapter appears in Chapter 9. The appropriateness and limitations of both Boolean and fuzzy classifications in determining change detection are discussed. The chapter also encompasses the contributions of the research to the study of land use and land cover change in Tripoli, the limitations of the research and area for further work. Chapter 10 links the results of the analysis to the research aim and objectives to present the conclusions of the research. The last sections of the chapter offer some suggestions as to possible areas of consideration for future research, in addition to recommendations.

Chapter 2: Background Literature Review

2.1 Introduction

Rapid changes in population, urbanization, and demands for food place a demand for planners and policy makers to quantify infrastructures and resources and how they change over time. Among the various methods, remote sensing techniques provide an efficient means for quantifying land cover and land use changes. However, traditional Boolean approaches to land mapping from remote sensing data, where each location is allocated to one and only one class, may miss many of the subtle landscape patterns, do not describe any of the uncertainties associated with the classification. Unlike the Boolean approach, fuzzy sets do not impose sharp boundaries on the landscape, can accommodate gradients between different land cover classes and use changes and explicitly accommodate some the uncertainty associated with classifying land. This provides flexibility in how pixels are represented by showing that they may belong to more than one class and thus fuzzy classifications are able to handle uncertainties in land classification and classifications of change. This chapter reviews literature pertinent to change detection for urban areas, vegetation and woodland. A discussion of selected change detection techniques and their application is presented first, followed by a summary of each technique, with its key characteristics, advantages, disadvantages and application areas. A discussion on satellite imagery that can be used in change detection and the classification and validation of fuzzy change is then presented.

2.2 Classification

Image classification is defined as the process of automatically categorizing all pixels according to their spectral properties into land cover classes (Navalgund et al., 2007). Similarly, Dutta et al. (2010) describe image classification as the process of creating thematic maps from satellite imagery. The two primary methods of image classification are supervised and unsupervised. Jensen (1996) highlighted that supervised classification is dependent on the input from the user and on informational classes or types known a priori. Yikalo et al. (2010) also argue that training data from the field and maps form the basis of the supervised classification approach. Supervised classifications identify homogeneous areas or samples of known land cover and land use types. This means the pixels are assigned to known information classes (Jensen et al., 1999). These areas, which are known as samples or training sites, contain numerical properties that are used to train the classification algorithm by providing statistical descriptions of each class's properties in image feature space. Training is the procedure of defining the criteria by which these patterns are recognized. The outcome of training is a set of signatures, which form the criteria for a set of proposed classes (Lizarazo and Elsner, 2009a). With the supervised approach, calibration pixels are chosen and statistics are produced for the classes of interest. The result of such a classification is a thematic map with a label for each pixel of the class for which it has the highest strength of membership.

Such crisp classifications are based on Boolean set theory. A Boolean classification of remotely sensed imagery models the study area as a number of unique, internally homogeneous classes that are mutually exclusive. However, these assumptions are often invalid, especially in areas where transition zones and mixed pixels occur (Small, 2004). Land cover types are rarely internally homogeneous and mutually exclusive and as a result, classes can rarely be separated by sharp or Boolean boundaries, in feature space as well as geographic space. In addition, complex relationships exist among spectral responses recorded on the ground and by the sensor, where similar categories, pixels or objects show diverse spectral responses, and similar spectral responses may relate to different classes, pixels or objects (Bateson and Curtiss, 1996). Furthermore, remotely sensed images contain many pixels where boundaries or sub-pixel objects cause pixel mixing, with several land cover classes occurring within a single pixel. Lastly, classes are often hard to define, resulting in vagueness and ambiguity in a classification scheme (Foody, 1996).

2.3 Fuzzy sets

Fuzzy classification is based on the concept of fuzzy sets (Zadeh, 1965). Most geographical phenomena are poorly defined to some extent, and, therefore, fuzzy set theory as an expression of concepts of vagueness is an appropriate model for working with remotely sensed imagery (Fisher et al., 2004; Zhang and Foody, 2001). To accommodate to the uncertain characteristics of many natural phenomena, especially land cover, fuzzy classification approaches have been proposed (Foody, 1996; Wang, 1990; Zhang and Foody, 2001). In the fuzzy set model, the category assignment function attributes to every element a grade of membership in the real interval [0, 1] for each defined set. This grade of membership corresponds to the degree to which the element is similar to the idea or prototype represented by that set. Accordingly, fuzzy sets allow the representation of imprecisely defined categories such as land cover classes. There are a number of ways of deriving the fuzzy membership values (FMVs), depending on the specific classification techniques used for computerised classification of digital images such as remotely sensed imagery (Zhang and Foody, 2001). For example, FMVs may be calculated from probability density functions used in the maximum likelihood classification, as discussed in Fisher and Pathirana (1989). Zhang and Foody (1998) developed a technique for the fuzzy classification of multispectral satellite image data. By adopting a fuzzy c-means clustering technique similar to that used by

Bezdek et al. (1984) and applying it to training sets of pixels that were of a certain class, they derived FMVs to describe the degree of membership of every pixel to each class. The technique was used to derive a fuzzy measure of classification accuracy, with improved kappa statistics produced by allowing fuzzy matching between ground and image classes. Zhang and Kirby (1997) proposed the use of indicator kriging as a theoretically sound means of deriving a fuzzy classification of land cover that allows FMVs to be assigned according to the certainty of the expert's manual interpretation.

In recent years, many advanced classification approaches, for instance fuzzy c-means, fuzzy sets, and expert systems, have been extensively applied for image classification. Fuzzy sets have been widely suggested as a basis for the representation of vague phenomena (Kolehmainen, 2008; Mendel, 2001; Ross, 2004). The representation of environmental phenomena as fuzzy sets (Fisher, 2000a, b; Jara, 2009; Robinson, 2003) has included vegetation (Moraczewski, 1993a, b), land cover classification from remotely sensed images (Foody, 1992, 1996), and landform classes (Cheng and Molenaar, 1999; Mucher et al., 2000).

Much research has been grounded in a related argument, that many class descriptions for natural resources are inherently vague. Moraczewski (1993a), for instance, identified the linguistic vagueness in textual explanations of vegetation classes. Fisher et al. (2004) argued that the vagueness of a class depends on many factors, including the spatial resolution of the data: for example, the degree of vagueness in Landsat ETM data; is not the same as that of Landsat MSS data due to differencing resolutions.

The existence of mixed pixels has been documented as a major problem, affecting the effective use of remotely sensed data in per-pixel classifications (Cracknell, 1998, Fisher, 1997). Fuzzy-set classification and spectral mixture modelling are the approaches most often used to solve the mixed pixel problem (Foody, 1996, 1998, 2000; Giri et al., 2003; Lizarazo and Elsner, 2009b; Lu et al., 2003; Shalan et al., 2003). In these analyses, sub-pixel classification methods have been developed to present a more appropriate representation and precise area estimation of land cover than per-pixel methods, especially when coarse spatial resolution data are used (Foody and Cox 1994; Woodcock and Gopal, 2000).

Fuzzy set theory was designed to overcome the rigid concepts of the terms ‘true’ and ‘false’ in Boolean theory (Fritz et al., 1999; Jara, 2009). Fuzzy classification has been tested in remote sensing for natural phenomena that are scattered increasingly and continuously over space. Fuzzy logic and fuzzy set theory have also been applied to a variety of ecological mapping and land cover features.

Fisher et al. (2006) have supported the use of fuzzy models for environmental data, land cover mapping and landscape ecology because in such cases there are no hard rules dividing geographic objects. As highlighted earlier, fuzzy logic is a suitable technique where there are heterogeneous pixels which have not been completely occupied by a single phenomenon: i.e. there is no pure pixel of a homogenous class. Fuzzy sets have been helpful in describing classification schemas for understanding environmental phenomena (Fisher and Arnot, 2007). Many studies have used different fuzzy models, as shown in Table 2.1.

Table 2.1 Studies which have used different fuzzy models for change detection

Author and date	Country	Method
Ahlqvist (2007)	USA	Fuzzy and Boolean
Al-Ahmadi (2009)	Saudi Arabia	Fuzzy set
Dutta et al. (2009)	India	Fuzzy c-means
Fisher et al. (2006)	Bolivia	Fuzzy change matrix
Foody (1999)	UK	Fuzzy c-mean
Haglund, (2000)	Sweden	Fuzzy set and Fuzzy c-means
Hall and Hay (2003)	Sweden	Object change
Hegde (2003)	India	Fuzzy and Boolean
Jara (2009)	Chile	Fuzzy and Boolean
Lizarazo and Elsner (2009)	USA	Fuzzy object
Lizarazo and Elsner (2009a)	USA	Fuzzy image segmentation
Mather (2006)	USA	Fuzzy and Boolean
Metternicht (1999)	Australia	Fuzzy change
Sowmya and Sheelarani (2011)	India	Fuzzy c-means
Tang et al. (2005)	China	Fuzzy object
Yikalo et al. (2010)	Portugal	Object oriented

2.4 Fuzzy c-means (FCM) algorithms

The fuzzy c-means (FCM) algorithm is an unsupervised or supervised classification or clustering algorithm. This is a method for determining fuzzy set memberships of each class for each pixel. It has been applied successfully to a number of problems involving feature analysis, clustering and classifier design, in applications such as agriculture, remote sensing, geology, image analysis, and shape analysis. The most widespread method for fuzzy classification is the fuzzy c-means algorithm (Dutta, 2010). The fuzzy c-means classifier (FCM) uses an iterative process that establishes an initial random portion of the objects to be classified into clusters. Given the cluster portion, the centre of every cluster is calculated as the average of the attributes of the objects. In the next stage, objects are reallocated between the classes according to the relative similarity among objects and clusters based on a recognized distance measure. Zhang and Foody, 2001 apply a modified version of the fuzzy c-means algorithm in order to develop a fully supervised fuzzy classification technique. In the supervised fuzzy c-means, the category centroids are determined from the training data. This reduces the clustering algorithm to a one-step calculation, resulting in fuzzy membership values for every pixel in each of the defined classes. As in the hard techniques, the fuzzy classification method (also known as fuzzy clustering) does not need an extensive prior knowledge of the area, and unique classes are recognized as distinct units. Foody (2000) explained that supervised FCM may be used to derive precise estimates of sub-pixel land cover composition, particularly when all classes have been defined and integrated and where the presence of mixed pixels will affect accuracy and validation measures (Yang and Lo 2003). Fuzzy c-means it is a clustering algorithm that has commonly been applied for supervised classification of remotely sensed imagery (Deer, 1998; Deer and Eklund, 2003; Foody, 1996). The modification from unsupervised to supervised classification involves the specification of fuzzy c-means and sometimes also fuzzy covariance matrices, and needs only a single pass of the data through the algorithm (Deer, 1998; Foody, 2000; Tang, 2004).

2.5 Boolean model

Boolean classification uses a statistical model that attempts to map every pixel by assigning it exclusively to one particular class. The spectrally similar data will explain thematically similar objects for every pixel (Jensen, 2004; Lillesand et al., 2008). Traditional Boolean classification uses binary logic to establish class membership, in that every observation can belong to one class (Foody, 1999). Because of the heterogeneity of land cover and the limitation in spatial resolution of remote sensing imagery, mixed pixels are present in medium- and spatial resolution data. The presence of mixed pixels has been recognized as a major problem affecting the effective employment of remotely sensed data in pixel-based classification (Fisher, 1997; Hu and Weng, 2010).

Boolean classification can be further divided into two broad categories: supervised and unsupervised. The supervised classification for pixel labelling needs the user to select representative training data for each of a predefined number of categories. Moreover, supervised classification techniques use prior knowledge about the field, which is very useful in getting improved classification (Key et al., 2002; Mather, 2004). Supervised classification is chosen by many researchers because it usually gives more precise class definitions and higher accuracy than the unsupervised method (Jensen, 2000). The most common classifiers in general use are the maximum likelihood algorithm and the minimum distance classifier (Mather and Brandt, 2009). The maximum likelihood process is a supervised statistical method for prototype recognition. The probability of a pixel belonging to each of a pre-defined set of categories is calculated, and the pixel is then assigned to the category for which the probability is the greatest (Mather and Brandt, 2009). The maximum likelihood classifier is the most general supervised classification technique for parametric entry data. The maximum likelihood classifier supposes that a pixel has a certain probability of belonging to a specific class. These probabilities are equivalent for all categories and the input data in every band follow the normal distribution function (Lillesand et al., 2008; Schowengerdt, 2007). It is important to recognize that the maximum likelihood method is based on the assumption that the frequency distribution of the category membership can be estimated by the multivariate normal probability distribution (Lillesand et al., 2008; Mather, 2006).

Unsupervised classification is defined by which pixels in an image are assigned to spectral categories without the user having foreknowledge of the existence assignment of those categories. It is performed most frequently using a clustering approach. These procedures can be used to determine the number and position of the spectral categories to determine the spectral class of every pixel (Richards and Jia, 2006). Many studies have used Boolean classification to determine change detection. Table 2.2 shows some examples of the use of a Boolean model for change detection.

Table 2.2 Studies which have used a Boolean model for change detection

Author and date	Country	Advantage	Disadvantage
Ahmed (2006)	Sweden	Minimizes impacts of atmospheric, sensor and environmental differences between multi-temporal images; Provides a complete matrix of change information.	Requires a great amount of time and expertise to create classification products; The final accuracy depends on the quality of the classified image of each date.
Bentum (2009)	Ghana		
Brian et al. (2011)	South Africa		
Foody (1999)	UK		
Khiry (2007)	Sudan		
Otukei and Blaschke. (2010)	Uganda		
Pillay (2009)	South Africa		
Recanatesi et al. (2011)	Italy		

2.6 Land use and land cover change detection

Land cover change is one of the main variables in most environmental issues of importance to the human–environmental sciences (Turner et al., 2007). According to Lillesand et al. (2004), land use relates to the human activity connected with a particular parcel or area of land. Examples of land use include agriculture, urbanization, grazing and mining. Land cover, on the other hand, relates to the composition and character of land surface elements (Cihlar, 2000). Regions across the world experience rapid changes in land cover due to human activities and natural phenomena, but these changes are mostly determined by human use (Jensen, 1996; Meyer, 1995). Detecting land cover change is important in order to manage and monitor processes such as urbanization and climate change, especially in regions experiencing radical and dramatic changes like those that are commonly found in developing countries (Foody, 2003). These features make it desirable to develop a time series analysis of land use and land cover (LULC) to understand the motivating forces of these changes in addition to projecting the future spatiality of the change (Giri et al., 2003; Recanatesi et al., 2011).

While land use and land cover changes can be monitoring traditional studies, for example using topographic map surveys and recording the land cover and land use by using field surveys, satellite remote sensing gives more information on the geographic distribution of land use and land cover changes, along with the advantages of cost and time efficiencies for larger areas (De Jong and Freek, 2006). Remotely sensed imagery supplies an efficient means of getting the information on temporal trends and spatial distribution of land cover and land use that is required for understanding and projecting land change (Elvidge et al., 2004; Foody, 2002, 2008; Rindfuss et al., 2004; Strahler et al., 2006). The integration of remote sensing and geographic information systems has been broadly applied, and has been documented as a powerful and active tool in monitoring land cover and land use changes throughout the world (Harris and Ventura, 1995; Franklin and Wulder, 2002; Treitz et al., 1992). Alberti et al. (2004) have shown that satellite remote sensing has the potential to give accurate and timely geospatial information describing changes in land cover and land use in urban regions. According to Coppin et al. (2002), visual and digital analyses are the two approaches for detecting changes in land cover and land use. Visual interpretation using aerial photography will give analysis at better resolutions, but different interpreters may present different results. Automated, repeatable, defensible approaches also give different results. To apply digital change detection techniques, three main steps are outlined (Lu et al., 2004):

(1) Image pre-processing, which consists of image registration, image enhancement and geometrical rectification;

(2) Selecting a suitable change detection methodology. Many change detection approaches have been developed since the 1970s, such as image differencing, image rationing, post-classification comparison, vegetation index differencing, background subtraction, image regression, and the use fuzzy set operation;

(3) Accuracy assessment of any error encountered during the classification procedure, mainly due to the interaction between the spatial structure of the landscape, sensor resolutions and classification algorithms.

The reliability of the change detection procedure is strongly affected by different environmental characteristics and atmospheric effects (Lillesand et al., 2004). For effective use of remote sensing for change detection, data applied for monitoring should be taken by the same sensor using the same spatial resolution, spectral band, and viewing geometry, at the same time of day (Cakir et al., 2006). In order to detect change, many methods have been developed to define change features using remotely sensed data (Mundia and Aniya, 2005).

The post-classification approach is one of the most commonly used techniques (Brian et al., 2011; Foody and Boyd, 1999; Lu et al., 2004). Given that it is possible to overcome issues of required expert knowledge to produce reliable land cover classifications, the major advantages of this method is the amount of information that can be obtained from the produced change matrix and the limited impact of image calibration and environmental differences (Lu et al., 2004). Another advantage of the post-classification approach is its intuitive interpretation as opposed to numerically based image analysis methods that need careful interpretation to evaluate what the identified changes mean. This advantage is mainly due to the rich semantics of land cover class labels. However the semantics are also noted by many authors as problematic because of the generally limited descriptions of the precise meanings of land cover labels (Comber et al., 2004b). Moreover, some studies have found that data on land cover and land use from different times are classified using different classification methods (Comber et al., 2004a). In these situations a normal post-classification change assessment can be very complicated (Otukei and Blaschke, 2010). As an alternative, the fuzzy sets theory (Zadeh, 1965) has been implemented as a way to handle vagueness in concepts or in allocation (Fisher and Pathirana, 1990). Every object or pixel is allowed to have a degree of membership in each category so that one place can be assigned to many categories with partial membership.

However, another understanding of pixels, which potentially could also include probabilistic or fuzzy reasoning, is that of mixed pixels or sub-pixels (Foody and Cox, 1994). Because they need to find potential sub-pixel classification algorithms and models to give a more appropriate illustration of remote sensing imagery, researchers have been developing algorithms that could be capable of managing mixed pixels in a scene, mainly when images from satellite multi-spectral sensors are used. Types of classification algorithms which deal with the mixed pixel problem are fuzzy classification algorithms (Lu and Weng, 2007; Sowmya and Sheelarani, 2011). Soft classification allows the assignment of one pixel to multiple classes, or a partial membership of that pixel to a specific class, applying membership functions to generate a degree of membership in a range from 0 to 1. The membership functions of the soft input variables could be obtained from statistical values of band training samples to separate certain features. Soft classifiers estimate the involvement of each class in the pixel. The pixel has no requirement to have a contribution from all classes (Foody, 2001).

2.7 Fuzzy land cover and land use change detection

The study of land cover change and land use has played a key role in recent landscape research and landscape ecology (Coppin et al., 2004; See and Fritz, 2006). Fuzzy analysis and mapping of a geographical area has been used to replace the traditional Boolean area-class map (Metternicht, 1999), which determines each pixel (or area) as belonging to only one class with a set of maps, describing the membership to each class. In each of the maps, for each pixel, the membership value is recorded as a real number in the interval [0, 1], where 1 represents a complete match between the characteristics of the position and those of the class, and 0 shows an absolute mismatch. Values between 0 and 1 show the amount of matching (Fisher, 2000a). In this form of analysis is the spatial extent of the membership can be intergraded among classes (Fortin et al., 2000), and Arnot et al. (2004) have explained the problems of using any of the metrics recommended in landscape ecology when explicit models of spatial uncertainty are used. The amount of work on fuzzy change detection is large, and has been explained in a number of research projects (Bouziani et al., 2010; Coppin et al., 2004; Lu et al., 2004; Lunetta and Elvidge, 1999). A number of approaches to change detection have been suggested, but post-classification comparison of information from more than one date is one of the most widely applied and most intuitive (Coppin et al., 2004; Jensen et al., 1999). Some studies have applied fuzzy spatial objects which have attracted considerable attention and have been implemented for spatial data handling (Tang and Kainz, 2002). Research results include explanations of fuzzy spatial objects change and the fuzzy semantic import model (Cheng et al., 2001; Tang et al., 2005; Tang et al., 2003). Fisher et al. (2006) tested the change detection matrix and discussed the implementation of the fuzzy change matrix, using fuzzy logic statements and determining the intersection between the categories.

In this research three approaches were used to determine the amount of change that happened in the study area. This study used the fuzzy change matrix suggested by Fisher et al. (2006). It accommodates descriptions and measures of sub-pixel change, and is more informative than Boolean change, which depends on pixel-by-pixel comparison and accepts only binary change. It also used fuzzy change object as (Tang et al., 2005), which is dependent on converting the membership to polygon, and the last model is Boolean change; after that we will compare the three approaches.

2.8 Classification accuracy assessment and evaluation of fuzzy change

Generally, accuracy assessment is based on the accuracy or error matrix, which compares ground truth data with the equivalent classification for a given set of validation samples (Congalton and Green, 1999; Foody, 2002). Accuracy assessment usually includes three essential mechanisms: sampling design, response design, and estimation and analysis procedures (Stehman and Czaplewski, 1998). Selection of a suitable sampling strategy is a critical step (Congalton, 1991). The main components of a sampling plan include sampling unit (pixels or polygons), sampling design, and sample size (Muller et al., 1998). Possible sampling designs include random, stratified random, systematic, double, and cluster sampling. Green and Congalton, (2004) have shown that classification accuracy significantly decreases with an increasing heterogeneity of the landscape, and in contrast the accuracy improves with increasing area size. Classification methods can be assessed in terms of reproducibility, strength to noise, dependency on the training pattern, or computational advantages (Fei et al., 2005). A detailed overview is given by Congalton and Green (1999) and Foody (2002).

Recently, there has been an increasing requirement for sub-pixel evaluation of classification products, made evident by the latest remote sensing research (Latifovic and Olthof, 2004; Okeke and Karnieli, 2006; Ozdogan and Woodcock, 2006; Shabanov et al., 2005). The assessment of the conventional allocation of image pixels to separate classes has been standardized through the confusion matrix and some consequent measures (Congalton, 1991; Congalton and Green, 1999). However, this method is appropriate only for hard classifications, where it is assumed that each pixel is related to only one class in both the reference and assessed datasets. For the assessment of soft classifications in general, different suggestions have been made, such as a fuzzy error matrix and cross tabulation (Binaghi et al., 1999; Foody, 1995; Green et al., 2004; Lewis and Brown, 2001; Pontius and Cheuk, 2006; Townsend, 2000; Woodcock and Gopal, 2000). The fuzzy error matrix (Binaghi et al., 1999) is one of the most important approaches, as it represents a generalization of the ground on the fuzzy set method of the conventional confusion matrix. Mainly, for a cross-comparison to be consistent with the traditional confusion matrix, it is usual for the cross-comparison to result in a diagonal matrix when a map is compared to itself, and for its marginal totals to be equivalent to the sum of membership grades. Furthermore, a cross-comparison should convey readily interpretable information on the confusion between the classes. To date, the capability of the fuzzy error matrix has been mostly concentrated on applying accuracy indices: for example, the overall accuracy, the user and producer accuracy, the kappa and the conditional kappa coefficients (Binaghi et al., 1999; Okeke and Karnieli, 2006; Shabanov et al., 2005). Recently, a composite operator was proposed for computing a cross-comparison matrix that exhibits some of the abovementioned attractive characteristics (Pontius and Connors, 2006). Pontius and Connors, 2006 showed how the composite operator can be used for a multi-resolution assessment of raster maps, and compared it with other alternatives, including the Boolean hardening of pixels, the minimum operator (Binaghi et al., 1999), and the product operator (Lewis and Brown, 2001). This composite operator was also recommended as a viable tool for the sub-pixel comparison of maps (Pontius and Connors, 2006).

In a typical accuracy assessment analysis, the derivation of accuracy measures such as the kappa coefficient of agreement and the overall classification accuracy (Janssen and Molenaar, 1995) is related to only one class in the classification and its matching class in the ground or reference data. These accuracy measures are only suitable for Boolean classification (e.g. where a pixel is classified as only one class). For soft, fuzzy classifications, accuracy assessments are slightly different. The pure pixels of the classified data can be compared with the ground data, and, therefore, accuracy measures can be determined (Foody and Arora, 1996; Zhang and Foody, 1998). While this provides a basis for evaluating the accuracy measures of soft classification, the accuracy may remain uncertain because of the difficulty in relating mixed, fuzzy pixels to the ground truth reference data set (Lunetta et al., 2001). This may lead to serious confusion in the resulting map (Joria and Jorgenson, 1996). It can be noted that, in an accuracy assessment, a pixel is used as a spatial unit, and it is necessary to bring the ground data to the same spatial unit as the remotely sensed data for a meaningful comparison (Fisher, 1997). As a result, information about fuzzy ground data is needed for accuracy assessment in a fuzzy classification.

Zhang and Foody, (1998) applied the maximisation process in determining the accuracy measures using soft classification and fuzzy ground data. This enabled them to label a pixel of fuzzy classification and fuzzy ground data as belonging to the individual class having the maximum fuzzy membership value, with the result that Boolean classification accuracy measures could be employed. The value of maximum fuzzy membership with reference to a pre-determined threshold can also be used to harden the output of a soft classification and fuzzy ground data in order to enable the use of conventional accuracy measures, as done by Grenier et al. (2008). Others utilized the correlation among the proportions of corresponding memberships of reference and classified data by means of the coefficient of determination in assessing the accuracy measures of the soft classified data (Foody and Arora, 1996).

The above argument suggests that the accuracy assessment of a soft classification requires fuzzy ground data. The idea of using hardened fuzzily classified data and fuzzy ground data in a traditional error matrix suffers a loss of information; the derived accuracy measures do not essentially reflect how well the class membership of the fuzzy classification equates to the fuzzy ground data. In the same way, the measure of closeness and fuzzy similarity between the fuzzy membership of classified and reference data suffers from the difficulty in implementing an appropriate sampling design: it is sometimes problematic to determine the precise sub-pixel reference data locations on which fuzzy validation depends.

Another important point is that these measures go beyond the traditional error matrix and do not give site-specific accuracy (Congalton, 1991). In an accuracy assessment which is not site-specific, location accuracy is completely ignored. A fuzzy error matrix, which is a generalization of the conventional error matrix, designed to accommodate the fuzzy memberships of the classified and reference data together with a fuzzy confusion index, can be implemented to assess site-specific accuracy of fuzzy classification (Binaghi et al., 1999).

To overcome the problem of ground data, this study determined the referenced membership from the field to compare against the classified membership. To assess and evaluate the accuracy of the classification, this study used a kappa co-efficient and a confusion matrix for Boolean classification. The kappa coefficient is a measure of overall statistical agreement of an error matrix, which takes non-diagonal basics into account. Kappa analysis used in this project is recognized as a powerful method for analysing a single error matrix and for comparing the differences in various error matrices (Congalton, 1991; Foody and Doan, 2007; Kumar et al., 2010). A fuzzy error matrix and cross-tabulation were used for fuzzy classification. Table 2.3 shows examples of some studies which used different fuzzy validation models for fuzzy change accuracy.

Table 2.3 Studies which have used fuzzy validation models for fuzzy change

Author and date	Country	Method
Atkinson (1999)	UK	RMS error and correlation coefficient
Foody (2010)	UK	Ground reference
Grenier et al. (2008)	Canada	Fuzzy error matrix
Gómez and Montero (2011)	France	Fuzzy error matrix
Kumar et al. (2006)	India	Sub-pixel
Kumar et al. (2010)	India	Fuzzy accuracy
Lowry et al. (2007)	USA	Fuzzy error matrix
Mukherjee et al. (2005)	India	Fuzzy accuracy
Okeke and Karnieli (2006)	Israel	Fuzzy error matrix
Shalan et al. (2004)	UK	Fuzzy error matrix and Euclidean
Silván et al. (2007)	USA	Sub-pixel confusion– uncertainty matrix
Stephen (2009)	USA	Error matrix
Woodcock and Gopal, (2000)	USA	Fuzzy accuracy

2.9 Summary of literature review

From the literature review it is clear that many studies have considered change detection because it is a global phenomenon and has major consequences for the environment. Additionally, many of these have used Boolean classification methods such as maximum likelihood to detect change, and algebraic methods to calculate the degree of change. Other studies have used fuzzy classification methods and have shown that they are suitable for the extraction of mixed pixel information (the same problem that exists in the study area). Furthermore, the literature survey has shown that remote sensing is a useful tool in detecting land change, and the fuzzy set models for change detection may give better results than traditional Boolean approaches. Boolean techniques such as maximum likelihood classification (MLC) have been used for land use data categorization because of their wider application in remote sensing. However, some researchers have shown that fuzzy sets have the ability to handle uncertainty in land cover and in land cover change. Therefore, fuzzy sets, fuzzy c-means models and maximum likelihood have been selected as an existing method to detect change in land cover and land use in the study area. The fuzzy set approach has not yet been used in land use and land cover change detection in either urban or semi-arid areas. The literature review also covered accuracy assessment, showing their importance. Whilst many studies have applied fuzzy classifications, but very few have carried out a validation of fuzzy classification and none of them has determined fuzzy membership from the field. In this study, a kappa co-efficient and a confusion matrix were applied to the Boolean classification and a fuzzy error matrix with cross-tabulation was used for the fuzzy classification.

Chapter 3: Methodology

3.1 Introduction

This chapter describes the research methodology used to compare different methods for determining fuzzy validation and fuzzy land cover change. It describes the development and application of a method for evaluating the results of fuzzy classification and fuzzy change detection.

3.2. The study area

The study area is located in the north-western part of Libya (the north part of the Jifara plain), as shown in Figure 3.1. This region is heavily populated, mostly along the Mediterranean coast; it comprises the city of Tripoli, the capital of Libya, and major towns such as Janzour, Tajura, soq-Aljoma, Al-Suany, Azhra, Al-Qarabulli, and Bin-Ghashir. These settlements are experiencing growth and expansion due to population increase and migration; the built-up area of Tripoli city increased from 8,011.4 ha in 1966 to 19,236 ha in 2000 (El-Zannan, 2000). The increase in people, settlements and infrastructure consequently decreases the areas of agricultural land and woodland around the cities, and increases pressure on other natural resources, particularly water. Uncontrolled settlement growth may also lead to increasing amounts of waste generation, and improper dumping of waste causes land and water pollution. In Libya, the demands of a rapidly increasing population have been the main driving force of land cover and land use change in the study area. The total population of Libya has increased over recent decades. In 1970 it was 1.986 million, whereas in 2003 it had risen to 5.551 million. Compared with the Figure for 1970, the total population had doubled by 1980 and trebled by 2003 (FAOSTAT, 2004). And in 2008, the total population was 6,173,579, with annual growth at 2.216 per cent (National Information Authority of Libya, 2008). According to the General Authority for Information elementary census of 2006, the population of Libya will be more than 10 million in 2025. Approximately 90 per cent of the Libyan people will be living in urban areas and only 10 per cent will be residing in rural areas. Increased supplies of food are needed to match this growth. Population growth plus the absence of control and planning policies has resulted in some serious problems in Libya. One of these problems is the increased competition between urban and agricultural lands (*Libyan Statistics Book*, 2007). Increases in population have been a significant and important driver of land cover changes in urban areas and are expected to continue and to place significant demands on the land resources.

Figure (3.1) shows the study area location (http://www.geographicguide.net/africa/libya.htm)

Study area

3.3 Research data availability

A range of different data was available for this research. For change detection, high- to medium-resolution multi-temporal remote sensing data were used, including high-resolution aerial photos taken at different times, medium-resolution satellite imagery, and other auxiliary data, as described in Table 3.1.

Table 3.1 Availability and sources of data for the research

Data	Description	Sources
High-resolution data for accuracy assessment	Aerial photo 1976 for some parts of the study area Aerial photo 1989 for most parts of the study area Aerial photo 2005 for all parts of the study area Quick-bird 2001-2005	Libyan survey department Birune remote sensing center
Medium-resolution data (Multi-spectral band 4, 3, 2)	Landsat MSS acquired in 1976 Landsat 5 TM 1989 b:2,3,4 Landsat 7 ETM 2005 b:2,3,4 Spot 5 2009	Birune remote sensing center
Other auxiliary data	Topographic maps available at a scale of 1:50,000	Birune remote sensing center

3.4 Classification scheme

Before initiating any change detection analysis it is very important to define all those phenomena which are of interest. This study focuses on observed changes in five classes: urban areas, woodland, vegetation, grazing land and bare areas. These classes were used so that the classifier could distinguish between the classes easily and they could be unambiguously defined, and because using a small number of classes allows the transitions or changes between them to be more easily analysed, especially in relation to fuzzy classification and fuzzy change. In this context, an understanding of land cover classification is essential for defining these classes; there is a brief definition for every class FAO (1993) as shown in Table 3.2, and these classes are explained in more detail in Chapter 6.

Table 3.2 Land cover classes used in the study

Land cover classes	Descriptions of land cover classes
Urban	Areas characterized by buildings, asphalt, and concrete, suburban dominated by man-made structures; including cities, towns, villages, strip developments along highways, transportation.
Woodland	Areas dominated by trees; including natural woodland and plantations
Vegetation	All types of vegetation; crops, irrigated and rain-fed
Grazing land	Grazing land generally describes a type of predation in which a herbivore feeds on plants, and any vegetated land that is grazed or that has the potential to be grazed by animals, such as land with small shrubs
Bare areas	The Bare land class is composed of bare rock, sand, silt, gravel or other earthen material, with little or no vegetation; including beaches and sandy areas
Water (sea)	All types of water, such as sea and water bodies

3.5 Outline of stages

This study adopted a six-stage change detection model to detect land use change and land cover transformation in the study area (Figure 3.2).

3.5.1. Stage 1: Image pre-processing

Multi-resolution and multi-temporal time series, including historical satellite imagery, aerial photographs and other data, were used to determine land use and land cover changes over the study period between 1976 and 2009. Mosaic and image enhancement processes using edges, texture and high- and low-frequency components extract important information that could otherwise be missed. Were applied for data preparation and pre-processing for reliability of the images 1976, 1989, 2005 and 2009. Two partially overlapping images covering the study area were merged to the same map projection and datum using the same pixel size. This study was used image-to-image registration for geometric correction; one of the images was selected as the base to which the other was compared. Topographic maps were used as base maps and geometric registration was done on all images, using triangulation registration points.

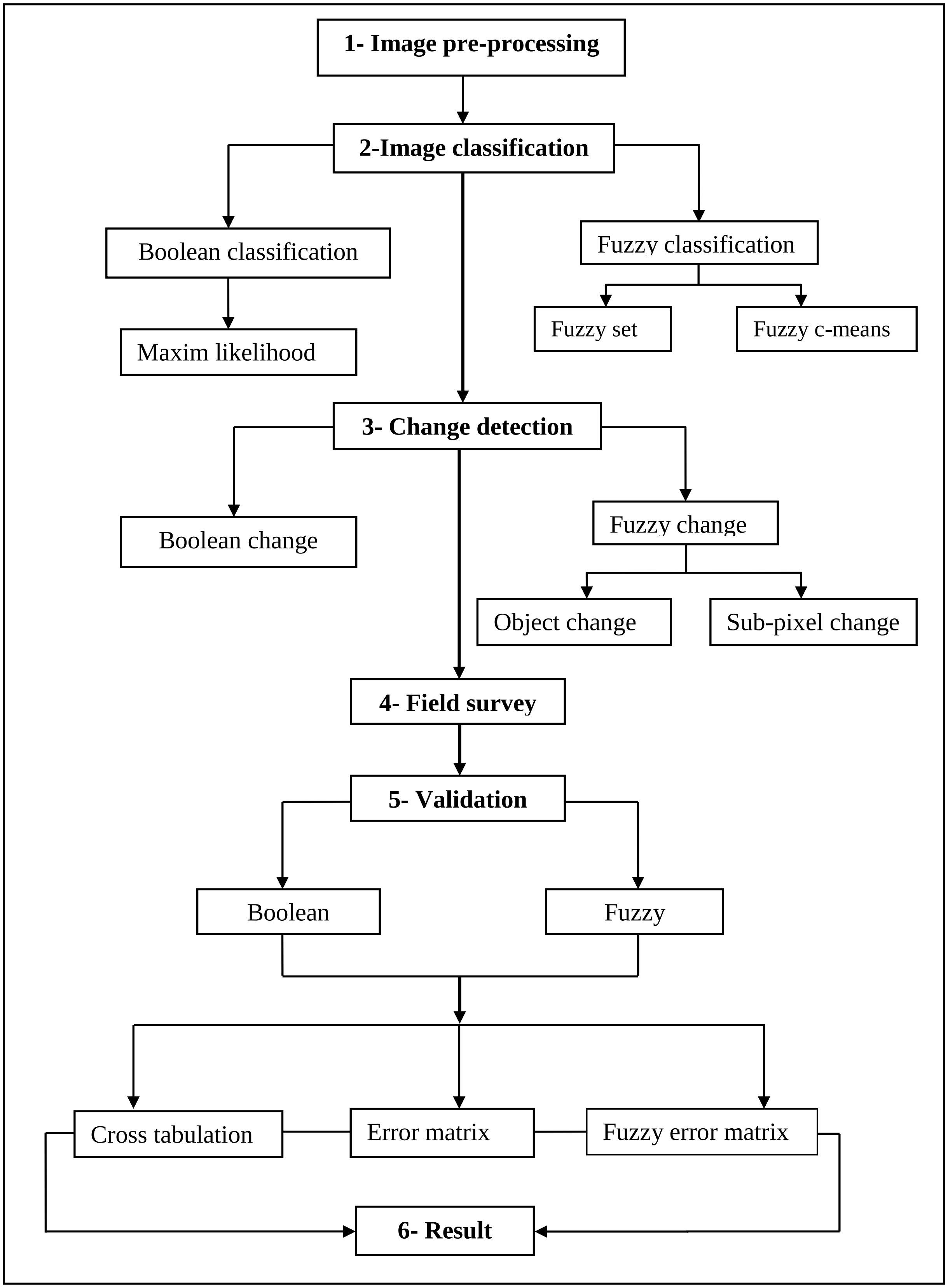


Figure 3.2 illustrates the methods used in this research

3.5.2 Stage 2: Classification

Different fuzzy classification methods were applied to the data: Fuzzy sets, Fuzzy c-means classification, and Boolean maximum likelihood classification. The fuzzy classification was performed using the IDRISI module, and the Landsat MSS 1976 image and Thematic mapper TM 1989, ETM 2005 and SPOT 5 2009 were classified in the following way:

1. Training sites were created for each class by selecting representative pixels for each class. The following classes emerged: urban areas, vegetation, woodland, bare areas, grazing land, and water (sea).
2. Training data were chosen for every class such that their spectral signature was captured before the classification process.
3. The signature file was created containing statistical information about the reflectance values of the pixels within the training sites for each class.
4. The fuzzy classification was run to generate the fuzzy spatial database.

A fuzzy c-means classification was generated, using the same steps, the using Parabat software, available from http://www.lucieer.net/research/thesis.html and described in Lucier (2004), and the same training sites. Three methods of fuzzy classification were applied (fuzzy sets, fuzzy c-means and Boolean classification) for all images from 1976, 1989, 2005 and 2009.

3.5.2.1 Method 1: Fuzzy set

As was explained in chapter 2 the literature survey has shown that using fuzzy set models for change detection gives better results than Boolean techniques, because they are able to overcome the problems that were found in Boolean theory. Fuzzy approaches allow more information on the relative strengths of the class membership at pixel level to be made available to end users. Thus, for instance, both data producers and users can be made aware of the potential areas vulnerable to misclassification. The information on per-pixel class membership may also be used for post-processing of image classifications (e.g. Barnsley and Barr, 1996; Pathirana and Fisher, 1991). The fuzzy set theory is particularly interesting as the analyst controls the degree of fuzziness and intergrade due to the continuous nature of vegetative land cover (Foody, 1996; Zhang and Foody, 1998; Zhang and Foody, 2001).

Other empirical studies have shown that the fuzzy set technique has the ability to handle uncertainty in land cover and land use change. According to Zoran et al., (2004), fuzzy sets have the ability to work with the task of land cover change. Fisher et al. (2006) discussed the use of fuzzy classification techniques in land cover changes. Zhang and Kirby, (1997) used fuzzy classification techniques to categorize sub-urban land cover classes by using remote sensing data. Fuzzy set methodology can solve the problems that were found in the Boolean method; in recent times, fuzzy set methodology has seen increasingly widespread use for land use and land cover studies (Foody and Cox, 1994; Atkinson et al., 1999).Therefore, fuzzy set models have been selected as an existing method to guide land cover classification in the study area. This fuzzy set approach has not previously been carried out in the study area for change detection.

Mathematically, a fuzzy set A in x is described by a membership function as a set of pairs as shown in equation 3.1:

$$A = \{X, \mu a(x)\}\ for\ each\ \ x\ \in \mathrm{x} \qquad (3.1)$$

where μa(x) is the membership grade of x in A and $x \in X$ means that X is found in the universe of discourse x. The membership value μa (x) ranges from one to zero, with a gradual transition from full membership at 1 to no membership at 0.

If X = {x1, x2, x3, xn} the previous equation can be written as follows:

$$A = X1, \mu a(x1) + X2, \mu a(x2) + X3, \mu a(x3) + Xn1, \mu n(xn) \tag{3.2}$$

Fuzzy set classification algorithms produce membership maps (sometimes called fraction images) as output, one for each class, in which the pixel value represents the degree of membership for that class. Figure 3.3 illustrates four pixels comprising three land cover classes, urban, woodland, and grazing land, and shows how soft and hard classification approaches the assigning of each pixel. As can be seen in Figure 3.3, hard classification ignores the mixing between land cover types, and assigns each pixel to one and only one specific class. On the other hand, soft classification produces for each pixel a degree of membership in a range from 0 to 1 associated to the urban, woodland, and grazing land informational classes, as shown in Figure 3.3. For instance, the lower right pixel in Figure 3.3 (mosaic) comprises woodland and grazing land types of land cover. As can be seen in Figure 3.3, soft classification assigned this pixel to woodland and grazing land classes with degrees of membership of 0.7 and 0.3, respectively. The present research focuses on the use of soft classification based on fuzzy sets and fuzzy c-means.

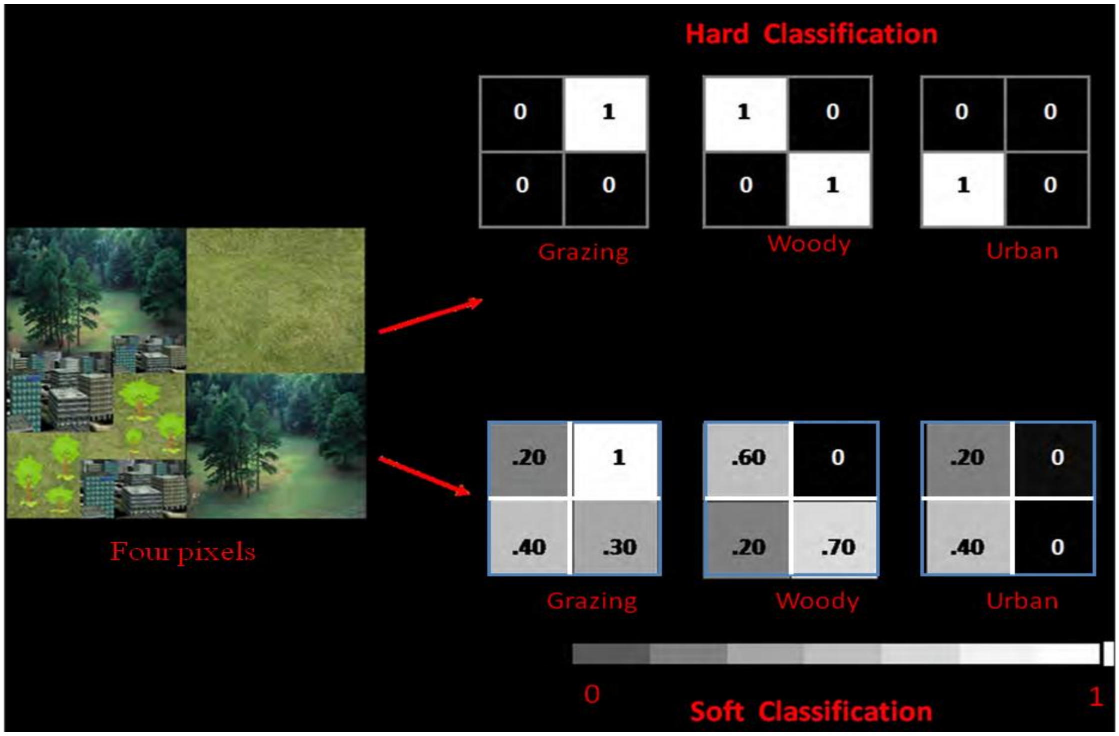


Figure 3.3: Hard and soft classification approaches applied to an example of a four-pixel mosaic (Nydia, 2008)

Figure 3.4 illustrates different ways of generating fuzzy set memberships: Gaussian, trapezoidal, sigmoid and triangular. In this study trapezoidal membership was used. The triangular approach was not used because the triangular function is not suitable for describing the data in the training set; it has only peak value, at which membership equals 1. The bell-shaped Gaussian function gives rise to a similar problem, indicating only one peak value but many values near to the peak. This is therefore not appropriate for supervised classifications because this model cannot represent all the pixels on the image. A trapezoidal function or a function that results in a fuzzy set with a central core region and upper and lower transition zones with different widths can be successfully used for fuzzy supervised classification. The width of transition zones can be statistically calculated by equation 3.3 and 3.4:

$$TW(L) = (mean - SD) - min \qquad (3.3)$$

$$TW(R) = \max - (mean + SD) \qquad (3.4)$$

where *TW(L)* is the Left transition width, *TW(R)* is the Right transition width, *min* is the minimum pixel value of the training set, *max* is the maximum pixel value of the training set and *SD* is the standard deviation.

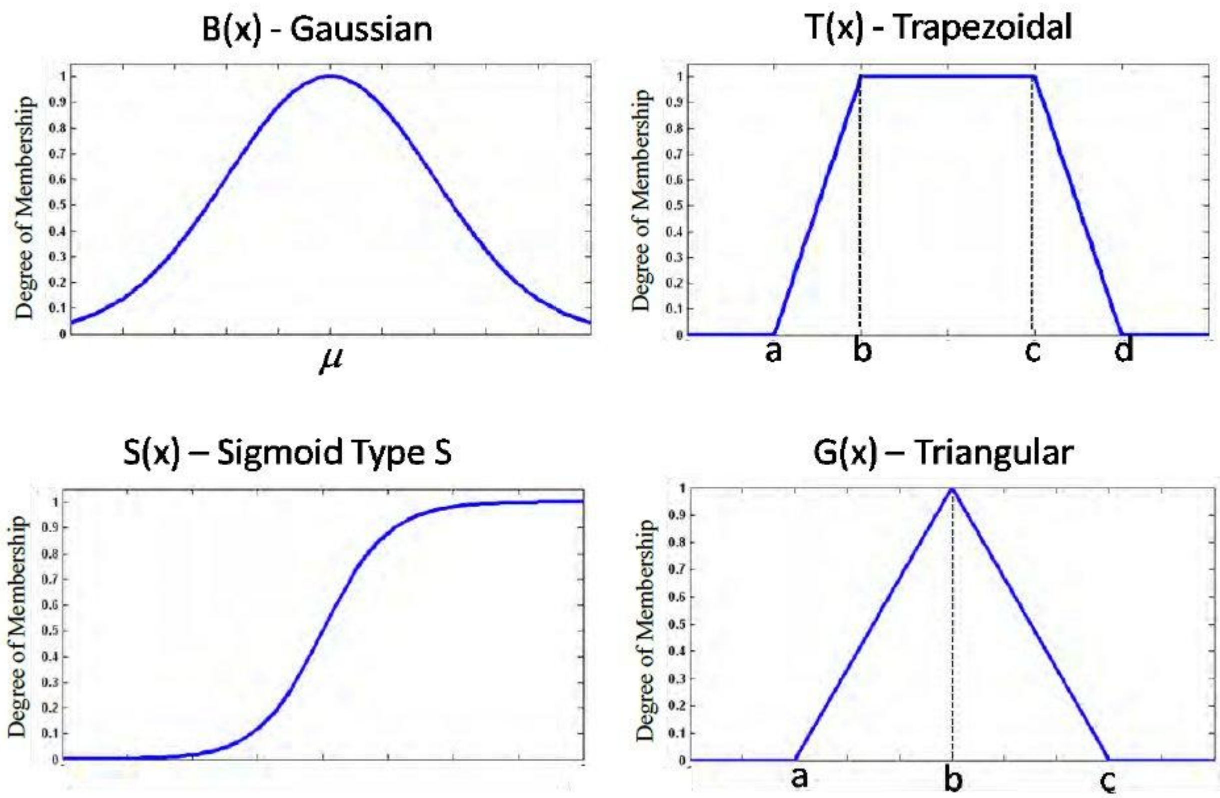


Figure (3.4) Different types of membership functions (from Wilma, N., 2008)

Trapezoidal The trapezoidal membership function T(x) with end points in (a, 0) and (d, 0) and high points in (b, 1) and (c, 1) can be defined by equation 3.5:

$$T(X) = \begin{cases} \left(\frac{X-a}{b-a}\right) \\ 1 \\ \left(\frac{d-x}{d-c}\right) \\ 0 \end{cases} \quad (3.5)$$

If a≤ x ≤ b if b≤ x ≤ c if c≤ x ≤ d 0 otherwise

Triangular: A triangular membership function G (x) with end points in (a, 0) and (c, 0) and high points in (b, 1) is defined by equation (3.6):

$$G(x) = \begin{cases} \left(\frac{x-a}{b-a}\right) \\ \left(\frac{c-x}{c-b}\right) \\ 0 \end{cases} \quad (3.6)$$

If a≤ x ≤ b if b≤ x ≤ c 0 otherwise

Sigmoid –Type S: Sigmoid membership function S(x) is given by the following equation 3.7:

$$S(x) = \frac{1}{1+e^{-x+1}} \quad (3.7)$$

Gaussian: Gaussian is a widely used membership function on image classification. It can be written as equation 3.8:

$$B(x) = \exp\left(-\frac{(x-\mu)^2}{2\sigma^2}\right) \quad (3.8)$$

where μ and σ correspond to mean and standard deviation, respectively.

Typically, these membership functions (for instance *G(x), T(x), S(x), and B(x)*) are combined with mathematical operators such as minimum and maximum.

Figure 3.5 illustrates the membership functions for a Boolean and a fuzzy set using an example with three classes: vegetation, grazing land, and water. The membership value $\mu(x)\epsilon\{0,1\}$ measures the degree of the element x belonging to the class. For a Boolean set function, binary logic is applied to the land cover distribution; that is, the value of membership is either 0 or 1. A Boolean boundary used to divide an otherwise gradual boundary into two classes. By contrast, a fuzzy set function allows the classes to intergrade spatially among the boundary areas of the two classes.

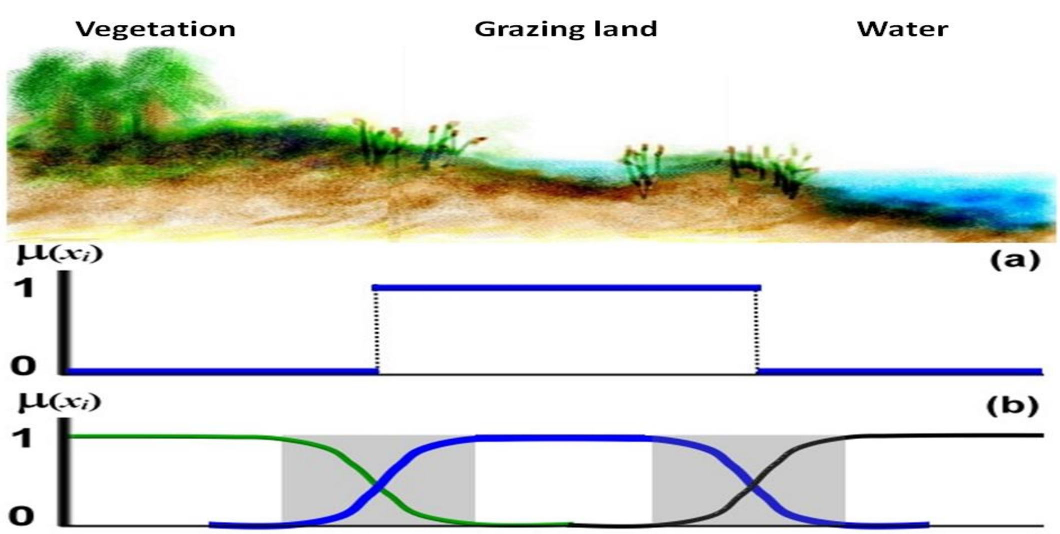


Figure 3.5. Illustration of the membership functions for (a) a crisp and (b) a fuzzy set (from Wen-Ya, 2005)

3.5.2.2 Method 2: Fuzzy C-means

As was explained in chapter 2 (section 2.4), the fuzzy c-means algorithm has been shown in different studies to be one of the most popular soft classification techniques (Wang et al., 2002; Wu and Yang, 2002; Yang and Lo, 2003). For this reason, the fuzzy c-means has been chosen for comparison in this study with fuzzy sets and the Boolean method.

Mathematically, the fuzzy c-means can be determined as:

$$Jm\ (U, v) = \sum_{k=1}^{n} \sum_{i=1}^{c} (uk) m \| yk - vi \|_{A}^{2} \quad A = \pi r^2 \qquad (3.9)$$

where U is a fuzzy c-partition of the data set *Y* containing *n* pixels, *c* is the number of classes, || || is an inner product norm, *v* is a vector of cluster centres, *vi* is the centre of cluster *i* and *m* is a weighting component which determines the degree of fuzziness. The inner product norm is derived from

$$\| yk - vi \|_{A}^{2} = (yk - vi\,)^2\, A(yk - vi) \qquad (3.10)$$

To implement the fuzzy c-means algorithm, additional parameters are required to guide the partitioning process. These parameters are the selection of a distance measure and the choice of a weighting exponent. The weighting exponent controls the ‘hardness’ or ‘fuzziness’ of the classification. The fuzzy c-means algorithm is particularly helpful in circumstances where it is not reasonable to make assumptions about the statistical distributions of sample data (e.g. where training sets of pure pixels are small). For every pixel a fractional value is obtained for each category in the form of a real number between 0 and 1, and these numbers will usually add up to 1.0 across all candidate classes. An additional output is a residual error map showing the RMS error across the image. This study used the scatter plot and regression method to obtain the relationship between field points and classified points.

3.5.2.3 Method 3: Boolean classification

As was explained in the previous chapter**,** Boolean logic theory is mostly employed as a technique refers to only true or false in the classification procedures. The Boolean method takes no account of measurement errors or uncertainties, because it is inflexible for estimating real ambiguity. Boolean mapping refers to a clearly defined boundary and only two possibilities are represented in the Boolean procedure: an object is either 0 or 1 in a set.

3.5.3 Stage 3: Change detection

The area of each land cover class identified by each of the different classification methods was determined. Three models were used to determine fuzzy change.

3.5.3.1 Model 1: Fuzzy objects.

Fuzzy objects were created by converting the pixels to polygons with the same membership values according to the method described in Power et al. (2001). The fuzzy land cover objects and their fuzzy memberships at different times are compared and the degree of change is calculated using fuzzy reasoning of land-cover based on fuzzy change. Many studies have used fuzzy spatial objects which have attracted considerable attention and which have been directly implemented for spatial data handling (Tang and Kainz, 2002). Research results contain definitions of fuzzy spatial objects, fuzzy relationships, fuzzy spatial data modelling, fuzzy classifications and fuzzy change (Cheng et al., 2001; Tang et al., 2003). Cheng and Molenaar, (1999) and Tang et al. (2005) determined objects from scenes classified by a fuzzy import approach. After that they discussed the handling of fuzzy characteristics of those objects. Metternicht (1999) applied a direct method to fuzzy change detection, using as input the ratio of reflectances at the different dates, and deriving the possibility that change had happened at any position. Meanwhile, Gong (1993) applied fuzzy set theory to join principal component images resulting from multi-temporal imagery.

Other researchers applied post-classification comparison of multi-temporal images and show the fuzzy set membership as a simple vector of belonging to a forest category (e.g. Foody and Boyd, 1999; Foody, 2001). The arithmetic difference among fuzzy set memberships at different times was used to illustrate changes in equatorial forests. This study used a fuzzy change object, as described in Tang et al. (2005), which converts contiguous areas of similarly valued class memberships to generate polygons or objects. This method can give more accurate change detection results than Boolean as all the memberships inside the object can be used in change calculations.

3.5.3.2 Model 2: Sub-pixel change

The fuzzy model of spatial information has been implemented for a number of different ecological and landscape related phenomena (Fisher, 2000), including terrain classes (Fisher et al., 2004; Schmidt and Hewitt, 2004), landscape ecology metrics (Arnot et al., 2004), and land cover mapping resulting from satellite remote sensing (Fisher, 1997; Foody, 1996). Some studies have tested the consequences and possibilities for change analysis when the landscape is located under uncertainty with fuzzy sets. Fisher et al. (2006) evaluated how the fuzzy memberships can be used to detect boundary change where Boolean change is indicated not to have happened. Fisher et al. (2006) examined the change detection matrix and discussed how the fuzzy change matrix can be populated, using fuzzy logic statements and determining the intersection between the classes. They showed that the fuzzy change matrix is easy to apply and gives a precise result compared with the Boolean method. Deer (1998) has concluded the logic of change pixel-by-pixel in the output from a classification process.

This study used the same fuzzy change matrix as Fisher et al. (2006), which with sub-pixel change, and has been shown to be more accurate than Boolean change. A fuzzy change matrix for both fuzzy sets and fuzzy c-means was generated in order to compute the fuzzy change, fuzzy loss, fuzzy gain and fuzzy boundaries. Section 5.1.5 describes these methods in more detail.

3.5.3.3 Model 3: Boolean change

Boolean change compares the maximum values of fuzzy membership at every pixel for each time interval. The Boolean change technique depends on 'date 1' and 'date 2' images which are classified separately and compares class values on a pixel–by-pixel basis between the dates (Ernani and Gabriels, 2006). A number of approaches to change detection have been suggested, of which post-classification comparison of information from more than one date is one of the most widely applied and most intuitive (Coppin et al., 2004; Jensen et al., 1999). However, Hurskainen and Pellikka, (2004) found that the post-classification comparison technique had limitations as it was unable to detect small changes. The advantages of Boolean classification change are:

1. The technique avoids the requirement for the impacts of atmospheric, sensor and environmental differences among multi-temporal images to be strictly minimized.
2. The technique gives a complete matrix of change directions, unlike image differencing. Macleod and Congalton, (1998) have emphasized that post-classification comparison has

significant limitations because the comparison of land cover classifications for different dates does not allow the detection of small changes within land cover categories.

Some limitations exhibited are that it requires knowledge, expertise, and time to create classification products (Lu et al., 2004). It can be concluded that the Boolean change technique is widely used in land use and land cover applications, and hence was selected for use in this study, to compare its results with those of fuzzy change.

3.5.4 Stage 4: Field survey

The field survey is a commonly used approach for collecting ground data (reference data) to be compared with classified data and used in the validation of classified remotely sensed data. The field survey in this study involved the following tasks:

- Recording ground point data using a global positioning system (GPS) in the study area;
- Visiting the Libyan Remote Sensing Center (LRSC) for the collection and use of GPS, digital camera and some remote sensing data;
- Obtaining documentary materials on agriculture and woodland from some previous agricultural projects in the study area;
- Visiting the Libyan Agricultural Research Center to access current and past research in the study area that is not available on the Internet;
- Arranging interviews and meetings with local experts and heads of public organizations;
- Providing results which would serve as a reference point for fuzzy and Boolean classification and accuracy assessment.

3.5.5 Stage 5: Validation

Accuracy assessments are commonly presented in a confusion error matrix and a kappa coefficient is typical measure of accuracy for Boolean classifications (Congalton and Green, 1999). The term ‘accuracy’ describes the level of agreement between labels assigned by the classifier and class allocations based on ground data collected by the user (Mather and Brandt, 2009). The confusion matrix compares error values for each class that was classified with its respective value in the ground truth data. The main errors in change detection include data errors such as image resolution, accuracy of position and image quality; pre-processing errors affecting the accuracy of geometric correction and radiometric correction; errors arising from change detection methods and post procedures; and errors in field validation affecting the accuracy of ground reference data (Powell et al., 2004). This analysis applied an error matrix approach to the comparison of field and classified data (Foody, 2002) and calculated kappa coefficients for each class (Congalton, and Plourde, 2002). This study used both Boolean and fuzzy validation data and compared fuzzy land cover data collected in the field with fuzzy land cover data derived from remote sensing analysis. This is described in Chapter 6.

3.5.5.1 Model 1: Cross-tabulation

A cross-tabulation analysis based on a soft classification analysis was used to derive the overall agreement between the maps. The soft cross-tabulation allocates all pixels to have simultaneous part membership of more than one class (IDRISI 15.0 help, Clark labs, 2006). It has three different operators: minimum, multiplication, and composite. These operators were defined by Pontius and Cheuk (2006) as follows:

1- **Minimum operator**: The minimum operator (MIN) is the common fuzzy set intersection operator. The minimum operator has been assumed to be the natural choice for generating cross-comparison matrices for fuzzy classifications. The minimum operator is also useful in situations where the category membership is uncertain (Pontius and Cheuk, 2006). A variant of the minimum operator is sometimes used as a similarity index (SI) for comparing fuzzy classifications. Equation 3.11 describes a measure of agreement and disagreement among cross-tabulated data using the minimum operator:

$$Pnij = MIN(Pni \bullet, Pn \bullet j) \qquad (3.11)$$

2- Multiplication operator: This operator compares class membership values directly. For calculating the disagreement and agreement for the maps that are cross-tabulated using the multiplication operator, the following equation is used:

$$Pnij = Pni \bullet \times Pn \bullet j \qquad (3.12)$$

where *Pni* is the membership of pixel n to class i in the comparison map and *Pnj* is the membership of pixel *n* to class *j* in the reference map. The multiplication operator has many disadvantages. The main critical issue is that when a pixel is not Boolean-classified, the agreement between a pixel and itself is smaller than unity (Pontius and Cheuk, 2006). As a result, if the multiplication operator evaluates a map to itself, the resulting cross-tabulation matrix is not a diagonal matrix. Additionally, it is possible to find a counter-intuitive result where the agreement between a pixel and itself is less than the agreement between the pixel and a different pixel.

3- **Composite operator**. The interpretation of the composite operator in the situation of sub-pixel agreement–disagreement is associated with an assumption of maximum overlap between corresponding classes, followed by the allocation of the residual sub-pixel fractions to the other classes. The disagreement between two membership values measure corresponds to the expected overlap by chance constrained to the unmatched sub-pixel fraction. The composite rule has several positive advantages, the most significant being that it produces the identity matrix when a fuzzy-classified image is compared to itself. For agreement, equation 3.11 can be used, while for disagreement, for the maps that are cross-tabulated using the composite operator, equation 3.13 is employed:

$$Pnij = (Pni\bullet - Pnii) \times \left[\frac{(Pn\bullet j - Pnjj)}{\sum_{j=1}^{j}(Pn\bullet j - Pnjj)}\right] \quad \text{For i} \neq \text{j} \qquad (3.13)$$

where is *n*, the pixel in the map, $Pni\bullet$ - $Pnii$, since the sum membership function is $Pni\bullet$ and the agreement is $Pnii$. For disagreement, *n* is the pixel in the reference map for the class j is $Pni\bullet$ - $Pnjj$. The composite operator, with a different scale of resolution, is good for comparing the maps because it resolves the problems of computing the cross-tabulation matrix derived from the use of the multiplication and minimum operators (Pontius and Connors, 2006). The composite operator is useful in showing how well two maps or layers agree in terms of how the classes are clustered spatially.

3.5.5.2 Model 2: Fuzzy error matrix

For the assessment of fuzzy classifications in general, different suggestions have been made, such as a fuzzy error matrix, entropy, and cross-tabulation (Binaghi et al., 1999; Foody, 1995;

Green and Congalton, 2004; Lewis and Brown, 2001; Pontius and Connors, 2006; Townsend, 2000; Woodcock and Gopal, 2000). The fuzzy error matrix (Binaghi et al., 1999) is one of the most attractive approaches, as it represents a generalization of the traditional confusion matrix. Specifically, for a cross-comparison to be consistent with the traditional confusion matrix, it is popular for the cross-comparison to result in a diagonal matrix when a map is compared to itself, and for its marginal totals to match the total of membership grades. More significantly, a cross-comparison should convey readily interpretable information on the confusion between the classes. To date, the ability of the fuzzy error matrix has been mostly concentrated on applying accuracy indices, for example the overall accuracy, the user and producer accuracy, and the kappa and conditional kappa coefficients (Binaghi et al., 1999; Okeke and Karnieli, 2006; Shabanov et al., 2005). The fuzzy error matrix (Binaghi et al., 1999), which is an extension of the confusion error matrix using the principles of the fuzzy set method, could be a better alternative for evaluating the performance of soft classifiers when soft ground truth data are available. The reliability of soft reference data is essential to avoid under- or over-estimation in accuracy assessments. The first advantage here is that it was not assumed that all pixels present in a better resolution dataset are pure and that no information was lost because of the hardening of soft classification outputs. The second advantage is that here the membership value is due to vagueness in class definition. So the disadvantage of the Boolean method can be avoided by this method. The main disadvantage of this method is in determining the accuracy of the soft referenced data. To tackle this problem this study generates memberships from the field by using a sub-pixel approach to collecting reference data, which no one has used before. This study’s fuzzy error matrix is presented and implemented as one of the approaches to determine the soft validation by comparing fuzzy membership from the field against the fuzzy membership from a classified image.

3.5.5.3 Model 3: Error matrix

The error matrix can be used to improve the assessment of the classification for the user (Morisette and Khorram, 2000) but may be more appropriate for traditional methods of classification where it is assumed that pixels at the reference locations can be assigned to single classes, and accuracy measures based on the proportion of area correctly classified are then calculated from the number of pixels that are correctly classified (Green and Congalton, 2004). While there have been several current advances, the recent status of validation indicates that a lot of problems remain to be solved. Therefore, although the subject has developed considerably, there is scope for significant improvement. A key concern is that the commonly used methods for accuracy assessment and reporting are often flawed. Despite the apparent objectivity of quantitative measures of accuracy, it is important that accuracy statements be interpreted with care. Numerous factors might result in a misleading analysis being derived from an apparently objective validation. These circumstances could have serious implications for several users. This research addresses different models of accuracy assessment for Boolean and soft classification and applies different types of error matrix.

3.5.6 Stage 6: Analyses of the results

After completion of stages one to five, stage six compares the results. This stage is divided into three parts. Part one will analyse the results of the classified images derived from fuzzy classification (fuzzy sets and fuzzy c-means) and Boolean classification. The second part will analyse the results from the change detection (Boolean and Fuzzy change) from the three models: object change, pixel change (change matrix) and Boolean change. Part three will analyse the results from the validation for both methods (Boolean and fuzzy).

3.6 Conclusion

This chapter has described information about the study area and outlined the methodology of this. Fuzzy set, fuzzy c-means and Boolean models have been selected as land cover classification techniques. For change detection, change object, fuzzy change matrix and Boolean change models have been presented and implemented. This chapter has also described selected validation models that will be used such as: cross tabulation, which contained thee models; the composite operator, which has been shown to be more suitable than the other methods and has been chosen for this study; and the fuzzy error matrix.

Chapter 4: Fuzzy and Boolean classification

4.1 Introduction

Land use and land cover classification is one of the most important applications of remote sensing data. Either Boolean (pixel-by-pixel) or fuzzy (sub-pixel) classification may be performed to obtain land use and land cover maps. However, in general, and particularly in medium spatial resolution images such as Landsat, most of the pixels may be mixed. This chapter will generate baselines of fuzzy and Boolean land cover/land use mappings and the main objective of this chapter is to compare the three models: fuzzy sets, fuzzy c-means and Boolean classification.

4.2 First model: Fuzzy set theory

As was explained in chapter 2 (section 2.3), the basis of fuzzy set theory is the notion of imprecise membership functions, which provide ways of dealing with the limitations of traditional data classifiers (Klir and Folger, 1988). Rigid spatial models consisting of discrete, sharply defined, homogeneous classes ignore the geographic variability and complexity existing within nature and the error inherent in the measurement of it (Burrough, 1989). Thus, a considerable amount of information is lost when such crisp entities are combined. Fuzzy set theory provides more appropriate classifiers, because it models cases whose attributes have soft transitions rather than hard boundaries. The satellite images were classified into six land-cover categories – urban areas, vegetation, woodland, bare areas, grazing land and water (sea) – using a fuzzy set model. The analysis was performed in a variety of software, including ER-Mapper and ERDAS for image processing, IDRISI Andes for fuzzy classification, and GIS. The following steps were applied:

Step 1. Mosaic

Image-to-image registration and image enhancement were applied for data preparation and pre-processing for reliability. Two partially overlapping images covering the study areas were merged to the same map projection and datum using the same resampling parameters and pixel size. One of the images was selected as the base to relate the other. The resolution of the 1976 MSS image was changed from 80m to 30m to match the 1989 and 2005 image resolution and SPOT 2009 from 10m to 30m. Nearest neighbour, bi-linear or cubic convolutions are the commonest image registration methods. However, this study adopted cubic convolution for all resolution up-scaling and down-scaling because it is similar to the bilinear interpolation except that it weighs the values of sixteen surrounding pixels. Topographic maps were used as base maps, and the geometric registration was done on all images, using triangulation registration points. This process has been done in ER-Mapper software, using Geodetic Datum WGS84 and NUTM 33 map projection. At this stage this study also applied histogram equalization to all the images for enhancement. The image enhancement process uses edges, texture and high and low frequency components to extract important information that could otherwise be missed.

Step2. Training site development

Determining the training set is an essential step in supervised image classification. A training set can be defined as a sample of pixels of known category membership collected from reference data such as existing maps, ground data, and aerial photographs (DeFries et al., 1998). These training pixels are used to obtain various statistics such as standard deviation and mean for every land cover category. A training sample in soft supervised classification differs in practice from the traditional training set in training-site selection. Traditionally, training sites are chosen for every training category and the sites must be sufficiently homogeneous on the ground. Therefore, these are selected subjectively and purposefully to exclude mixed pixels containing two or more categories. For soft classification, the condition for being homogeneous is less important, and a training sample can be used to produce statistical factors for more than one category (Wang, 1990). In this research, training sites were selected in areas which contained pure and mixed pixels to be used in fuzzy and Boolean classifications for the IDRISI model. For fuzzy c-means, pure and mixed training sets were chosen using the ENVI software. The current study used two experiments with two different training sets; although the training sets were different there was a very good correspondence between the two training sets (IDRISI and ENVI) for all of the classes, as shown in the tables below (4.1, 4.2, 4.3 and 4.4), because the most suitable training sets were chosen carefully to get the best results.

Tables 4.1, 4.2, 4.3 and 4.4 illustrate the training set for the three bands which were chosen for the current study (4, 3, 2), for all the classes (urban, vegetation, woodland, grazing land and bare areas). The Tables listed below provide the statistical analyses of average mean and standard deviation in IDRISI and ENVI software for images taken in 1976, 1989, 2005 and 2009. In Table 4.1, which shows the training set for 1976, there are slight differences in the mean and standard deviation between IDRISI and ENVI software: for example, for the urban class in 1976, the mean of the pixels using IDRISI software for band 1 is 134.132, while using ENVI software it is 108.585; and the standard deviation using IDRISI is 11.932, while using ENVI it is 15.244.

Table 4.1 illustrates the training set for the three bands and provides the mean and standard deviation from IDRISI and ENVI software packages for image in1976

		IDRISI		ENVI	
classes	Bands	mean	Standard deviation σ	mean	Standard deviation σ
urban	Band2	134.132	11.932	118.585	15.244
	Band3	127.652	12.624	115.466	14.425
	Band4	167.543	17.376	151.319	24.060
Woodland	Band2	91.378	13.529	70.949	16.471
	Band3	66.217	10.294	82.591	15.691
	Band4	39.382	14.639	41.233	18.023
Vegetation	Band2	30.961	12.995	39.304	20.053
	Band3	36.431	8.001	38.826	7.823
	Band4	50.693	12.899	36.217	10.055
Grazing land	Band2	151.259	12.427	149.306	13.765
	Band3	142.354	7.245	120.889	11.686
	Band4	96.584	10.361	111.748	12.089
Bare land	Band2	237.538	7.983	251.179	9.875
	Band3	249.339	7.165	252.235	8.152
	Band4	219.613	10.528	248.215	14.672

Table 4. 2 illustrates the training set for the three bands and provides the mean and standard deviation from IDRISI and ENVI software packages for image in 1989

		IDRISI		ENVI	
classes	Bands	mean	Standard deviation σ	mean	Standard deviation σ
urban	Band2	222.386	13.515	192.348	9.465
	Band3	210.931	13.922	217.659	8.137
	Band4	184.513	12.424	229.635	7.872
Woodland	Band2	154.635	5.469	175.461	6.874
	Band3	183.986	6.263	134.925	7.386
	Band4	169.264	6.941	144.59	8.152
Vegetation	Band2	185.762	12.562	224.352	10.763
	Band3	156.743	13.611	131.808	11.872
	Band4	144.651	10.447	150.485	9.438
Grazing land	Band2	189.533	9.656	217.079	13.743
	Band3	177.769	10.325	194.849	12.031
	Band4	197.462	14.763	203.035	11.765
Bare land	Band2	221.548	7.642	247.121	13.223
	Band3	237.432	8.349	250.443	11.564
	Band4	254.233	12.604	231.786	14.768

Table 4. 3 illustrates the training set for the three bands and provides the mean and standard deviation from IDRISI and ENVI software packages for image in 2005.

		IDRISI		ENVI	
classes	Bands	mean	Standard deviation σ	mean	Standard deviation σ
urban	Band2	127.734	13.678	142.969	10.857
	Band3	138.321	15.763	159.926	18.090
	Band4	169.376	17.298	197.134	20.002
Woodland	Band2	151.453	14.311	165.532	11.683
	Band3	140.476	13.347	124.037	10.127
	Band4	132.659	15.365	126.192	13.365
Vegetation	Band2	26.899	13.428	51.267	14.176
	Band3	24.469	11.193	27.232	13.843
	Band4	42.246	12.245	31.064	15.446
Grazing land	Band2	193.452	7.561	223.803	9.605
	Band3	181.653	9.783	185.348	11.795
	Band4	166.328	11.651	179.399	12.498
Bare land	Band2	237.431	12.453	249.945	10.686
	Band3	225.324	13.917	246.856	12.790
	Band4	228.673	15.672	241.981	17.458

Table 4.4 illustrates the training set for the three bands and provides the mean and standard deviation from IDRISI and ENVI software packages for image in 2009

		IDRISI		ENVI	
classes	Bands	mean	Standard deviation σ	mean	Standard deviation σ
Urban	Band2	148.943	12.438	137.253	15.236
	Band3	131.437	14.562	129.641	17.372
	Band4	167.642	16.543	153.132	18.913
Woodland	Band2	163.78	4.751	169.360	7.463
	Band3	113.646	14.855	120.489	12.598
	Band4	92.302	13.721	112.078	11.659
Vegetation	Band2	107.651	10.112	125.188	13.670
	Band3	87.121	15.665	94.691	17.906
	Band4	65.549	15.013	83.905	17.473
Grazing land	Band2	179.438	17.652	197.241	12.858
	Band3	153.759	15.768	173.815	16.299
	Band4	149.654	16.873	163.184	15.610
Bare land	Band2	218.320	13.916	240.074	10.493
	Band3	237.231	14.623	246.807	13.468
	Band4	229.342	15.276	238.000	12.289

Figures 4.1, 4.2, 4.3 and 4.4 below show the mean spectrum of every band (2, 3 and 4) for the selected training set, and the standard deviation spectrum of each band at different times (1976, 1989, 2005, 2009), for all the classes (urban, woodland, vegetation, grazing land and bare areas). Figure 4.1 shows the mean and standard deviation for all the classes in 1976 obtained using IDRISI and ENVI software. In Figure 4.1, the left column represents the mean (red colour by IDRISI and blue colour by ENVI), and the right column represents the standard deviation. Although the training sets were different, there is a very good correspondence between the two training sets (IDRISI and ENVI) for most of the classes; for example, the mean for the vegetation class in band 3 obtained using the IDRISI software is 36.431, while using ENVI it is 38.826, which is nearly the same; and the standard deviation for the same class and band obtained using the IDRISI software is 8.001, while using ENVI it is 7.823. Figure 4.2 shows the mean and standard deviation for all the classes for the image from 1989 obtained using the IDRISI and ENVI software. There is also, there is correspondence between the two training sets (IDRISI and ENVI) for most of the classes in the images taken in 1989; for example, the mean for the woodland class in band 4 obtained using the IDRISI software is 169.264, while using ENVI it is 144.59, so there is a little difference; and the standard deviation for the same class and band obtained using IDRISI software is 6.941, while using ENVI it is 8.153.

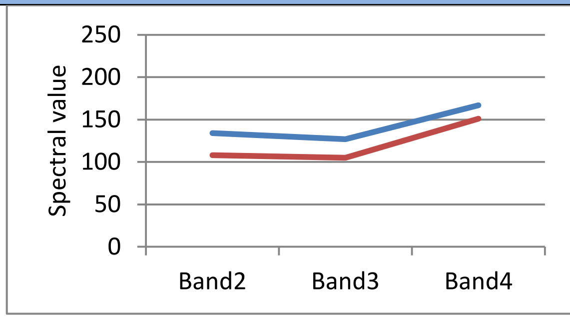
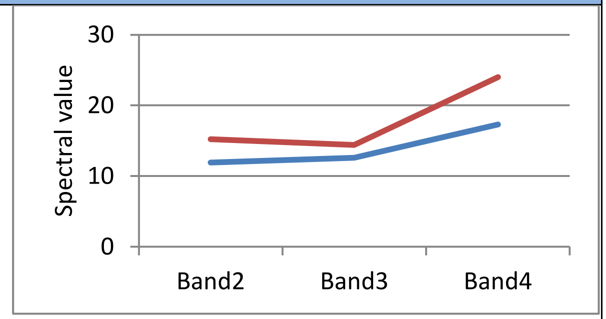
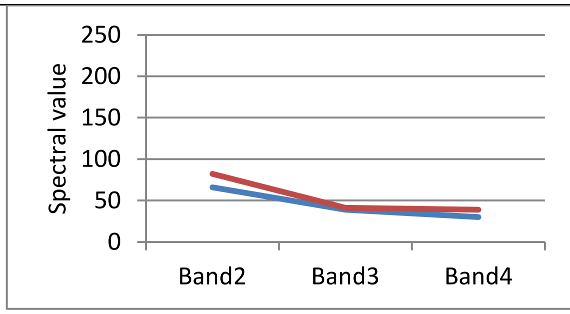
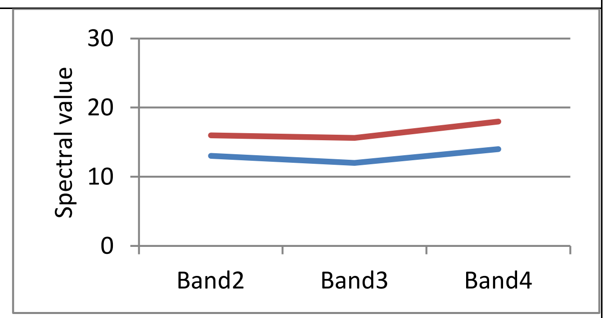
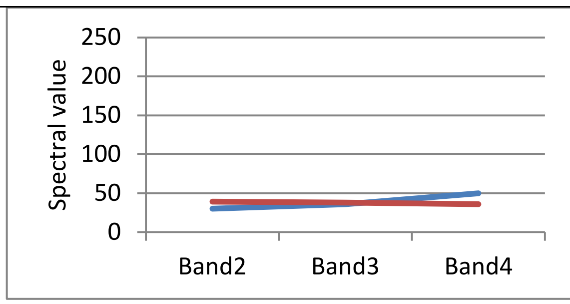
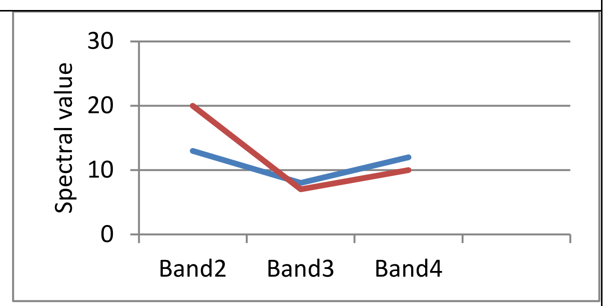
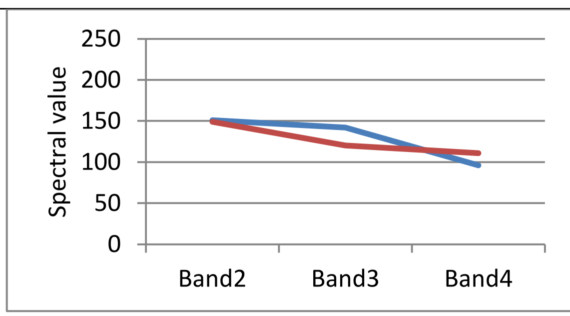
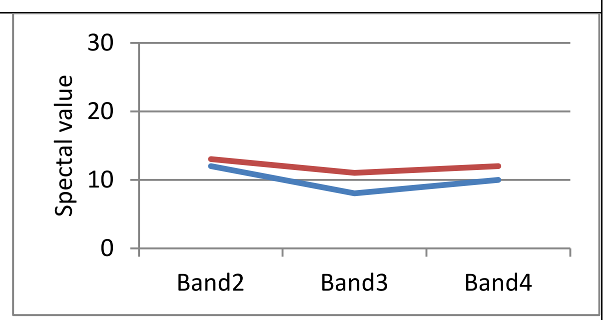
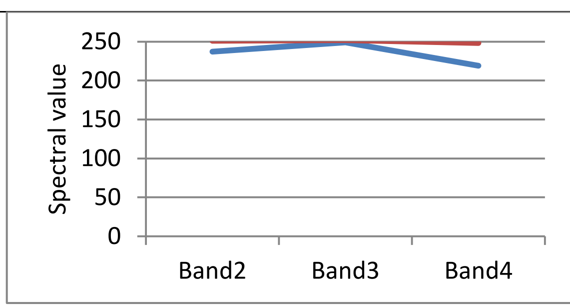
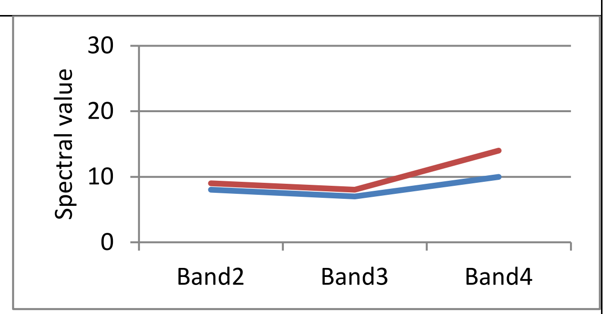
Classes	Mean of training set by IDRISI and ENVI 1976	Standard deviation of training set by IDRISI and ENVI
Urban		
Woodland		
Vegetation		
Grazing land		
Bare area		

Figure 4.1 shows the mean and standard deviation of the training set for different classes and bands from the image in 1976 from IDRISI and ENV

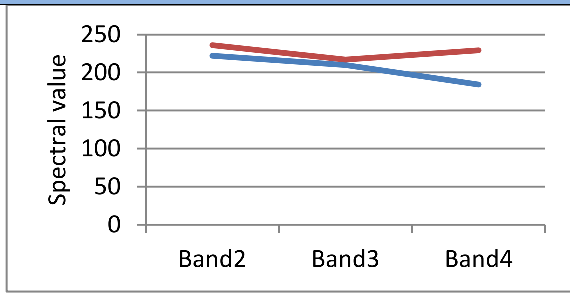
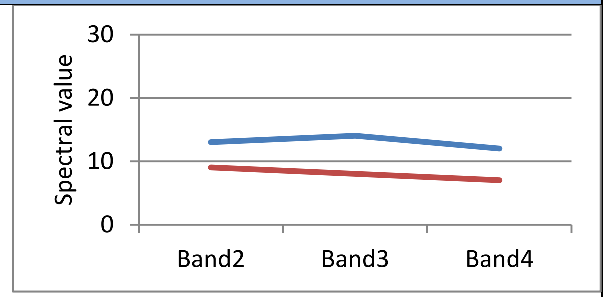
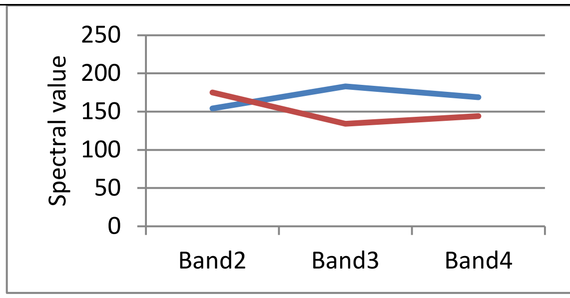
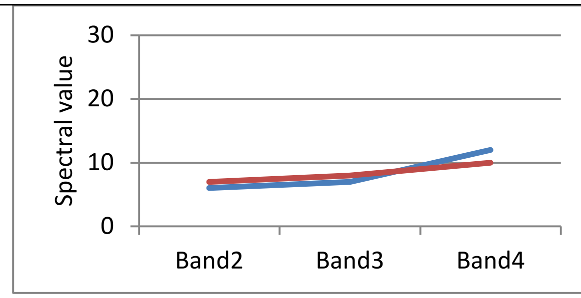
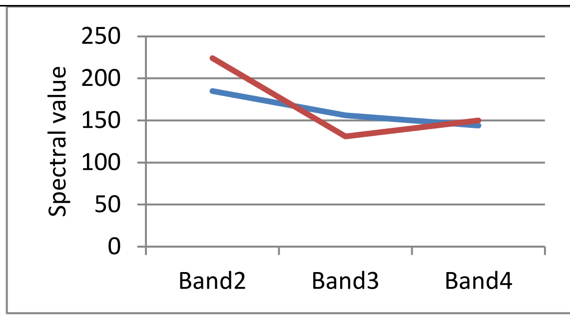
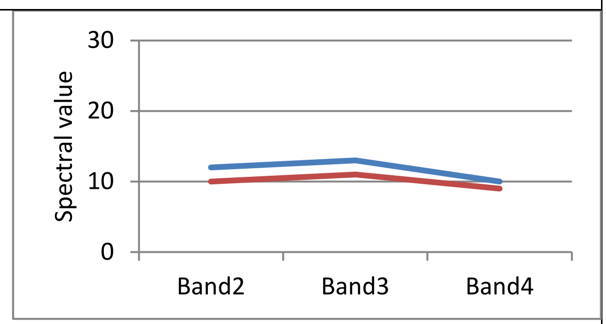
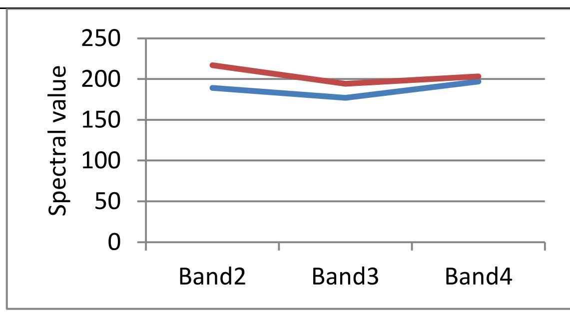
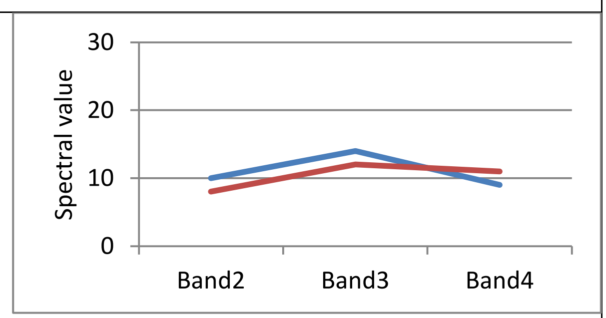
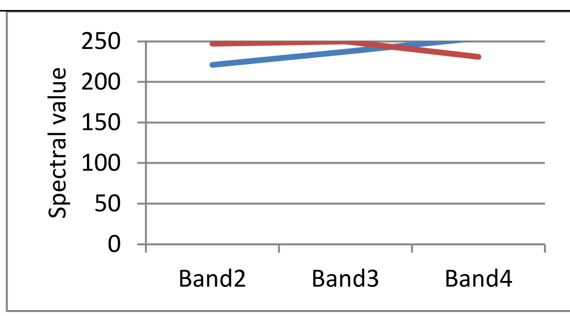
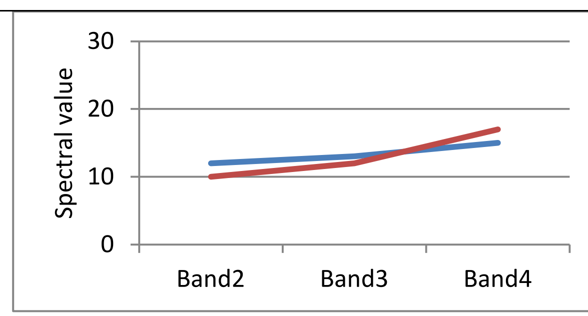
Classes	Mean of tanning set by IDRISI and ENVI 1989	Standard deviation of training set by IDRISI and ENVI
Urban		
Woodland		
Vegetation		
Grazing land		
Bare area		

Figure 4.2 shows the mean and standard deviation of the training set for different classes and bands from the image in 1989 from IDRISI and ENVI

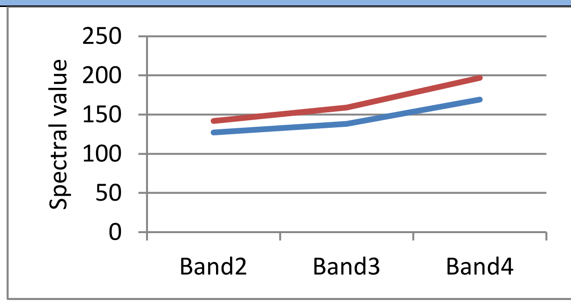
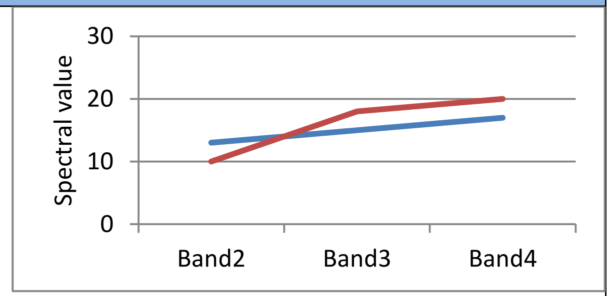
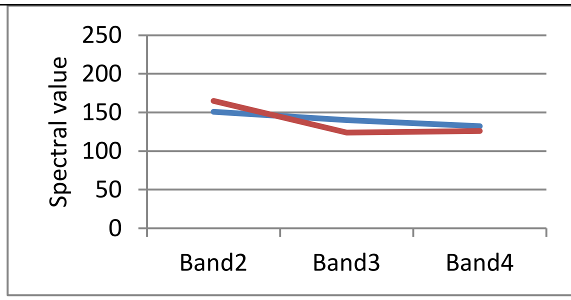
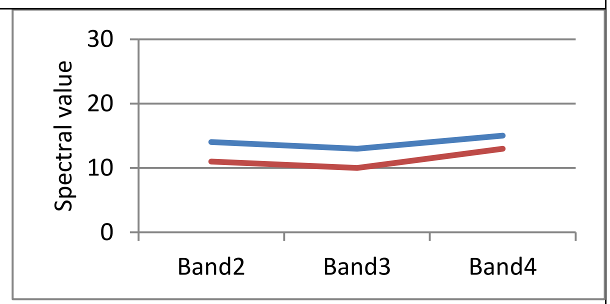
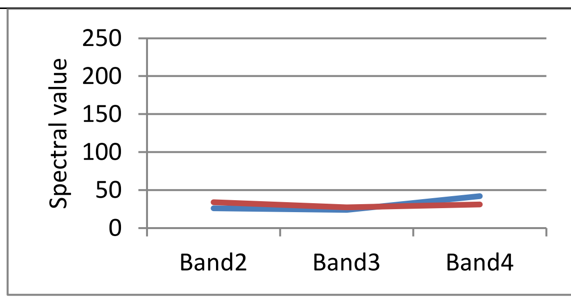
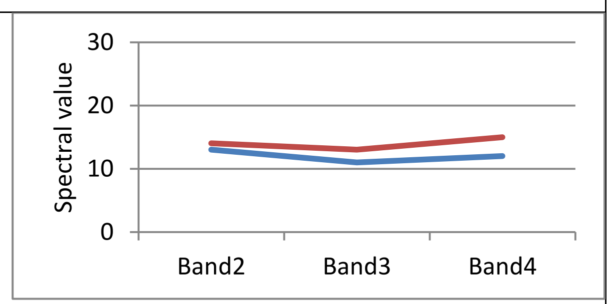
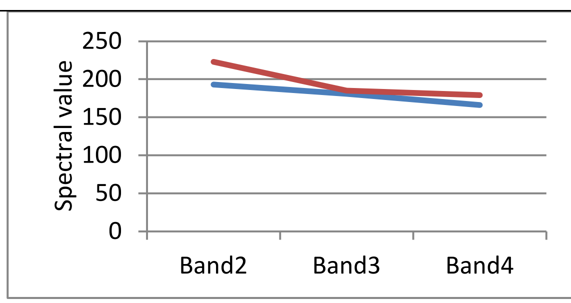
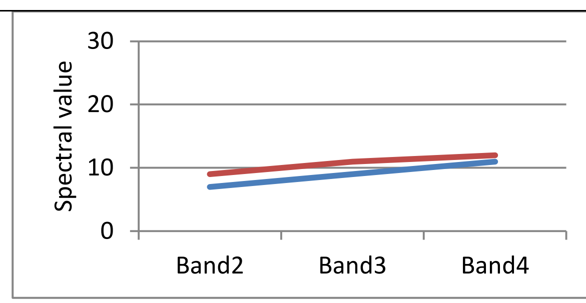
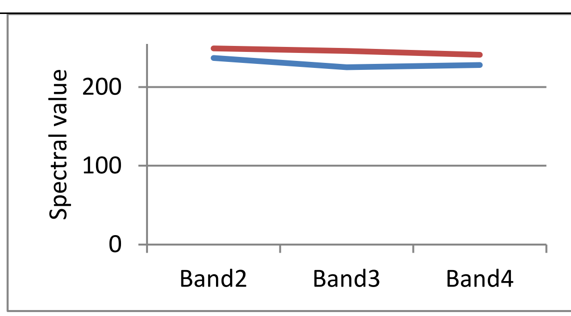
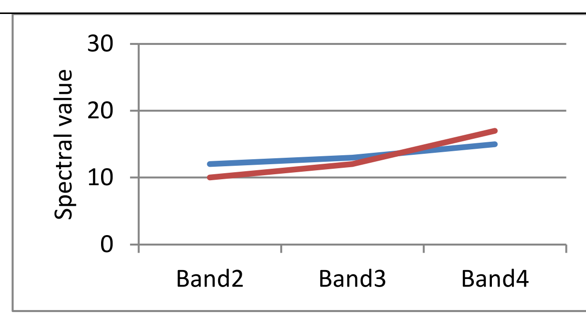
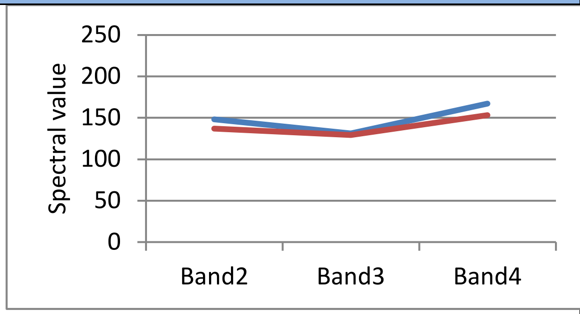
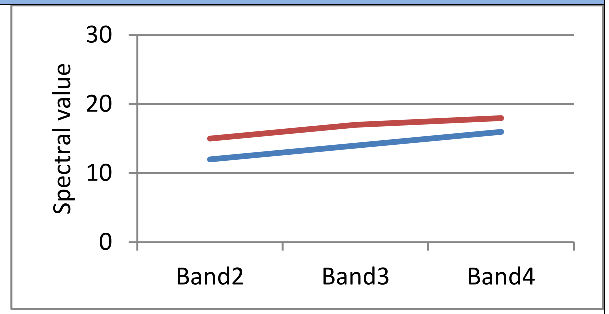
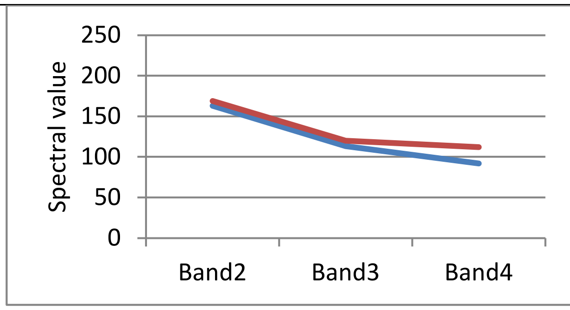
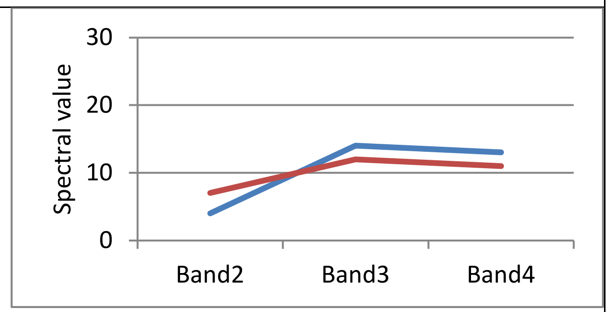
<table>
<tr><th>Classes</th><th>Mean of tanning set by IDRISI and ENVI 2005</th><th>Standard deviation of training set by IDRISI and ENVI</th></tr>
<tr><td>Urban</td><td></td><td></td></tr>
<tr><td>Woodland</td><td></td><td></td></tr>
<tr><td>Vegetation</td><td></td><td></td></tr>
<tr><td>Grazing
land</td><td></td><td></td></tr>
<tr><td>Bare area</td><td></td><td></td></tr>
</table>

Figure 4.3 shows the mean and standard deviation of the training set for different classes and bands from the image in 2005 from IDRISI and ENVI

<table>
<tr><th>Classes</th><th>Mean of tanning set by IDRISI and ENVI 2009</th><th>Standard deviation of training set by IDRISI and ENVI</th></tr>
<tr><td>Urban</td><td>
</td><td>
</td></tr>
<tr><td>Woodland</td><td>
</td><td>
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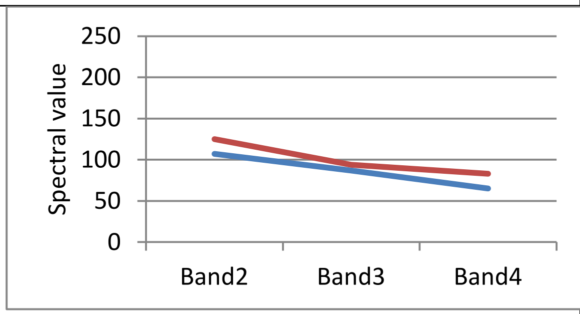
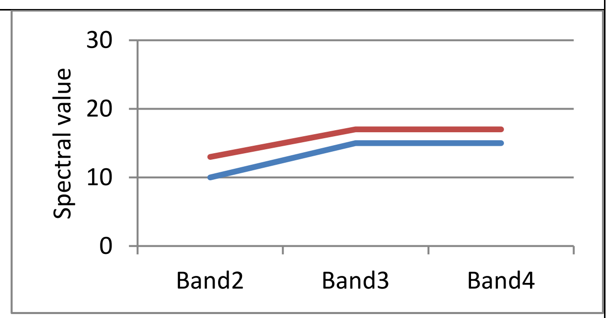
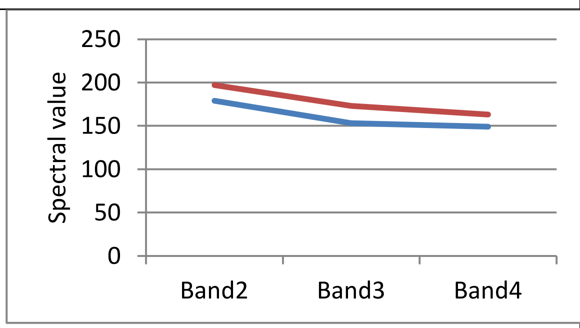
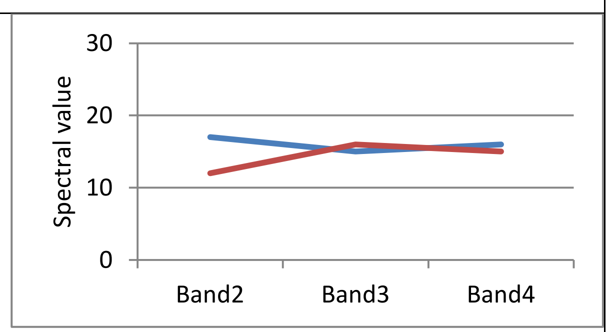
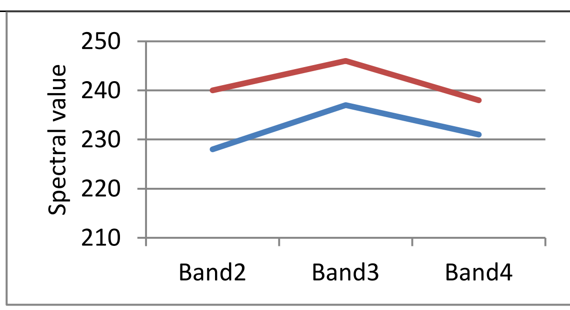
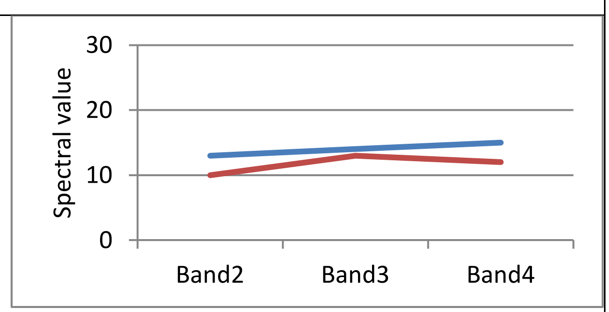
<tr><td>Vegetation</td><td>
</td><td>
</td></tr>
<tr><td>Grazing land</td><td>
</td><td>
</td></tr>
<tr><td>Bare area</td><td>
</td><td>
</td></tr>
</table>

Figure 4.4 shows the mean and standard deviation of the training set for different classes and bands from the image in 2009 from IDRISI and ENVI

Step 3. Signature development

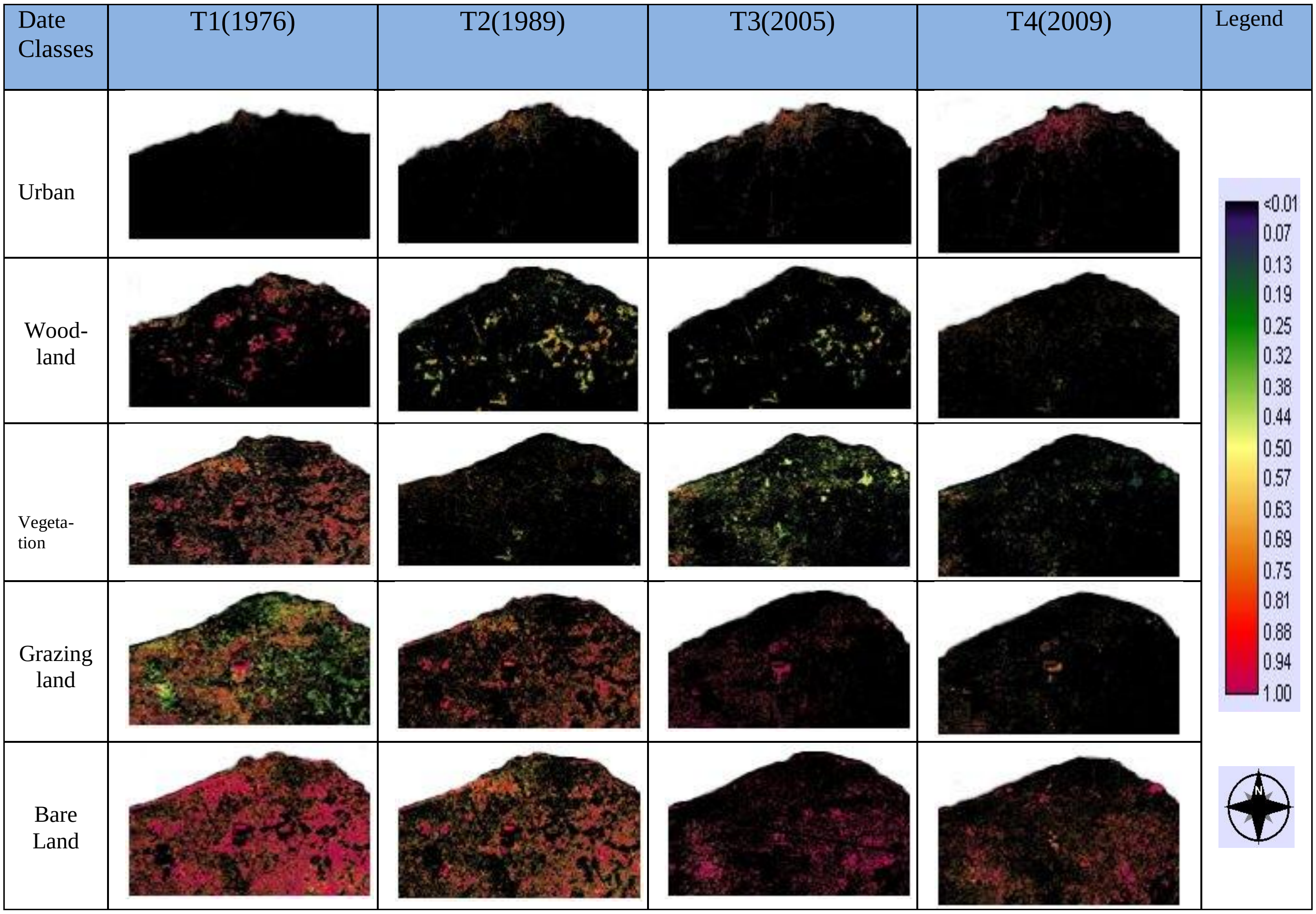
Signature files of the reflectance values of the reference pixels within the training sites for each class were created. These describe the statistical properties of the different classes. The charater-sitics of the data were examined by considering the maximum, minimum, and mean values as well as a class covariance matrix. Histogram plots for the class signatures were also examined. These signatures were used to assess the performance of the trained areas before classification. The training site polygons were defined as a vector file of polygons. The vector file was converted to a raster image during the development. This vector file was created using the onscreen digitizing feature of the display system. With either raster or vector, training site classes are indicated by integer codes.

Step 4. Supervised classification

This is a process for spectral identification of the same areas on an image by identifying training sites of known objectives and then extrapolating those spectral signatures to other areas of unknown targets. In supervised classification, the individual characteristics and location of some of the land-cover categories are known a priori through a combination of fieldwork, interpretation of aerial photography, map analysis and personal experience (Hodgson et al., 2003).

Generally, the images in Figure 4.5 below show the results of fuzzy set classification for all classes – urban areas, woodland, vegetation, grazing land and bare land – at different times: T1, T2, T3 and T4. From Figure 4.5 it is clear that the urban class increases over time, from T1 (1976) to T4 (2009), while the woodland class decreases. Also, from Figure 4.5, it is clear that fuzzy set classification results in many layers, each belonging to one class; inside the class, different memberships from 0 to 1 are shown.

Figure 4.5 illustrates fuzzy set classification at different times: T1, T2, T3 and T4



4.2.1 Results of fuzzy set model

This study used a classification algorithm as described in the IDRISI implementation by Wang (1990). Membership functions were based on the maximum likelihood algorithm, with a fuzzy mean and fuzzy covariance matrix replacing the conventional mean and covariance matrix. These approaches are fuzzy in the sense that they allow for multiple and partial class membership properties (note that the approaches are often based more on soft computing than fuzzy logic). In this way they allow more information on the relative strengths of the class membership at pixel level to be made available to end users.

Table 4.5 below shows the areas of classes by hectares at different dates (from fuzzy set classification). In the urban class it is clear that the urban area is small at T1 (9104.8 hectares), increases at T2 and T3, and is a large area at T4 (30127.8 hectares). In the woodland class, the highest area (57063.7 hectares) is at T1, whereas the lowest area is at T4 (20376.4 hectares), which means that the area of woodland decreases from T1 to T4. In the vegetation class, the area is quite large at T1 (61173.3 hectares) while at T4 it is 41742.7 hectares. In the grazing land class, the area is lowest at T1 (23931.6 hectares), and 34821.3 hectares at T4; and in the bare area class, the area is 19891.2 hectares at T1 and increases to 45365.1 hectares at T2.

Table 4.5: The areas of classes by hectares at different dates (fuzzy sets)

Classes	1976 MSS	1989 TM	2005 ETM	Spot 5-2009	Difference 2009-1976
Urban area	9104.8	17355.6	28491.6	30127.8	21023
Woodland	57063.7	36879.3	19338.6	20376.4	-36687.3
Vegetation	61173.3	49468.1	43201.9	41742.7	-19430.6
Bare area	19891.2	17203.4	41699.2	45365.1	25473.9
Grazing land	23931.6	48789.2	32891.8	34821.3	10889.7

Figures 4.6, 4.7, 4.8, 4.9, and 4.10 below show how the classes change over time, at T1 (1976), T2 (1989), T3 (2005) and T4 (2009); the data come from the results of fuzzy set classification (Table 4.1). Figure 4.6 illustrates the urban class; the area is 9104.8 hectares at T1, then starts to increase at T2 (17355.6 hectares); at T3 it is 28491.6 hectares, and at T4 it is 30127.8 hectares, which means that the urban class has more than tripled during the period of time from T1 (1976) to T4 (2009), about 33 years. Figure 4.7 illustrates the woodland class; the area it is 57063.7 hectares at T1, and then starts to decrease at T2 (36879.3 hectares); at T3 it is 19338.6 hectares and

at T4 is 20376.4 hectares, which gives an indication that the woodland class area has decreased. Figure 4.8 illustrates the vegetation class at T1, T2, T3 and T4. Figure 4.9 illustrates the grazing land class at T1, T2, T3 and T4. Figure 4.10 illustrates the bare land class at T1, T2, T3 and T4.

Figure 4.6 illustrates the urban class at T1, T2, T3 and T4

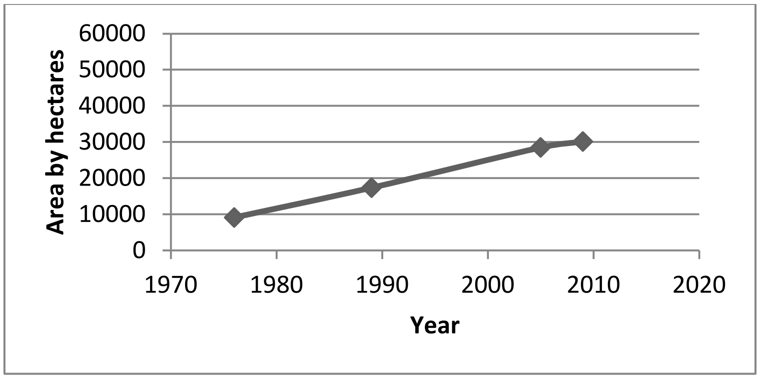


Figure 4.7 illustrates the woodland class at T1, T2, T3 and T4

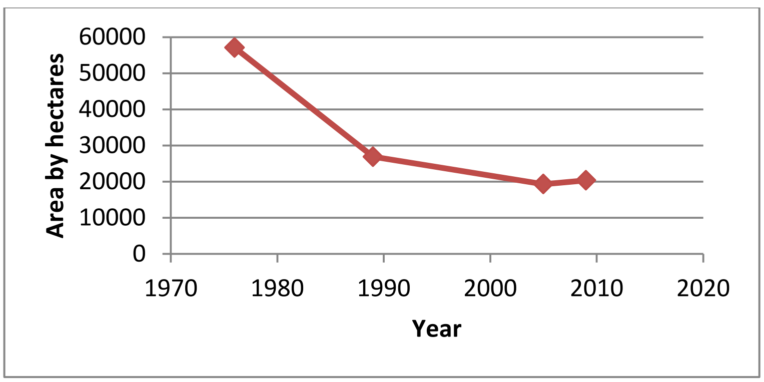


Figure 4.8 illustrates the vegetation class at T1, T2, T3 and T4

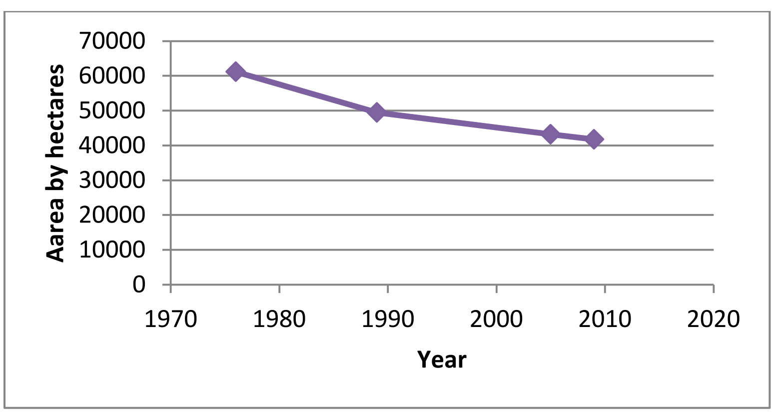


Figure 4.9 illustrates the grazing land class at T1, T2, T3 and T4

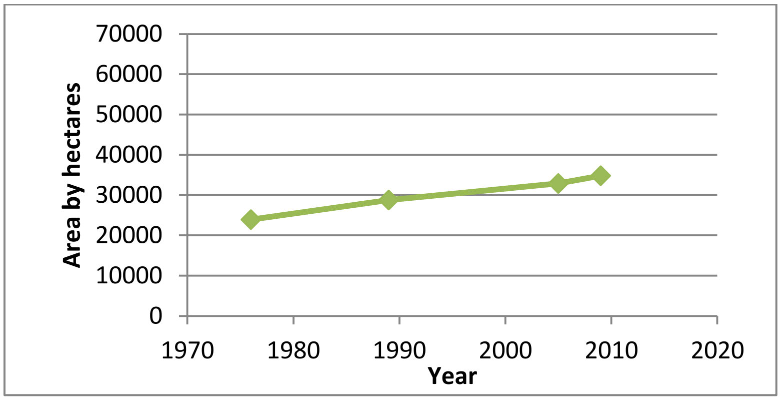
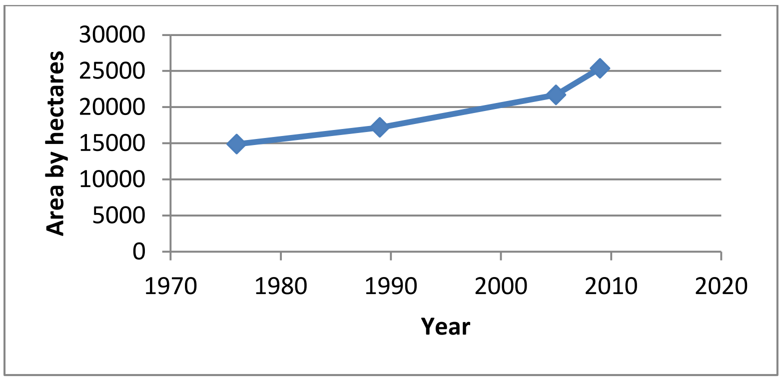


Figure 4.10 illustrates the bare area class at T1, T2, T3 and T4



4.3 Second model: Fuzzy c-means (FCM)

As was explained in chapter 2 (section 2.4), one of the most commonly used fuzzy classification methods is the fuzzy c-means (FCM) classifier (Fisher et al., 2007), which has been applied successfully to a number of problems relating to feature analysis, clustering and classifier design, in applications such as remote sensing, agricultural engineering, land use/land cover, geology, image analysis, and shape analysis (Deer, 1998). It is a clustering algorithm that has commonly been adapted for supervised classification of remotely sensed imagery (Deer and Eklund, 2003; Foody, 1996). The modification from unsupervised to supervised classification engages the specification of fuzzy means and sometimes also fuzzy covariance matrices, and needs just a single pass of the data through the algorithm (Deer and Eklund, 2003; Foody, 2000). The Parabat software was used to implement the fuzzy c-means classification using the same classes and the same training data.

4.3.1 Results of fuzzy c-means model

Generally the images in Figure 4.11 below show the results of fuzzy c-means classification for all classes – urban areas, woodland, vegetation, grazing land and bare land – at times T1, T2, T3 and T4. From Figure 4.11 it is clear that the urban class increases from time T1 (1976) to T4 (2009) whereas the woodland class decreases at the same time. In fuzzy c-means can set the control / fuzziness parameter (M), we want to identify a specific number of classes, we will always end up with the same number of classes and the fuzzy membership in any pixel is just related to the input data and the output is the fuzzy membership, so the main distance that will occur will be the numerical value of the memberships in the transition zones, but all this does is fluctuate the values around the transitions. The parameter of M is constant and the value of M is between 0 and 1. The fuzzy c-means classification was done many times with different values of M. This study concludes that when M is low, near to 0, there are many memberships, giving a hazy classification. When M is high, near to 1, the result is that there is only one membership for every class, which means that the classification will change from fuzzy to Boolean. But when M is at the middle, 0.5, this study found that this is the best result and every class is represented by membership in the pixel.

Figure 4.11 illustrates fuzzy c-means classification at different times: T1,T2,T3 and T4

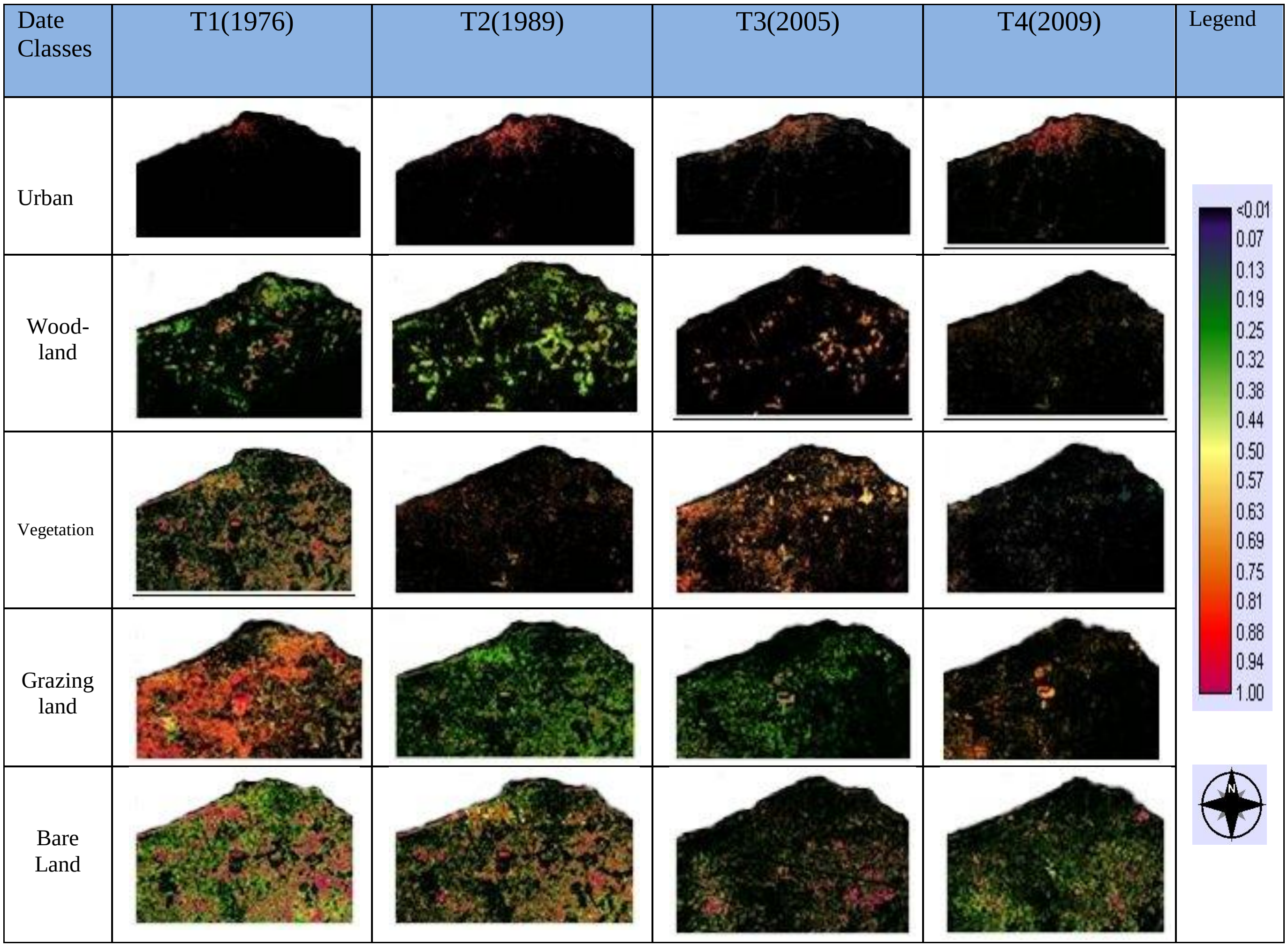


Figure 4.12(a) shows the distribution of membership for the urban class, which increases gradually from 0 to 1. Figure 4.12(b) shows the distribution of membership for the woodland class. Table 4.6 below shows the area of classes by hectares at different dates – T1, T2, T3 and T4 – by using the fuzzy c-means method. From Table 4.6 below it is clear that the urban area is small at T1 (6475.1 hectares), increases at T2 and T3, and is large at T4 (35760.2 hectares). In the woodland class, the highest area is at T1 (56913.2 hectares) and the lowest area is at T4 (22567.4 hectares), which means that the area of woodland decreases from T1 to T4. In the vegetation class

the area at T1 is quite high (60945.8 hectares) while at T4 it is 42761.7 hectares. In the grazing land class the lowest area is at T1 (25879.5 hectares) whereas at T4 it is 28563.8 hectares; and the bare area is 26932.1 hectares at T1 and increases to 47156.6 hectares at T4.

Figure 4.12(a) shows the distribution of membership for the urban class

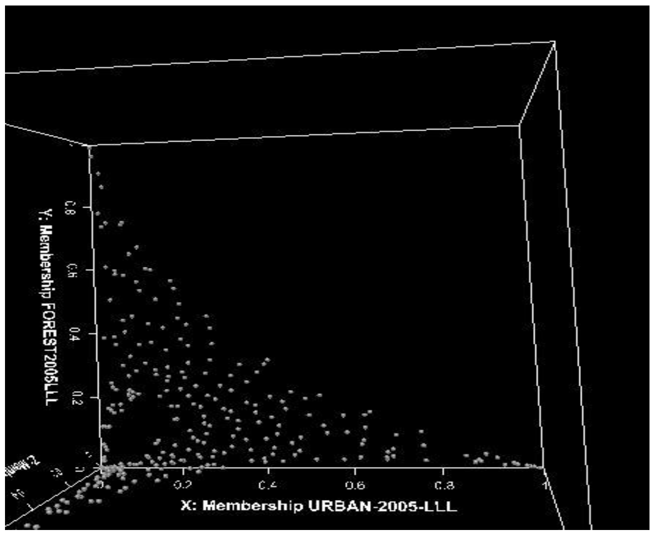


Figure 4.12(b) shows the distribution of membership for the woodland class

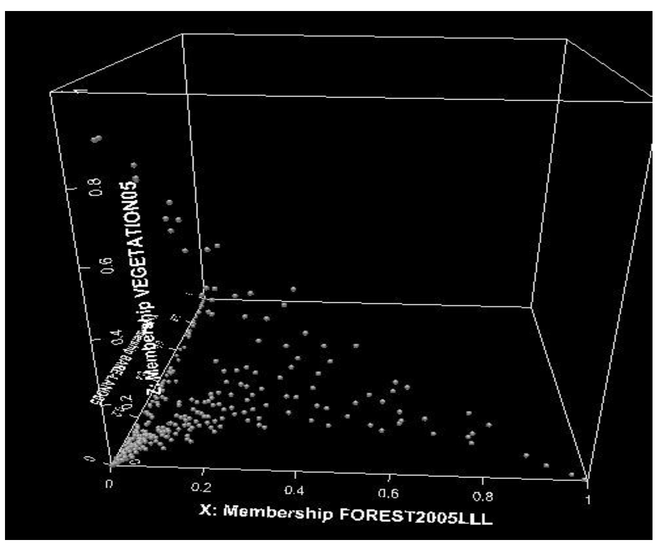


Table 4.6: The area of classes by hectares at different dates (Fuzzy c-means)

Classes	1976 MSS	1989 TM	2005 ETM	Spot 5-2009	Difference 2009-1976
Urban area	6475.1	15809.7	23834.5	35760.2	29285.1
Woodland	56913.2	31638	24355.8	22567.4	-34345.8
Vegetation	60945.8	45980.3	38541.8	42761.7	18184.1
Bare area	26932.1	28769.3	45376.5	47156.6	20224.5
Grazing land	25879.5	52714.7	41966.9	28563.8	2684.3

4.4 Third model: Boolean classification

As was explained in chapter 2, in Boolean classification in remote sensing, discrete pixels are used, i.e. the result is only one class per pixel. Much information about the memberships of the pixels to other classes is lost. Mixed pixels occur because the pixel size may not be fine enough to capture the detail on the ground necessary for specific applications, or where the ground properties, such as vegetation and soil types, vary continuously, as they do almost everywhere. This problem of mixed pixels, of course, also occurs along the boundaries between different land-cover classes. In zones of highly heterogeneous land use such as suburban areas, the occurrence of mixed pixels often makes it difficult to obtain spectrally dissimilar class signatures, and may ultimately lead to a low proportion of correctly classified pixels. Problems with Boolean classification methods are mostly due to the inability of these methods to deal with attribute uncertainty for individual pixels. This is reflected in the methods that are used for the determination of class signatures as well as in the classification procedures themselves. In supervised classification the explanation of every class is based on the statistics obtained from a set of training pixels which are considered to be representative for that class. Fuzziness proposes that a specified pixel, owing to its spectral reflectance properties, may be located in more than one spectral class. The product of a fuzzy classification is a set of images (one per class) that express for each pixel the degree of membership in the class in question. Soft classifiers can be useful in delineating woodland boundaries, shorelines and other continuous classes. They can also bring out objects that cover small areas, which would have disappeared with conventional classifiers. In training and testing of a classification, mixed pixels are usually avoided. But it may be difficult to acquire a training set of an appropriate size if only pure pixels are selected for training, since large homogenous regions of each class are needed in the image. The training statistics obtained may not be fully representative of the classes and may therefore provide a poor base for the remainder of the analysis. According to Jensen (2004), the Boolean decision rule is based on probability, where, first, the probability of each pixel belonging to each predefined class is calculated, and then each pixel is assigned to the class with the highest probability. It is a parametric technique that assumes normally distributed remote sensing data and is one of the most widely used supervised classification algorithms. The same training set as used in the fuzzy set classification was used in the IDRISI software to perform a Boolean classification with the maximum likelihood algorithm.

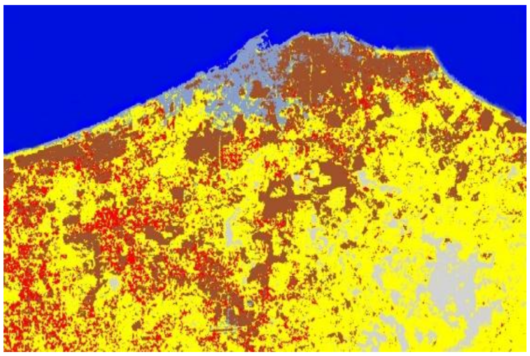
4.4.1 Results of Boolean classification

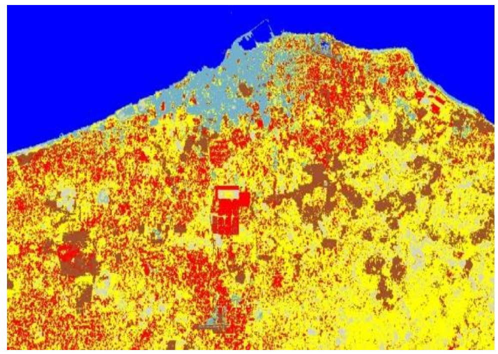
Figures 4.13(a), 4.13(b), 4.13(c) and 4.13(d) show the classified images produced by the Boolean classification model in 1976, 1989, 2005 and 2009; from the Figures it is clear that the urban class increases while the woodland decreases. Table 4.7 below shows the area of classes in hectares at different dates using Boolean classification. The area of the urban class is 13780.2 hectares at T1 (1976), starts to increase at T2 (1989) (19187.8 hectares), and is 32161.3 hectares at T3 (2005) and 39874.9 hectares at T4 (2009); the difference in area between T1 and T4 is equal to 26094.7 hectares, which means that in thirty-three years there has been a huge increase in the area of the urban class. Table 4.7 also shows that the area of woodland is 40821.5 hectares at T1

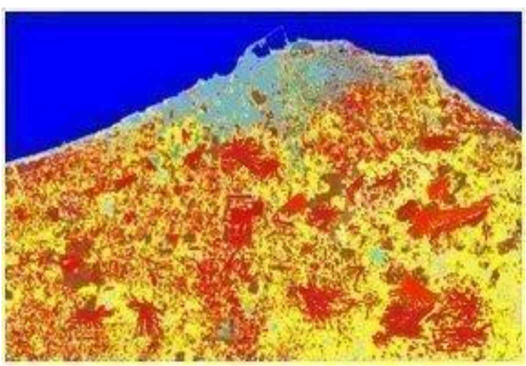
(1976), then starts to decrease at T2 (1989) (25193.9 hectares), and is 18187.1 hectares at T3 (2005) and 16673.4 hectares at T4 (2009); the difference in area between T1 and T4 is equal to 24148.1 hectares, which means that in thirty-three years there has been a huge decrease in the woodland class.

Figure 4.13(a) illustrated Boolean classification 1976

Figure 4.13(b) illustrated Boolean classification 1989







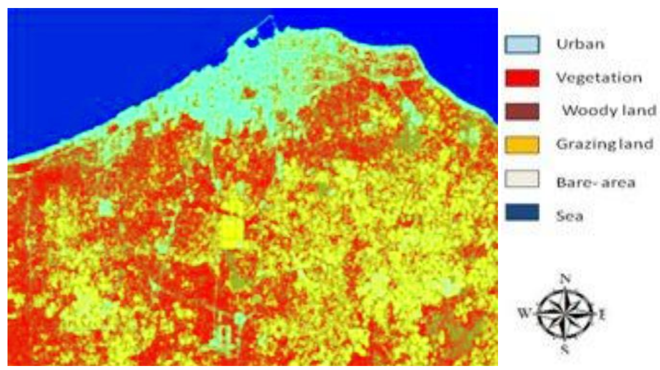


Figure 4.13(c) illustrated Boolean classification 2005

Figure 4.13(d) illustrated Boolean classification 2009

Table 4.7: Shows the area of classes by hectares at different dates using maximum likelihood classification.

Classes	1976 MSS	1989 TM	2005 ETM	Spot 5-2009	Difference 2009-1976
Urban area	13780.2	19187.8	32161.3	39874.9	26094.7
Woodland	40821.5	25193.9	18187.1	16673.4	-24148.1
Vegetation	70316.7	51290.8	46539.7	48563.6	-21753.1
Bare area	21766.9	37855.2	29845.3	32762.7	10995.8
Grazing land	30419.3	41914.5	52317.1	38439.3	8020

4.5 Uncertainty

Interest in uncertainty in geographical information systems has increased since data errors may lead to incorrect results and to wrong conclusions. Thus a complete GIS analysis includes some accuracy assessment. The more accurate the map of land cover is, the less uncertainty it has (Foody, 2002). Users should be aware that any model of the massively complex real world requires abstraction and generalization, and therefore all maps are no more than acceptable representations of the mapped phenomenon (Fisher, 1989 and Pathirana). The absolute uncertainty defined by Shi (1998) and the relative maximum probability deviation present similar uncertainty information.

Fisher (2003) introduces the similarities among uncertainty and data quality components, pointing out their insufficiency in describing the quality of indeterminate objects. Different methods have been suggested to manage the uncertainty. They all find the correct conceptualization of and insight into the nature of uncertainty fundamental to an understanding of the problem. Any user using uncertain information needs to think carefully about the possible causes of uncertainty and how they could be addressed (Fisher, 1999).

It is possible to divide uncertainty into ambiguity and vagueness (Klir and Folger, 1988). Ambiguities arise when different perceptions of the same phenomena exist, for instance classifications according to different applications (Virrantaus, 2003). For example, in remote sensing, land cover is often mapped using Boolean classification (in which each pixel in an image is allocated to one of several classes). Each hard allocation is made with some ambiguity, as it is possible to allocate the pixel quite reasonably to more than one class. Vagueness, on the other hand, relates to the poor definition of the class of an object (Fisher et al., 2006); such uncertainty is not well treated by Boolean classifications, but is by fuzzy or rough sets. For instance, in remote sensing, land cover often varies continuously from place to place (e.g. transition zones or ecotones). In these circumstances, it is more appropriate to define the categories as fuzzy as Boolean. This fuzziness allows for an expression of vagueness.

The uncertainty present in the land cover class can be measured by calculating the confusion index. The confusion index (CI) is the ratio of the second highest class membership value to the highest. The higher the CI, the greater the uncertainty. The confusion index value is on a scale from 0 to 1. The confusion index (CI) can be represented by equation 4.1:

$$Ci = \frac{P2(i)}{P1(i)} \qquad (4.1)$$

where *P2* is the second maximum membership value, *P1* is the maximum membership value and *i* is the pixel index. Table 4.8 shows an example of calculating the confusion matrix for only 12 pixels. In some cases the resulting confusion matrix is low, which means good classification, and in some cases the confusion matrix is high, which means bad classification. The confusion matrix was calculated for all the field points (210) and is included in an appendix at the end of this thesis.

Table 4.8 illustrates the amount of uncertainty using the confusion index (eq.4.1)

Pixel	Class					Maximum Membership Class	Second Highest	Confusion index
	Urban	Vegetation	Wood-land	Grazing land	Bare area			
1	0.103	0.189	0.673	0	0.032	0.673	0.189	0.280
2	0.811	0	0	0.187	0	0.811	0.187	0.219
3	0	0.076	0.216	0.053	0.651	0.651	0.216	0.331
4	0.112	0.372	0.215	0.185	0.11	0.372	0.215	0.577
5	0.265	0.473	0.147	0	0.112	0.473	0.265	0.560
6	0	0.365	0.312	0.143	0.175	0.365	0.321	0.879
7	0.2	0.021	0.654	0.029	0.095	0.654	0.2	0.305
8	0.741	0	0.132	0.073	0.121	0.741	0.132	0.177
9	0.053	0.742	0	0	0.132	0.742	0.132	0.178
10	0	0.217	0.564	0	0.214	0.564	0.217	0.384
11	0	0.234	0.217	0.121	0.547	0.547	0.234	0.427
12	0.659	0	0.105	0	0.225	0.659	0.225	0.341

4.6 Discussion

This study used three approaches for classification at different times and gives different results. The results from the fuzzy set approach showed that using fuzzy approach may generate better results than a Boolean classification of a satellite image to map land cover classes. The major reason is that fuzzy operators can resolve overlapping problems better than Boolean operators. A pixel is no longer measured as indecomposable, and information in a pixel can be processed further for many applications such as change detection. The results also show that the output of a Boolean classification method is of poor quality in the boundary zones, for example, in differentiating vegetation and grazing land.

The uncertainties of bare land and vegetation were found to be high because of the complex area and mixed pixels between vegetation and grazing land. The uncertainties associated with the urban class and woodland classes were low.

From Tables 4.5, 4.6 and 4.7 it is clear that there is little difference between the results from the fuzzy set model and fuzzy c-means, while in the Boolean model there is a difference; for example, the area of the urban class in classified image T1 (1976) is 9104.8 hectares according to the fuzzy set model and 6475.1 hectares according to the fuzzy c-means, while in the Boolean classification it is 13780 hectares. From the image classification for the three models, as explained above in Figures 4.5, 4.11, 4.13(a), 4.13(b), 4.13(c) and 4.13(d), it is clear that using fuzzy sets and fuzzy c-means makes more information available about the land cover features, with membership graded from 0 to 1, whereas using Boolean classification has limitations, small features will disappear, and the membership value of a pixel is 0 or 1 only. Furthermore, when using Boolean classification the boundary between sets is clearly defined, while with fuzzy logic there is a transition zone where one set has a lower membership grade in relation to the other. Also, the result of image classification has shown that fuzzy set theory can deal with images containing a complex mixture of spatial and spectral information. Unlike the Boolean classifiers, the fuzzy c-means clustering algorithm assigns multiple memberships to a pixel to represent land use class mixtures and intermediate conditions.

4.7 Conclusions

In this chapter, three land cover classification techniques have been presented and implemented: Fuzzy sets, fuzzy c-means and Boolean classification. Chapter 8 compares three land cover classification techniques: fuzzy sets, fuzzy c-means and Boolean classification. The advantages of soft classifiers are that small classes will not vanish as they do with maximum likelihood classification, and they give a measure, not in whole pixels, of the occurrence of the classes. The results show that fuzzy classification deals with uncertainty and gives information about boundary transition. To receive an acceptable classification result, the training areas need to be spectrally separable. This can be done with clustering or expert knowledge. It is also necessary to collect enough training areas to obtain the spectral variation of each class.

The main advantages derived from applying the fuzzy approach to land cover change in the study area, as with the fuzzy set methodology, are the ability to define the uncertainties associated with describing the phenomenon itself and the ability to take into consideration the effect of land properties which happen to have values close to category boundaries. The main conclusion in general of this study is that fuzzy classification (fuzzy set and fuzzy c-means) theory overcomes the weaknesses of Boolean classification by accounting for soft class boundaries due to the inherent ambiguity and vagueness of the landscape structure. Each location in the landscape can be a partial member of one or more landform classes, as indicated by continuous degrees of membership in the range [0, 1], with 1 equal to a prototypical or full membership, and 0 equal to non-membership.

Chapter 5: Fuzzy and Boolean Change

5.1 Overview

This chapter will calculate fuzzy and Boolean change from the baseline mappings (Chapter 4) in order to determine the amount of fuzzy gain and fuzzy loss in every class for the study area. Analysis of change in multi-temporal fuzzy classifications is less well known than analysis of Boolean change and will be presented in this research. Fuzzy logic is based on intersection operations, including minimum and composite operator; this research will show the amount of change in the study area. Chapter 4 defined five land classes: urban areas, vegetation, woodland, grazing land and bare areas. These classes have been produced from different multi-temporal images at times T1 (1976), T2 (1989), T3 (2005) and T4 (2009), and these images have been classified by using two models, fuzzy sets and fuzzy c-means, as described in Chapter 4.

In this chapter three models have been used to determine the fuzzy change. The first model (the Mamdani method) is dependent on fuzzy objects by converting the pixels and sub-pixels to polygons which have the same membership values. In this method, land cover is regarded as a set of polygon objects rather than crisp objects. The fuzzy land cover is derived from a fuzzy classification. The degree of change is then calculated using fuzzy reasoning of land cover based on fuzzy change. In this method, land cover is directly represented as fuzzy spatial objects. The second model depends on the sub-pixel change (fuzzy change matrix) for both fuzzy sets and fuzzy c-means to compute the fuzzy change, fuzzy loss, fuzzy gain and boundary; these will be explained in Section 5.5.1 in more detail.The third model is Boolean change, which depends on pixel-by-pixel change from one time to the next.

5.2 First Method (fuzzy object)

5.2.1 Introduction

Fuzzy spatial objects are objects which depend on converting the fuzzy membership to a polygon, which could be a settlement, woodland, bare area or grazing land that has the same membership value. They can be used to compare maps containing a complex mixture of spatial information and can determine the amount of fuzzy change. Edwards and Lowell (1996) pointed out that, by using a fuzzy implication algorithm, fuzzy objects can be evaluated to identify the sections that are different due to error and those that are different because of actual land use disagreement. The flexibility of a fuzzy representation of land use patterns offers the potential for avoiding the problems in the traditional comparison procedures.

5.2.2 Method

A methodology for change detection is proposed, based on fuzzy change objects, and consists of the following steps: (1) calculation of membership differences; (2) conversion of membership (sub-pixel) to polygons; (3) use of inference rules.

5.2.2.1 Calculation of membership differences

In Boolean change, the membership values of every land cover are derived. The variation between membership values is either 0, when two land-cover objects have the same class, or 1, when the classes of two land-cover objects are different. If the registration and the classifications are all without error, the change can then be detected directly by the variation between two land-cover images.

In fuzzy sets, the condition is more complex. A pixel might have many membership values. For instance, a pixel has membership values at one time of 0.7 for urban land and 0.3 for vegetation; these change to 0.6 for grazing land and 0.4 for bare areas. There are many possibilities, such as the change from forest to grazing land, and the change from urban to bare areas. When the changes are complex, it is difficult to tell which class has changed. As a result, the differences between the membership values of different classes do not help in change detection. Nevertheless, the differences can be compared if the membership values for one pixel refer to the same class. For instance, if the membership value of a pixel is 0.3 for urban at time T1, and the membership value of that pixel is 0.8 for urban at time T2, then the membership difference (0.5) can be explained as a 50% increase in the degree of urban membership of that pixel between times T1 and T2. In this way, we will create $n*n$ fuzzy comparison maps if there are n land-cover categories.

Figures 5.1(a), 5.1(b) and 5.1(c) below show part of the woodland class at times T1, T2 and T3, in green, with membership values converted to polygons to describe different objects. Figure 5.1(a) shows the polygon object woodland class in 1976, Figure 5.1(b) shows the woodland class in 1989, and Figure 5.1(c) shows the woodland class in 2009. In Figure 5.1(a) we can see a lot of green, which means that much of the area is woodland; in Figure 5.1(b) the green colour has started to reduce, which means that the woodland class is decreasing, and in Figure 5.1(c) the green colour has reduced further.

Figure 5.1(a) Sample area of woodland 197

Figure 5.1(b) Sample area of woodland 1989

Figure 5.1(c) Sample area of woodland 2009

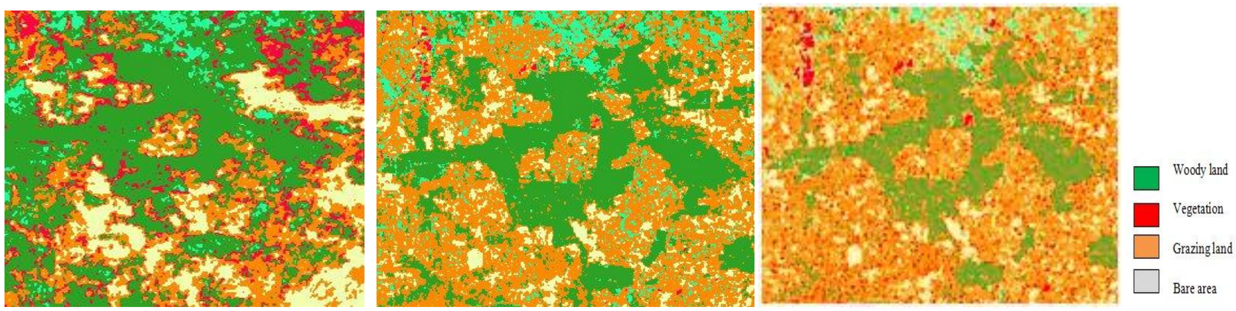


Figure 5.1 Sample of woodland area at time 1976, 1989 and 2009

5.2.2.2 Reasoning of land-cover changes

The current study uses a fuzzy inference system to compute the degrees of change between land cover maps using linguistic variables that are represented by membership functions. By converting the linguistic expressions into membership functions, the degree of change will be produced from the input maps. There are two fuzzy reasoning methods, namely the Mamdani and Tsukamoto methods (Zimmerman, 1985). The Mamdani reasoning system is a rule-based decision model that generates mathematical organized statements as output membership functions, to handle the interactions of the inputs to the system. Tsukamoto is a method for fuzzy object approaches, but this method does not have fuzzy membership functions as an input; it gives the result in the form of a real number or crisp value.

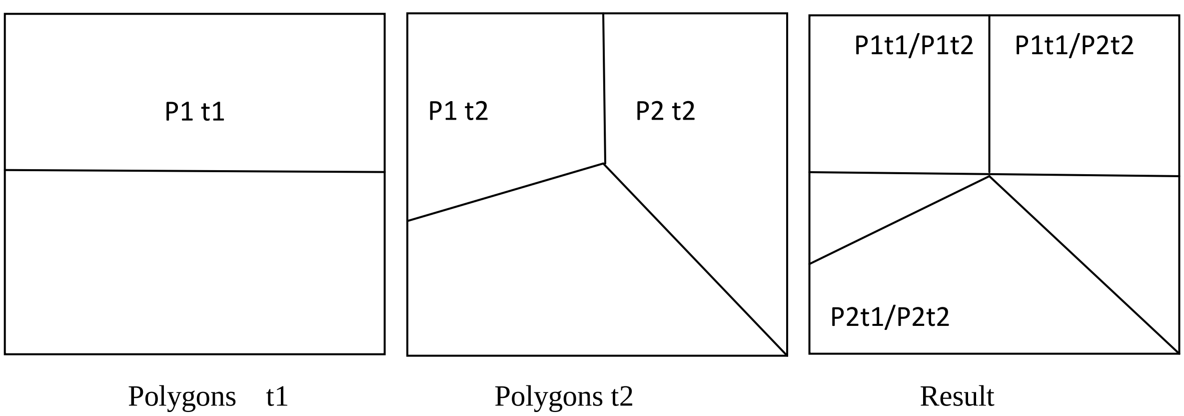
The fuzzy inference system requires a developer to generate both input and output membership functions from linguistic interpretations of a subject. The advantage of Mamdani's fuzzy inference system is that the fuzzy input and output membership functions are better at handling fuzziness and data uncertainty, and are improved with human input. Unlike the Mamdani system, the

Tsukamoto system does not include output fuzzy membership functions and cannot give information about uncertainty. This system cannot propagate fuzziness from input to outputs in an appropriate way. For this reason, the Mamdani method is chosen for reasoning about degrees of change of land cover.

5.2.2.3 Average of membership values

If the classifications and membership values, as well as the registration, are all error-free, then comparisons can be made directly from the differences in *n* land cover classes (Power et al., 2001). The fuzzy polygons are identified by the intersection between the old land-cover map at T1 and the new land-cover map at T2. By intersecting each polygon with the comparison maps, the result will give new polygons indicating the amount of change between T1 and T2, as shown in Figure 5.2.

Figure 5.2 The results of different polygons at time T1 and time T2



5.2.2.4 Creation of membership functions

The creation of input membership functions depends on the development of a linguistic scaling of the degree of change of the polygons from the membership values of these polygons. Semantic expressions are required as answers to the question, ‘To what extent has the land cover changed for a specific polygon?’ A five-point scale is generated, from a tiny change to a medium change to a huge change, in the variations in membership of polygons.

The meanings of these scaling values are as follows:

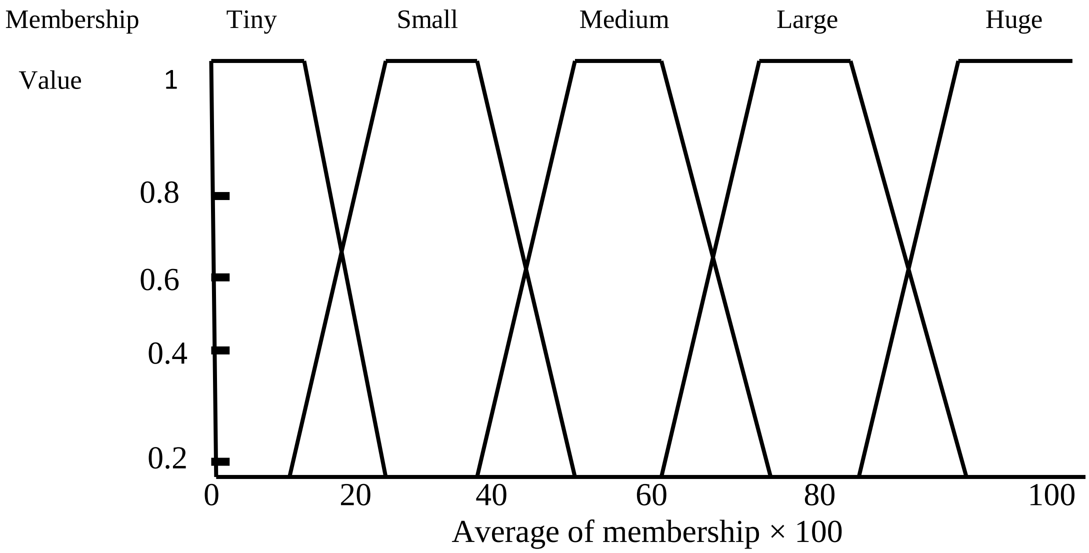
The maximum difference is 100, representing a total change from one land cover to another. Five linguistic terms are designed to represent the membership differences: tiny, small, medium, large and huge (Table 5.1). A trapezoidal membership shape was used in this study, as was explained in Chapter 3.

Table 5.1 Types of membership difference (Tang et al., 2005)

Type	Description	Value
Tiny	The average of the membership differences is very small	0 - 14
Small	The average of the membership differences is small	15 - 45
Medium	The average of the membership differences is medium	35 - 65
Large	The average of the membership differences is large	55 - 85
Huge	The average of the membership differences is very large	75 - 100

These membership functions match human intuition about the magnitude of difference. If the difference is less than a small value, then the difference is tiny. If the difference is greater than a large number, then the difference is huge. The transition between these linguistic terms is smooth. Figure 5.3 shows the membership function of input variable membership difference.

Figure 5.3 Membership function of input variable membership difference (Tang et al., 2005)

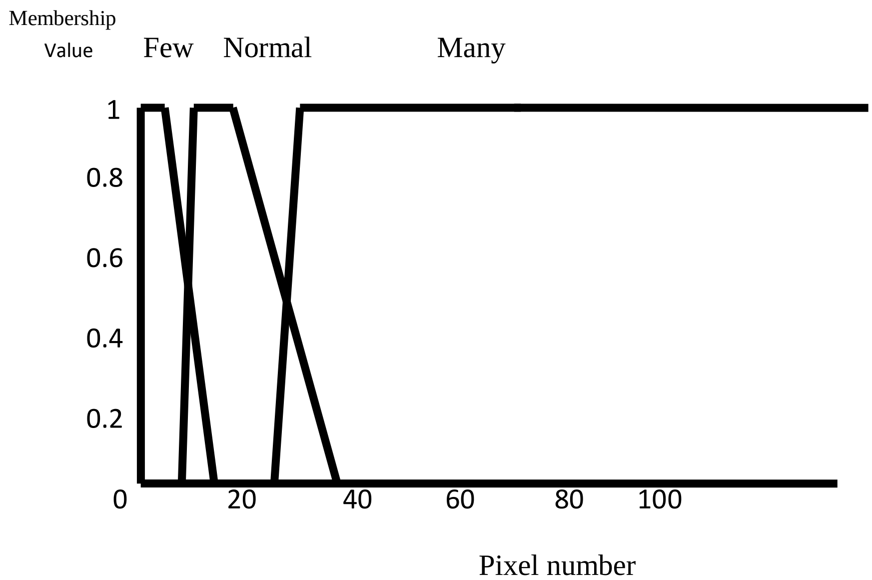


Similar membership functions are adopted to represent the linguistic terms for the polygon area, which is converted to pixel numbers. Following the idea of Power et al. (2001), three linguistic terms are designed to represent the pixel numbers: few (0–40), normal (20–50) and many (60-100), as shown in Figure 5.4. For the output, five linguistic terms are used to represent the degree of change for the land cover categories: tiny, small, medium, large and huge.

5.2.2.5 Inference rules

The most important part of a fuzzy inference system is a set of fuzzy rules that are associated by means of a fuzzy implication function and a compositional rule of inference. Fuzzy rules are a collection of linguistic 'if-then' statements that explain how a fuzzy inference system makes a decision about categorizing an input or controlling an output. The implication is that this process defines the relations between the input membership functions and determines the result of a rule. Furthermore, the fuzzy implication of a rule depends on its 'if-then' connective operator, which expresses how a fuzzy rule is delineated by a fuzzy relation.

Figure 5.4 Membership function of input variable pixel number (Tang et al., 2005)



The premise variables *a* and *b* of the rules are associated by the minimum operator *min (a, b)*. The fuzzy rules are expressed as: IF *a and b, then c*. Fifteen rules are adopted subjectively for the fuzzy reasoning (Table 5.2). They are in the form 'If the membership difference is tiny, and the pixel number is few, then the degree of change is tiny' (rule 1). For instance, rule 4 reads 'If the membership value difference is large, and the pixel number is few, then the degree of change is small'.

5.2.2.6 Composition of results of fuzzy reasoning

The reasoning is individually processed for each category of fuzzy land cover. Therefore, we will obtain *n* results of degree of change for *n* land cover categories.

Table 5.2 Reference rules for first-step reasoning (Tang et al., 2005)

Rule no.	Membership difference	Pixel number	Degree of change
1	Tiny	Few	Tiny
2	Small	Few	Tiny
3	Medium	Few	Small
4	Large	Few	Small
5	Huge	Few	Medium
6	Tiny	Normal	Tiny
7	Small	Normal	Small
8	Medium	Normal	Medium
9	Large	Normal	Medium
10	Huge	Normal	Large
11	Tiny	Many	Tiny
12	Small	Many	Small
13	Medium	Many	Medium
14	Large	Many	Large
15	Huge	Many	Huge

Where the polygons overlap with each other, the result is also overlapping. That is, we will obtain two results for each pixel, showing the degree of change. In order to determine the degree of change for each polygon, we have to create a composition of these results. The composition is calculated by the sum of the degrees of change of each land cover category for each pixel. That is, suppose there are *n* fuzzy land-cover categories; the degree of change is given below by the equation 5.1:

$$\mathrm{CD} = \sum_{i=1}^{n} \mathrm{zi} \qquad (5.1)$$

where *CD* is the value representing the categorical degree of change, and zi is the value of the degree of change for each land cover object.

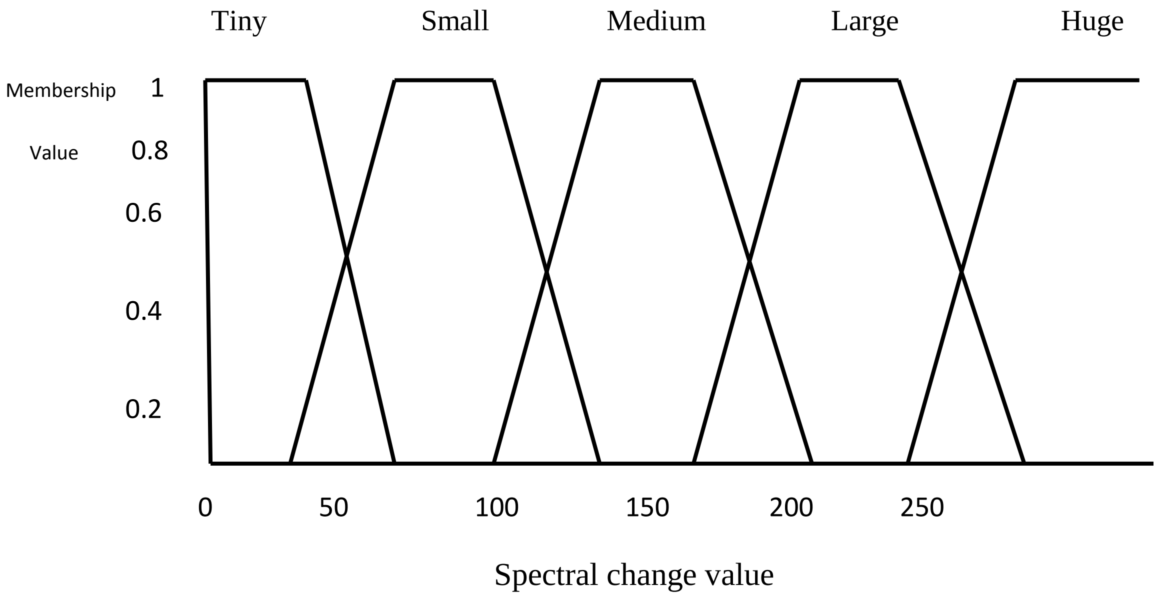
5.2.2.7 Reasoning of land cover changes with incorporation of spectral value differences

The result after the above reasoning shows the degree of change of land cover objects based on categorical polygons. If the categories are suitably classified, and membership values at each pixel are accurately calculated, then the above result is able to show the degree of change of land cover. However, there are always errors in image classification. The fuzzy land cover objects include errors in categories as well as in membership values. The input linguistic variables are the categorical degree of change and the spectral value differences. The study area contains a lot of mixed pixels; it is important to analyse the spectral value difference, because it is allows us to identify and recognize heterogeneous pixels and to compute a membership value for each pixel. The values of spectral changes are derived from the comparisons between two images. The input of the spectral value change for the fuzzy reasoning is represented by five linguistic terms: tiny, small, medium, large, and huge. The meaning of these terms is explained as:

- tiny: the spectral value change is tiny;
- small: the spectral value change is small;
- medium: the spectral value change is medium;
- large: the spectral value change is large;
- huge: the spectral value change is very large.

The membership functions of these five terms are illustrated in Figure 5.5. For example, ‘if the spectral value change is large, and the categorical change is tiny, then the degree of change is small’. This is because, although the spectral value change is large, it can refer to the same land cover. Therefore, the degree of change is still classed as small.

Figure 5.5 Membership functions of input variable spectral value change (Tang et al., 2005)



5.3 Results for fuzzy objects

Tables 5.3 and 5.4 shows the changes based on the new land cover map and the net change percentages. Percentage 1 is the percentage increased in land cover from other land cover types. Percentage 2 is the percentage decrease in land cover into other types. The net change is percentage 1 minus percentage 2. This shows that, over thirty years, woodland decreased by 27% according to the fuzzy set model and 30.6% according to the fuzzy c-means model, and the urban class increased by 56.9% according to the fuzzy set model and 46.6% according to the fuzzy c-means model. Grazing land increased by 22.4% according to the fuzzy set model and 32.5% according to the fuzzy c-means model, and vegetation decreased by 26% according to the fuzzy set model and 24.9% according to the fuzzy c-means model.

Table 5.3 Percentage change by using fuzzy objects from fuzzy set classification, from T1 (1976) to T4 (2009)

Classes	Total area	Amount of change	Percentage1 Increase in land cover	Percentage2 decrease in land cover	Percentage Net change
Urban	43389.6	28619.4	65.9	9	56.9
Vegetation	39865.3	26741.6	41	67	-26
Woody land	57373.8	19543.3	7	34	-27
Grazing land	55873.3	24769.2	26.8	4.4	22.4
Bare area	43658.4	12970.5	38.5	17.6	20.9

Table 5.4 Percentage change by using fuzzy objects from fuzzy c-means classification, from T1 (1976) to T4 (2009)

Classes	Total area	Amount of change	Percentage1 Increase in land cover	Percentage2 decrease in land cover	Percentage Net change
Urban	47327.9	25373.8	53.6	7	46.6
Vegetation	35674.2	21543.2	35.4	60.3	-24.9
Woodland	61549.5	23962.3	8.3	38.9	-30.6
Grazing land	59836.1	28654.8	47.8	15.3	32.5
Bare area	40187.3	17632.2	43.8	19.6	24.2

5.3.1 Magnitude of change

To quantify the total amount of change, we need to calculate the magnitude of change. This is calculated according to the principle used in spectral change vector analysis.

The amount of change between two fuzzy classified images is calculated using the fuzzy difference operator. This is the summation of absolute difference between membership functions, in each class, at two different times.

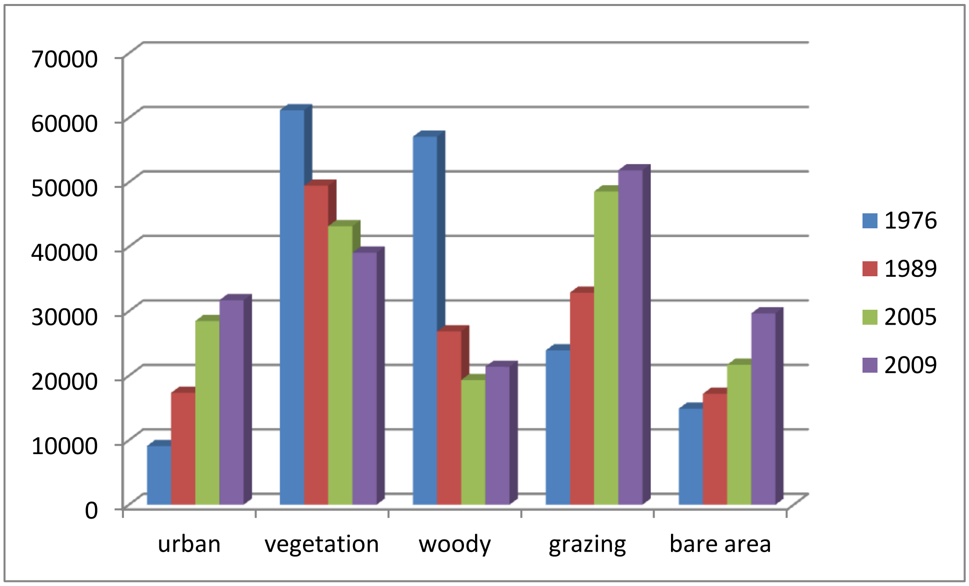
The function used to calculate magnitude of change is given below by the equation 5.2.

$$MC\ (i) = \sum_{c=1}^{k} \mu 1c(i) - \mu 2c(i)/k \qquad (5.2)$$

where $\mu 1c(i)$ and $\mu 2c(i)$ are the membership functions of pixel i of class at date one and date two respectively.

Figure 5.6 shows the area of classes (urban, vegetation, woodland, grazing land and bare area) in hectares between the dates 1976 and 2009, using the polygon change model. From the Figure we can see that the urban class more than doubles, from only 9104.8 hectares in 1976 to 30127.8 hectares in 2009; on the other hand, the woodland decreases from 57063.7 hectares in 1976 to 20376.4 hectares in 2009, which means that the urban increase takes place at the expense of the woodland.

Figure 5.6 The area of all the classes at different times in hectares, using the fuzzy set model



5.4 Second method: Fuzzy change by using pixel change

5.4.1 Method (Fuzzy change matrix)

The second method for evaluating fuzzy change uses a different approach, based on a change matrix, which has been used by Fisher et al. (2006). In this method the logic of change can be expressed basically as those cells where the land cover is Ci at T1 and Ci at T2, which is to explain the intersection of the two sets (Deer, 1998). For off-diagonal cases, the logic is a little different. This study is actually interested in two different classes, Ci at T1 and Cj at T2, and these have to be approached with a different logic. For diagonal elements of the change matrix, this study concerned in Ci at T1 and T2, which is to say the intersection of that cover type at the two times. The standard intersection operator for fuzzy sets is to obtain the minimum of the two fuzzy membership values (Zadeh, 1965; Eq. 5.3). Therefore, if we have 0.4 membership in Ci at T1 and 0.6 membership at T2, the membership of the intersection will be 0.4, which is logical; the lower value records the total unchanged, and therefore this is the operator especially used here for category-to-category comparisons.

The off-diagonal elements of the matrix are a different issue; it is clear that these elements can also be interpreted as the intersection of the two cover types (sets) CiT1 and CjT2 where i≠j, or as the intersection of the gain in Ci and the loss in Cj over the interval T1 to T2.

$$\mu(CiT1, CiT2) = \min\left(\mu(Ci, T1), \mu(CiT2)\right) \qquad (5.3)$$

Figure 5.7 illustrates the changed and unchanged area of all the classes – urban areas, vegetation, woodland, grazing land and bare areas – at different times from 1976 to 2009, by using a change matrix model; from the bar-chart it is clear that there is a large change in all the study area, especially in the urban class and the woodland class.

Figure 5.7 The changed and unchanged area of all the classes at different times

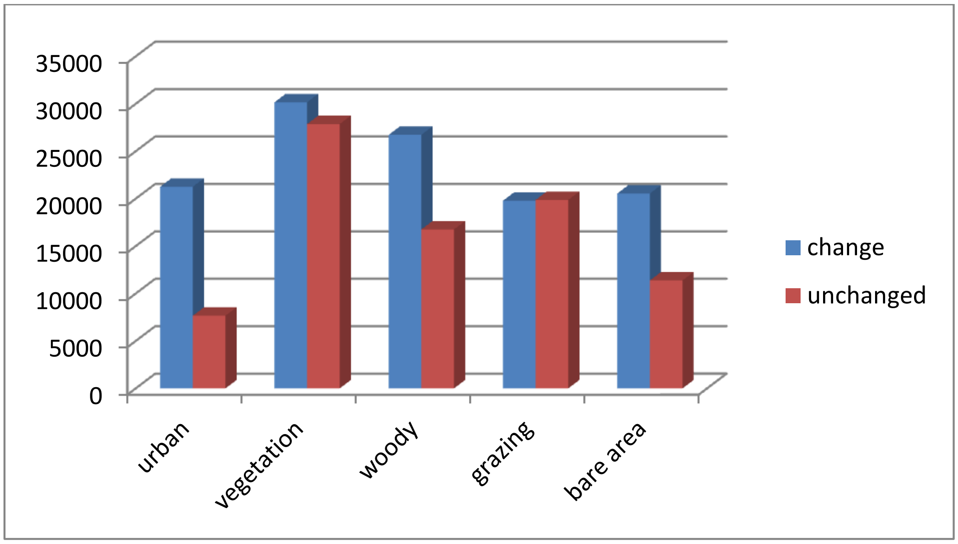


Figure 5.8 shows the fuzzy change matrix for all the classes – urban areas, vegetation, woodland, grazing land and bare areas – in 1976 and 2009 by using fuzzy set model. The intersection between two maps gives the amount of change; for example, the intersection between the urban 2009 and woodland 1976 the area (41760.7 hectares) that means that the woodland change to urban.

One way of visualising the fuzzy change over time it is essential to display ten maps to show the five land covers at the two dates, rather than just two maps. This is because every pixel may contain membership in all five land cover classes at any one date, rather than having just the one land cover class at that date. Moreover, because of the multiple memberships, the spatial change of fuzzy membership is observable and small changes can be traced, as whole zones of modest membership are revealed which never become apparent in the Boolean mapping.

Figure 5.8 illustrates maps of the fuzzy set change table between the fuzzy maps of class types in 1976 and class types in 2009

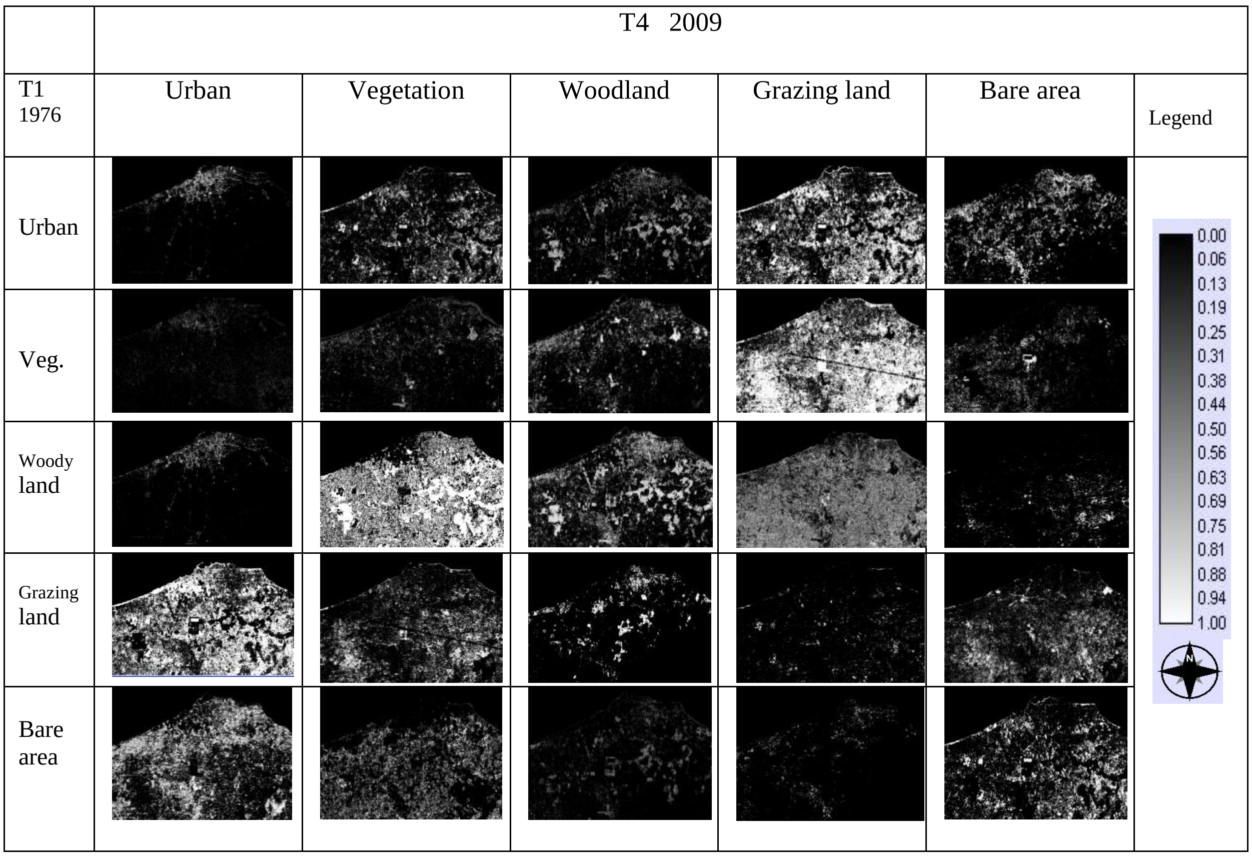
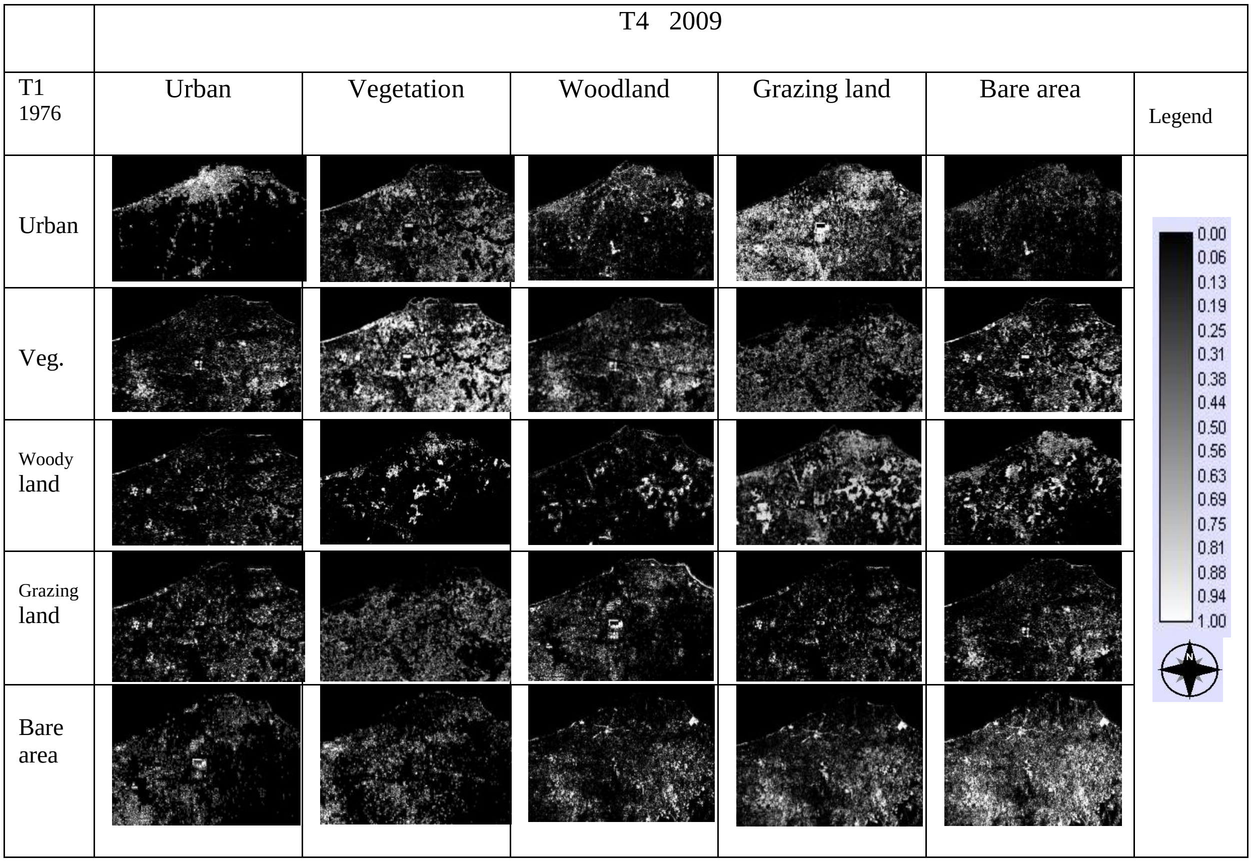


Figure 5.9 shows the fuzzy change matrix for all the classes – urban areas, vegetation, woodland, grazing land and bare areas – in 1976 and 2009 by using fuzzy c-means model. The intersection between two maps gives the amount of change; for example, the intersection between the urban 2009 and woodland 1976 the area (36549.8hectares) that means that the woodland change to urban.

Figure 5.9 illustrates maps of the fuzzy c-means change table between the fuzzy maps of class types in 1976 and class types in 2009



5.5 Result of change matrix

5.5.1 Fuzzy gain and loss

Change in a part-cover type is determined by those positions which at time T1 belong to category C1 and at time T2 do not. The reverse of this query is, of course, those positions which at time T2 belong to category C1 and at time T1 do not. These two questions state the loss and the gain, respectively, of Class C1.

To track this logic, it is first essential to take the inverse of the fuzzy membership of a land cover type: the possibility that the land cover is not present where the normal negation operator is used (Eq. 5.4). It is then possible to model the change in land cover by two steps:

1- The areas which gain land cover category C1 are given by establishing those positions where C1 exists at time T2 but does not at T1: the intersections of the memberships of not-C1 at T1 and C1 at T2.

2- Those areas which lose C1 can be established and the intersection of C1 at T1 and not-C1 at T2.

$$\mu(\neg C1, T1) = (1 - \mu(C1, T1) \qquad (5.4)$$

Fuzzy boundary $$\mu(A \cap B) = max(0, \mu(A) + \mu(B) - 1 \qquad (5.5)$$

$$\mu(GainC1) = \max(0, \mu(\neg C1, T1) + \mu(C1, T2) - 1) \qquad (5.6)$$

$$\mu(LossC1) = \max(0, \mu(C1, T1) + \mu(\neg C1, T2) - 1) \qquad (5.7)$$

For loss and gain, the minimum operator for the intersection is a bit difficult. The problem of the minimum operator for the intersection is explained in Table 5.5. Table 5.5 illustrates a few test values of fuzzy memberships: for example, a location where the membership of the set in question has not changed still has a membership in the intersection, and so would be identified as changed (Table 5.5). Thus, as explained by Fisher et al. (2005), if C1 at T1 has membership 0.6 and at T2 0.6, the inverse at T2 will be 0.4, and the minimum of 0.6 and 0.4 (the intersection or loss of fuzzy land cover) will also be 0.4. A membership of 0.4 in the loss of C1 does not give clear logic, and it should be noted that there will also be a membership of 0.4 in the set of gain positions for the cover class.

Table 5.5 Test of intersection operations: minimum and bounded difference (BD). Note that in every case illustrated in this table, BD (μ(A), μ(¬B))=0

(A)μ	(B)μ	(¬A)μ	(¬B)μ	Min(μ(A), μ(¬B))	Min(μ(B), μ(¬A))	BD(μ(B), μ(¬A))
0	0.2	1	0.8	0	0.2	0.2
0.4	0.6	0.6	0.4	0.4	0.6	0.6
0	0.6	1	0.4	0	0.6	0.6
0.2	0.8	0.8	0.2	0.2	0.8	0.8
0.8	0.6	0.2	0.4	0.4	0.2	0.2
0.8	0.8	0.2	0.2	0.2	0.2	0.2
1	0.8	0	0.2	0.2	0	0
0.4	0.4	0.6	0.6	0.4	0.4	0.4
0	0	1	1	0	0	0
0	0.8	1	0.2	0	0.8	0.8
0.4	1	0.6	0	0	0.6	0.6
0.4	0.8	o.6	0.2	0.2	0.6	0.6
0.6	0.4	0.4	0.4	0.4	0.4	0.4
0.8	1	0.2	0	0	0.2	0.2

Tables 5.6 and 5.7 show the amount of gain and loss in all the classes – urban areas, vegetation, woodland, grazing land and bare areas – resulting from fuzzy set method and fuzzy c-means classifications. There are slight differences between the two sets of results; these differences from many factures such as the methodology of every method (fuzzy sets and fuzzy c-means). From the two tables we can see the lowest value of loss is in the urban class (2534.5 hectares) and the highest loss is in the woodland class (46073.7 hectares); on the other hand the highest value of gain is in the urban class (25095.4 hectares) and the lowest is in the woodland class (7821.8 hectares): these results mean that the urban class increases and the woodland decreases.

Table 5.6 Gain and loss for all the classes from fuzzy set classification

Years	1976-1989		1989-2005		2005-2009		1976-2009	
Loss& Gain classes	loss	gain	loss	gain	loss	gain	loss	gain
Urban	1127.3	9378.1	579.2	11136	876.1	2512.3	2582.6	23605.6
Vegetation	18021	6315.8	10586.5	4320.3	2248.8	789.6	30856.3	11425.1
Woodland	37545.6	7361.2	10214.4	2673.6	651.3	1689.1	46073.7	9386.4
Grazing	2635.1	7492.7	3015.4	7118	865.3	2794.8	6515.8	17405.5
Bare land	923.1	3235.3	1417.5	5913.3	1013.7	4679.6	3354.3	13828.2

Table 5.7 Gain and loss for all the classes from fuzzy c-means classification

Years	1976-1989		1989-2005		2005-2009		1976-2009	
loss&gain classes	loss	gain	loss	gain	loss	gain	loss	gain
Urban	869.1	8946.5	1079.3	12277	586.1	3871.9	2534.5	25095.4
Vegetation	19955.8	8567.3	16422.7	6361.9	6284.8	1663.1	42663.3	16592.3
Woody	35668.3	5439.7	8331	1394.5	3681.6	987.6	47680.9	7821.8
Grazing	1986.4	6936.2	2066.1	6233.7	1674.3	5567.8	5726.8	18737.7
Bare land	1374.7	3955.6	1939.2	6361.6	1369.7	6092.2	4683.6	16409.4

Figure 5.10 shows the fuzzy classification of woodland in 1976 and 2009. From the image there are different colours representing the gain and loss in woodland. On the right side we can see the legend of the map which gradually increases from -1 to 0.97: -1 equivalent black means loss of woodland and 0.97 equivalent red means gain in woodland. From the classified image it is clear that most of the black area represents woodland lost during that period of time. Figure 5.11 illustrates the fuzzy classification of woodland from 1976 to 1989; from the classified image we can see different colours, but the red has increased, showing gain in woodland during that period of time (which is to be expected as government policies resulted in the starting of reforestation)

Figure 5.10 Fuzzy classification of woodland 1976 – 2009: loss (-1) and gain (+1)

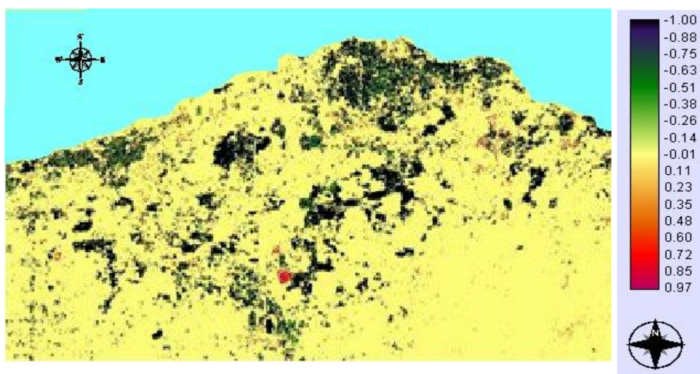


Figure 5.11 Fuzzy classification of woodland 1976 – 1989: loss (-1) and gain (+1)

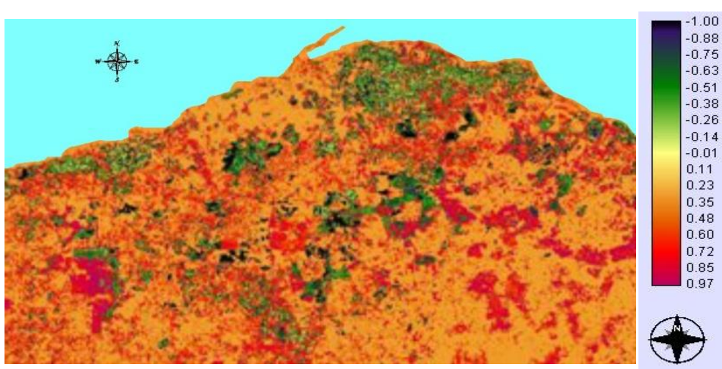


Figure 5.12 shows the fuzzy classification of bare land in 1976 and 2009; from the image there are different colours representing the gain and loss in woodland. On the right side we can see the legend of the map which gradually increases from -1 to 0.97: -1 equivalent black means loss of bare land and 0.97 equivalent red means gain in bare land. From the classified image it is clear that most of the area is black; that indicates the bare land lost during that period of time. Figure 5.13 illustrates the fuzzy classification of urban land from 1976 to 2009; from the classified image we can see different colours, but the red has increased, which means an urban land gain, as new building took place during that period of time. Figure 5.14 shows the vegetation class from 1976 to 2009. From the image there are different colours, red, black and green, which means there was a gain in some areas and a loss in other

Figure 5.12 Fuzzy classification of bare areas 1976 – 2009

Figure 5.13 Fuzzy classification of urban areas 1976 – 2009

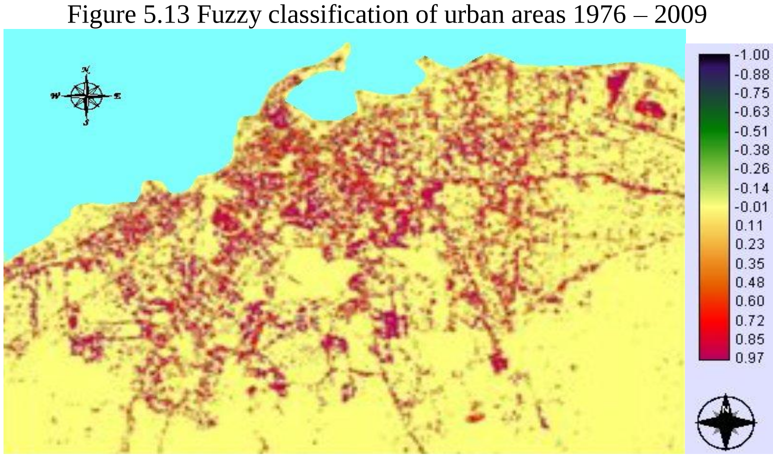


Figure 5.14 fuzzy classification of vegetation 1976 – 2008: loss and gain

5.5.2 Changing fuzzy land cover

The full spatial pattern of change in the fuzzy set is shown in Table 5.8 by using a change matrix model, which explains the intersection between the classes in T1 (1976) and T4 (2009).The amount of fuzzy change is explained in Tables 5.8 and 5.9 below. The amount of gain and loss will be explained in more detail in the section below for both fuzzy sets and fuzzy c-means.

Tables 5.8 and 5.9 show the fuzzy change matrix between T1 (1976) and T4 (2009) resulting from the fuzzy set and fuzzy c-means classifications, which differ slightly between the two models. For example, the intersection between the woodland class in T1 and the urban class in T4 is 16539.8 in the fuzzy set change matrix, while in the fuzzy c-means matrix it is 20587.3. That means the area of woodland in T1 changed to urban in T4.

Table 5.8 Fuzzy change matrix from fuzzy set classification

Years	2009					
1976	Classes	Urban	Vegetation	Woody land	Grazing land	Bare area
	Urban	7342.8	13765.4	16539.8	10842.3	12685.1
	Vegetation	37528.1	25176.3	21032.6	18173.2	29164.4
	Wood land	41760.7	9873.1	19768.3	14649	9873.6
	Grazing land	11875.4	17543.2	12978.5	13061.9	18348.2
	Bare area	18674.3	21564.6	15691.9	11653.7	27357.1

Table 5.9 Fuzzy change matrix from fuzzy c-means classification

Years	2009					
1976	Classes	Urban	Vegetation	Wood land	grazing land	Bare area
	Urban	6745.7	11689.2	20587.3	5873.4	8795.3
	Vegetation	31893.2	19548.7	13874.1	12984.2	21654.8
	Woodland	36549.8	14763.9	16921.8	9874.3	13942.5
	Grazing land	14652.7	12389.3	19844.9	8791.5	22349.2
	Bare area	13987.1	17485.9	11675.3	18764.3	20174.8

5.5.3 Detection, visualisation and assessment of change analysis

When aerial photography is available it could be used to trace membership change by visualization at the same pixel at times T1, T2, T3 and T4. This study sampled some pixel changes at the same location and explains how the pixels change from one class to another at different times, as shown in Tables 5.10 – 5.13 below; these points will be used for accuracy assessment in Chapter 7 where they will be compared with the classified images.

Table 5.10 shows some examples of membership at time T1 (1976) taken from interpretations of aerial photographs. From this Table it is clear that the classes with the highest membership values are woodland, vegetation and grazing land, and the lowest is urban areas, which means that most of the area is covered by woodland, vegetation and grazing land. Table 5.11 shows some examples of membership at time T2 (1989): the membership values of the woodland, vegetation and grazing land have started to decrease and the urban land to increase. Table 5.12 shows some examples of membership at time T3 (2005) in the same location as time T2: there has been a further increase in urban membership and decrease in woodland, vegetation and grazing land. Table 5.13 shows some examples of membership at time T4 (2009): many pixels have changed completely to urban areas, which means that the area of woodland, vegetation and grazing land has changed to urban.

Table 5.10 Interpretations of some pixels from aerial photographs in 1976

East	West	Urban	Vegetation	Woodland	Grazing land	Bare area
306103	3625908	0	0	1	0	0
313942	3625155	0	0.75	0	0	0.25
304480	3631008	0	0	0.65	0.15	0.2
328978	3641311	0	0	0.2	0.65	0.15
313942	3625155	0	0.65	0	0	0.35
332254	3629608	0	0.55	0	0	0.45
306998	3626639	0	0	0.15	0.55	0.3
310893	3618240	0	0	1	0	0
346449	3613481	0	0	0.25	0.5	0.25
344575	3634982	0	0	0	0.55	0.45
328978	3641311	0	0	0.15	0.6	0.25
329008	3641144	0.25	0.55	0	0	0.2
313327	3633219	0	0	0	0.75	0.25
313942	3625155	0	0.85	0	0	0.15

Table 5.11 Interpretations of some pixels from aerial photographs in 1989

East	West	Urban	Vegetation	Woodland	Grazing land	Bare area
306103	3625908	0.35	0	0.5	0	0.15
313942	3625155	0	0.6	0	0	0.4
304480	3631008	0.25	0	0.3	0.1	0.35
328978	3641311	0.2	0	0.15	0.45	0.2
313942	3625155	0.25	0	0	0	0.75
332254	3629608	0.3	0.45	0	0	0.25
306998	3626639	0.45	0	0.1	0	0.45
310893	3618240	0.25	0	0.35	0	0.4
346449	3613481	0.2	0	0.2	0.35	0.25
344575	3634982	0.15	0.2	0	0.25	0.4
328978	3641311	0.35	0	0.1	0.4	0.15
329008	3641144	0.4	0.35	0	0	0.25
313327	3633219	0.15	0	0	0.5	0.35
313942	3625155	0.35	0.3	0	0	0.45

Table 5.12 Interpretations of some pixels from aerial photographs in 2005

East	West	Urban	Vegetation	Wood land	Grazing land	Bare area
306103	3625908	0.55	0.25	0.35	0	0.2
313942	3625155	0.2	0.2	0	0	0.6
304480	3631008	0.35	0	0	0.2	0.45
328978	3641311	0.5	0	0	0.15	0.35
313942	3625155	0.6	0	0	0	0.4
332254	3629608	0.45	0.25	0	0	0.3
306998	3626639	0.7	0	0	0	0.3
310893	3618240	0.45	0.15	0.2	0	0.1
346449	3613481	0.5	0	0.1	0.15	0.25
344575	3634982	0.55	0.15	0	0.2	0.1
328978	3641311	0.6	0	0	0.1	0.3
329008	3641144	0.65	0	0	0	0.35
313327	3633219	0.4	0	0	0.3	0.3
313942	3625155	0.5	0.1	0	0	0.4

Table 5.13 Interpretations of some pixels from aerial photographs in 2009

East	West	Urban	Vegetation	Wood land	Grazing land	Bare area
306103	3625908	0.65	0.1	0.1	0	0.15
313942	3625155	0.55	0.15	0	0	0.3
304480	3631008	0.8	0	0	0.2	0.2
328978	3641311	0.9	0	0	0	0.1
313942	3625155	0.75	0	0	0	0.25
332254	3629608	0.85	0	0	0	0.15
306998	3626639	1	0	0	0	0
310893	3618240	0.9	0	0	0	0.1
346449	3613481	0.8	0	0	0	0.2
344575	3634982	0.9	0	0	0	0.1
328978	3641311	1	0	0	0	0
329008	3641144	0.9	0	0	0	0.1
313327	3633219	0.6	0	0	0	0.4
313942	3625155	0.8	0.1	0	0	0.2

Figures 5.15 and 5.16 illustrate how the same pixel changes over time from T1 (1976) to T2 (1989), T3 (2005) and T4 (2009). Figure 5.15 shows the urban membership in the pixel at T1, T2, T3 and T4: at T1 the urban membership is 0, at T2 the value of the membership has started to increase and is 0.35, at T3 the value is 0.55 and at T4 it is 0.65; this means that most of the pixel changes to ‘urban’. On the other hand, Figure 5.16 shows the same pixel as Figure 5.15: the woody membership at T1 is 1, which means that all the pixel is woodland, while at T2 the value is 0.5, at T3 the value is 0.35 and at T4 the value is only 0.1, which means that this pixel changes from woodland at T1 (1976) to urban land at T4 (2009).

Figure 5.15 shows how the urban membership Change in the pixel at T1, T2, T3 and T4

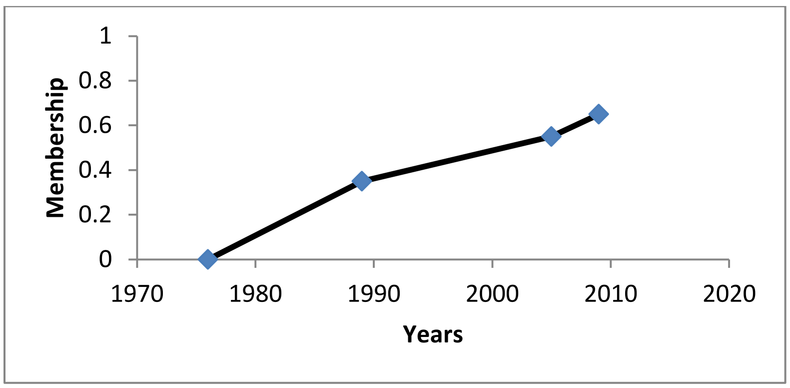


Figure 5.16 shows how the woody membership Change in the same pixel at T1, T2, T3 and T4

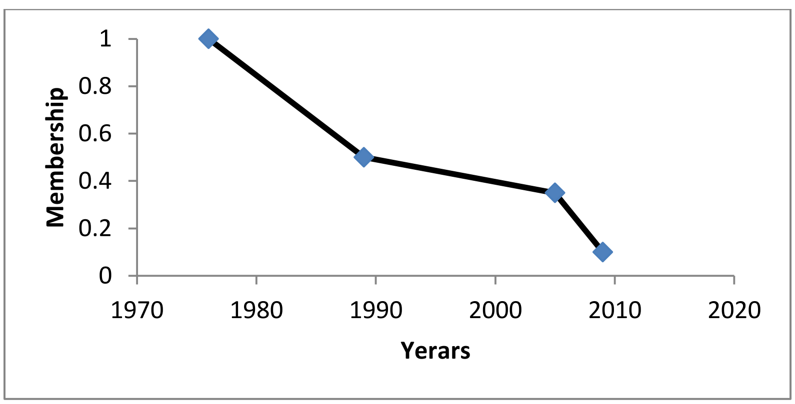


Table 5.14 shows the sequence of results for pixels (urban class) from aerial photographs of the same location at times T1, T2, T3 and T4. From Table 5.16, in which column 1 represents the

pixels from aerial photographs, it is clear that at T1 (1976) most of the area is woodland, grazing land or vegetation, at T2 (1989) the woodland and vegetation start to change to urban areas, at T3 it is the same, (2005) and at T4 (2009) the area changes completely to urban, as shown in column 4. Table 5.15 shows the sequence of results for pixels (vegetation class) from aerial photographs of the same location at times T1, T2, T3 and T4. In Table 5.15, in which column 1 represents the pixels from aerial photographs, at T1 (1976) most of the area is vegetation, then at T2 (1989) the vegetation class starts to change to the urban class, the same situation continues at T3, and at T4 the membership has completely changed to urban. In Table 5.16, in which column 1 represents the pixels from aerial photographs, at T1 (1976) most of the area is woodland, then at T2 (1989) the woodland class starts to change to urban, the same situation continues at T3, and at T4 the membership has completely changed to urban. Table 5.17 shows the sequence of results for the grazing land class.

Table 5.14 The sequence of results for the urban class in the same location at different times (T1, T2, T3, T4)

East	West	Urban76	Urban89	Urban05	urban09
306103	3625908	0	0.35	0.55	0.65
313942	3625155	0	0	0.2	0.55
304480	3631008	0	0.25	0.35	0.8
328978	3641311	0	0.2	0.5	0.9
313942	3625155	0	0.25	0.6	0.75
332254	3629608	0	0.3	0.45	0.85
306998	3626639	0	0.45	0.7	1
310893	3618240	0	0.25	0.45	0.9
346449	3613481	0	0.2	0.5	0.8
344575	3634982	0	0.15	0.55	0.9
328978	3641311	0	0.35	0.6	1
329008	3641144	0.25	0.4	0.65	0.9
313327	3633219	0	0.15	0.4	0.6
313942	3625155	0	0.35	0.5	0.8

Table 5.15 The sequence of results for the vegetation class in the same location at different times (T1, T2, T3, T4).

East	West	Veg.76	Veg89	Veg05	Veg09
306103	3625908	0	0	0.25	0.1
313942	3625155	0.75	0.6	0.2	0.15
304480	3631008	0	0	0	0
328978	3641311	0	0	0	0
313942	3625155	0.65	0	0	0
332254	3629608	0.55	0.45	0.25	0
306998	3626639	0	0	0	0
310893	3618240	0	0	0.15	0
346449	3613481	0	0	0	0
344575	3634982	0	0.2	0.15	0
328978	3641311	0	0	0	0
329008	3641144	0.55	0.35	0	0
313327	3633219	0	0	0	0
313942	3625155	0.85	0.45	0.1	0

Table 5.16 The sequence of results for the woodland class in the same location at different times (T1, T2, T3, T4)

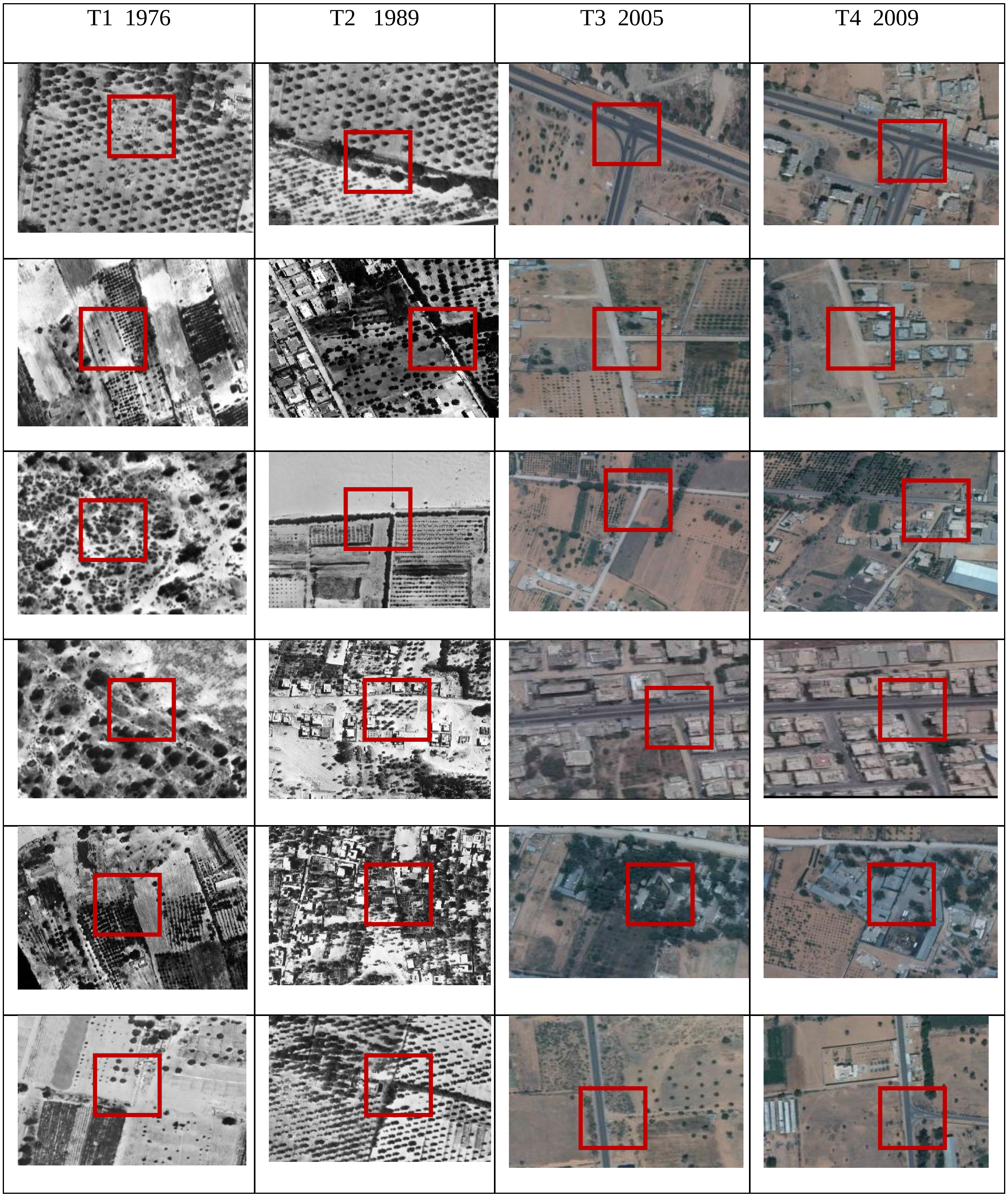
East	West	Woody76	woody89	woody05	woody09
306103	3625908	1	0.5	0.35	0.1
313942	3625155	0	0	0	0
304480	3631008	0.65	0.3	0	0
328978	3641311	0.2	0.15	0	0
313942	3625155	0	0	0	0
332254	3629608	0	0	0	0
306998	3626639	0.15	0.1	0	0
310893	3618240	1	0.35	0.2	0
346449	3613481	0.25	0.2	0.1	0
344575	3634982	0	0	0	0
328978	3641311	0.15	0.1	0	0
329008	3641144	0	0	0	0
313327	3633219	0	0	0	0
313942	3625155	0	0	0	0

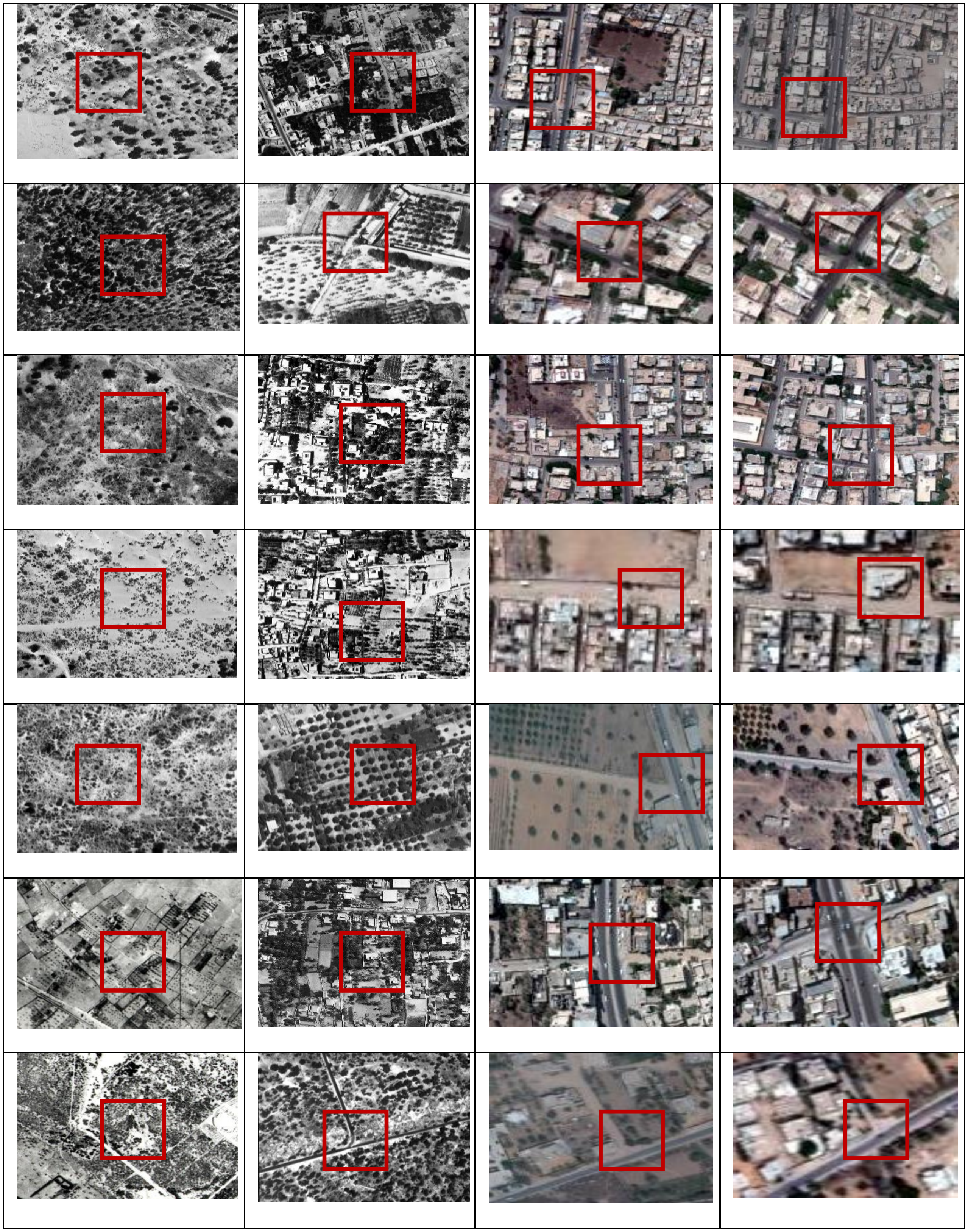
Table 5.17 The sequence of results for the grazing land class at different times (T1, T2, T3, T4)

Urban	West	Grazing76	Grazing89	Grazing05	Grazing09
306103	3625908	0	0	0	0
313942	3625155	0	0	0	0
304480	3631008	0.15	0.1	0.2	0.2
328978	3641311	0.65	0.45	0.15	0
313942	3625155	0	0	0	0
332254	3629608	0	0	0	0
306998	3626639	0.55	0	0	0
310893	3618240	0	0	0	0
346449	3613481	0.5	0.35	0.15	0
344575	3634982	0.55	0.25	0.2	0
328978	3641311	0.6	0.4	0.1	0
329008	3641144	0	0	0	0
313327	3633219	0.75	0.5	0.3	0
313942	3625155	0	0	0	0

Figure 5.17 below shows the sequence of results for pixels from aerial photographs in the same location at times T1, T2, T3 and T4 (the red square). From Figure 5.17 we can see that column 1 represents the pixels from aerial photographs at T1 (1976), when most of the area is woodland, grazing land or vegetation; at T2 (1989) the woodland and vegetation start to change to urban areas; it is the same situation at T3 (2005); and at T4 (2009) the area has completely changed to urban, as shown in column 4.

Figure 5.17 The sequence of results for pixels (red squares) from aerial photographs at different times (T1, T2, T3 and T4)





5.6 Boolean change

5.6.1 Method

Many approaches to change detection have been used, such as those of Coppin et al., (2004) and Jensen (1981), but traditional classification comparison is that where classifications at two different times are evaluated. The common way that the remote sensing community has concentrated on environmental change, where the landscape has been classified into classes of one type or another at two different times, has been through a change detection matrix (Table 5.18; Jensen, 1999; Jensen et al., 1996) similar to the error matrix used in accuracy assessment (Congalton and Green, 1999). In this case the rows show the *i* classes at time T1 and the columns the *j* classes at T2; generally not only does $i=j$, but the sets of possible classes at T1 and T2 are matching. If the classes are not equal, then the more difficult problem of mixed semantics makes analysis complex (Comber et al., 2004a). The cells in the change table explain the areas which were class Ci at time T1, and class Cj at T2. If classes 1 to *i* match classes 1 to *j*, then, for each class, the area that has stayed unchanged is determined by the diagonal elements in Table 5.19; thus for class C1, the area unchanged is given by LC1,1 (Table 5.19). The area of C1 which has become C2 is known as the element LC1, 2, and the area of C1 that has become Cn is known as 'Loss' (C1). The whole area of class C1 which is lost, 'Loss', is given by the total of off-diagonal elements in the row C1 (Eq. 5.8). In contrast, the area of land cover C1 which is gained, 'Gain', is the total of all off-diagonal elements in the column C1 (Eq. 5.9); an area lost from one cover type is gained by another. Lastly it should be noted that in a traditional mapping of the landscape the total of all elements in the table will be equivalent to the amount of the study area.

$$Loss(C1) = \sum_{n=1}^{j} LC1, n - LC1{,}1 \qquad (5.8)$$

$$Gain\ (C1) = \sum_{n=1}^{i} LCn, 1 - LC1{,}1 \qquad (5.9)$$

Table 5.18 The change table used in remote sensing

		T2		
		C1	C2	…………..Cj
T1	C1	LC1,1	LC1,2	…………LC1,J
	C2	LC2,2	LC2,2	…………LC2j
	. . . Ci	. . . LCi,1	. . . LCi,2	. . . LCij

5.6.2 Result of Boolean change

5.6.2.1 Boolean change (loss and gain)

Table 5.19 illustrates the gain and loss in all classes – urban areas, vegetation, woodland, grazing land and bare areas – by applying equations 5.8 and 5.9. From Table 5.19 we can see that the total loss in the urban class from T1 (1976) to T4 (2009) is only 3785.5 hectares and the gain 29863.2 hectares; on the other hand the total loss in woodland in the same period is 50361.7 hectares and the total gain 5874.5 hectares, which means the urban class increases and the woodland decreases.

Table 5.19 Gain and loss for all classes from Boolean classification

Years	1976-1989		1989-2005		2005-2009		1976-2009	
gain&loss classes	loss	gain	loss	gain	loss	gain	loss	gain
Urban	670.3	1207.4	891.3	1417.8	1027.8	4735.1	3785.5	29863.2
Vegetation	22871.6	11763.3	12851.9	9192.7	8324.2	3294.1	37918.4	13583.3
Woody	41697.4	9186.7	13272.6	8476.1	5427.8	2497.4	50361.7	5847.9
Grazing	4911.5	10638.2	6829.6	9187.3	5632.5	8374.9	10362.2	23739.7
Bare land	3694.4	5678.9	4831.3	9476.5	3821.6	9580.1	7294.8	20867.2

Figures 5.18, 5.19 and 5.20 show the change in Boolean classification at times T1 (1976), T2 (1989), T3 (2005) and T4 (2009). On the right of the images there is a legend which is graduated from -5, indicating high loss (black), through 0 (yellow), which means no change, to +5 (red), indicating high gain. From the Figures we can see that some classes increase, such as urban and other classes decrease, such as woodland and vegetation.

Method one showed how the fuzzy objects change at different times (T1, T2, T3 and T4). This method depended on converting the membership value to polygons to describe different objects.

The advantage of this method is that it can compare two objects at times T1 and T2; the disadvantage is that it is a bit difficult to apply and there are a lot of steps.

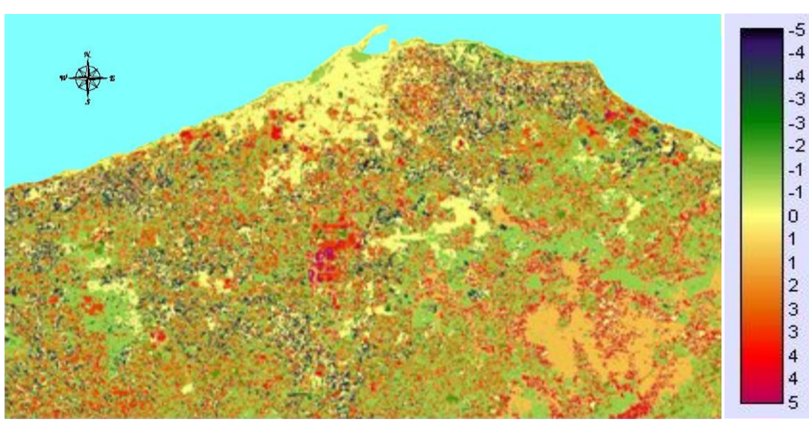
Method two showed the fuzzy change matrix at times T1 and T2 and its dependence on the intersection of the memberships. In this method, ten maps can be displayed to show the five land covers at the two dates, rather than just two maps. This is because every pixel may contain membership in all five land cover classes at any one date, rather than having just the one land cover at that date. Furthermore, because of the multiple memberships, the spatial change of fuzzy membership is observable and small changes can be detected, as whole zones of modest membership are revealed which completely fail to appear in the Boolean mapping.

Method three showed the Boolean change at times T1 and T2. This method is usually adopted to compare the differences based on the classified images. This performs a pixel-by-pixel overlay of two thematic maps to generate a similarity map and associated statistics that indicate regions of disagreement of spatial objects. The normal procedure of classification is to develop a set of training areas that represent each of the land cover types, and then to use statistical methods from those areas as a base for a numerical procedure to attempt to assign each pixel to a type. The disadvantage of this method is that any pixel belongs to one and only one land cover type and the whole area of that pixel is assigned to that type.

Figure 5.18 Boolean classification difference between 2005 and 1976

Figure 5.19 Boolean classification difference between 2005 and 1989

Figure 5.20 Boolean classification difference between 2009 and 1976



The traditional Boolean method usually compares the differences on the basis of a crisp pixel-by-pixel method. Such similarity operations often cannot adequately account for the errors and complexity inherent in spatial information. A fuzzy method may mitigate these difficulties. In this work the fuzzy approaches resulted in calculating fuzzy change by using different methods.

This chapter describe a method for using fuzzy land cover objects, Boolean change, a fuzzy change matrix and calculating the intersection between the classes at times T1 (1976) and T4 (2009) were used to improve the understanding of land cover changes. The results show that there are slight differences between the approaches. For example, by using the fuzzy object model, the results show that, over thirty years, woodland decreases by 30.6%, and urban areas increase by 46.6%. Grazing land increases by 32.5% and vegetation decreases by 24.9%. By using the fuzzy change matrix, we can see that the lowest value of loss is in the urban class (2534.5 hectares) and the highest loss in the woodland class (46073.7 hectares); by contrast, the highest value of gain is in the urban class (25095.4 hectares) and the lowest is in the woodland class (7821.8 hectares). These figures mean that the urban class increases and woodland decreases. When the current study compared the two models it was clear that the fuzzy change matrix is easy to apply, whereas the fuzzy change object is difficult to apply and there are many steps to determining the change.

5.7. Conclusion

In this chapter two models have been used to determine fuzzy change: the first model, the fuzzy change matrix, depends on sub-pixel change, and the other depends on the object change. Both of the models indicate that a change has happened in the study area even when there is a slight difference between the models. This research also used Boolean change, which is assessed pixel by pixel. All of these models give results which show that there is a large area of the land cover that has changed. For example, the urban area has more than doubled, whereas the woodland and vegetation areas have decreased. The results also show that using a fuzzy change analysis presents a subtle mapping of change, suitable for a heterogeneous area, where mixed pixels are common. Furthermore, the fuzzy methods combine the advantages of both post-classification comparison and algebraic methods of change detection. These models will be validated in Chapter 7 by using the information from the field survey (Chapter 6) and determined which model is the most suitable and accurate.

Chapter 6: Collection of data for validation

6.1 Introduction

This chapter will describe the field survey which took place in December 2009 and January 2010, which involved data collection from the field, and the determination of the memberships to different land cover types for each sampled area. The field data was used to validate the classification (fuzzy set, fuzzy c-means, Boolean classification). This chapter will also explain the problem of the mixed pixel in the study area and information about the field data will be described in the next chapter.

Measuring the accuracy of a land cover map requires a better observation of reality on a sample of points to check the classification (Boolean and soft). According to Comber et al., (2005) there are two primary methods for capturing information on land cover: field survey and analysis of remotely sensed data. Comparison of classified remote sensing data with data collected in the field gives a method of testing the reliability of the classification and the comparison gives a measure of objectivity. In these cases reference data for accuracy assessment should come from a ground survey. Ground validation has these objectives: (1) to obtain a set of reference data suitable for map assessment; (2) to measure thematic accuracy; (3) to test calibration methods for area estimates.

6.2 Definition of classes

Before the field survey it is necessary to identify each class. These brief definitions of land cover and land use, which were taken from different sources, such as Middle East conference (1997), Habitat UK and local Libyan experts will be used in the study area for the field survey.

6.2.1 Urban or built-up areas

Urban or built-up land is defined as areas characterized by buildings, asphalt, concrete and sub-urban areas which are dominated by manmade structures. They include cities, towns, villages, and strip developments along highways. Classes of urban development include residential, commercial, industrial, transportation, communications, utilities, mixed urban, and undeveloped land completely surrounded by developed areas, such as cemeteries and urban parks. The area coverage is more than 0.25 hectares.

6.2.2 Woodland

Woodland is defined as an area dominated by trees, and includes natural woodland and plantations. The term is used to refer to land with a tree canopy cover of more than 10 per cent and an area of more than 0.5 hectares; it is used for all types of tree such as coniferous and broadleaf. The average height of the trees is more than 5 m.

6.2.3 Bare land

The bare land class is composed of bare rock, sand, silt, gravel or other earthen material with little or no vegetation. It includes beaches; other sandy areas; bare exposed rock; strip mines, quarries, gravel pits; transitional areas; and mixed barren land. The area coverage is more than 1 hectare.

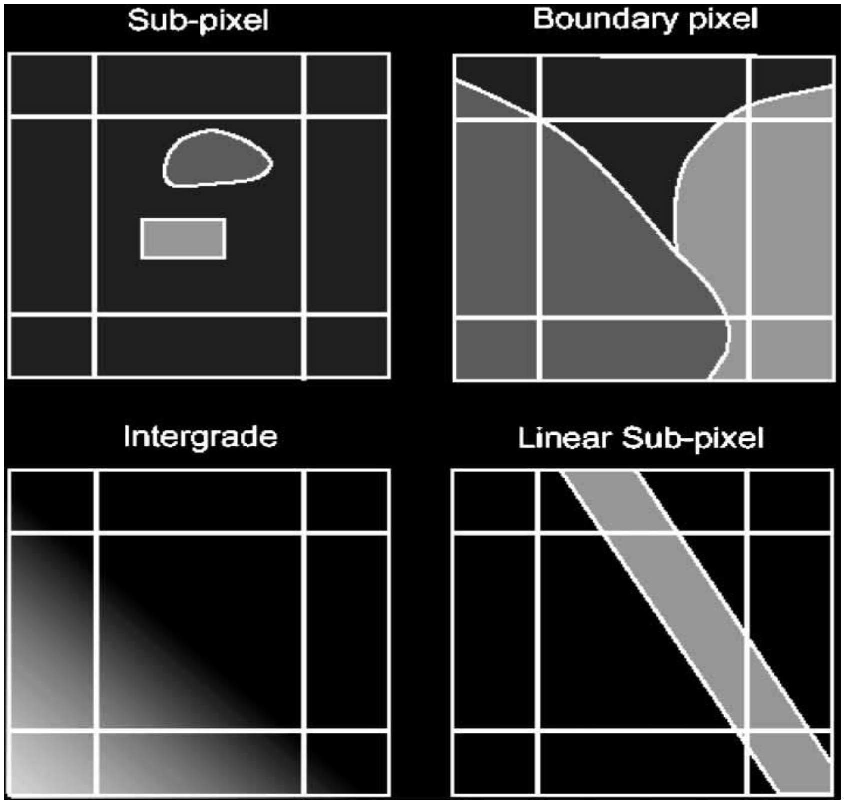
6.2.4 Grazing land

Grazing land generally describes a type of predation in which a herbivore feeds on plants, or any vegetated land that is grazed or that has the potential to be grazed by animals, such as small shrubs, grassland, and natural and managed herbaceous areas. The area coverage is more than 1 hectare.

6.3 Mixed Pixels

One of the big challenges of modelling land cover using remotely sensed imagery is the mixed pixel problem: the level of detail of the spatial features captured is less than what we would like, and this sub-pixel level heterogeneity is important but not readily knowable. In Boolean classification, each pixel is classified into one of many land cover types (hard classification). This implies that land cover fits exactly within the bounds of one or multiple pixels. However, several pixels have a mixed land cover class composition. Mixed pixels are normally found at boundaries between two or more mapping units, along gradients, etc., when any linear or small sub-pixel object occurs, as shown in Figure 6.1. The solution to the mixed pixel problem typically centres on soft classification, which allows proportions of each pixel to be partitioned between classes.

Figure 6.1 Four causes of mixed pixels (Fisher, 1997).



According to Fisher (1997), there are four causes of mixed pixels, all of which are present in the study area; the four causes are:

(a) boundaries between two or more mapping units (field-woodland boundary)

(b) the intergrade between central concepts of mappable phenomena (ecotone)

(c) linear sub-pixel objects (e.g. a road)

(d) small sub-pixel objects (e.g. a house or tree).

All these types of mixed pixels are present in the study area. The 210 points were visited and taken, and then analysed. The results show that only 49 points (23.33%) are pure and 161 (76.66%) are mixed, which means that the study area is almost heterogeneous and covered with mixed pixels, as shown in the next photographs, which represent the same locations as on the aerial photograph.

Figures 6.2 to 6.6 show different points of the field survey location within the study area. The left-hand column show parts of aerial photographs taken in September 2009, and the right-hand column shows some photographs which were taken during the field survey in December 2009. Figure 6.2(a) shows the mixed pixel containing urban areas, bare areas, vegetation and some woodland, while Figure 6.2(b) shows the location of the point which shows a mixed pixel containing vegetation and woodland. Figure 6.3(a) shows a part of the study area which contains urban areas, bare areas and some vegetation, while Figure 6.3(b) shows the position of the point where a new urban area has been built over a bare area. Figure 6.4(a) shows the boundary between grazing land and woodland while Figure 6.4(b) shows the location of a mixed pixel of grazing land and the woodland. Figure 6.5(a) shows part of an aerial photograph which shows new building over grazing land and bare areas, while Figure 6.5(b) shows the position of the point which contains the new urban area. Figure 6.6(a) shows part of an aerial photograph of woodland where part of it has started to be removed, and Figure 6.6(b) shows the location of the point which contains woodland.

Figure 6.2 (a) Part of aerial photo

Figure 6.2 (b) Photo 1

Figure 6.3 (a) Part of aerial photo

Figure 6.3 (b) Photo 2

Figure 6.4 (a) Part of aerial photo

Figure 6.4 (b) Photo 3

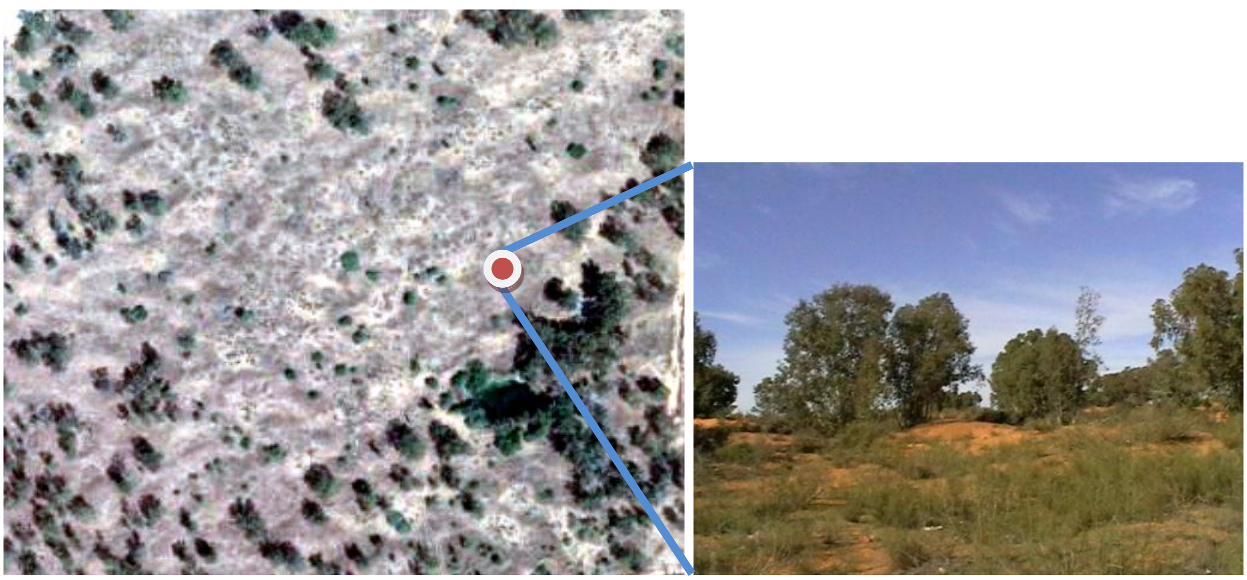


Figure 6.5 (a) Part of aerial photo

Figure 6.5 (b) Photo 4

Figure 6.6 (a) Part of aerial photo

Figure 6.6 (b) Photo 5

6.4. Method for field survey: Determining membership from the field

The fuzzy land cover information generated from remotely sensed data (different fuzzy classifications) identifies fuzzy memberships in five land cover classes (urban areas, vegetation, woodland, grazing land and bare areas). There are five predicted fuzzy membership values for each pixel. Fieldwork was undertaken, recording the sub-pixel memberships at 210 locations. Each of the 210 pixels was sub-divided into 16 and the land cover recorded at each point. This gives observed fuzzy memberships for the same five classes. The next step is to compare the two sets of predicted and observed fuzzy memberships to determine some measure of fuzzy and Boolean validation; a full description will be provided in the next chapter.

The study area was divided into 21 parts with every grid square measuring 10 km^2, and inside each square 10 points were taken by stratified random sampling, as shown in Figure 6.7. Each took one day to survey with the 210 pixel points selected being either mixed or pure pixels. Each pixel was divided into 16 parts (4x4, as shown in Figure 6.8) and the land cover at these 16 points recorded as shown in Figure 6.9. A number of pictures were taken with a digital camera. These pictures will show the current land use, landscape type and mixed pixels in the study area. All these geographic points were recorded by using GPS. The membership values from each of the 16 sub-pixel locations were summed for each class, for each pixel, such that the membership is 0.1 or less, which means that the class covers 10% of the pixel. A representation of the pixel is shown in Table 6.1.

Figure 6.7 The squares covered in the field survey

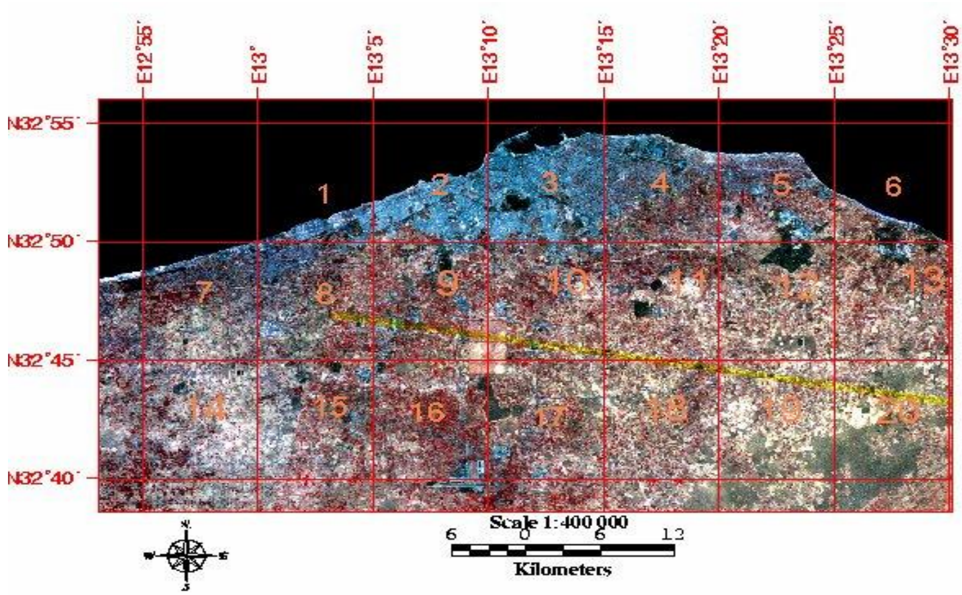


Figure 6.8 The 4*4 pixel subdivisions

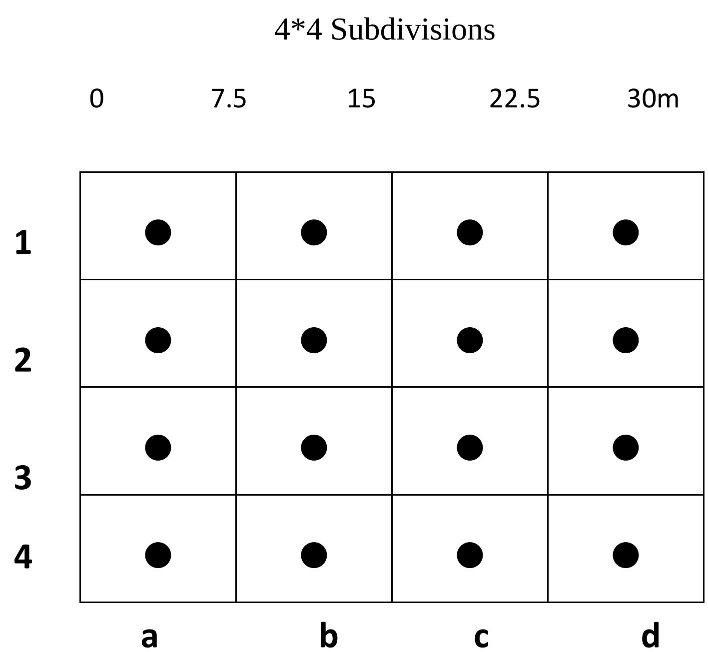
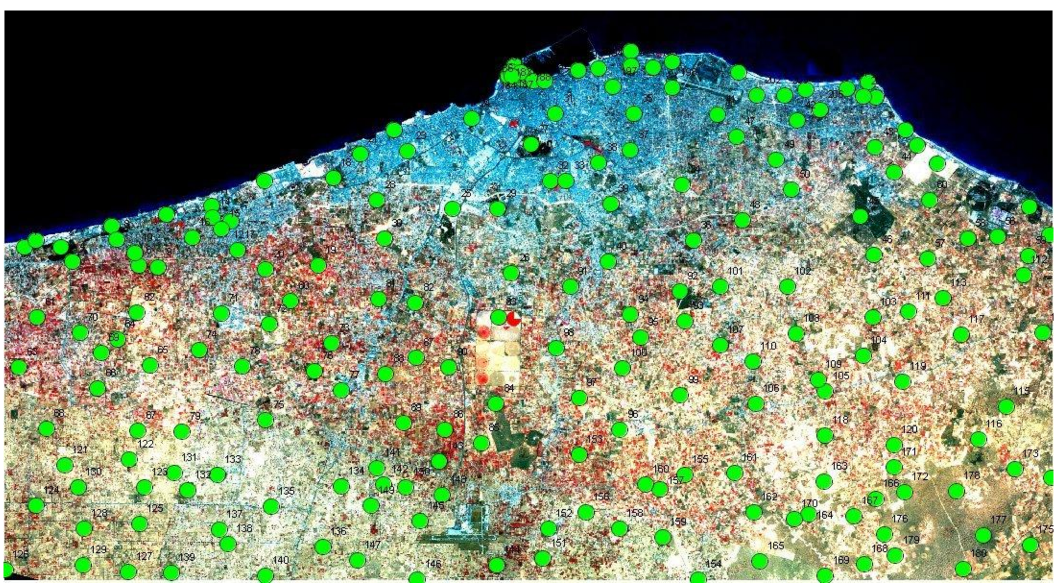


Table 6.1 The subdivision of points inside the pixel

Fraction	percentage
1/16	6.2 %
2/16	12.5 %
3/16	18.7 %
4/16	25%
5/16	31.2 %
6/16	37.5 %
7/16	43.7 %
8/16	50%
9/16	56.2 %
10/16	62.5 %
11/16	68.7 %
12/16	75 %
13/16	81.2 %
14/16	87.5 %
15/16	93.7 %
16/16	100%

Figure 6.9 The field points in the study area

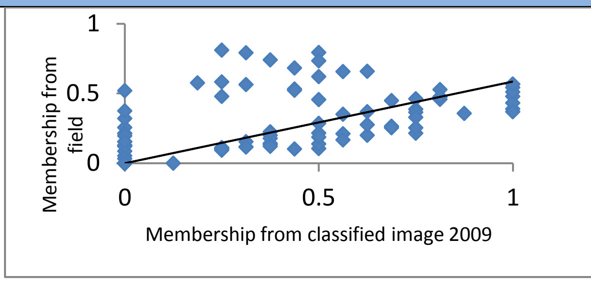


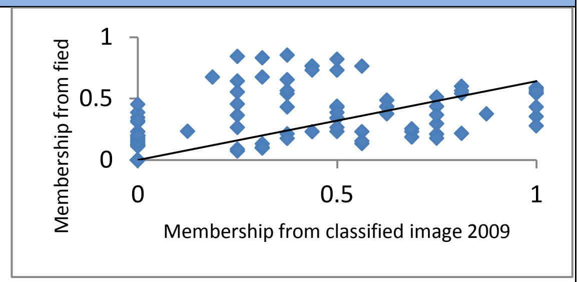
6.5 Relationship between fuzzy memberships from the classification image at T4 (2009) and field survey

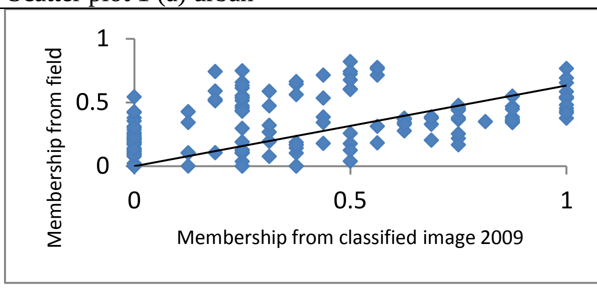
6.5.1 Scatter plots (T4, field)

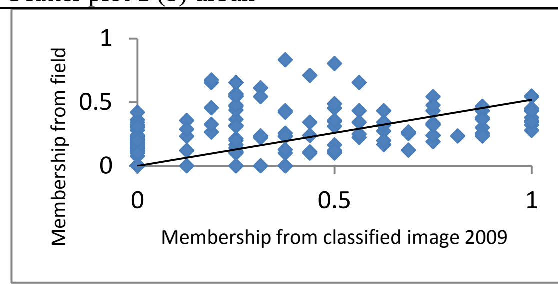
Scatter plots were used to compare the predicted and actual classes of membership (Figure 6.10) to be used in fuzzy validation, as explained in Chapter 7. Generally these scatter plots show the degrees of membership of field points and classification points for all the classes; there are many points scattered and there is a variation between the field points and the classification points. The first column illustrates the field points and fuzzy set classification, while the second column illustrates the field points and fuzzy c-means. There is a slight difference between the two classifications and these differences may originate from factors such as the quality of the images, time difference and the methodology of each approach (fuzzy sets and fuzzy c-means).

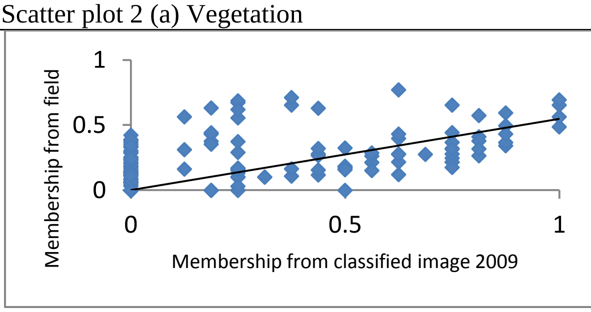
Figure 6.10 Membership of field points and classification points

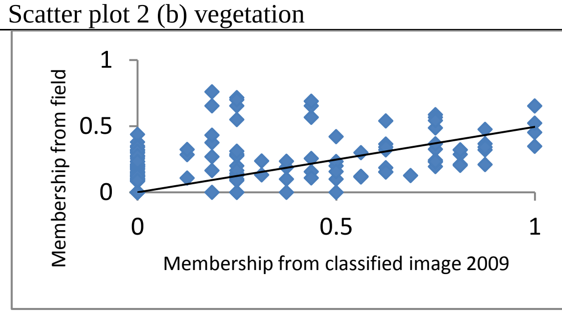
<table>
<tr><th>Membership of field points and classification points from fuzzy set classification</th><th>Membership of field points and classification points from fuzzy c-means classification</th></tr>
<tr><td>


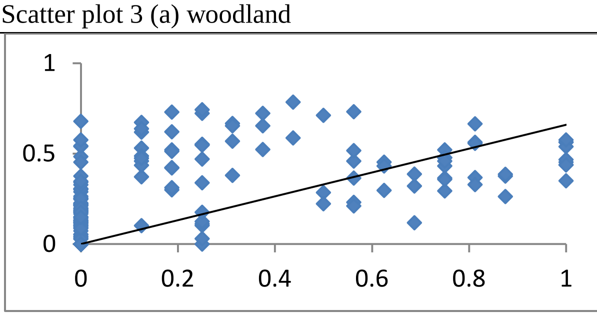
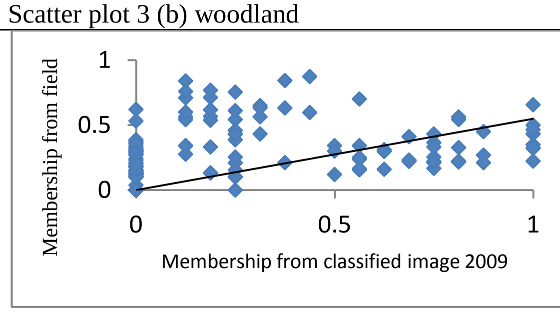
Scatter plot 1 (a) urban
</td><td>


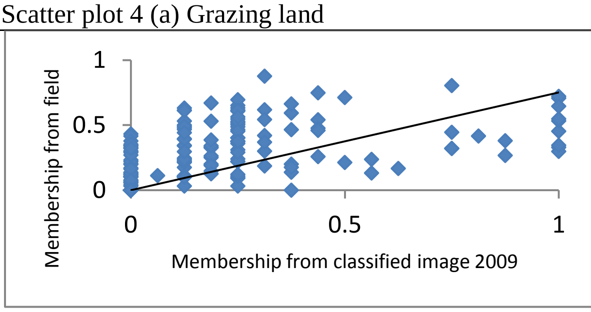
Scatter plot 1 (b) urban
</td></tr>
<tr><td>


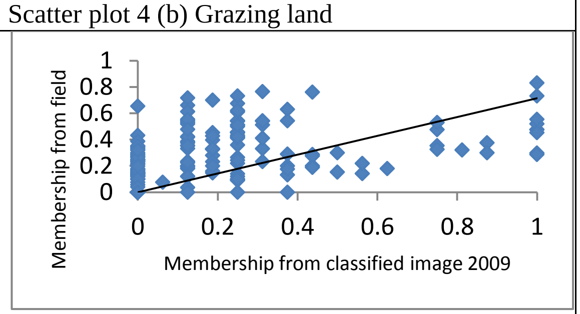
Scatter plot 2 (a) Vegetation
</td><td>


Scatter plot 2 (b) vegetation
</td></tr>
<tr><td>


Scatter plot 3 (a) woodland
</td><td>


Scatter plot 3 (b) woodland
</td></tr>
<tr><td>

Scatter plot 4 (a) Grazing land
</td><td>


Scatter plot 4 (b) Grazing land
</td></tr>
<tr><td>


Scatter plot 5 (a) Bare area
</td><td>


Scatter plot 5 (b) Barea area
</td></tr>
</table>

Table 6.2 shows some examples of membership from field surveys and membership from classified images (2009) where there is a big difference between the points. For both classifications (fuzzy set and fuzzy c-means), from Table 6.2 it is clear that there are variations between the field and classification points. In general, the reasons for that are: firstly, the difference in time between the capture of the image and the field trip; secondly, the rapid land use changes in the area; thirdly, the large amount of new building over the vegetation and woodland in the study area; and fourthly, shortage of water and the dry season, which leads to slight confusion in classification between the vegetation, grazing land and bare area classes.

Table 6.2 Variation of points between field and classification

Classes	Fuzzy set		Fuzzy c-means	
	Field	Classification	Field	Classification
Urban	1	0.369	0.75	0.211
	0	0.52	0.25	0.843
	0.812	0.475	0.231	0.6875
	0.25	0.811	0.6875	0.231
Vegetation	0.1875	0.742	0.375	0.832
	0.75	0.167	0.625	0.089
	0.5	0.038	1	0.45
	0	0.543	0.1875	0.654
Wood Land	1	0.564	0.75	0.195
	0.1875	0.632	0	0.625
	0.25	0.784	0.1875	0.76
	0.75	0.217	0.625	0
Grazing Land	1	0.35	1	0.432
	0	0.484	0.1875	0.713
	0.25	0.551	0.432	1
	0.75	0.231	0.843	0.375
Bare Area	1	0.584	0.25	0.732
	0.461	1	0.875	0.376
	0.125	0.613	1	0.298
	0.75	0.304	0.125	0.661

6.5.2 Regression T4

The regression was used to compare the referenced data from the field with the data from the classification image. Table 6.3 illustrates regression statistics for multiple R in the urban, vegetation, woodland, grazing land and bare classes, comparing the results from fuzzy set classification and fuzzy c-means against the observations in the field; when the R are high that means the correlation and classification are good. From Table 6.3 we can see that the multiple R is higher in the fuzzy set than fuzzy c-means in all the classes. The value of R in the urban class is the highest in fuzzy set classification (R=0.717); in fuzzy c-means R=0.694. The value of R in the bare area class in the lowest in fuzzy set classification (R=0.561) in fuzzy c-means (R=0.489). These figures indicate that the urban class is more accurate than the others, because the bare area and vegetation classes were changing from time to time and from season to season.

The correlation and scatter plots are different methods but the data for both methods are the same.

Table 6.3 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means as compared against the observations in the field

Class	R fuzzy set	R c-means
Urban	0.71725	0.69495
Vegetation	0.62448	0.49900
Woody land	0.61410	0.51514
Grazing land	0.58384	0.44515
Bare area	0.56217	0.48901

6.6 Results

Tables 6.4 and 6.5 below show tested membership results from the field and fuzzy classification (fuzzy set and fuzzy c-means).

Table 6.4 shows membership points from the field and membership points from fuzzy set classification. Table 6.5 shows some membership points from the field and membership points from fuzzy c-means classification. From both tables (6.4 and 6.5) we can see that there are slight variations between the field points and classification points, and most of the points are mixed.

Figure 6.10 and Table 6.3 above (scatter plot and regression) show that the urban class has the highest correlation between the field membership and classification membership in both classifications (fuzzy set and fuzzy c-means); the second class is woodland and the lowest class is bare areas.

The information from the field survey will be used to validate the fuzzy classification and Boolean classification in the next chapter (Chapter 7).

Table 6.4 illustrates some membership points from field and fuzzy set classification

Urban field	Urban classification	Vegetation field	Vegetation classification	Woodland field	Woodland classification	Grazing land field	Grazing land classification	Bare land field	Bare land classification
0.25	0.103	0.25	0.189	0.25	0.673	0.25	0	0	0.032
0	0.256	0.25	0.036	0	0.387	0	0	0.75	0.321
0	0	0	0.076	0.75	0.216	0	0.053	0.25	0.651
0.25	0.112	0.625	0.372	0	0.215	0	0.185	0.125	0.11
0.6875	0.265	0.25	0.473	0	0.147	0	0	0.0625	0.112
0	0	0.75	0.365	0.125	0.312	0	0.143	0.125	0.175
0.375	0.2	0	0.021	0.375	0.654	0	0.029	0.25	0.095
0.375	0.741	0.375	0	0.25	0.132	0	0	0	0.121
0	0.053	0.1875	0.742	0.25	0	0	0.073	0.5625	0.132
0	0	0.75	0.217	0.125	0.564	0	0	0.125	0.214
0	0	0	0.234	0.75	0.217	0	0	0.25	0.547
1	0.389	0	0.286	0	0.083	0	0.121	0	0.118
0.125	0	0	0	0	0.297	0.125	0.372	0.75	0.321
0.25	0.093	0.5	0.723	0.25	0.1	0	0	0	0.074
0.375	0.142	0.375	0.642	0.25	0	0	0.212	0	0
0	0	0.75	0.167	0	0.304	0	0.151	0.25	0.376
0	0.086	0	0.378	0.75	0.176	0	0	0.25	0.359
0.5	0.456	0.125	0.104	0	0.294	0	0	0.375	0.138
0	0	0.5	0.605	0.25	0.291	0.25	0.103	0	0
0	0	0	0	0	0	0.75	0.365	0.25	0.632
1	0.479	0	0.097	0	0	0	0.221	0	0.203
0.5	0.286	0	0	0	0.38	0	0.121	0.5	0.213
0.375	0.178	0.3125	0.194	0	0	0	0	0.3125	0.618
0.5	0.794	0.375	0.102	0	0	0	0	0.125	0.101
0	0	0.25	0.189	0	0	0	0	0.75	0.804
0	0	0.25	0.748	0.75	0.247	0	0	0	0
0.25	0.583	0	0	0.625	0.217	0	0.167	0.125	0.032
0.25	0.811	0.25	0	0.5	0	0	0.187	0	0
0	0.032	0.25	0.658	0.375	0.109	0	0	0.375	0.2
0.3125	0.117	0.375	0.167	0	0.109	0	0.054	0.3125	0.543
0.875	0.357	0	0.217	0	0	0	0.179	0.125	0.246
0	0.128	0	0.089	0.75	0.279	0	0	0.25	0.504
0.75	0.387	0.125	0	0	0.286	0	0.11	0.125	0.216
0.375	0.134	0	0.169	0.25	0.687	0	0	0.375	0
0.5	0.105	0.25	0.613	0	0	0	0.038	0.25	0.24
0	0	0.375	0.186	0.375	0.712	0	0	0.25	0.092
0.75	0.462	0.125	0.427	0	0	0	0	0.125	0.103
1	0.567	0	0	0	0.134	0	0	0	0.298
0	0	0	0	0.625	0.398	0	0	0.375	0.593
0	0	0.125	0.342	0.5	0.185	0	0	0.375	0.465
0.75	0.365	0.25	0.457	0	0	0	0.132	0	0.041

Table 6.5 illustrates some membership points from field and fuzzy c-means classification

Urban field	Urban classification	Vegetation field	Vegetation classification	Woodland field	Woodland classification	Grazing land field	Grazing land classification	Bare land field	Bare land classification
0.25	0.073	0.25	0.104	0.25	0.716	0.25	0	0	0.1
0	0.167	0.25	0.165	0	0.298	0	0	0.75	0.354
0	0	0	0.218	0.75	0.195	0	0.123	0.25	0.457
0.25	0.089	0.625	0.273	0	0.182	0	0.269	0.125	0.183
0.6875	0.231	0.25	0.365	0	0.211	0	0.107	0.0625	0.076
0	0	0.75	0.239	0.125	0.285	0	0.279	0.125	0.196
0.375	0.54	0	0.167	0.375	0.189	0	0	0.25	0.095
0.375	0.854	0.375	0	0.25	0	0	0	0	0.145
0	0.176	0.1875	0.456	0.25	0.2	0	0	0.5625	0.142
0	0	0.75	0.543	0.125	0.324	0	0	0.125	0.121
0	0.132	0	0	0.75	0.587	0	0	0.25	0.265
1	0.543	0	0.134	0	0.083	0	0.121	0	0.118
0.125	0.234	0	0	0	0	0.125	0.276	0.75	0.476
0.25	0.364	0.5	0.348	0.25	0.276	0	0	0	0
0.375	0.432	0.375	0.234	0.25	0	0	0.331	0	0
0	0	0.75	0.432	0	0.276	0	0.151	0.25	0.14
0	0.154	0	0	0.75	0.487	0	0	0.25	0.359
0.5	0.43	0.125	0.232	0	0.196	0	0	0.375	0.132
0	0	0.5	0.453	0.25	0.289	0.25	0.103	0	0.145
0	0	0	0.156	0	0	0.75	0.167	0.25	0.675
1	0.578	0	0.106	0	0	0	0.12	0	0.176
0.5	0.342	0	0	0	0.38	0	0.121	0.5	0.153
0.375	0.213	0.3125	0.235	0	0	0	0	0.3125	0.543
0.5	0.438	0.375	0.256	0	0.108	0	0	0.125	0.18
0	0	0.25	0.467	0	0	0	0	0.75	0.53
0	0.116	0.25	0.315	0.75	0.567	0	0	0	0
0.25	0.643	0	0	0.625	0.186	0	0.132	0.125	0.036
0.25	0.843	0.25	0	0.5	0	0	0.154	0	0
0	0.346	0.25	0.438	0.375	0	0	0	0.375	0.2
0.3125	0.097	0.375	0.1	0	0.15	0	0.121	0.3125	0.512
0.875	0.376	0	0.2	0	0	0	0.189	0.125	0.234
0	0.2	0	0	0.75	0.326	0	0	0.25	0.456
0.75	0.296	0.125	0	0	0.321	0	0.183	0.125	0.2
0.375	0.654	0	0.2	0.25	0.143	0	0	0.375	0
0.5	0.731	0.25	0.14	0	0	0	0.038	0.25	0.09
0	0.23	0.375	0.432	0.375	0.235	0	0	0.25	0.1
0.75	0.512	0.125	0.356	0	0.124	0	0	0.125	0
1	0.589	0	0	0	0.178	0	0	0	0.231
0	0	0	0	0.625	0.365	0	0	0.375	0.63
0	0	0.125	0.287	0.5	0.421	0	0	0.375	0.29
0.75	0.211	0.25	0.543	0	0	0	0.137	0	0.098

Both of the tables illustrate that, when membership points from the field are compared to membership points from the classified image (2009), the differences between the results are due to differences in the method (Table 6.4 shows the fuzzy set method and Table 6.5 shows the fuzzy c-mean approach). The completed tables, describing all samples, are included as an appendix.

6.7 Summary

This chapter presented the field survey, the aim of which was to collect the fuzzy and Boolean validation data. Validation was through comparing fuzzy class membership from the field against fuzzy class membership generated through the remote sensing analysis. Identifying the land cover at each point in a 4*4 subdivision of each sample location allowed the fuzzy field data to be generated. A total of 210 points were sampled, selected from a random stratified sample of twenty-one 10km*10km blocks. At each sample location surveyed, position was specified by GPS and photos were taken. The relationship between the two datasets was analysed using regression and visualised using scatter plots.

Chapter 7 Validation

7.1 Overview

This chapter will describe the validation of Boolean and fuzzy change estimates arising from Chapter 5 and using the information from the field survey (Chapter 6). The main objective of this part of the research is to carry out a comparative study of different accuracy assessment measures to check the accuracy of fuzzy and Boolean classified images.

This chapter also addresses different models for determining the validation of soft classification. To check the accuracy of fuzzy classified images, complete information about the class proportions in each pixel needs to be known.

The current study used four Landsat images taken at different times – T1 (1976), T2 (1989), T3 (2005) and T4 (2009) – which were classified in Chapter 4 by three models: fuzzy sets, fuzzy c-means and Boolean classification. In Chapter 5 the fuzzy change was determined by three models: fuzzy change by pixel, fuzzy change by object and Boolean change. This chapter will evaluate the modelling for change at time T4 (2009) using information from the field survey (Chapter 6). Aerial photographs taken at times T1, T2 and T3 were used to determine the amount of change, and an accuracy assessment of the Landsat images was carried out at the same time.

Different methods for fuzzy accuracy measures are explained in detail in the next sections of this chapter, including fuzzy error matrix, which is an extension of the confusion error matrix, and cross-tabulation; overall map accuracy was computed in the a fuzzy error matrix. Euclidean distance was used to compare the degree of membership from the soft classifier and the ground truth data. A kappa value was also computed for each error matrix to measure how the classification performs as compared to the reference data.

7.2 Introduction

In general the accuracy assessment is based on the accuracy or confusion matrix, which compares ground truth data with the equivalent classification for a given set of validation samples (Congalton and Green, 1999; Foody, 2002). The accuracy matrix enables the calculation of the most common evaluation criteria: firstly overall accuracy, secondly producer accuracy, and finally user accuracy. A detailed overview is given by Foody (2002) and Congalton and Green, 1999).

For the assessment of soft classifications in general, various suggestions have been made, such as the fuzzy error matrix, entropy, cross-entropy and cross-tabulation (Binaghi et al., 1999; Foody, 1995; Green and Congalton, 2004; Lewis et al., 2001; Pontius et al., 2006; Townsend, 2000; Woodcock et al., 2000). The fuzzy error matrix (Binaghi et al., 1999) is one of the most attractive approaches, as it represents a generalization (grounded on fuzzy set theory) of the traditional confusion matrix. Specifically, for a cross-comparison to be consistent with the traditional confusion matrix, it is common for the cross-comparison to result in a diagonal matrix when a map is compared to itself, and for its marginal totals to match the total of the membership grades. More significantly, a cross-comparison should convey readily interpretable information on the confusion between the classes. To date, the application of the fuzzy error matrix has been mostly concentrated on generating accuracy indices such as the overall accuracy, the user and producer accuracy, the kappa, and the conditional kappa coefficients (Binaghi et al., 1999; Okeke and Karnieli, 2006; Shabanov et al., 2005).

Recently, a composite operator was proposed for computing a cross-comparison matrix that exhibits some of the abovementioned desirable characteristics (Pontius and Connors, 2006). Pontius and Connors, 2006 showed how the composite operator can be used for a multi-resolution assessment of raster maps, and compared it with other alternatives, including the traditional hardening of pixels, the minimum operator (Binaghi et al., 1999), and the product operator (Lewis et al., 2001). This composite operator was also suggested as a viable tool for the sub-pixel comparison of maps (Pontius and Connors, 2006). This research applied the composite operator in the study for all the images for both Boolean and soft classification.

7.2.1 Use of the error matrix

The error matrix has been applied mostly to provide an essential explanation of thematic map validation and for the comparison of accuracies. Nevertheless, it might be possible to apply the information contained in the matrix to obtain significantly more useful information. Furthermore, the error matrix might be helpful in refining approximations of the areal extent of categories in the area. The error matrix could be used to improve the assessment of the classification for the user. In particular, it might be possible to use the matrix to assist in optimizing the thematic map for an exacting user (Morisette and Khorram, 2000). For instance, the matrix might be helpfully employed with information on the real costs of errors of the map to get a classification for an exacting application. Smits et al. (1999) have shown how an error matrix may be applied together with information on the economic cost of misclassification to improve a thematic mapping study. In particular, they showed that the consequences of such an analysis might be used to refocus the study or the techniques used in deriving the classification. The value of such techniques obviously depends on the reliability of the error matrix. Forming a reliable error matrix in which one might be confident that subjects discussed above (e.g., ground data accuracy, registration of the data sets, sample design, etc.) have not had a detrimental effect is, however, complicated (Smits et al., 1999).

The error matrix lies at the core of a lot work on validation and is usually employed without question as to its appropriateness. The error matrix is used to conduct a site-specific assessment of the correspondence among the ground situation and image classification. The error matrix also might be applied to summarize the nature of the category allocations made by a classification, and is the source of several quantitative measures of classification accuracy (Woodcock and Gopal, 2000).

7.3 Relationship between fuzzy classification membership and aerial photos

7.3.1 Scatterplots (T1, T2, T3 and Aerial photo)

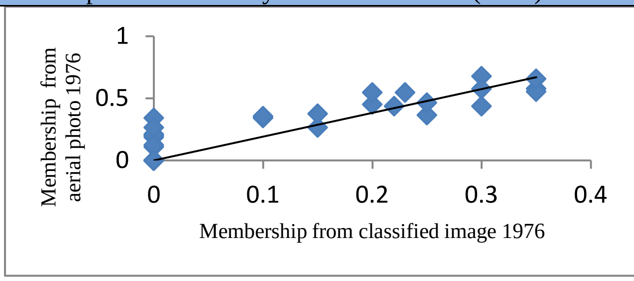
Figures 7.1, 7.2 and 7.3 show the degrees of membership of aerial photo points and classification points for all the classes at times T1 (1976), T2 (1989) and T3 (2005). From the scatter plots there are many points scattered and there is a variation between the aerial photo points and classification points. The first left column illustrates the aerial photo points and fuzzy set classification, while the second column illustrates the aerial photo points and fuzzy c-means; there are slight differences between the two classifications.

Figure 7.1 illustrates some points of degree of membership of aerial photo and classification points; there are only 62 points in total because there is a shortage of aerial photo data covering the study area, for urban land, vegetation, woodland, grazing land and bare areas, at time T1 (1976), for both classifications (fuzzy set and fuzzy c-means). Figure 7.2 illustrates some points of degree of membership of aerial photo and classification points for all the classes, at time T2

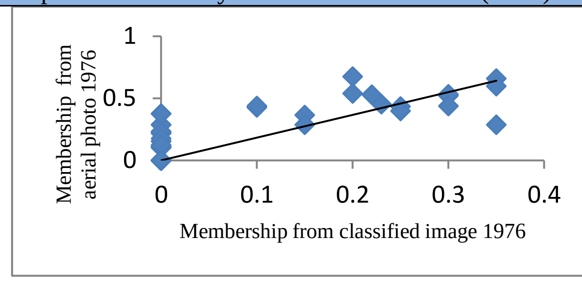
(1989), for both classifications (fuzzy set and fuzzy c-means). Figure 7.3 illustrates some points of degree of membership of aerial photo and classification points for all the classes, at time T1 (1976), for both classifications (fuzzy set and fuzzy c-means).

From Figures 7.1, 7.2 and 7.3 it is clear that there are small variations between the aerial photos and the classification points. The reasons are, firstly the difference in time between the capture of the image and the aerial photo, secondly the speed of change in the area, thirdly the amount of new building over the vegetation and woodland in the study area, and, fourthly the shortage of water and the dry season. There is also some confusion in the classification between the vegetation class and the grazing class.

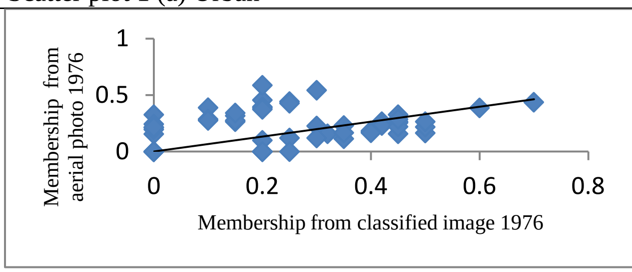
Membership of aerial photo points and classification points from fuzzy set classification (1976)	Membership of aerial photo points and classification points from fuzzy c-means classification (1976)



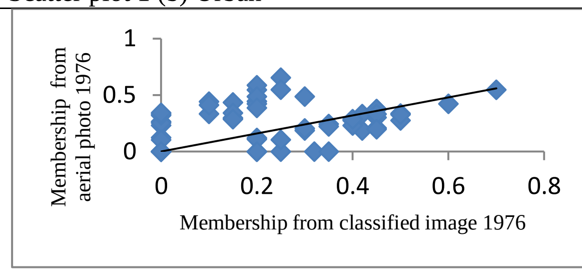
Scatter plot 1 (a) Urban



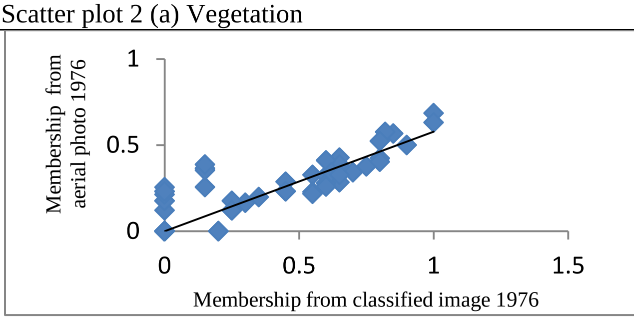
Scatter plot 1 (b) Urban



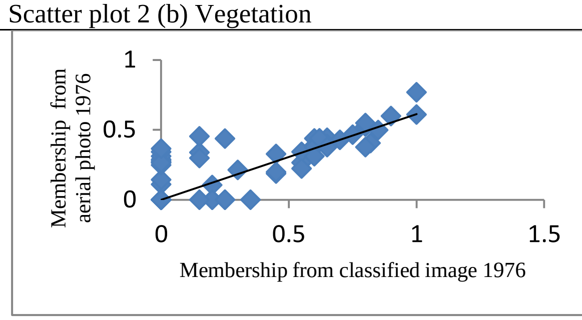
Scatter plot 2 (a) Vegetation



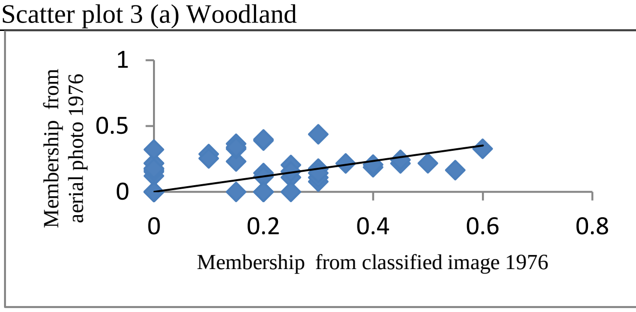
Scatter plot 2 (b) Vegetation



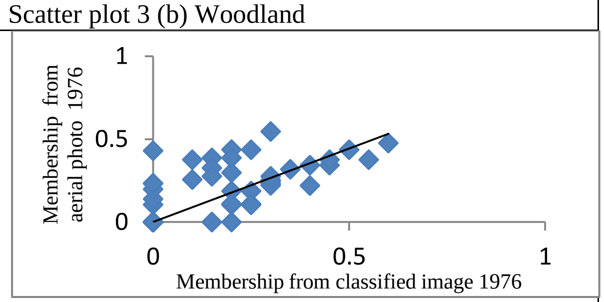
Scatter plot 3 (a) Woodland



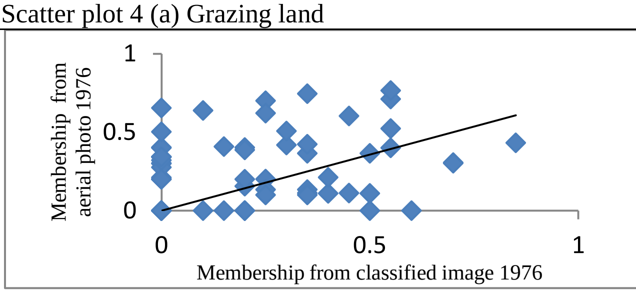
Scatter plot 3 (b) Woodland



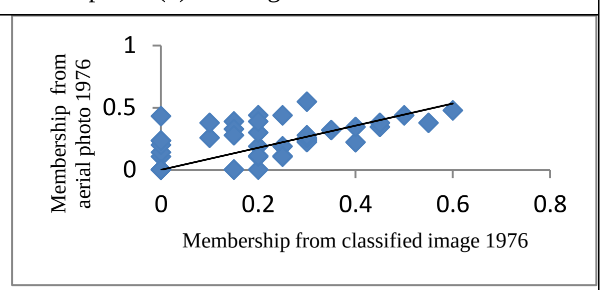
Scatter plot 4 (a) Grazing land



Scatter plot 4 (b) Grazing land



Scatter plot 5 (a) Bare area

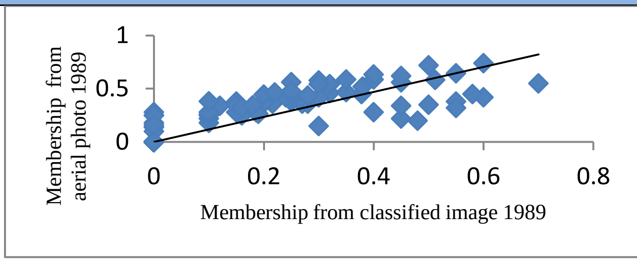


Scatter plot 5 (b) Bare area

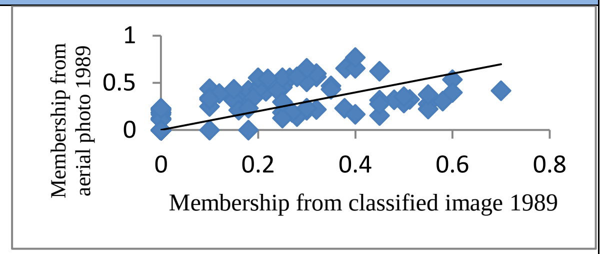
Figure 7.1 Membership of aerial photo points and classification points (1976)

Figure 7.2 Membership of aerial photo points and classification points (1989)

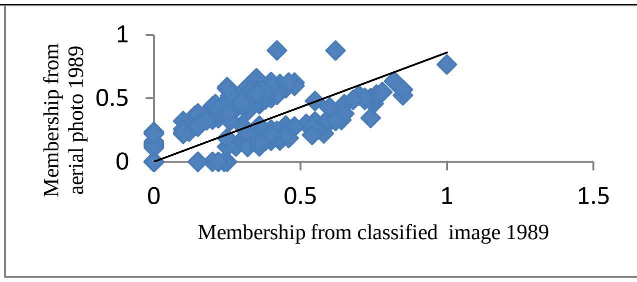
Membership of aerial photo points and classification points from fuzzy set classification (1989)	Membership of aerial photo points and classification points from fuzzy c-means



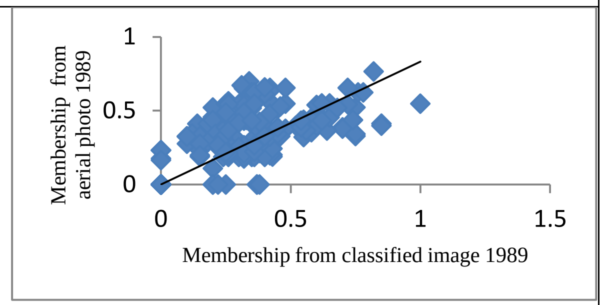
Scatter plot 1 (a) Urban



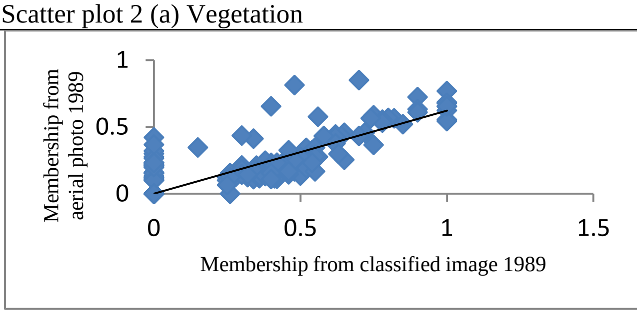
Scatter plot 1 (b) Urban



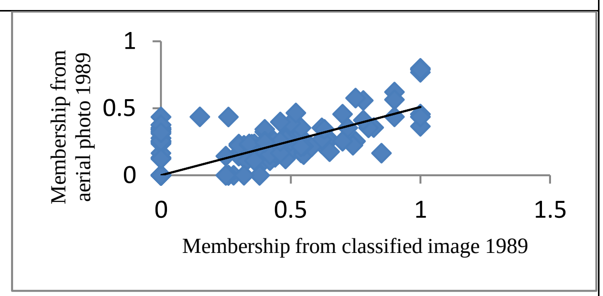
Scatter plot 2 (a) Vegetation



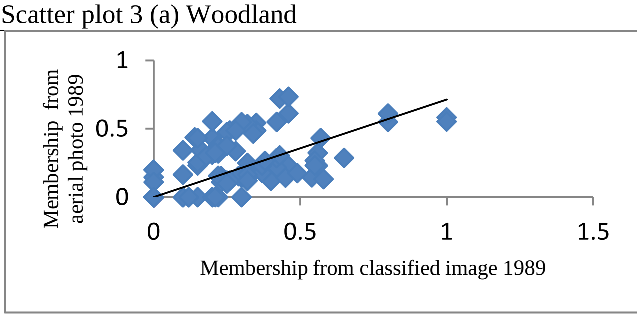
Scatter plot 2 (b) Vegetation



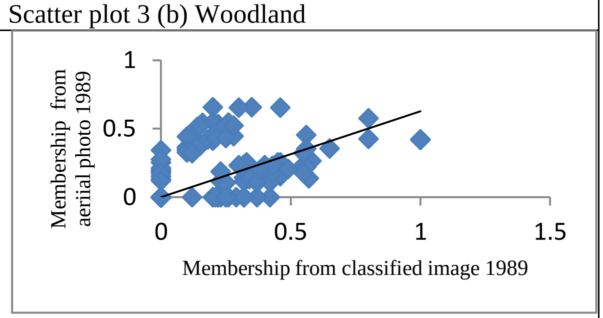
Scatter plot 3 (a) Woodland



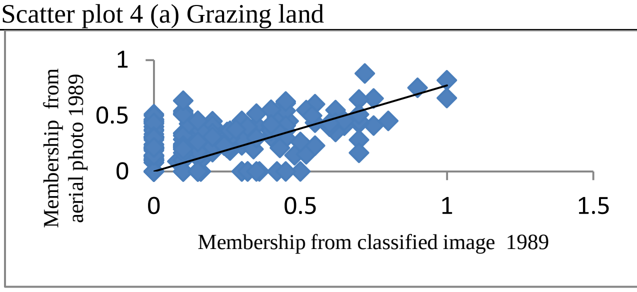
Scatter plot 3 (b) Woodland



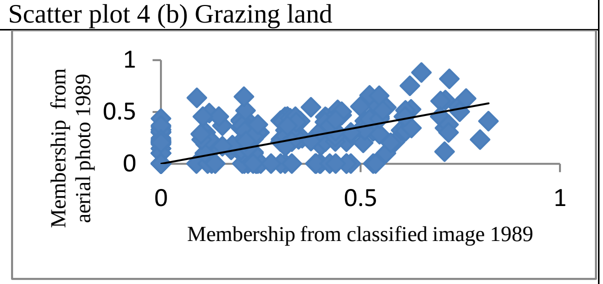
Scatter plot 4 (a) Grazing land



Scatter plot 4 (b) Grazing land

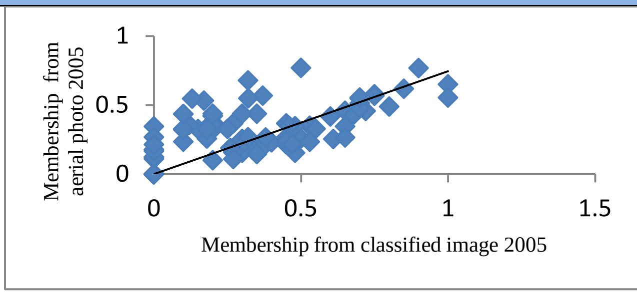


Scatter plot 5 (a) Bare area

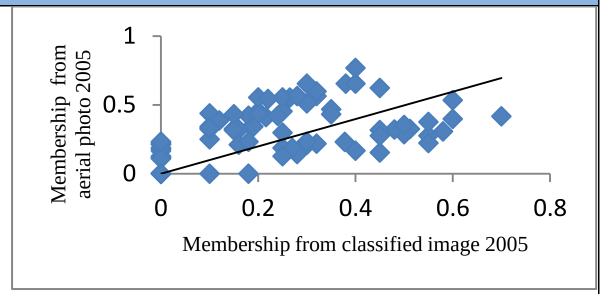


Scatter plot 5 (b) Bare area

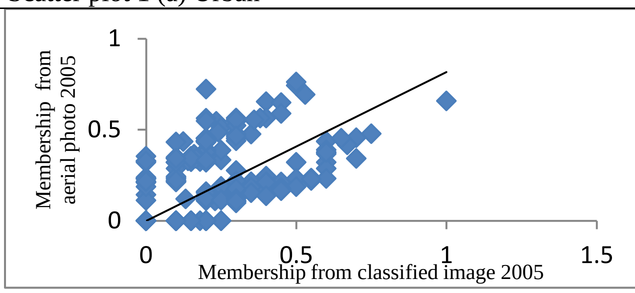
Membership of aerial photo points and classification points from fuzzy set classification (2005)	Membership of aerial photo points and classification points from fuzzy c-means



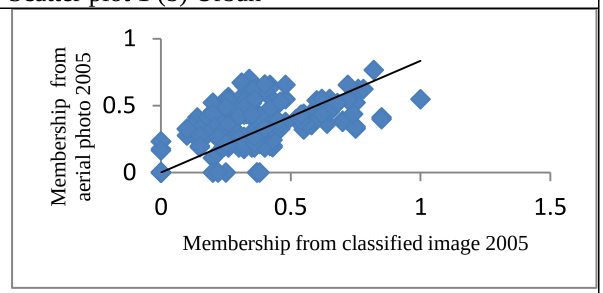
Scatter plot 1 (a) Urban



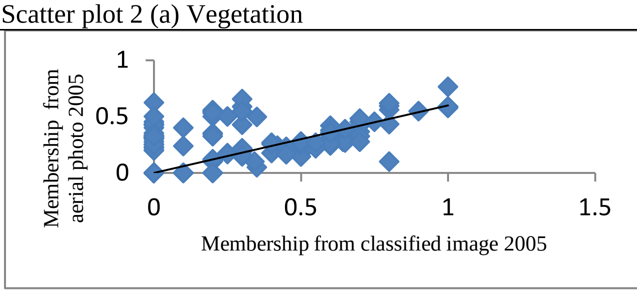
Scatter plot 1 (b) Urban



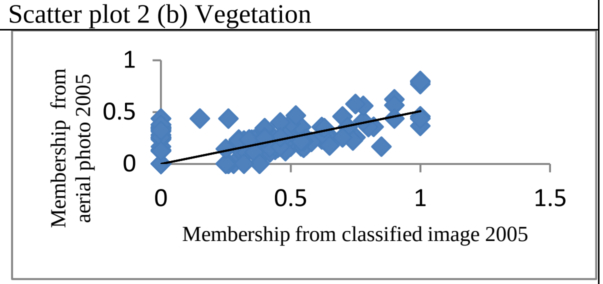
Scatter plot 2 (a) Vegetation



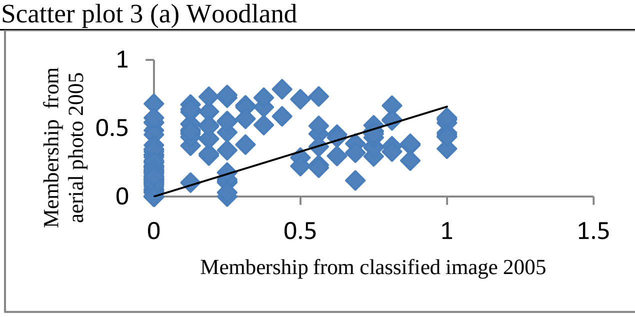
Scatter plot 2 (b) Vegetation



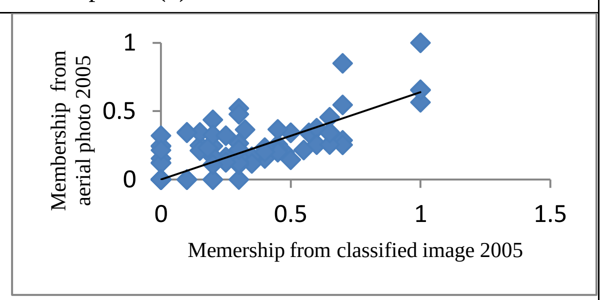
Scatter plot 3 (a) Woodland



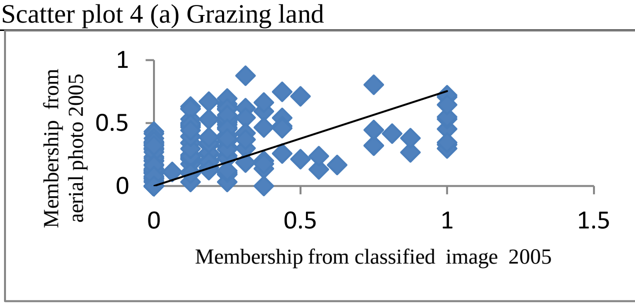
Scatter plot 3 (b) Woodland



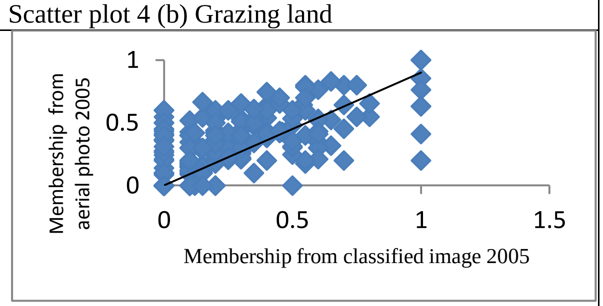
Scatter plot 4 (a) Grazing land



Scatter plot 4 (b) Grazing land



Scatter plot 5 (a) Bare area



Scatter plot 5 (b) Bare area

Figure 7.3 Membership of aerial photo points and classification points (2005)

7.3.2 Regression T1, T2, T3

A regression analysis was used to compare the reference data from the aerial photo with data from the classification image (2005). Table 7.1 illustrates regression statistics for multiple R in the urban, vegetation, woodland, grazing land and bare area classes at time T3 (2005), resulting from fuzzy set classification and fuzzy c-means. High R values indicate a good correlation between the classified and the field data. From Table 7.1 we can see that the multiple R is higher in the fuzzy set than the fuzzy c-means in all the classes. The highest value of R in fuzzy set classification is in the urban class (R=0.804) and in fuzzy c-means R=0.756. The lowest value of R in the fuzzy set is in the bare area class (R=0.484) and in fuzzy c-means R=0.482. This gives an indication that the urban class is more accurate than the others because the bare area and vegetation classes were changing from time to time and from season to season.

Table 7.1 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means as compared against the membership from aerial photos (2005)

Class	R fuzzy set	R c-means
Urban	0.80463	0.75649
Vegetation	0.65873	0.61234
Woody land	0.76549	0.71328
Grazing land	0.50762	0.47943
Bare area	0.48495	0.42958

Table 7.2 illustrates regression statistics for multiple R in the urban, vegetation, woodland, grazing land and bare area classes at T2 (1989), resulting from fuzzy set classification and fuzzy c-

means. From Table 7.2 we can see that the multiple R is higher in the fuzzy set than in the fuzzy c-means in all the classes. The highest value of R in fuzzy set classification is in the urban class (R=0.752); in fuzzy c-means R=0.702. The lowest value of R in the fuzzy set is in the bare area class (R=0.562); in fuzzy c-means R=0.489.

Table 7.2 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means as compared against the membership from aerial photos (1989)

Class	R fuzzy set	R c-means
Urban	0.75281	0.70248
Vegetation	0.59833	0.52836
Woody land	0.70167	0.63291
Grazing land	0.53295	0.48943
Bare area	0.53298	0.50327

Table 7.3 illustrates regression statistics for multiple R for all classes at T1 (1976), resulting from fuzzy set classification and fuzzy c-means. From Table 7.6 we can see that the multiple R is higher in the fuzzy set than in the fuzzy c-means in all the classes. The highest value of R in fuzzy set classification is in the urban class (R=0.717); in fuzzy c-means R=0.694. The lowest value of R in the fuzzy set is in the grazing land class (R=0.553); in fuzzy c-means R=0.445.

Table 7.3 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means compared against the membership from aerial photos (1976)

Class	R fuzzy set	R c-means
Urban	0.63751	0.54983
Vegetation	0.51982	0.55231
Woody land	0.48365	0.42198
Grazing land	0.41874	0.38964
Bare area	0.44382	0.42194

7.4 Evaluation of Soft Classifiers' Performance

7.4.1 Error matrix

Accuracy assessment is a significant component of any image classification procedure and is used to give a quantitative measure of classifier performance. The confusion or contingency matrix (Landgrebe, 2003) shown in Table 7.4 is often used as an assessment technique to evaluate Boolean hard classifiers. The rows in the matrix list the categories and show how the pixels labeled for every category were assigned by the classifier. For a principle classification, the matrix will just have values on the diagonal, and off-diagonal values will be zero. Off-diagonal elements characterize errors by omission or commission in the confusion matrix methodology. Omission errors refer to pixels that belong to an exacting category and were incorrectly assigned to other informational categories. Conversely, the commission errors refer to pixels which do not belong to an exacting category and were erroneously assigned to it.

Table 7.4: Layout of a confusion error matrix and computation of user’s and producer’s accuracy (Landgrebe, 2003)

Predicted class							
Number of samples	C1	C2	C3	C4	…….	………	Cm
	C1	nc1	nc1c1	nc1c2	……	nc1c4	%nc1
	C2	nc2	nc2c1	nc2c2	……	nc2c4	%nc2
Actual class	.	…..	…….	…….	……	……	……
	. .	nc4	ncmc1	ncmc2	…..	ncmcm	%ncm
	cm	$\sum_{i=1}^{m} nci$	$\sum_{i=1}^{m} ncic1$	$\sum_{i=1}^{m} ncic2$	……	$\sum_{i=1}^{m} ncicm$	$\sum_{i=1}^{m} ncic1$

m = number of classes
k = class for which the user’s or producer’s accuracy is calculated

$$\text{User Accuracy (\%nck)} = \frac{nkk}{\sum_{i=1}^{m} nci} \; x100\ \% \qquad (7.1)$$

$$\text{Producer Accuracy (\%nck)} = \frac{nkk}{nk} \; x\ 100\% \qquad (7.2)$$

$$\text{Overall Accuracy} = \frac{\sum_{i=1}^{m} ncici}{\sum_{i=1}^{m} nci} \; x\ 100\% \qquad (7.3)$$

The confusion matrix is not the best way to assess the performance of soft classifiers because it assumes that classes are equally exclusive and that each observation belongs to a single category. However, several researchers have evaluated the thematic map produced by a hardening or defuzzyfication process using a Boolean classifier assessment such as a confusion error matrix. Additional research studies have proposed the use of entropy (Foody, 1996; Van Der Meer, 2006) to show the strength of category memberships, Euclidean distance (Foody 1996) to ap-proximate the division of two data sets based on the proportion of every category in the pixel, and/or the fuzzy error matrix, which is an extension of the confusion matrix using the principles of fuzzy set theory (Foody, 2002; Lu and Weng, 2007; Varshney and Arora, 2004). Those approaches are discussed in the next section.

Tables 7.5, 7.7, 7.9, 7.11, 7.13, 7.15, 7.17 and 7.19 illustrate the accuracy assessments for all the fuzzy set and fuzzy c-means classifications. From the tables it is clear that the highest accuracy assessment is for the fuzzy set at all the dates: T1 (1976): 65%, T2 (1989): 67.3%, T3 (2005): 80%, and T4 (2009): 79.73%; the second highest is fuzzy c-means: T1: 59.6%, T2: 61.81%, T3: 75.5%, and T4: 72.12%; while the lowest accuracy assessment is for Boolean classification: T1: 55.26%, T2: 63.15%, T3: 75.17%, and T4: 66.19%.

Table 7.5 Accuracy assessment for fuzzy set classification (2009)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	37	33	26	70.27%	78.78%
Vegetation	45	40	35	77.77%	87.75%
Woodland	53	57	48	90.56%	84.21%
Bare area	44	35	30	68.18%	85.71%
Grazing land	31	45	28	90.32%	62.22%
Totals	210	210	167	Average	79.73

Table 7.6 Kappa for all classes (average value 0.695)

Class name	Kappa
Urban	0.7836
Vegetation	0.5943
Woodland	0.8452
Bare area	0.6871
Grazing land	0.5673

Table 7.7 Accuracy assessment for fuzzy c-means classification (2009)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	37	32	24	83.78%	64.86%
Vegetation	45	37	31	72.41%	68.88%
Woodland	53	58	42	84.37%	79.24%
Bare area	44	32	27	51%	61.36%
Grazing land	31	51	26	71.42%	83.87%
Totals	210	210	150	Average	72.12%

Table 7.8 Kappa for all classes (average value 0.650)

Class name	Kappa
Urban	0.6984
Vegetation	0.5567
Woodland	0.7894
Bare area	0.6075
Grazing land	0.5983

Table 7.9 Accuracy assessment for fuzzy set classification (2005)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer’s Accuracy	User’s Accuracy
Urban	35	32	27	77.14%	84.3%
Vegetation	41	39	32	78%	82%
Woodland	50	41	39	78%	95.1%
Bare area	47	43	33	70.21%	76.74%
Grazing land	37	55	35	94.59%	63.63%
Totals	210	210	166	Average	80%

Table 7.10 Kappa for all classes (average value 0.724)

Class name	Kappa
Urban	0.7793
Vegetation	0.6894
Woodland	0.8043
Bare area	0.6874
Grazing land	0.6597

Table 7.11 Accuracy assessment for fuzzy c-means classification (2005)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer’s Accuracy	User’s Accuracy
Urban	35	31	25	80.64%	71.42%
Vegetation	41	38	32	84.21%	78%
Woodland	50	49	37	75.5%	74%
Bare area	47	41	32	78%	68%
Grazing land	37	51	31	60%	83%
Totals	210	210	157	Average	75.5%

Table 7.12 Kappa for all classes (average value 0.662)

Class name	Kappa
Urban	0.7342
Vegetation	0.6574
Woodland	0.7218
Bare area	0.5985
Grazing land	0.6014

Tables 7.6, 7.8, 7.10, 7.12, 7.14, 7.16, 7.18 and 7.20 illustrate the average kappa for all the classifications, fuzzy set, fuzzy c-means and Boolean. From the tables it is clear that the highest kappa is for the fuzzy set at all the dates (average kappa: 0.724), and the lowest kappa is for Boolean classification (average kappa: 0.565). The results of accuracy assessments for each year show that the highest is in 2005 for fuzzy set and fuzzy c-means (80% and 75.5%, respectively), with similar results in 2009 (79.73% and 72.12%), in 1989 (67.3% and 61.81%), and in 1976 (65% and 59.6%). The reasons are the difference in the resolution between the images, the quality of the images, and the fact that in 1976 and 1989 the reference points from the aerial photo were not clear.

Table 7.13 Accuracy assessment for fuzzy set classification (1989)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	39	34	29	74.35%	85.29%
Vegetation	43	40	25	58.1%	62.5%
Woodland	44	39	31	70.45%	79.84%
Bare area	38	43	26	68.42%	60.46%
Grazing land	46	54	30	65.21%	55.55%
Totals	210	210	141	Average	67.3%

Table 7.14 Kappa statistics (average value 0.591)

Class name	Kappa
Urban	0.6543
Vegetation	0.5132
Woodland	0.6948
Bare area	0.5342
Grazing land	0.5617

Table 7.15Accuracy assessment for fuzzy c-means classification (1989)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	39	37	27	72.9%	69.23%
Vegetation	43	44	24	54.5%	55.8%
Woodland	44	43	29	67.44%	65.9%
Bare area	38	39	24	61.53%	63.15%
Grazing land	46	47	25	53.19%	54.34%
Totals	210	210	129	Average	61.81%

Table 7.16 shows kappa statistics (average value 0.580)

Class name	Kappa
urban	0.6194
Vegetation	0.5563
Woodland	0.6745
Bare area	0.5184
Grazing land	0.5327

Table 7.17 Accuracy assessment for fuzzy set classification (1976)

Classes Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Urban	10	8	6	60%	75%
Vegetation	14	10	7	50%	70%
Woodland	13	15	11	84.61%	73.33%
Bare area	11	13	7	63.63%	53.84%
Grazing land	14	16	9	64.28%	56.25%
Totals	62	62	40	Average	65%

Table 7.18 Kappa statistics (average value 0.604)

Class name	Kappa
urban	0.6237
Vegetation	0.5856
Woodland	0.7493
Bare area	0.5432
Grazing land	0.5186

Table 7.19 Accuracy assessment for fuzzy c-means classification (1976)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	10	6	4	66.6%	40%
Vegetation	14	11	7	63.6%	50%
Woodland	13	13	8	61.5%	61.5%
Bare area	11	15	7	46.6%	63.6%
Grazing land	14	17	11	64.7%	78.5%
Totals	62	62	37	Average	59.6%

Table 7.20 Kappa statistics (average value 0.593)

Class name	Kappa
Urban	0.6983
Vegetation	0.4965
Woodland	0.6765
Bare area	0.5843
Grazing land	0.5132

7.4.2 Fuzzy Error Matrix (FEM)

The fuzzy error matrix is an extension of the confusion error matrix using the principles of fuzzy set theory. It can be used to evaluate the performance of soft classifiers when soft ground truth data are available (Binaghi et al., 1999). The reliability of soft reference data is necessary to avoid under- or over-estimation in accuracy assessment. Let R_i and C_i be the soft ground truth data (referenced data), $R1$, $R2$ and $R3$ are the different memberships in the pixel and soft classification output for class i. R_i and C_i can be considered as fuzzy sets in the soft classification context having a membership function as follows:

$$XRi : Y \rightarrow [0,1] \qquad (7.4)$$

$$XCi : Y \rightarrow [0,1] \qquad (7.5)$$

where [0, 1] denotes the interval of real numbers from 0 to 1. XRi (y) and XCi (y) are the degrees of membership of the sample element y in class i for the soft ground truth data and classification data. The fuzzy error matrix can be determined by using equation (7.6):

$$XCi \cap XRi\,(X) = min(XCi\,(X), XRi\,(X)) \qquad (7.6)$$

The Total Grades at the bottom of the matrix corresponds to the sum of the soft ground truth data for every informational class sample available (Table 7.21) and the Total Grades column at the right side of the matrix corresponds to the sum of the degrees of membership for each informational class sample available (Table 7.22). As with the confusion error matrix method Producer's Accuracy is associated with omission errors and the User's Accuracy is related to errors of commission in the computation of the fuzzy error matrix. Overall Accuracy can be determined as a measure of the total match between membership of soft ground truth data and membership of soft classification output. It can be a simple way to evaluate a soft classifier in a single number. Accurate soft ground truth data are not available in many of the cases. A as a result, computation of the fuzzy error matrix is not possible with hard ground truth data where each pixel is allocated to one specific class. For that reason several researchers have used hard thematic maps produced by a hardening process (defuzzyfication) to compute the confusion error matrix. This approach does not allow partial membership, resulting in a loss of information and errors in accuracy estimation.

Table 7.21 and Table 7.22 illustrate sampled data (membership ground data and membership classified data from the fuzzy set classification) by applying an underestimation model and an overestimation model. Unfortunately there is no data for a perfect matching model. The results show that the overall accuracy for the underestimation model is 88.6%, the overall accuracy for the overestimation model is 70.5%, and the average for both models is 76.2%. When this model is applied to all 210 points from the field we get an overall underestimation accuracy of 80.4%, an overestimation accuracy of 68.5%, and an average of 74.4%. When this model is applied to the results from fuzzy c-means, the overall underestimation accuracy is 76.8%, the overestimation accuracy is 65.9%, and the average is 71.3%.

Table 7.21 Fuzzy error matrix – Underestimation

C&R	R1	R2	R3	Total Grades	User´s accuracy	Soft Reference Data	Degree of Membership
Urban	0.4	0.4	0.4	0.6	100%	XR1(Y)=0.6	XC1(Y)=0.4
Vegetation	0.5	0.5	0.5	0.6	83%	XR2(Y)=0.5	XC2(Y)=0.6
Woodland	0.4	0.4	0.4	0.7	100%	XR3(Y)=0.7	XC3(Y)=0.4
Grazing land	0.3	0.3	0.3	0.5	100%	XR4(Y)=0.3	XC4(Y)=0.5
Bare land	0.6	0.6	0.6	0.8	100%	XR5(Y)=0.8	XC5(Y)=0.66
Total Grades	0.6	0.6	0.6		96.6%		
Producer Accuracy	66%	100%	66%				
Overall Accuracy	88.6%						

Table 7.22 Fuzzy error matrix – Overestimation

R&C	R1	R2	R3	Total grades	User´s accuracy	Soft Reference Data	Degree of Membership
Urban	0.5	0.4	0.5	0.6	83%	XR1(Y)=0.6	XC1(Y)=0.5
Vegetation	0.6	0.4	0.7	0.7	100%	XR2(Y)=0.4	XC2(Y)=0.7
Woodland	0.5	0.4	0.5	0.8	62.5%	XR3(Y)=0.8	XC3(Y)=0.5
Grazing land	0.2	0.2	0.2	0.4	50%	XR4(Y)=0.4	XC4(Y)=0.2
Bare land	0.3	0.3	0.3	0.6	50%	XR5(Y)=0.3	XC5(Y)=0.6
Total grades	0.5	0.5	0.5		69.1%		
Producer accuracy	83%	71%	62%		72%		
Overall Accuracy	70.5%						

7.4.3 Euclidean Distance

The first approach to evaluating the performance of a soft classifier when soft ground truth data are available is to measure the distance between the degree of membership obtained by a soft classification and the soft reference ground truth. There are a number of ways to determine this distance; Euclidean distance (ED) (Foody, 1996) is an easy way to do this. ED can estimate the separation of two data sets (soft classification and soft reference data) based on the proportion coverage associated with each class in the pixel. Lower values of ED can be interpreted as an accurate estimate of degree of membership for all defined informational classes. The ED derived for each pixel can be given as in equation 7.

$$ED(X) = \frac{1}{m}\sqrt{(\sum_{i=1}^{m}(y(i) - x(i))^2} \qquad (7.7)$$

where *y(i)* refers to the proportion coverage of class *i* in the soft ground truth data; *x(i)* is the degree of membership derived by a soft classification for class *i*; and *m* is the number of informational classes.

Table 7.23 and Table 7.24 show some tested pixels from ground data (G) from the field survey and classified data from fuzzy set classification and fuzzy c-means; the data are tested, used and calculated for Euclidean distance, and the results are shown in Tables 7.25 and 7.26.

Table7.23 Tested ground data (G) and classified data (C) from fuzzy sets for all the classes

Urbn		Vegetation		Woodland		Grazing land		area Bare	
G	C	G	C	G	C	G	C	G	C
0.25	0.103	0.25	0.189	0.25	0.673	0.25	0	0	0.32
0	0.256	0.25	0.036	0	0.387	0	0	0.75	0.321
0	0	0	0.076	0.75	0.216	0	0.053	0.25	0.651
0.25	0.112	0.625	0.372	0	0.215	0	0.185	0.125	0.11
0.687	0.265	0.25	0.473	0	0.147	0	0	0.062	0.112
0	0	0.75	0.365	0.125	0.312	0	0.143	0.125	0.175

Table 7.24 Tested ground data (G) and classified data (C) from fuzzy c-means for all the classes

Urbn		Vegetation		Woodland		Grazing land		Bare area	
G	C	G	C	G	C	G	C	G	C
0.25	0.073	0.25	0.104	0.25	0.716	0.25	0.716	0	0.1
0	0.167	0.25	0.165	0	0.298	0	0.298	0.75	0.354
0	0	0	0.218	0.75	0.195	0	0.195	0.25	0.457
0.25	0.089	0.625	0.273	0	0.182	0	0.182	0.125	0.183
0.687	0.231	0.25	0.365	0	0.211	0	0.211	0.062	0.076
0	0	0.75	0.239	0.125	0.285	0	0.285	0.125	0.095

Table 7.25 shows the result for Euclidean distance for fuzzy set classification and field survey obtained by applying equations 7.7, for all the classes (urban, vegetation, woodland, grazing land and bare area). Table 7.26 shows the result for Euclidean distance for fuzzy c-means classification and field survey obtained by applying equations 7.7, for all the classes. When we compare the results of the two tables for the urban class, we can see that, for fuzzy set classification, the average value of the Euclidean distance is 0.01273, while for fuzzy c-means classification the average value of the Euclidean distance is 0.0126; the result shows that there is a slight difference between the two models. The Euclidean distance was calculated for all sample pixels and is included in an appendix at the end of the thesis.

Table 7.25 Result for Euclidean distance for fuzzy set classification and field survey obtained by applying equations 7.7.

Urban	Vegetation	dwooland	Grazing land	Bare area
0.0054	0.0009	0.0447	0.015	0.0256
0.0218	0.0114	0.0374	0	0.0460
0	0.0003	0.0712	0.0028	0.0402
0.0047	0.0160	0.0115	0.0085	0.0005
0.0445	0.0124	0.0054	0	0.0006
0	0.0370	0.0087	0.0051	0.0006

Table 7.26 Result for Euclidean distance for fuzzy c-means classification and field survey obtained by applying equations 7.7.

Urban	Vegetation	woodland	Grazing land	Bare area
0.0442	0.0365	0.1165	0.0625	0.025
0.041	0.0212	0.0745	0	0.099
0	0.0545	0.1387	0.0307	0.0517
0.0402	0.088	0.0455	0.0672	0.0145
0.114	0.028	0.0527	0.0267	0.0035
0	0.1277	0.04	0.0697	0.0177

7.4.4 Fuzzy Cross-tabulation

Cross-tabulation offers four rules for comparing soft-classification images: composite, multiplication, minimum and hard, as shown in Table 7.27. In Multiplication, each pixel has membership in a class according to the probability that a randomly selected point within the pixel belongs to that class. The concept of location within the pixel exists in terms of infinitely small points, whose spatial distribution within the pixel is random. Minimum: each pixel has membership according to fuzzy set theory, in order to acknowledge ambiguity. The sum of the class memberships can be different from 100%. Under multiple resolutions, each pixel has membership according to the proportion of the pixel that the class constitutes. The composite rule has many attractive characteristics that the other rules lack, the most important being that it produces the identity matrix when a soft-classified image is compared to itself. Pontius and Cheuk, (2006) carried out a study of all the rules and proved that, if the composite rule defines the pixel count matrix, then diagonal entries increase monotonically as the resolution becomes coarser. This shows that, if the multiplication rule or minimum rule defines the matrix, then agreement as a percentage of the pixel counts can either increase or decrease, depending on how the conversion of resolution groups clusters of finer pixels. This dilution occurs by spreading more uniformly in space the categories that agree. The same principles apply for the minimum rule. Specifically, Pontius and Connors (2006) also proved that if the minimum rule defines the pixel count matrix, then all entries increase monotonically as the resolution becomes coarser. The study shows that the diagonal entries reach their maximum at the medium resolution because all of the location agreement reaches its maximum at the medium resolution. Moving to the coarse resolution increases only the off-diagonal entries. Consequently, the diagonal entries account for a smaller percentage of the total. All rules produce the same results when the images are hard-classified.

The Table 7.27 below gives four rules for pixel-level agreement and disagreement. *Cgni•* is the membership of pixel *n* in category *i* for the comparison image at resolution *g*. *Cgn•j* is the membership of pixel *n* in category *j* for the comparison image at resolution *g*. *Cgnij* is the calculated correspondence at resolution *g* between pixels at position *n* for category *i* of the comparison image and category *j* of the reference image. Cross-tabulation generates the map-level tabular matrix by adding together the pixel-level correspondences.

Table 7.27 Cross-tabulation rules: hard, multiplication, minimum and composite

Rule	Agreement for I = j	Disagreement for i= j	
Hard	Cgnij=lifCgij=Cgnj else 0	Cgii=lifCgni=Cgnj else=0	(12)
Multiplication	Cgnjj=Cgnj× Cgnj	Cgnij=Cgni x Cgnj	(13)
Minimum	Cgij=MIN(Cgnj.,Cgn.j)	Cgnij=MIN(Cgn.,Cgn.j)	(14)
Composite	Cgnij=MIN(Cgnj. ,Cgn.j)	$Cgnij = \frac{(Cgni.-Cnii)x(Cgn.j-Cgnjj)}{1-\sum_{j-1}^{j} Cgnij}$	(15)

Table 7.28 illustrates the results of cross-tabulation of fuzzy classification images 1989 and 2005 with resolution 1*1 by using the composite rule for all five classes (urban, woodland, vegetation, grazing land and bare areas), and Table 7.29 illustrates the cross-tabulation of fuzzy classification images 1989 and 2005 with resolution 30*30. From Table 7.28 it is clear that, when the resolution increases, the overall agreement increases; this means that when the resolution decreases, the detail of the pixel is not as clear as at 30*30: the resolution will be 900m and the agreement increases. The overall agreement between 2005 and 1989 for the fuzzy classification is low (0.4907 at pixel resolution 1*1 and 0.6284 at resolution 30*30). This gives an indication of a large change in the area during this time, with the precise amount of change measured being dependent on the image resolution as well as the amount of change in the study area.

Table 7.28: Cross-tabulation of fuzzy classification images 1989 and 2005 with resolution 1*1 By using composite rule

Classes	1	2	3	4	5	6	Total
1	0.3115	0.0008	0.0514	0.0005	0.0035	0.0230	0.3907
2	0.0524	0.0030	0.0212	0.0001	0.0006	0.0138	0.0912
3	0.1378	0.0010	0.1302	0.0004	0.0020	0.0074	0.2789
4	0.0038	0.0038	0.0038	0.0198	0.0038	0.0000	0.0349
5	0.0011	0.0000	0.0004	0.0000	0.0010	0.0001	0.0025
6	0.0230	0.0192	0.0185	0.0986	0.0175	0.0252	0.2019
Total	0.5296	0.0278	0.2254	0.1193	0.0284	0.0695	1.0000
Overall agreement = 0.4907							

Table 7.29: Cross-tabulation of fuzzy classification images 1989 and 2005 with resolution 30*30 By using composite rule

Classes	1	2	3	4	5	6	Total
1	0.3752	0.0001	0.0061	0.0002	0.0009	0.0082	0.3907
2	0.0532	0.0051	0.0063	0.0005	0.0021	0.0240	0.0912
3	0.0757	0.0002	0.1918	0.0004	0.0017	0.0090	0.2789
4	0.0023	0.0023	0.0023	0.0256	0.0023	0.0000	0.0349
5	0.0001	0.0000	0.0000	0.0000	0.0024	0.0000	0.0025
6	0.231	0.0201	0.0188	0.0927	0.0190	0.0283	0.2019
total	0.5296	0.0278	0.2254	0.1193	0.0284	0.0695	1.0000
Overall agreement = 0.6284							

7.5 Accuracy assessment for Boolean classification

A total of 210 pixel points, which may be from mixed or pure pixels, were randomly selected from the study area (field survey), and were compared against the classified image from 2009. By using the ERDAS IMAGINE software accuracy assessment routines, the result shows the accuracy assessment (producer accuracy and user accuracy) for all classes (urban, vegetation, woodland, grazing land and bare areas). The overall classification accuracy was 66.19 per cent, as shown in Table 7.30. Table 7.31 provides the overall kappa statistic of 0.574.

Table 7.30 Accuracy assessment for Boolean classification (2009)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	37	29	21	56.76%	72.41%
Vegetation	45	41	27	60.00%	65.85%
Woodland	53	64	40	75.47%	62.50%
Bare area	44	37	27	61.36%	72.97%
Grazing land	31	35	24	77.42%	68.57%
Totals	210	206	139	Average	66.19%

Table 7.31 Kappa for all classes (average value 0.574)

Class name	Kappa
Urban	0.6651
Vegetation	0.5654
Woodland	0.4984
Bare area	0.6581
Grazing land	0.6313

Tables 7.32, 7.34 and 7.36 show the accuracy assessment for the Boolean classification; the reference data taken from aerial photos at T1 (1976), T2 (1989) and T3 (2005) were compared against the classified image; the results show that the class with the highest accuracy is the urban class and the class with the lowest accuracy is grazing land. Tables 7.33, 7.35 and 7.37 show the kappa statistics for Boolean classification at T1, T2 and T3.

Table 7.32 Accuracy assessment for Boolean classification (2005)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	35	37	31	88.75%	71.42%
Vegetation	41	35	25	60.9%	71.42%
Woodland	50	45	41	82%	91%
Bare area	47	45	33	70.21%	73.33%
Grazing land	37	48	27	72.97%	56.25%
Totals	210	210	157	Average	75.17

Table 7.33 Kappa statistics (2005)

Class name	Kappa
Urban	0.6176
Vegetation	0.5894
Woodland	0.7642
Bare area	0.5879
Grazing land	0.6327

Table 7.34 Accuracy assessment for Boolean classification (1989)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	39	38	28	71.79%	73.68%
Vegetation	43	45	25	58.13%	55.55%
Woodland	44	41	33	75%	80.48%
Bare area	38	36	23	60.58%	63.88%
Grazing land	46	50	27	58.69%	54%
Totals	210	210	136	Average	63.15%

Table 7.35 Kappa statistics (1989)

Class name	Kappa
Urban	0.6632
Vegetation	0.5187
Woodland	0.6985
Bare area	0.5032
Grazing land	0.4983

Table 7.36 Accuracy assessment for Boolean classification (1976)

Class Name	Reference Totals	Classified Totals	Number Correct	Producer's Accuracy	User's Accuracy
Urban	10	6	5	50%	83.33%
Vegetation	14	11	6	42.85%	54.54%
Woodland	13	16	9	69.23%	56.25%
Bare area	11	14	7	63.63%	50%
Grazing land	14	15	6	42.85%	40%
Totals	62	62	33	Average	55.26%

Table 7.37 Kappa statistics 1976

Class name	Kappa
Urban	0.6432
Vegetation	0.5204
Woodland	0.6183
Bare area	0.5542
Grazing land	0.4894

7.6. Results and Discussion

The accuracy assessment shows that all of the measures discussed in the previous sections can be used to successfully check the accuracy of the classification. Among these, the confusion matrix suffers from the disadvantage that it is based only on Boolean classification: it works only on a pixel-by-pixel basis and therefore does not take into account the information uncertainty in class allocation. When accuracy assessment is applied to all the models (fuzzy set, fuzzy c-means and Boolean classification), the results show that the highest value obtained by using the error matrix method is for fuzzy set classification (80%), the second is for the fuzzy c-means (75.5%), and the lowest value is for the Boolean classification (66.19%). When the fuzzy error matrix is applied for accuracy assessment, the result for the fuzzy set is 83.4% and the result for the fuzzy c-means is 79.6%.

Some of the methods which have been discussed here for evaluating the accuracy of classification suffer from a few disadvantages. First of all, most of these measures are applicable only when both the reference data and the classification output are soft. Therefore, a generalized approach is required which will be applicable to hard as well as soft reference and classified data. Secondly, most of these methods are probabilistic measures of accuracy assessment. As a result, both reference and classified data need to be probabilistic in nature, i.e., summation of membership grades over each pixel should be a possibilistic approach of accuracy assessment to overcome this disadvantage. Possibilistic measures, such as fuzzy correlation, the fuzzy error matrix and fuzzy functions are methods already available for accuracy assessment. The results obtained by applying these measures should also be checked so that a judgment about the best method for a particular classification can be carried out.

7.7 Conclusion

Accuracy assessment of soft classifiers is still a relatively new approach in remote sensing. This study looked at methods of evaluating the performance of soft classifiers. It found them to be sensitive to the use of a more accurate proportional coverage of each informational class per pixel in soft ground truth data which in practical situations are sometimes a bit difficult to obtain. Further investigation is needed on how we can assess soft classifiers, taking into consideration the multiclass assignment problem, and using soft ground truth data. Among these the measure of Euclidean distance may be stated to be the best method, since this measure takes into account the ambiguity and vagueness in the data, can be used for any probability distribution, and provides a suitable accuracy index of classification. The value is zero for perfect classification and increases as errors in classification increase. Monitoring land cover changes is a key component of different applications such as Woodland, environment, grazing land, vegetation, and others. It could be useful to study how soft classification can be used to detect the transition zones of diverse classes (membership maps) by the use of temporal images and change detection algorithms and by applying soft accuracy assessment.

Chapter 8: Synthesis of results

8.1 Introduction

The results from quantifying land cover and land cover change (fuzzy classification, fuzzy change and fuzzy validation) are compared, and the model that best describes and predicts land cover and land cover change is assessed. Theoretically, fuzzy change and fuzzy classification allow the decision-making process to accommodate the uncertainties associated with land mapping that are hidden or removed in Boolean analyses. The results summarized in this section evaluate whether fuzzy classification is more suitable than Boolean classification. This chapter also describes the results of validation of fuzzy classification using different models such as the fuzzy error matrix and cross-tabulation. Many studies have applied fuzzy classification but very few have validated the results.

8.2 Result of Image classification

As mentioned in Chapter 4, three models were applied for image classification (fuzzy set, fuzzy c-means and Boolean). Table 8.1 compares the results derived from the use of the fuzzy set, fuzzy c-means and Boolean approaches for all classes at times T1, T2, T3 and T4. Each model generated different results in terms of the areas of different land cover they identify and thus the post-classification changes that can be determined. For example, the area of the urban class determined by using the three models (fuzzy set, fuzzy c-means and Boolean) is small at T1 (9104.8, 6475.1and 1380.2 hectares, respectively), increases at T2 and T3, and is a large area at T4 (30127.8, 35760.2, 39874.9 hectares). In the woodland class, the largest area is at T1 (57063.7, 56913.2, 40821.5 hectares), and the lowest area is at T4 (20376.4, 22567.4, 16673.4 hectares), so the woodland decreases from T1 to T4. The vegetation class is higher at T1

(61173.3, 60945.8, 70316.7 hectares), and lower at T4 (41742.7, 42761.7, 48563.6 hectares). The grazing land class is lowest at T1 (23931.6, 25879.5, 30419.3 hectares), and higher at T4 (34821.3, 28563.8, 32762.7 hectares), while the bare area class is low at T1 (19891.2, 26932.1, 21766.9 hectares), and increases at T4 (45365.1, 47156.6, 32762.7 hectares).

Table 8.1 Comparison of the results of fuzzy set, fuzzy c-means and Boolean classification for all the classes at times T1, T2, T3 and T4, by hectares.

Classes	Urban			Woodland			Vegetation			Grazing land			Bare area		
Model Year	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy Set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean
1976	9104.8	6475.1	1380.2	57063.7	56913.2	40821.5	61173.3	60945.8	70316.7	23931.6	25879.5	30419.3	19891.2	26932.1	21766.9
1989	17355.6	15809.7	19187.8	36879.3	31638	25193.9	49468.1	45980.3	51290.8	48789.2	52714.7	41914.5	17203.4	28769.3	37855.2
2005	28491.6	23834.5	32161.3	19338.6	24355.8	18187.1	43201.9	38541.8	46539.7	32891.8	41966.9	52317.1	41699.2	45376.5	29845.3
2009	30127.8	35760.2	39874.9	20376.4	22567.4	16673.4	41742.7	42761.7	48563.6	34821.3	28563.8	38439.3	45365.1	47156.6	32762.7

Table 8.2 below shows the comparison of the results of fuzzy set, fuzzy c-means and Boolean classification for all the classes at times T1, T2, T3 and T4, by percentage. From Table 8.2 it is obvious that there are small differences between the fuzzy set and fuzzy c-means methods and large differences between both fuzzy methods and the Boolean method. For example, the amount of change in the urban area in 1976 using the fuzzy set method is 6%, and using fuzzy c-means it is 5%, while using the Boolean method the amount of change is 8%. Also, for the woodland class in 1976, the amount of change using fuzzy sets is 34%, using fuzzy c-means it is 36%, and using the Boolean method it is 23%.

Table 8.2 Comparison of the results of fuzzy set, fuzzy c-means and Boolean classification for all the classes at times T1, T2, T3 and T4, by percentage

Classes / Model / Year	Urban			Woodland			Vegetation			Grazing land			Bare area		
	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean	Fuzzy Set	Fuzzy c-means	Boolean	Fuzzy set	Fuzzy c-means	Boolean
1976	6	5	8	34	36	23	37	35	40	14	17	17	9	7	12
1989	13	10	11	19	20	14	35	32	29	21	23	24	12	15	22
2005	19	17	18	13	14	10	30	28	26	23	25	29	15	16	17
2009	20	21	23	13	14	9	27	27	27	23	24	22	17	14	19

Figures 8.1 to 8.5 below show the results of three models of classification (fuzzy set, fuzzy c-means and Boolean) for all classes: Figure 8.1 shows the results of applying the three models to the urban class. From Figure 8.1 and Table 8.1 it is clear that there are differences between the three models, with a large difference between Boolean and both soft classifications (fuzzy set and fuzzy c-means). The results also show a difference between the fuzzy set and fuzzy c-means; for example, the area of the urban class at T4 (2009) is 30127.8 hectares using fuzzy set classification, 35760.2 hectares using fuzzy c-means, and 39874.9 hectares using Boolean. The results from Figures 8.1 to 8.5 show that the classes which are most similar in all models are urban (as shown in Figure 8.1) and woodland (Figure 8.2), while the most diverse classes are grazing land (as shown in Figure 8.4) and bare areas (Figure 8.5), because of the rapid change in the land cover.

Fuzzy membership gives membership vectors for each sample for each class with values ranging from 0 to 1. Thus a pixel can belong to a class to a certain extent and may belong to another class to another extent and the extent is indicated by fuzzy membership values. In case of fuzzy membership grades, the feature space is not sharply portioned for different clusters; this is helpful for describing the uncertainty and vagueness of geomorphic features due to the continuity in reality.

The Boolean classification decision rule is based on the probability that a pixel belongs to a particular class, and assumes that these probabilities are equal for all classes, and that the input bands have normal distributions. However, in reality, there is a possibility that one particular pixel belongs to more than one class. This is because of vagueness in the boundary between classes clearly without any transition. In Boolean classification, in remote sensing, discrete pixels are used, i.e. the result is only one class per pixel. Much information about the membership of the pixel in other classes is lost. This information can be identified in the results of fuzzy classification. This is one of the reasons for better accuracy with fuzzy classification.

Figure 8.1 Change in area of urban class, using three models (fuzzy set, fuzzy c-means and Boolean classification), from 1976 to 2009

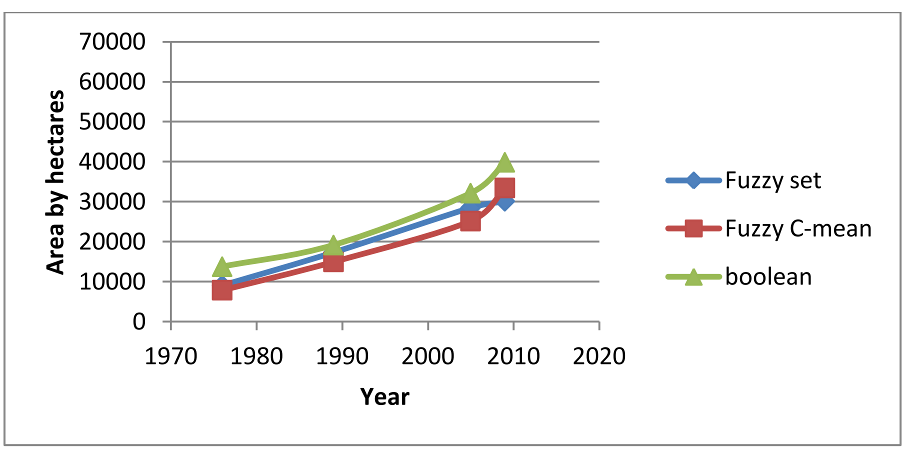


Figure 8.2 Change in area of woodland class, using three models (fuzzy set, fuzzy c-means and Boolean classification), from 1976 to 2009

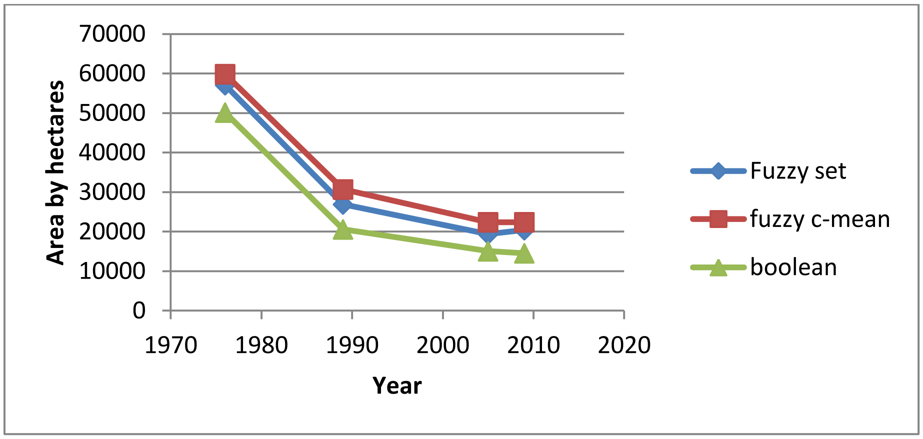


Figure 8.3 Change in area of vegetation class, using three models (fuzzy set, fuzzy c-means and Boolean classification), from 1976 to 2009

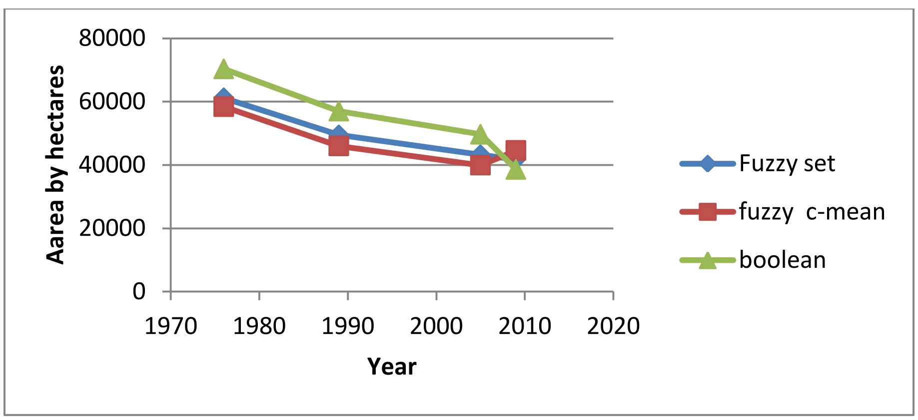


Figure 8.4 Change in area of grazing land class, using three models (fuzzy set, fuzzy c-means and Boolean classification), from 1976 to 2009

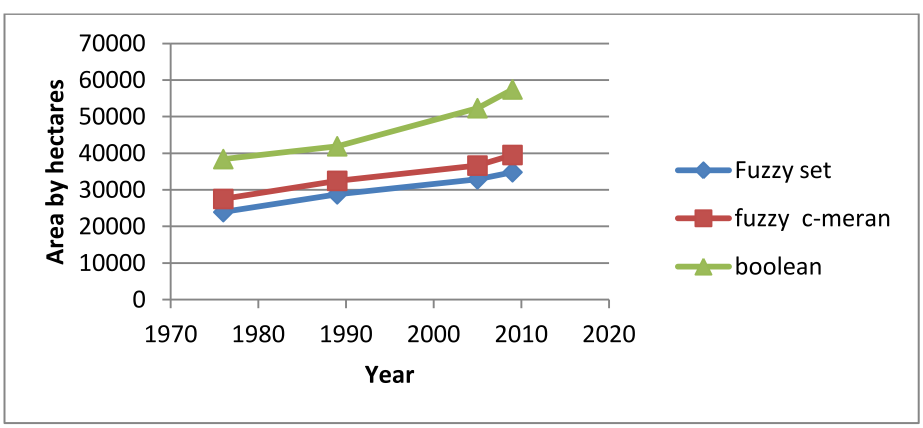
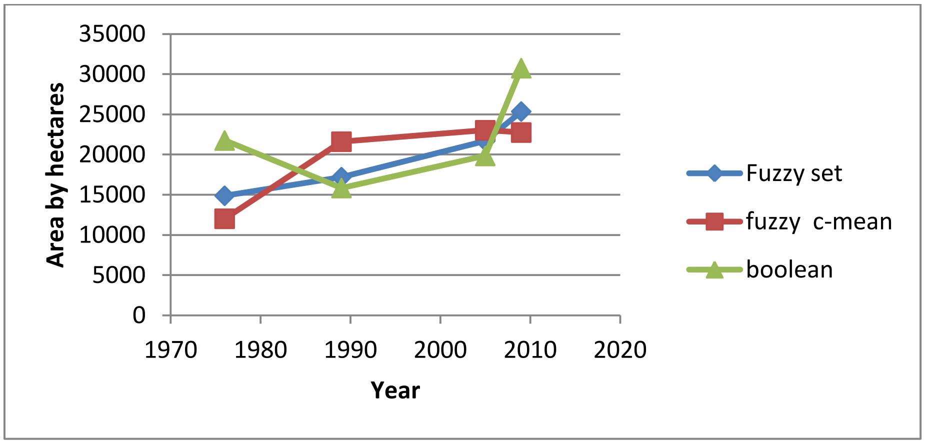


Figure 8.5 Change in area of bare area class, using three models (fuzzy set, fuzzy c-means and Boolean classification), from 1976 to 2009



8.3 Fuzzy change

8.3.1 Result of fuzzy change matrix

As mentioned in Chapter 5, three models have been used to determine the fuzzy change. The first model, fuzzy object, depends on converting the pixel to a polygon which has the same membership value. In this method, land cover is regarded as consisting of polygon objects rather than crisp objects. The fuzzy land cover is derived on the basis of a fuzzy classification. The degree of change is then calculated using fuzzy land-cover objects based on fuzzy change. In this method, land cover is directly represented as fuzzy spatial objects. The second model (fuzzy change matrix) depends on the sub-pixel change for both fuzzy sets and fuzzy c-means to compute the fuzzy change, fuzzy loss, fuzzy gain and boundaries. The third model is Boolean change, which depends on pixel-by-pixel change from one time to the next.

When the polygons overlap with each other, the result is also overlapping. That is, we will obtain two results for each pixel, showing the degree of change. In order to determine the degree of change for each polygon, we have to create a composite of these results. The composite is calculated by the sum of degrees of change of each land-cover class for each pixel.

Figures 8.6, 8.7 and 8.8 show the amount of gain and loss in all the classes (urban, vegetation, woodland, grazing land and bare area) resulting from the fuzzy set, fuzzy c-means and Boolean classifications by using the fuzzy change matrix. From the three Figures we can see that the lowest value of loss is in the urban class (2534.5 hectares) and the highest loss is in the woodland class (46073.7 hectares); on the other hand, the highest value of gain is in the urban class (25095.4 hectares) and the lowest is in the woodland class (7821.8 hectares). These Figures mean that the urban class increases and the woodland decreases.

With Boolean classification, each pixel is labelled with only one class. Information on the fractional amounts of spatially mixed spectral signatures belonging to different ground-cover features is not possible with hard classifiers. Hence, the traditional classification of mixed pixels may lead to information loss

The analysis shows that using a fuzzy change matrix dependent on sub-pixel change gives more information about the amount of land cover change.

Figure 8.6 Area of gain and loss for all classes from 1976 to 2009, using change matrix model with data from fuzzy set classification

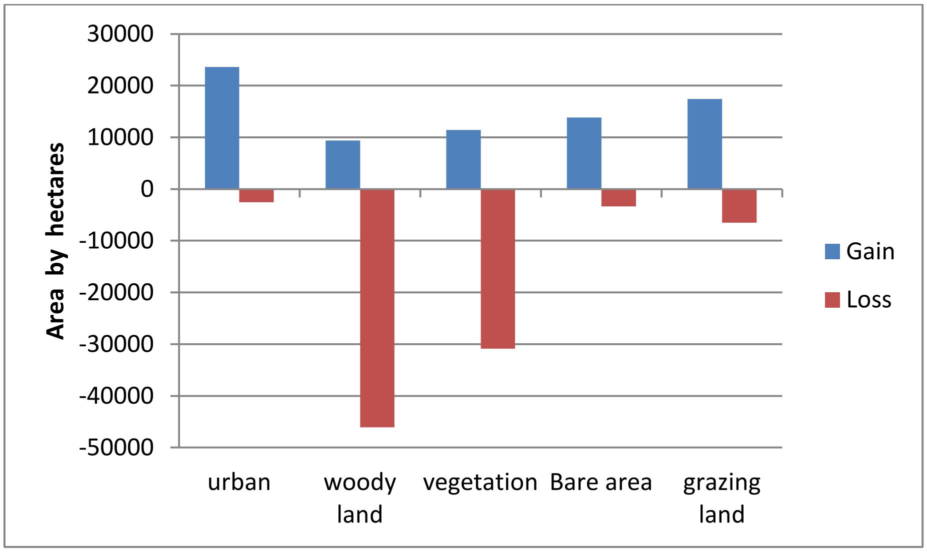


Figure 8.7 Area of gain and loss for all classes from 1976 to 2009, using change matrix model with data from fuzzy c-means classification

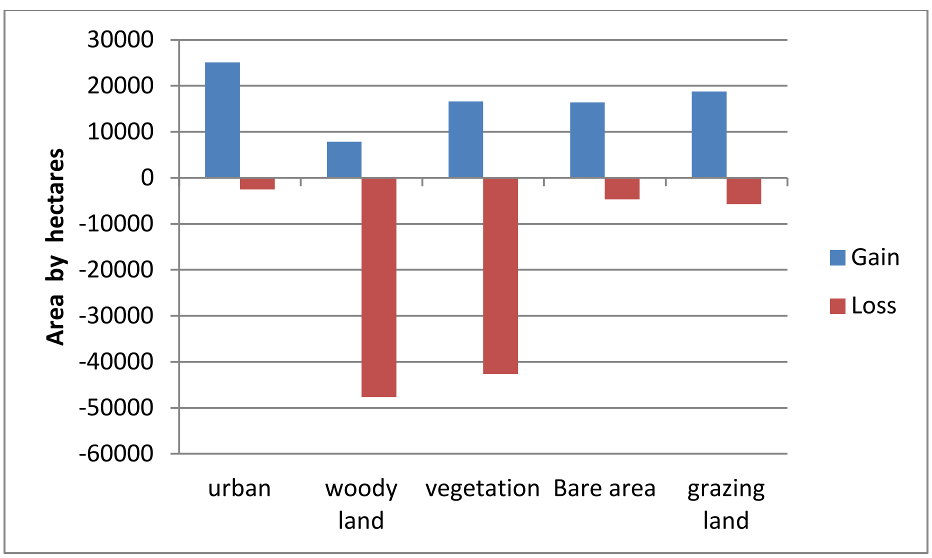
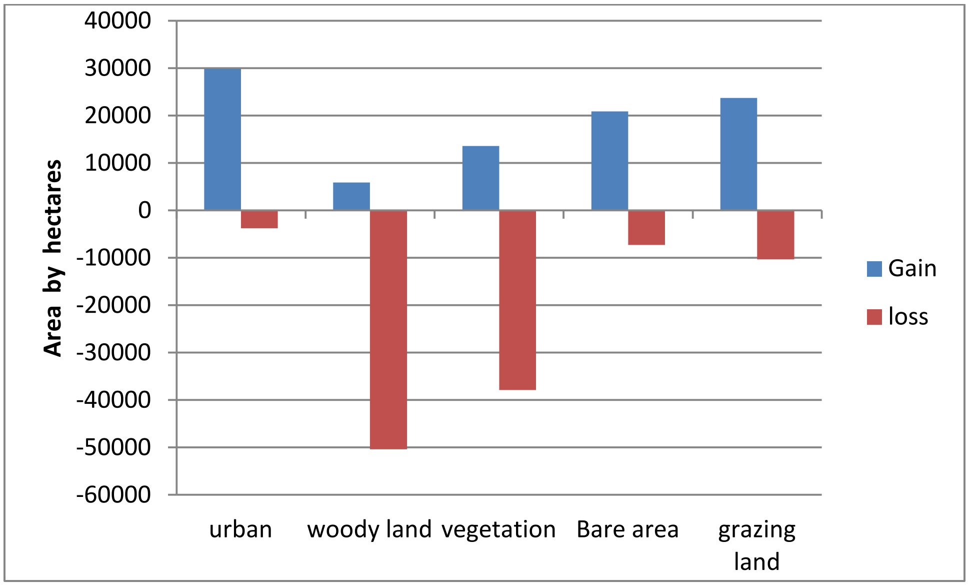


Figure 8.8 Area of gain and loss for all classes from 1976 to 2009, using change matrix model with data from Boolean classification



Figures 8.9a and 8.9b illustrate how the same pixel changes over time, from T1 (1976), to T2 (1989), T3 (2005) and T4 (2009); the location of this pixel is 3618240N and 310893E. Figure 8.9a shows the urban membership in the pixel at T1, T2, T3 and T4: at T1 the urban membership is 0, at T2 the value of the membership has started to increase and is 0.25, at T3 the value is 0.45, and at T4 it is 0.9, which means that most of the pixel has changed to urban. On the other hand, in Figure 8.9b the woodland membership in T1 is 1, which means that all the pixel is woodland, while at T2 the value is 0.35, at T3 the value is 0.2, and at T4 the value is 0, which means that this pixel changes from woodland at T1 (1976) to urban land at T4 (2009).

Figure 8.9a shows how the urban membership changes in one pixel at T1, T2, T3 and T4

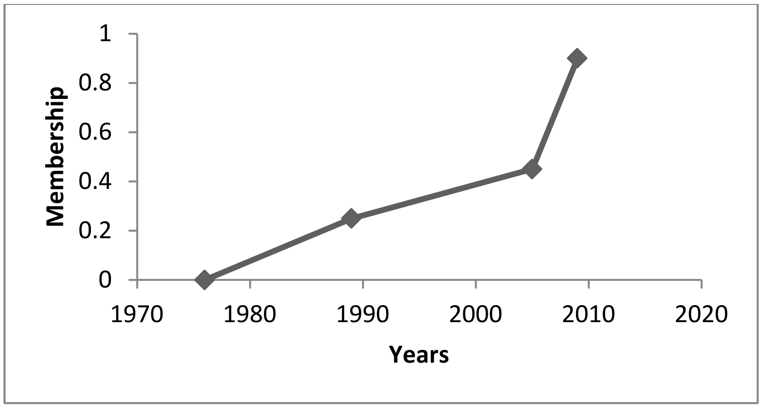
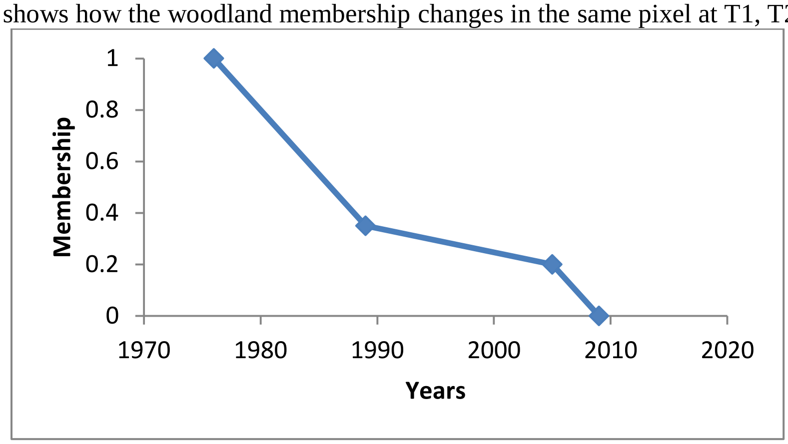


Figure 8.9b shows how the woodland membership changes in the same pixel at T1, T2, T3 and T4



Figures 8.10a and 8.10b illustrate how the same pixel changes over time, from T1 (1976), to T2 (1989), T3 (2005) and T4 (2009); the location of this pixel is 3625155N and 313942E. Figure 8.10a shows the urban membership in the pixel at T1, T2, T3 and T4: at T1 the urban membership is 0, at T2 the value of the membership has started to increase and is 0.25, at T3 the value is 0.6, and at T4 is 0.75, which means that most of the pixel changes to urban. On the other hand, Figure 8.10b shows that the vegetation membership at T1 in the same pixel is 0.75, which means most of the pixel is vegetation, while at T2 the value is 0.6, at T3 the value is 0.2, and at T4 the value is only 0.15, which means that this pixel changes from vegetation at T1 (1976) to urban land at T4 (2009).

Figure 8.10a shows how the urban membership changes in one pixel at T1, T2, T3 and T4

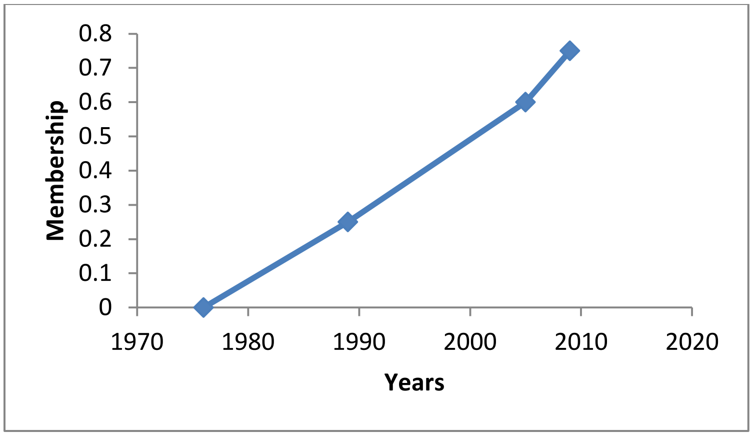
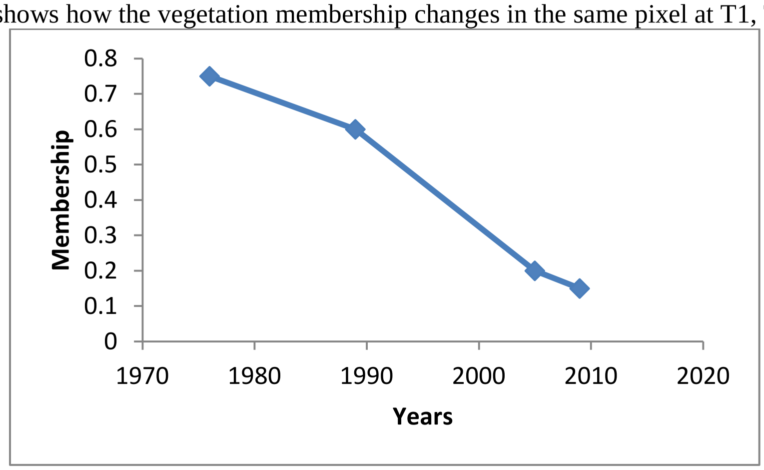


Figure 8.10b shows how the vegetation membership changes in the same pixel at T1, T2, T3 and T4



8.3.2 Result of fuzzy change object

Figures 8.11, 8.12 and 8.13 show the amount of change found by using fuzzy change objects when applying the data from fuzzy set classification, fuzzy c-means classification and Boolean classification. The results show that, over thirty years, woodland decreases by 27% using the fuzzy set model and 30.6% using the fuzzy c-means model, while the urban class increases by 56.9% using the fuzzy set model and 46.6% using the fuzzy c-means model. Grazing land increases by 22.4% using the fuzzy set model and 32.5% using the fuzzy c-means model, while the vegetation class decreases by 26% using the fuzzy set model and 24.9% using the fuzzy c-means model.

Figure 8.11 Area of change by percentage using fuzzy set object model from 1976 to 2009

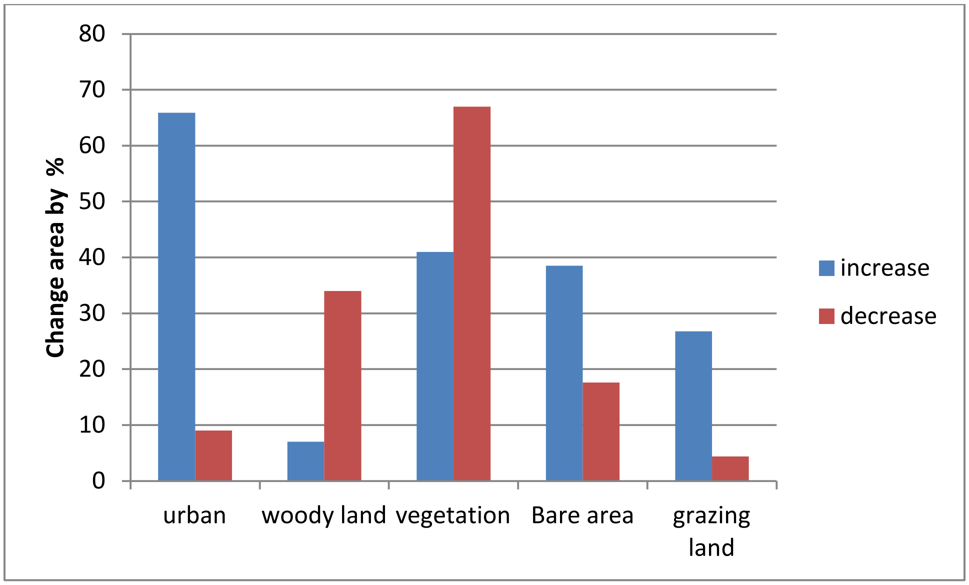


Figure 8.12 Area of change by percentage using fuzzy c-means object model from 1976 to 2009

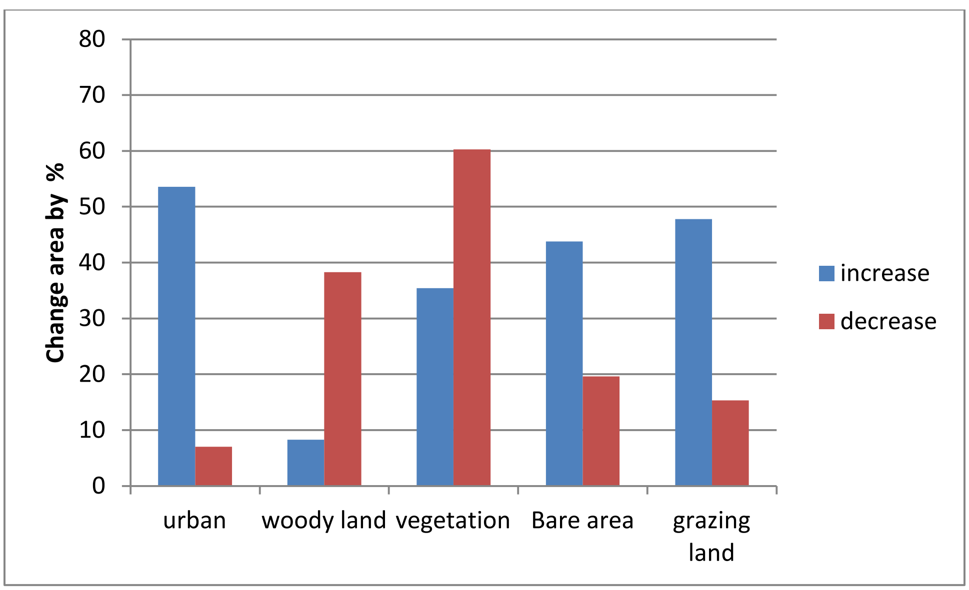
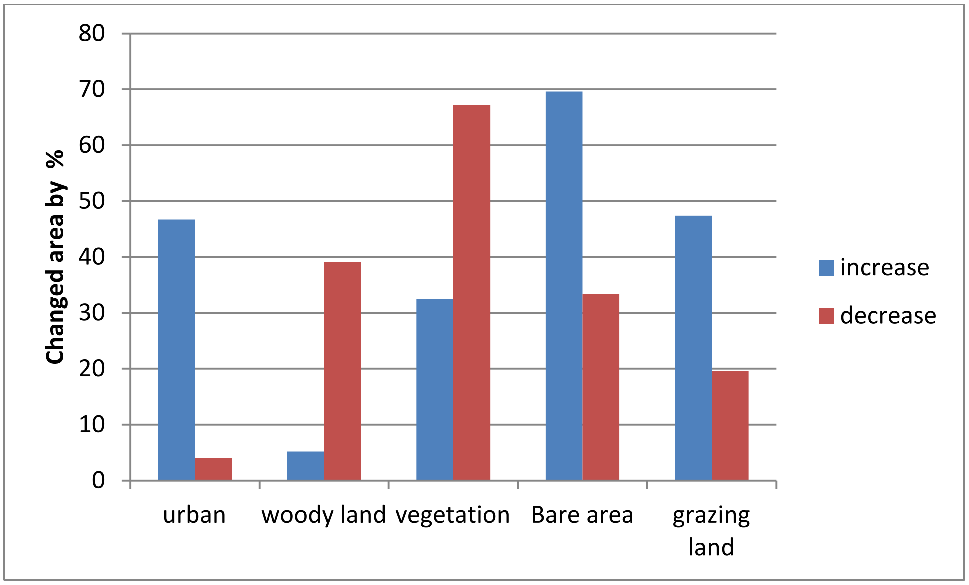


Figure 8.13 Area of change by percentage using Boolean object model from 1976 to 2009



8.3.3 Result of Boolean change

Figures 8.14, 8.15 and 8.16 illustrate the area of change by hectares for all classes (urban, vegetation, woodland, grazing land and bare area) by using three models (fuzzy set, fuzzy c-means and Boolean). From the Figures it is clear that there is a difference in results between the three models, mainly because in a fuzzy classification representation, each pixel is described by a group of membership which indicates the degree of similarity to the classes considered. Just like the class proportions. This pixel will be just like the class proportions. The basic assumption of the fuzzy approach is that membership grades are informative about the sub-pixel components, which gives more information about land cover. The Boolean classification algorithm does not take into account the continuous change in land cover classes and only assigns single class level which dominates in same the pixel, which leads to the loss of information.

Figure 8.14 Area of change using fuzzy set model from 1976 to 2009

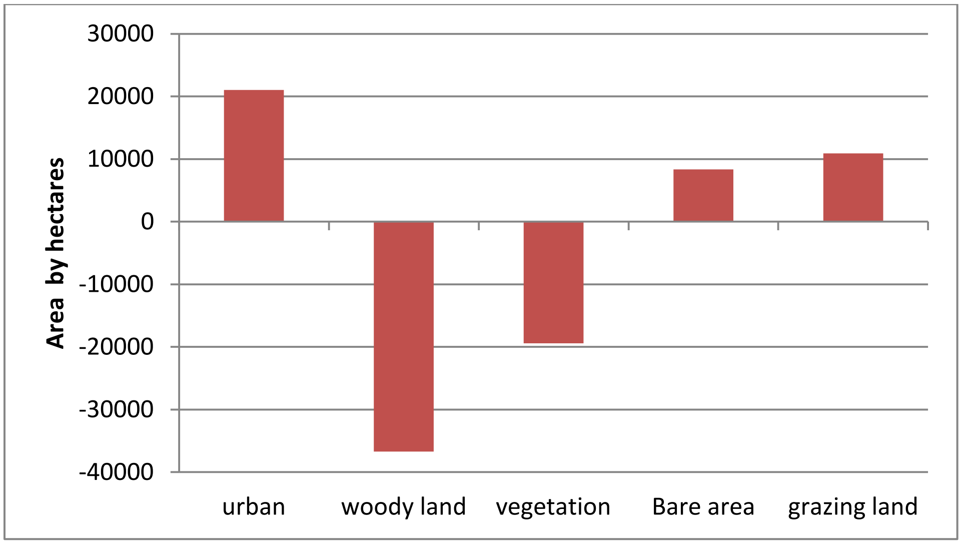


Figure 8.15 Area of change using fuzzy c-means model from 1976 to 2009

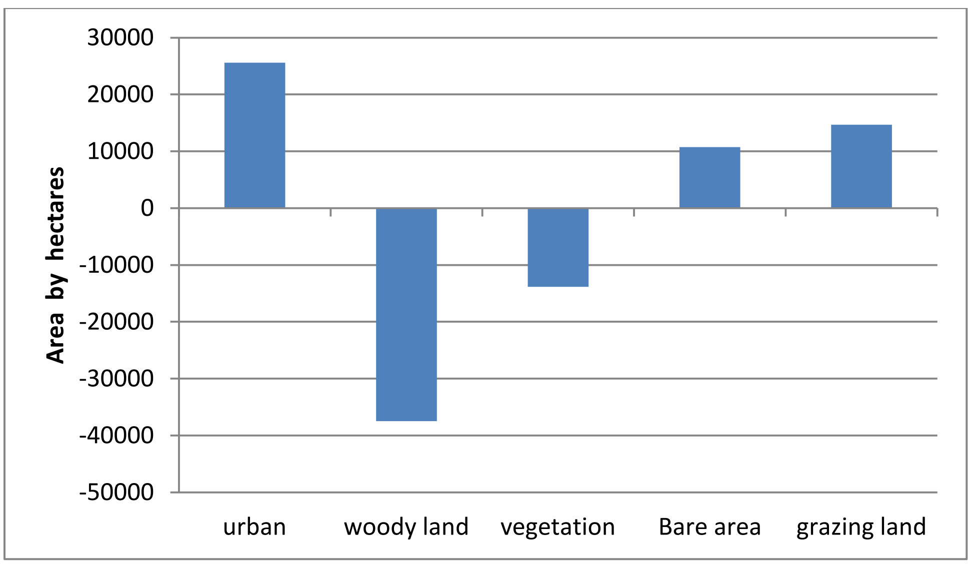
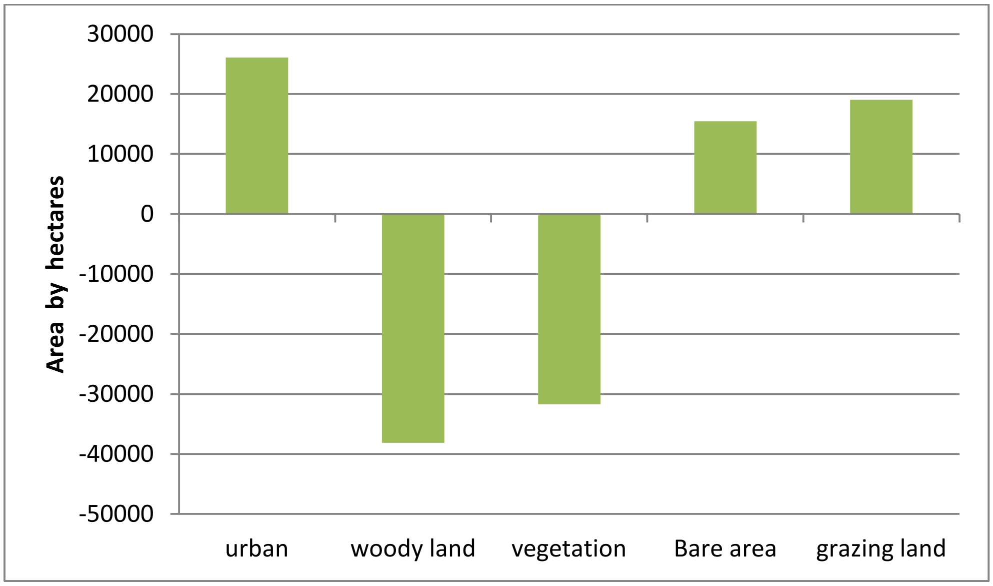


Figure 8.16 Area of change using Boolean model from 1976 to 2009



8.4 Result of Validation

8.4.1 Result of fuzzy classification

Accuracy assessment was applied to both classification methods (Boolean and fuzzy) using the calculation of a confusion matrix.

Table 8.3 illustrates the summary of the accuracy assessment for all the classifications (fuzzy set, fuzzy c-means and Boolean). From the Table 8.3 it is clear that the highest accuracy assessment at all the dates is for fuzzy set classification: 65% at T1 (1976), 67.3% at T2 (1989), 60% at T3 (2005), and 79.73% at T4 (2009); the second highest is for fuzzy c-means: 59.6% at T1, 61.81% at T2, 75.5% at T3, and 72.12% at T4; and the lowest accuracy assessment is for Boolean classification: 55.26% at T1, 63.15% at T2, 75.17% at T3, and 66.19% at T4.

Table 8.3 Summary of accuracy assessment for all images by different models

Classification /year	Fuzzy set	Fuzzy c-means	Boolean classification
2009	79.73%	72.12%	66.19%
2005	80%	75.5%	75.17%
1989	67.3%	61.81%	63.15%
1976	65%	59.6%	55.26%

Table 8.4 illustrates the summary of the average kappa for all the classifications (fuzzy set, fuzzy c-means and Boolean). From the Table 8.4 it is clear that the highest kappa is fuzzy set in all the dates the average kappa is 0.7240, then the fuzzy c-means is 0.6626 and the lowest kappa on Boolean classification the average is 0.5651.

Table 8.4 Summary of kappa for all images by different models

Kappa/year	Fuzzy set	Fuzzy c-means	Boolean classification
2009	0.6955	0.6500	0.5749
2005	0.7240	0.6626	0.6387
1989	0.5916	0.5802	0.5763
1976	0.6040	0.5937	0.5651

8.4.2 Result of Cross-tabulation

Cross-tabulation offers four rules for comparing soft-classification images: composite, multiplication, minimum and hard. Under Multiplication, each pixel has membership in a class according to the probability that a randomly selected point within the pixel belongs to that class. The concept of location within the pixel exists in terms of infinitely small points, whose spatial distribution within the pixel is random.

From Table 8.5 it is clear that when the resolution increases the overall agreement increases; this means that when the resolution decrease the detail of the pixel it is not clear as in 30*30 the resolution will be 900m and the agreement increase. The overall agreement between 2005 and 1976 both of the images fuzzy classification a bit low (0.3187 at resolution 1*1 and 0.4309 at resolution 30*30). This indicates that a large change happened to the area over about thirty years, as explained in Chapter 5. On the other hand, the overall agreement between the fuzzy classified images from 2005 and 1989 is a bit high (0.4907 at resolution 1*1 and 0.6284 at resolution 30*30) compared with 2005 to 1976 during 16 years, that means the change which was happened during that period of time is also low.

Table 8.5 also shows the comparison between the fuzzy classification and Boolean classification at the same year and same training set for example the overall agreement in image 1976 high (0.5052 at resolution 1*1 and 0.6285 at resolution 30*30) and in 2005 by applying fuzzy and Boolean classification to the same image the overall agreement 0.3869 at resolution 1*1 and 0.4369 at scale resolution 30*30.

Table 8.5 Relationship between scale resolution and overall agreement

Resolution	Overall Agreement 1976-2005 Fuzzy classification	Overall Agreement 1976-1989 Fuzzy classification	Overall Agreement 1989-2005 Fuzzy classification	Overall Agreement image 1976 Fuzzy & Boolean	Overall Agreement image 2005 Fuzzy & Boolean
1*1	0.3187	0.3292	0.4907	0.5052	0.3869
5*5	0.3686	0.3934	0.5593	0.5581	0.4179
10*10	0.3960	0.4272	0.5906	0.5870	0.4267
15*15	0.4103	0.4447	0.6067	0.6031	0.4307
20*20	0.4188	0.4554	0.6160	0.6136	0.4332
25*25	0.4258	0.4641	0.6235	0.6215	0.4355
30*30	0.4309	0.4707	0.6284	0.6285	0.4369

8.4.3 Result of Regression

As mentioned in Chapter 7, a regression analysis was performed to determine the correlation between the reference data from the field and data from the classification image at T4 (2009). Figure 8.17 illustrates the results from regression statistics for multiple R in the urban, vegetation, woodland, grazing land and bare area classes, comparing fuzzy set and fuzzy c-means classifications against the data observed in the field.

Figure 8.17 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means: 2009

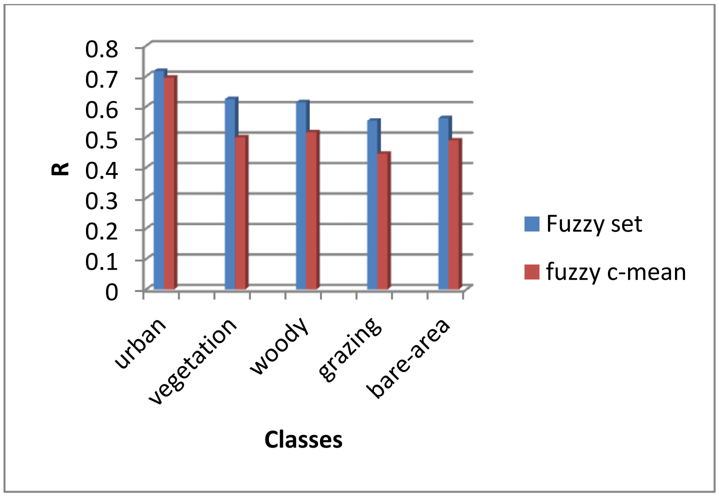


Figure 8.18 illustrates regression statistics for multiple R to determine the correlation between the reference data from the aerial photos and data from classification images resulting from fuzzy set classification and fuzzy c-means in all the classes (urban, vegetation, woodland, grazing land and bare area) at T3 (2005). From the Figure we can see that the multiple R is higher in fuzzy set classification than fuzzy c-means in all the classes.

Figure 8.18 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means: 2005

Figure 8.19 illustrates regression statistics for multiple R to determine the correlation between the reference data from the aerial photos and data from classification images resulting from fuzzy set classification and fuzzy c-means in all the classes (urban, vegetation, woodland, grazing land and bare area) at T2 (1989).

Figure 8.19 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means: 1989

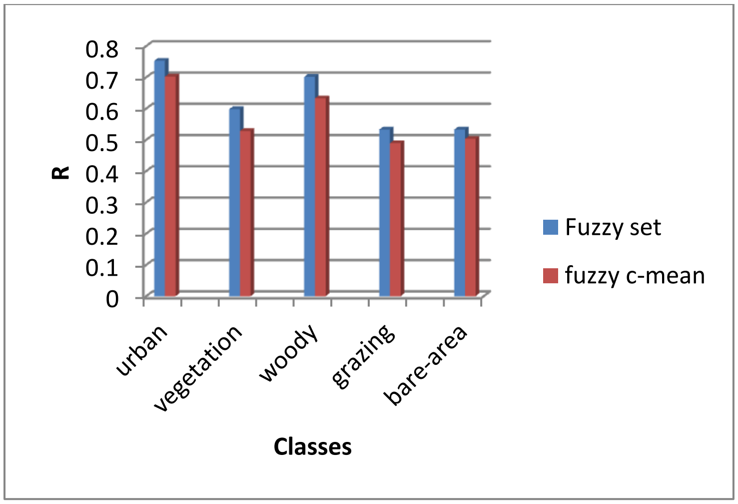
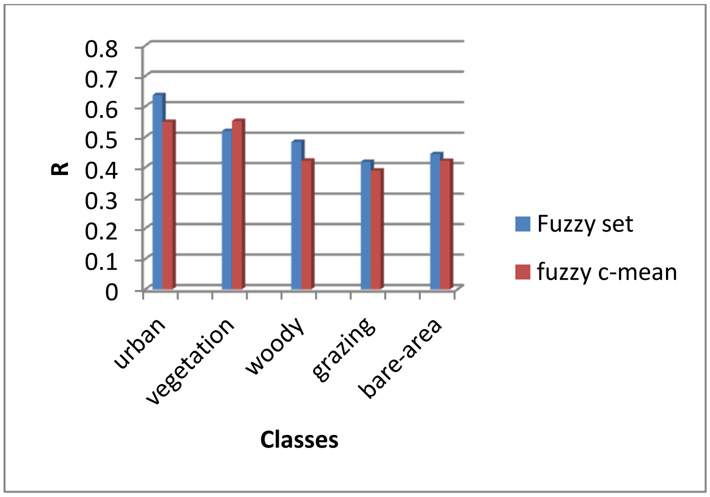


Figure 8.20 illustrates regression statistics for multiple R to determine the correlation between the reference data from the aerial photos and data from classification images for all classes resulting from fuzzy set classification and fuzzy c-means at T1 (1976).

Figure 8.20 Regression statistics for multiple R for fuzzy set classification and fuzzy c-means: 1976



8.4.4 Fuzzy error matrix

As mentioned in Chapter 7, a fuzzy error matrix was constructed as one of the models to determine the accuracy of soft classifications. The result for the fuzzy set classification was that the overall underestimation accuracy is 80.4%, the overestimation is 68.5%, and the average is 74.4%. When this model was applied to fuzzy c-means, the result was that the overall underestimation accuracy is 76.8%, the overestimation is 65.9%, and the average is 71.3%.

The fuzzy error matrix, which is an extension of the confusion error matrix using the principles of the fuzzy set method, could be a better alternative for evaluating the performance of soft classifiers when soft ground truth data are available. The reliability of soft reference data is essential to avoid under- or over-estimation in accuracy assessment. The first advantage here is that it was not assumed that all pixels present in the better resolution dataset are pure and that no information was lost due to the hardening of soft classification outputs. The second advantage is that here the membership value is due to vagueness in class definition. So the disadvantage of the Boolean method can be avoided by this method.

8.5 Conclusion

Mixed pixels are a major problem in the analysis of remotely sensed imagery. In land cover mapping applications, the solution to the mixed pixel problem has often been based on the use of fuzzy classification techniques that allow for multiple and partial class membership. For these techniques to be of value, the fuzzy classification output needs to indicate more accurately the class composition of pixels in the imagery.

The current chapter summarizes the result of image classification from the three models (fuzzy set, fuzzy c-means and Boolean classification). They were compared and then evaluated for their ability to explore the uncertainties associated with land cover classification. The comparisons illustrate that the results of the fuzzy set approach are more comparable to the fuzzy c-means results than those derived from the use of the Boolean approach. Moreover the comparison revealed that the fuzzy set approach is like the fuzzy c-means method in its ability to address and accommodate the uncertainties that are associated with boundary conditions in land cover.

This chapter also summarizes the result of the fuzzy change. Three models have been used to determine the fuzzy change: the first model, fuzzy change matrix, depends on the sub-pixel change; the second one, fuzzy objects, depends on the object change; the third model, Boolean change, depends on pixel-by-pixel change; it could be 0 or 1. The results show that this fuzzy method is able to identify the land cover changes more precisely than the Boolean method. All of these models give results which show that a large area of the land cover has changed in the study area, even though there is a slight difference between the models. This chapter summarizes the result of the accuracy assessment which was applied to validate both classification methods (fuzzy and Boolean); this study determined the membership from the field, which gives the flexibility to apply different accuracy models for fuzzy validation, such as fuzzy error matrix, cross-tabulation and regression. Even though the accuracy for both Boolean and fuzzy classification is not very high, in all models the results show that the fuzzy classification (fuzzy set and fuzzy c-means) is higher than the Boolean classification. This means that the fuzzy set and fuzzy c-means approaches have succeeded in overcoming the problems found in the application of the Boolean model to land cover classification in the study area.

Chapter 9: Discussion

9.1 Introduction

The fundamental focus of this thesis relates to fuzzy validation, fuzzy change and uncertainty. Several theoretical and practical issues are discussed in relation to defining fuzzy sets and fuzzy membership using fuzzy c-means and a fuzzy error matrix. The thesis also discusses the relationships between fuzzy memberships generated by field survey and those generated from the classification of remotely sensed data. In so doing it examines the spatial variation in the relationship between observed and predicted fuzzy land cover classes. Chapter 8 described the results derived from the three land classifications (fuzzy sets, fuzzy c-means and Boolean classification), three land cover change assessment methods (object change, change matrix and Boolean change), and three methods of validation (error matrix, fuzzy error matrix and cross-tabulation). The results of the land cover classification, the fuzzy change analysis and the validation models are discussed here. The appropriateness and limitations of the methods used in Chapters 4, 5 and 6 in relation to this study are discussed in this chapter, along with other methods.

9.2 Discussion of classification results

One of the research aims was the integration of different soft-classification methodologies (fuzzy set and fuzzy c-means) of Landsat images, in comparison with a Boolean classification, in order to determine the amount of land cover change in the study area.

This research found that there are clear differences between the three models (Chapter 8). Table 8.1 summarizes the results from the three models (fuzzy set, fuzzy c-means and Boolean classification).

From the image classification for the three models, as explained in Chapter 4 in Figures 4.3, 4.9, 4.11(a), 4.11(b) and 4.11(c), it is clear that using fuzzy set and fuzzy c-means makes more information available about the land cover features than Boolean classification.

The results from this study are the same as those of many previous studies such as (Bastin, 1997; Dutta et al., 2010; Fisher et al., 2006; Foody, 2000; Wang, 1990) in that using the fuzzy approach can give more suitable results than a Boolean classification of a satellite image in mapping land cover classes. The results also show that the output of a Boolean classification method is of poor quality in the boundary zones, e.g. in differentiating vegetation and grazing land. The main advantage of the fuzzy classifier is the extraction and representation of the information. Vagueness in the land cover can be extracted successfully and can be represented with different membership values.

Wang (1990) used a supervised fuzzy c-means approach to classify the Landsat MSS and TM data with seven land cover classes. In comparison with the Boolean classification he concluded that higher classification accuracy could be achieved while using fuzzy classification approaches. The current study shows the same result, that fuzzy classification is more suitable than Boolean classification. Bastin (1997) made a comparison between fuzzy c-means, linear mixture modelling and Boolean classification using Landsat TM. She concluded that the FCM gives the best prediction of sub-pixel land cover classes, followed by linear mixture modelling, and that the worst model is Boolean classification at different scales. However, in this study, among the three models compared, the fuzzy set method is more appropriate than fuzzy c-means and Boolean classification. Foody (2000), using an airborne thematic mapper (ATM) image of part of the western outskirts of the city of Swansea, showed that supervised fuzzy c-means may be used to derive accurate estimates of sub-pixel land cover composition, especially when all classes have been defined in the training stage of the classification, and that the presence of an untrained class decreases the accuracy of estimation of sub-pixel class composition. This research is agrees with the above study in comparing fuzzy c-means with Boolean classification.

The results of this study agree with Dutta (2010) by using AWiFS imagery when he compared fuzzy c-means, Metropolis algorithm and Boolean classification the results shows that fuzzy c-means classification it has been found more suitable than Boolean classification also they found that Metropolis algorithm could not handle the large number of possible membership values for any pixel within the range between 0 and 1. This research is going with the above study when compared fuzzy c-means with Boolean classification. From chapter7 the result of accuracy assessment is 76.43% for fuzzy c-means classification and Boolean classification is 66.19% by using error matrix.

As stated at the beginning of this study, the main aim of this study was to explore the added benefits for land cover change assessment of using fuzzy set and fuzzy c-means approaches, compared to a Boolean approach. There were many reasons for analysing and evaluating the results. One of these reasons was to explore the abilities of the fuzzy set and fuzzy c-means approaches in addressing the uncertainties associated with describing fuzzy land change processes. The comparison between the results from these three approaches showed that there are significant and clear differences between Boolean results and results from fuzzy models. The differences between fuzzy models and Boolean results were expected, because the Boolean approach is limited in dealing with mixed pixel areas, while the fuzzy set and fuzzy c-means approaches solve the mixed pixel problem and uncertainty. By contrast, this is the advantage of using fuzzy approaches in the process of land cover change assessment, as shown in Chapter 5 (Figures 5.10, 5.11, 5.12, 5.13 and 5.14).

9.3 Discussion of change detection results

One of the main aims of the research was to determine fuzzy change at the sub-pixel level using change matrix, change object and Boolean change. This research found that there are big differences between the three approaches (fuzzy land cover objects, Boolean change and fuzzy change matrix). The results of the fuzzy change matrix are obtained as values for each pixel and subpixel, while in the fuzzy change object the result is given as a percentage and a description of change such as ‘small’, ‘large’ or ‘huge’. Overall it is clear that the fuzzy change matrix is more suitable and easier to apply than fuzzy objects and Boolean change.

The comparison of land cover maps is the basis for the analysis of many factors in land use and land cover. The Boolean method usually compares the differences according to a crisp pixel-by-pixel method. These Boolean similarity operations often cannot adequately account for the errors and complexity inherent in spatial information. Not every pixel is homogeneous with respect to the land surface it represents but its classification is. A fuzzy method may overcome these difficulties. In the current work the fuzzy approaches resulted in calculating fuzzy change by a different method.

The results discussed above regarding the fuzzy change matrix are in agreement with the results found by Fisher et al. (2006), who compared a fuzzy change matrix method with a Boolean approach: the results show that using a fuzzy change matrix is more appropriate than using Boolean classification for change detection. They also concluded that the minimum operator may not be suitable for gain and loss determination, although the bounded difference does work. Furthermore, the results discussed above regarding fuzzy change objects are in agreement with the results found by Tang (2004), who used fuzzy change object by using a fuzzy reasoning method compared to a Boolean approach: the results show that using fuzzy change objects is more suitable and accurate than using Boolean classification for change detection.

This study agrees with Hester et al., (2009), who used the method of integrating fuzzy logic and change reasoning to develop land cover change index maps. A Boolean change map was separately generated for comparison purposes and for transformation into the final change map. In generating the final map, the two single-date land cover maps were first compared on the basis of fuzzy spatial agreement. These maps were compared with the Boolean method for land cover change by using high resolution data (Quick Bird) and the result shows that the accuracy of fuzzy logic is more suitable for change detection than the Boolean approach. This research and other studies show that the Boolean approach suffers from many disadvantages and limitations for change detection.

The main problem of the Boolean change model is that it only works well for pure pixels, as discussed earlier, but the most serious issue in the use of the Boolean approach, as many researchers have stated (Ahmed, 2006; Baja et al., 2006; Bentum, 2009; Khiry, 2007), is that it fails to describe the uncertainty and the values between the boundaries.

The major advantages resulting from applying the fuzzy set approach to change detection in the study area, as with the fuzzy set methodology, are the capability to define the uncertainties connected with describing the phenomenon itself and the capability to take into consideration the effect of land changes which happen to have values close to class boundaries.

As was pointed out in Chapter 5, and mentioned in Chapter 8, from the above discussion and the limitations of Boolean classification in change detection, this study conclude that land use and land cover are fuzzy in nature. There is no clear boundary between one class of land cover and another. Therefore, it is better to represent land cover changes directly with a fuzzy representation.

9.4 Discussion of uncertainty results

One of the most important research aims was to calculate the uncertainty. As explained before (Chapter 4), remote sensing and GIS products have many sources of uncertainty, due to the accumulation and propagation of errors and uncertainties from sampling, collection, processing and analysis of image and ground data, modelling, spatial variation of variables and their interactions. The errors and uncertainties vary temporally and spatially (Ge, 2005).

Therefore, how to identify the sources of uncertainties and analyse their types and how to weaken the influence of uncertainty on the consequent process become important issues in research on uncertainty in remote sensing information. In particular, an essential basic theoretical subject is the establishment of a set of measurement indices for the quality of remote sensing information (Shi, 2007).

The measurement of uncertainty can be described probabilistically by ascribing either the degree of certainty (accuracy) or the degree of uncertainty (error) to measurements which are made (Foody, 2001; Zhang and Goodchild, 2002). There are two ways to measure the uncertainty in remote sensing information: pixel-based indices and category-based indices (Bo, and Wang, 2003). Uncertainty measurement indices in pixel scale consist of entropy, fuzzy entropy, probability residual and confusion index (CI), while category-based indices include kappa coefficient and probability vector. Although these methods can represent the uncertainty in the classified category, it is assumed that all the pixels within a certain category have the same uncertainty. Other possible indices for the measurement of uncertainty may be based on correlation analysis and distance measures, including the Euclidean distance between the representations of the land cover in the image classification and ground data (Foody, 1996; Foody and Arora, 1996).

Zhang and Foody (1998) used the entropy method, which depends on probability theory, to determine the uncertainty. They concluded that the entropy method may be used to indicate the uncertainty of a fuzzy classification, and described the variations in class membership probabilities associated with each pixel. This is, however, only suitable when ground data are hard.

This study used the confusion index method, which can give more comprehensive measurements for classified remotely sensed imagery and Euclidean distance to determine the uncertainty from the fuzzy set and fuzzy c-means methods. The confusion index was calculated for all the field trip points (210 pixels) for both fuzzy classification (fuzzy set and fuzzy c- means), to determine the amount of uncertainty. When the values of two classes are similar, the confusion index *CI* is close to 1, meaning that there is a high degree of confusion about class membership. If a pixel is a pure pixel, it will have a maximum membership value to that class and other classes will have lower membership values. The confusion index *CI* will be close or equal to 0. As explained in Chapter 5, the average result of the confusion index was 0.487 for fuzzy set and 0.526 for fuzzy c-means. The result shows that the average of the confusion index using the fuzzy set method is less than the average result from fuzzy c-means. This means that the uncertainty of the fuzzy set method is less than the uncertainty of fuzzy c-means.

Also, the Euclidean distance was calculated for all the field trip points (210 pixels) for all the classes – urban, vegetation, woodland, grazing land and bare areas – for both fuzzy classification methods (fuzzy set and fuzzy c- means); the average result was 0.044048 for fuzzy set and 0.067023 for fuzzy c-means. The result shows that the average of Euclidean distance using the fuzzy set method is less than the result from fuzzy c-means.

The results from calculating both the confusion index and Euclidean distance are lower for the fuzzy set than fuzzy c-means; this gives an indication that the fuzzy set is more suitable than fuzzy c-means for land cover classification in this study. Moreover, these results are compatible with the accuracy assessment discussed before (Chapter 7). The reason for these differences is the way that the fuzzy c-means calculates memberships which are forced to sum across all classes for any given location (pixel, object). This means that the algorithm has difficulty in handling outlying points. Completed calculations of the confusion index and Euclidean distance are explained in an appendix at the end of the thesis.

9.5 Discussion of validation results

The most important aim of the research was to validate the fuzzy classifications (fuzzy set and fuzzy c-means) and Boolean classification by using different methods, such as an error matrix, a fuzzy error matrix and cross-tabulation.

9.5.1 Validation of fuzzy membership

One of the fundamental aims of the research is to validate the sub-pixel membership by comparing the membership from the field with the membership from the classified image by using regression analysis. This research found that, as mentioned in Chapter 7 and summarized in Tables 7.1, 7.2 and 7.3, the results of regression show that the multiple R is higher in the fuzzy set than fuzzy c-means in all the classes.

The use of fuzzy classification in remote sensing is explained by Fisher and Pathirana (1991) and by Foody (1996). This approach generates a degree of membership in every category for every pixel in a range from 0 to 1, as described by the training data and a similarity relation model. The literature, some methods to assess the performance of fuzzy classifiers are reported in terms of assessing the degree of mixing, the fuzzy error matrix, which is an extension of the traditional hard evaluation taking into consideration the analyses obtained per informational category.

This research used regression to analyse the relationships between fuzzy memberships generated by the field survey and those generated from the classification of remotely sensed data. In so doing it examined the spatial variation in the relationship between observed and predicted fuzzy land cover classes. Field data were collected at 210 sample positions and at each position the land cover at 16 points in a 4 x 4 grid was recorded. These sub-pixel measures of land cover composition were used to produce fuzzy memberships in the different land cover classes at each sample position. A fuzzy pixel is considered to have different membership values obtained from fuzzy classification, indicating the proportion of every cover class in a mixed pixel, such as those of the Landsat images (Fisher, 1997; Plaza et al., 2004; Small, 2004; Wang et al., 2007).

In the fuzzy c-means membership concept, every pixel can belong partially to several land cover categories. It presents membership vectors for every sample for every category in a range between 0 and 1. Thus a pixel can belong to a category to a certain degree and could belong to another category to another degree, and the degree of belongingness is indicated by fuzzy membership values. In the feature space, if any point is located closer to the centre of a cluster, then its membership grade is also higher (closer to 1) for the cluster. In the situation of fuzzy membership grades, feature space is not sharply partitioned into clusters, so the main advantage of the fuzzy c-means approach is that no spectral information is lost, as in the case of hard partitioning of feature space.

Table 9.1 and Table 9.2 illustrate the similarity and dissimilarity when a threshold of 0.1 is applied for the field points and classified points, using the fuzzy set and fuzzy c-means methods. From the two tables, the highest similarity is in the urban class for both methods; the lowest similarity by using the fuzzy set method is the bare area class, while by using fuzzy c-means the lowest class is vegetation.

Table 9.1 illustrated the similarity and dissimilarity when a threshold of 0.1 is applied for the field points and classified points by using fuzzy set method

Classes	similarity	dissimilarity	Percentage of similarity
Urban	143	67	68.09
Vegetation	113	97	53.8
Woodland	122	88	58
Grazing land	132	78	62.8
Bare area	107	103	50.9

Table 9.2 illustrated the similarity and dissimilarity when a threshold of 0.1 is applied for the field points and classified points by using fuzzy c-means method

Classes	similarity	dissimilarity	Percentage of similarity
Urban	131	79	62.3
Vegetation	109	101	51.9
Woodland	116	94	52.2
Grazing land	121	89	57.6
Bare area	118	92	56.1

9.5.2 Error matrix and fuzzy error matrix

The most important aim in this research was to validate the fuzzy classification by different models such as the error matrix, which is commonly used in Boolean classification, and the fuzzy error matrix, for fuzzy classification.

This research found that, as mentioned in Chapter 8 and summarized in Table 8.1, when an accuracy assessment was applied to all the models (fuzzy set, fuzzy c-means and Boolean classification), the results show that the highest value was for fuzzy set classification using the error matrix method (80%), the second highest was the fuzzy c-means (75.5%), and the lowest value was for the Boolean classification (66.19%).

When the fuzzy error matrix was applied for accuracy assessment, the result of the fuzzy set was 83.4% and the result of fuzzy c-means was 79.6%.

From the above results for the accuracy assessment, it is clear that the fuzzy error matrix gives the highest results for fuzzy set and fuzzy c-means, and that it is more appropriate for representing fuzzy classification validation than the error matrix, because the fuzzy error matrix deals with the sub-pixels and the error matrix deals only with whole pixels.

The most commonly used method for Boolean classification assessment is known as the Confusion Error Matrix, as mentioned in Chapter 7, Table 7.4. In the majority of cases, the image analyst does not have fuzzy ground truth data available to construct a fuzzy error matrix. In such cases, a traditional Boolean assessment could be conducted to assess a thematic map derived from a hardening procedure, although that is not the best way to assess the performance of fuzzy classifiers. However the crisp error matrix may be more suitable for traditional methods of classification where it is assumed that pixels at the reference location can be assigned to single categories. This may be an incorrect assumption as shown in this research. Every real image contains mixed-pixels. Generally, testing samples are chosen carefully from almost pure pixels because we have to identify the labels of those pixels in order to relate them to producer’s or user’s accuracy in error matrix analysis.

This research has shown that the fuzzy error matrix can solve the problem of sub-pixel area allocation when membership values correspond to land cover fractions, and the agreement and disagreement are defined in terms of the amount of sub-pixel overlap between the reference and assessed pixels. Also this study used a cross-comparison report to be useful for identifying a perfect match among the reference and assessed data, as it was essential to constrain the agreement measure at the pixel level.

Many studies have compared fuzzy and Boolean approaches to determine which model was more accurate; for example, Ibrahim et al. (2005) compared different fuzzy classification techniques to generate accurate land cover maps in the presence of uncertainties. In their study they concluded that a fuzzy c-means classification gives the highest precision in land cover mapping; in this study, when fuzzy sets were compared with fuzzy c-means and Boolean classification, the results show that fuzzy sets gives the highest accuracy, then fuzzy c-means, and Boolean gives the lowest. In the current study, when fuzzy sets and fuzzy c-means were compared, the results show that the fuzzy set classification is more accurate than fuzzy c-means; this is because the fuzzy c-means classification suffers from some disadvantages, chiefly that the sum of the membership values of a data point in all the clusters must be one, so the algorithm has difficulties in handling outlying points.

9.6 Contribution of this research

Based on the above aims, this study will contribute to an understanding of the appropriateness of a fuzzy model in detecting and predicting land use and land cover change.

The main contributions of this work are:

- comparison of different fuzzy models in fuzzy validation (fuzzy error matrix and cross tabulation)
- determining fuzzy change at the sub-pixel level using (change matrix and change object)
- validating / parameterising fuzzy change using a spatial model in field survey 4*4 subdivisions to determine the membership function in the field and compared with classified pixel
- integration of different soft-classification methodologies (fuzzy set and fuzzy c-means)

9.7 Limitations of the research and areas for further work

Some limitations were experienced in this study, which can be summarized as follows:

1- The Landsat image of 1976 was acquired with the multi-spectral scanner (MSS) which has a spatial resolution of 80 metres, whilst the images of 1989, 2005 and 2009 were acquired with Thematic Mapper ™ and Enhanced Thematic Mapper (ETM) respectively. These two have a spatial resolution of 30 metres. Also, this study used SPOT 5 (2009) with a spatial resolution of 10 metres; this limitation was solved through image thinning.

2- Accuracy assessment for images from 1976, 1989 and 2005 was done by using aerial photography but there is some difference in imaging times.

3- In the current study, when we compared fuzzy set and fuzzy c-means, the result shows that the fuzzy set is more suitable than fuzzy c-means, because fuzzy c-means suffers from some disadvantages, chiefly that the sum of membership values of a data point in all the clusters must be one, so the algorithm has difficulty in handling outlying points. This problem might be overcome in further studies by applying a modified fuzzy c-means algorithm or fuzzy-possibilistic c-means, which might be more appropriate than fuzzy c-means.

4- The current study used fuzzy set classification, which directly addresses the vagueness in the information, although many consider that any report about a vague phenomenon should itself be vague. This is recognized as higher order vagueness, and is handled in fuzzy set assumptions by type-2 and, by extension, type-n fuzzy sets (Fisher, 2010). A further study, using type-2 fuzzy set might be more suitable than using fuzzy sets.

9.8 Conclusions

In this research, three land cover classification techniques have been presented and implemented: fuzzy sets, fuzzy c-means and Boolean classification. This research has found that the fuzzy set approach is more suitable than fuzzy c-means and Boolean classification. This research, found that the fuzzy change matrix is more appropriate than the fuzzy object and Boolean models, when the fuzzy change matrix, the fuzzy object model and Boolean change were compared. The main advantages derived from applying the fuzzy approach to land cover change in the study area, as with the fuzzy methodology, are the ability to define the uncertainties associated with describing the phenomenon itself and the ability to take into consideration the effect of mixed pixels.

The main conclusions from this are the validation of the fuzzy memberships and fuzzy change. Fuzzy memberships calculated from classified images and collected in the field were analysed using a correlation method. In so doing it examines the spatial variation in the relationship between observed and predicted fuzzy land cover classes. The fuzzy validation in the field supports a deeper analysis of fuzzy sets and shows that it is more suitable than fuzzy c-means.

An additional general conclusion arising from this research is that fuzzy classification (fuzzy set and fuzzy c-means) theory overcomes the weaknesses of Boolean classification by accounting for soft class boundaries due to the inherent ambiguity and vagueness of the landscape structure. Each location in the landscape can be a partial member of one or more landform classes, as indicated by continuous degrees of membership in the range [0, 1], with 1 equal to a prototypical or full membership, and 0 equal to non-membership.

Chapter 10: Conclusions

This chapter 10 links the results of analysis to the research aim and objectives in order to present the conclusions of the research. The last sections of the chapter also offer some recommendations. This research has presented a case study, in which Boolean and fuzzy classifications were performed and tested using Boolean and fuzzy validation techniques. The results show that a fuzzy classification methodology may enable a suitable and effective classification and evaluation of remotely sensed imagery depicting inherently fuzzy phenomena, and could be more appropriate in heterogeneous and mixed-pixel areas than the Boolean method. To validate the fuzzy approaches, detailed ground data are necessary.

The comparison of land cover maps is the basis for many procedures in the analysis of land use and land cover. The Boolean method usually compares the differences on the basis of a crisp pixel-by-pixel method. These Boolean similarity operations often cannot adequately account for the errors and complexity inherent in spatial information. A fuzzy method may overcome these difficulties.

The advantages of soft classifiers are that small classes will not vanish as with Boolean classification and that they give a measure, not in whole pixels, of the occurrence of the classes.
The current research found that, by using the three models of classification (fuzzy sets, fuzzy c-means and Boolean classification), the results show that there is a large difference between Boolean and both soft classifications (fuzzy sets and fuzzy c-means), because the application of the fuzzy classification can deal with a lot of information and can cope with describing the uncertainty; the results also show similar results from the fuzzy sets and the fuzzy c-means.

The current research has produced the same result as Fisher et al. (2006), who found that the classic change detection matrix is based on a clear logic of set intersection which can be extended to fuzzy sets theory. Although many people have explored fuzzy classifications of land cover, only one previous study (Fisher et al., 2006) has attempted to populate a fuzzy change matrix. Also, the current research found that this can be accomplished using a fuzzy intersection matrix, but the mathematics of fuzzy logic is difficult because some less sensible results can be achieved , as explained before in the discussion on the minimum operator (section 5.5.1).

The current research, using a fuzzy change matrix and fuzzy object model, found that that there is a big difference between the two models: for example, the results show that, by using fuzzy objects and a fuzzy change matrix over thirty years, woodland decreases and the urban class increases. Also, grazing land increases and vegetation decreases.

The current research validates the fuzzy membership of classified images by using a correlation method to analyse the relationships between fuzzy memberships generated by the field survey and those generated from the classification of remotely sensed data. In so doing it examines the spatial variation in the relationship between observed and predicted fuzzy land cover classes. The results and the analyses found that there is high spatial variation in the extent to which fuzzy memberships in the field sample are predicted by the modelled fuzzy memberships, for a number of classes: urban and grazing land using a fuzzy c-means classifier, and vegetation and woodland using the fuzzy set classifier.

This research also found that the results of regression between observed and predicted fuzzy membership shows that the multiple R is higher in fuzzy sets than fuzzy c-means in all the classes; the highest value of R is in the urban class in fuzzy sets and in fuzzy c-means, and the lowest value of R is in the bare area class in fuzzy sets and in fuzzy c-means.

The uncertainty assessment on the classification of remotely sensed data is a serious problem both in applications and in the academic arena. The traditional solution to this problem is based on the confusion matrix and the kappa statistics resulting from the error matrix. The problem with using this method is that no information on spatial distribution of classification uncertainty can be presented by this method. To overcome this problem the current research used a fuzzy error matrix.

The general conclusions are listed in terms of the set of research questions posed in Chapter 1:

Research Question 1: What are the magnitude, rate and limits of fuzzy land cover changes that have taken place in the growing city of Tripoli from 1976 to 2009?

As mentioned in Chapter 4 (on fuzzy classification) and Chapter 5 (on fuzzy change), the area of each land cover class is computed by using fuzzy set, fuzzy c-means and Boolean classification, the results show that there are large changes detected in the study area, especially in the urban class, which has more than doubled within the time period, while the woodland and vegetation classes have decreased, as summarized in Table 8.1. The results also indicate that there is little difference between fuzzy set and fuzzy c-means. Both methods show that fuzzy classification gives better results in heterogeneous areas with mixed pixels as the value of the pixel gradually increases from 0 to 1.

Research Question 2: To understand this magnitude of change, which change model is most suitable for detecting these changes and accommodating the uncertainty, considering the developing nature of the city?

From the results and discussions it is very clear that the fuzzy set and fuzzy c-means methods of classification are better than the Boolean method, because these models have resolved the uncertainties associated with describing the boundaries and the phenomenon. They also give more information about the land cover and land cover changes.

Research Question 3: What are the advantages and disadvantages of a fuzzy supervised classification in change detection, compared to Boolean classification, in the context of a developing country like Libya?

As stated in Chapter 4, the application of the Boolean method to the model of land change has been criticized by many authors, because, with the Boolean technique, uncertainty cannot be explained, and boundaries between the classes are clearly defined, which does not always reflect reality, because many elements in nature are not so obviously defined. Also, a Boolean classification method, a "hard" classifier, is dependent on binary logic, which cannot give fine descriptions of mixed pixels and imprecise data since pixels are assumed to be pure. The fuzzy classification provided many advantages over the Boolean classification in this study: for example, a greater ability to investigate the mixed pixels. Also, for land cover classification in the study area, the fuzzy set and fuzzy c-means approaches produce important information for identifying major limitations on land cover. Furthermore, the fuzzy set and fuzzy c-means approaches can indicate land continuity in different land classes, and this is one of their advantages. Another advantage is that there is a transition in boundaries between the classes because, in fuzzy classification, membership is graduated between 0 and 1 while by the Boolean method it is 0 or 1 only.

Research Question 4: What is the most suitable model for assessing fuzzy classification at different times T1 (1976), T2 (1989), T3 (2005) and T4 (2009)?

From Chapter 7 (on validation) we see that there are many models that have been used, such as cross tabulation, an error matrix, and a fuzzy error matrix, to determine the accuracy of both Boolean and fuzzy classifications. This research found that the fuzzy error matrix is clearly more suitable than the error matrix for validating fuzzy classification by using ground data and that it gives the highest accuracy because it deals with sub-pixels.

For future analyses of land cover change in the study area of Tripoli, Libya, it is important that the decision makers take the following recommendations into consideration:

1. Libyan decision makers should take these research results into consideration for present and future land use planning.

2. The methods developed can be adapted for all parts and the same methodology can be implemented for different land cover changes.

3. Some awareness should be provided in the study area specially to the woodland and reforestation the area surrounded by Tripoli city

4. Funding is needed for studying land cover change in Libya, to control and monitor the changes in the study area every five years.

5. Grazing activities in the study area need improvement and management.
6. Detecting of transition zones is an important subject and the planners should be aware of changing boundaries

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Appendices

Appendix: A

Appendix: A: Summarised the result of Euclidean distance for the field points (210) by using fuzzy set method

Sample	East	North	Urban	Vegetation	wood land	Grazing land	Bare area
1	301847	3631819	0.03675	0.01525	0.10575	0.0625	0.008
2	302491	3632155	0.08533	0.07133	0.09675	0	0.10725
3	303834	3631818	0	0.02533	0.1335	0.01325	0.10025
4	304480	3631008	0.0276	0.06325	0.05375	0.04625	0.00375
5	306691	3632967	0.0845	0.05575	0.03675	0	0.012375
6	308175	3630784	0	0.09625	0.04675	0.03575	0.0125
7	309741	3633639	0.0437	0.00525	0.06975	0.00725	0.03875
8	306944	3632240	0.0915	0.09375	0.0295	0	0.03025
9	309266	3630660	0.0106	0.13863	0.0625	0.01825	0.10763
10	307978	3631483	0	0.13325	0.10975	0	0.02225
11	312262	3634117	0	0.0585	0.13325	0	0.07425
12	313327	3633219	0.1222	0.0715	0.02075	0.03025	0.0295
13	315202	3635488	0.0312	0	0.07425	0.06175	0.10725
14	312293	3633472	0.0392	0.05575	0.0375	0	0.0185
15	312794	3632829	0.0582	0.06675	0.0625	0.053	0
16	311171	3632324	0	0.14575	0.076	0.151	0.03775
17	313674	3631631	0.0215	0.0945	0.1435	0	0
18	319040	3635629	0.011	0.00525	0.0735	0	0
19	318170	3630783	0	0.02625	0.01025	0.147	0.03675
20	315259	3630588	0	0	0	0.385	0.09625
21	320523	3637000	0.13025	0.02425	0	0.221	0.05525
22	322427	3638315	0.0535	0	0.095	0.121	0.03025
23	323183	3637140	0.04925	0.02963	0	0	0
24	326767	3638985	0.0735	0.06825	0	0	0
25	325703	3633946	0	0.01525	0	0	0
26	328949	3630335	0	0.1245	0.12575	0	0
27	330043	3637533	0.08325	0	0.102	0.167	0.04175
28	321475	3634395	0.14025	0.0625	0.125	0.187	0.04675
29	328195	3633919	0.008	0.102	0.0665	0	0
30	321867	3632294	0.04888	-0.052	0.02725	0.054	0.0135
31	331414	3639239	0.1295	0.05425	0	0.179	0.04475
32	331133	3635461	0.032	0.02225	0.11775	0	0
33	332004	3635461	0.09075	0.03125	0.0715	0.11	0.0275
34	338470	3635262	0.06025	0.04225	0.10925	0	0

35	335810	3639212	0.09875	0.09075	0	0.038	0.0095
36	339088	3632155	0	0.04725	0.08425	0	0
37	335587	3637169	0.072	0.0755	0	0	0
38	333823	3636523	0.10825	0	0.0335	0	0
39	334495	3634199	0	0	0.05675	0	0
40	334355	3631007	0	0.05425	0.07875	0	0
41	340459	3639157	0.09625	0.05175	0	0.132	0.033
42	344883	3638875	0.0085	0	0.03625	0	0
43	349223	3637336	0.05725	0.1155	0.04675	0.264	0.066
44	350259	3635962	0.08025	0.081125	0.04688	0	0
45	348412	3633500	0	0.04675	0.12825	0.091	0.02275
46	349167	3631371	0	0.03275	0	0.54	0.135
47	341523	3637927	0.03625	0	0.05288	0.043	0.01075
48	341804	3633277	0	0.0865	0.01475	0.176	0.044
49	343708	3636663	0.03675	0.06075	0	0.029	0.00725
50	344575	3634982	0	0	0	0.436	0.109
51	350903	3638315	0	0	0.0865	0	0
52	351573	3637447	0.062875	0.01138	0.0525	0	0
53	352693	3636441	0	0.05325	0	0.484	0.121
54	357818	3634059	0	0	0.031	0.229	0.05725
55	358940	3632491	0	0.02525	0.01975	0.138	0.0345
56	356056	3632407	0.05325	0.025	0.13325	0	0
57	352135	3631170	0	0	0	0.215	0.05375
58	354373	3632295	0	0.037875	0.03963	0	0
59	357761	3631314	0	0.04525	0	0.172	0.043
60	352245	3634397	0	0.024125	0.02175	0	0
61	302548	3627899	0	0.07075	0	0.279	0.06975
62	308062	3628149	0	0.05375	0	0.547	0.13675
63	301511	3625128	0	0.104	0	0.216	0.054
64	306998	3626639	0	0.029	0	0.272	0.068
65	308818	3625238	0	0.03725	0.081	0.473	0.11825
66	305907	3623951	0	0	0.127	0	0
67	308148	3621571	0	0	0	0.456	0.114
68	303053	3621712	0	0.12425	0	0.493	0.12325
69	306103	3625908	0	0.0625	0.10725	0.679	0.16975
70	304926	3627059	0.13375	0.066	0.01125	0.223	0.05575
71	312766	3628096	0.142	0	0.03775	0	0
72	315457	3627503	0	0.066	0	0.334	0.0835
73	318925	3626470	0	0.11425	0.02875	0.342	0.0855
74	311536	3626051	0	0.081	0	0.212	0.053
75	315258	3622160	0.0535	0	0.126	0	0
76	318002	3624875	0	0.03525	0.0955	0	0

77	319488	3623812	0.10625	0.072	0.008	0	0
78	313942	3625155	0	0.0735	0.01625	0.101	0.02525
79	310612	3621545	0	0.04675	0.036	0.437	0.10925
80	316661	3628794	0	0.1225	0	0.127	0.03175
81	321561	3628881	0	0	0.0765	0.306	0.0765
82	323604	3628684	0.10525	0	0.037	0	0
83	328223	3627900	0	0.142	0.04125	0.101	0.02525
84	328110	3623083	0	0	0.07025	0	0
85	327271	3620871	0	0.05275	0.01475	0.499	0.12475
86	325254	3621628	0	0.0815	0	0.023	0.00575
87	323632	3625658	0.03025	0.05825	0	0	0
88	321951	3624734	0	0.13575	0	0.65	0.1625
89	322932	3622021	0	0.0465	0	0.193	0.04825
90	325478	3625127	0.08725	0.0055	0.05275	0.302	0.0755
91	332254	3629608	0.071	0.03575	0.0145	0	0
92	338332	3629327	0	0.04575	0.109	0.248	0.062
93	338640	3627703	0	0.071	0	0.392	0.098
94	335588	3628039	0	0.08	0.0825	0	0
95	336146	3626753	0	0.0585	0	0.227	0.05675
96	334998	3621626	0	0	0	0.289	0.07225
97	332728	3623386	0	0.028	0	0.272	0.068
98	331442	3626164	0.064	0	0.0095	0	0
99	338358	3623560	0	0	0	0.1035	0.02588
100	335161	3625040	0	0	0.0365	0.125	0.03125
101	340597	3629578	0	0.02063	0	0.1975	0.04938
102	344322	3629606	0	0.068625	0.0855	0	0
103	349082	3627871	0	0.07725	0	0.306	0.0765
104	348550	3625768	0	0	0.09475	0	0
105	346452	3623783	0	0	0	0.318	0.0795
106	342559	3623083	0	0	0	0.1475	0.03688
107	340598	3626359	0	0	0.07675	0.301	0.07525
108	344799	3627003	0	0	0.047125	0.328	0.082
109	346057	3624428	0.032	0.1335	0	0.406	0.1015
110	342392	3625406	0	0.09375	0.04375	0.548	0.137
111	351071	3628208	0	0	0	0.5695	0.14238
112	357511	3630223	0	0.100375	0.10038	0	0
113	353029	3628973	0	0.13675	0	0.543	0.13575
114	358551	3627059	0	0	0.08713	0.3475	0.086875
115	356560	3622943	0.049	0	0.0865	0.148	0.037
116	354963	3621096	0	0	0.0225	0.453	0.11325
117	354009	3626918	0	0	0.111125	0.4445	0.11113
118	346453	3621323	0.0385	0.13025	0	0.362	0.0905

119	350734	3624314	0	0.050125	0.07988	0.117	0.02925
120	350260	3620787	0	0.06225	0	0.2335	0.058375
121	304060	3619672	0	0.07675	0.0765	0	0
122	307670	3619974	0	0.0295	0	0.461	0.11525
123	308513	3618436	0	0	0.10838	0.4335	0.108375
124	302463	3617428	0	0.127	0.04675	0.311	0.07775
125	308239	3616392	0	0.046	0	0.562	0.1405
126	300757	3613845	0	0.09275	0.0925	0	0
127	307615	3613705	0	0.07575	0	0.277	0.06925
128	305119	3616138	0	0	0.08725	0.348	0.087
129	305067	3614094	0	0	0.061125	0.2495	0.06238
130	304814	3618406	0	0.102	0	0	0
131	310163	3619219	0	0	0	0.0455	0.01138
132	310893	3618240	0	0	0.024	0.089	0.02225
133	312571	3619136	0	0	0	0.494	0.1235
134	319458	3618491	0	0.078	0	0.302	0.0755
135	315568	3617371	0.08863	0.0535	0.01575	0	0
136	318448	3615102	0	0	0.04263	0.1695	0.042375
137	312681	3616081	0	0.07775	0	0.533	0.13325
138	313187	3615274	0	0.0645	0.024	0.35	0.0875
139	309997	3613676	0	0.069125	0.05263	0.074	0.0185
140	315228	3613508	0	0.13025	0	0.513	0.12825
141	321474	3619471	0	0	0.063625	0.2555	0.06388
142	321839	3618600	0	0.04675	0.02875	0	0
143	324947	3619891	0.03175	0.1155	0	0.328	0.082
144	328135	3614068	0	0.107	0	0.254	0.0635
145	323880	3616530	0	0	0	0.489	0.12225
146	323715	3613310	0	0.072	0.10263	0.1125	0.028125
147	320383	3614345	0.061375	0.09513	0	0	0
148	325114	3617989	0	0.117	0.0445	0	0
149	321112	3617400	0.0905	0.09575	0	0	0
150	323070	3618436	0	0	0.059	0.562	0.1405
151	330716	3614460	0	0.05375	0	0.291	0.07275
152	331021	3616112	0.08438	0.083875	0	0	0
153	332734	3620229	0.13	0.13	0	0	0
154	339366	3613283	0.09375	0.094	0.05475	0.22	0.055
155	338609	3619135	0	0.156	0.0885	0	0
156	333094	3617061	0	0	0.13688	0.5425	0.135625
157	337238	3618294	0	0.06263	0.048125	0	0
158	334970	3616111	0	0.0225	0	0.376	0.094
159	337380	3615635	0.023625	0.05025	0.07488	0	0
160	336429	3618604	0	0.08988	0	0.3545	0.088625

161	341383	3619219	0	0	0.0635	0.424	0.106
162	342474	3617036	0	0	0.11075	0.101	0.02525
163	346369	3618742	0	0	0	0.4835	0.12088
164	345527	3616925	0	0.14575	0	0.576	0.144
165	342810	3614319	0	0.06325	0.07038	0.3315	0.08288
166	349252	3617792	0.03025	0	0.046	0.347	0.08675
167	348046	3616837	0	0.0455	0.041625	0.3515	0.08788
168	348607	3614152	0	0	0.10288	0.3415	0.085375
169	346449	3613481	0.021375	0.0525	0	0.1245	0.031125
170	344713	3616672	0	0.07538	0.04688	0	0
171	350260	3619528	0	0	0.10575	0.3005	0.07513
172	350847	3618155	0	0	0.1085	0.297	0.07425
173	357008	3619441	0	0.11588	0	0.3335	0.083375
174	359023	3618967	0	0.06175	0	0.612	0.153
175	357846	3615215	0	0	0.05963	0.2355	0.058875
176	349726	3615830	0	0	0.06325	0.3665	0.09163
177	355244	3615774	0	0	0.12363	0.3255	0.081375
178	353731	3618185	0	0.0435	0	0.1495	0.037375
179	350339	3614624	0	0.06488	0.03275	0.2565	0.064125
180	354123	3613873	0	0.0605	0.02075	0.22	0.055
181	328756	3641200	0	0	0.05875	0.216	0.054
182	329008	3641144	0.15775	0.105	0.051	0	0
183	328755	3641339	0.119875	0.12113	0	0	0
184	329147	3641534	0.08788	0	0.0825	0	0
185	329176	3641927	0.11425	0	0	0.132	0.033
186	329595	3641143	0.10838	0.033	0.05775	0	0
187	328922	3641562	0.03963	0.01313	0	0	0
188	329819	3641367	0.05963	0.040125	0	0	0
189	329483	3641534	0.07113	0	0.03075	0	0
190	328978	3641311	0.023625	0.0365	0.02175	0	0
191	330154	3641060	0.0375	0.08725	0.06075	0.253	0.06325
192	330826	3641032	0.12225	0.05525	0.01625	0.194	0.0485
193	332701	3641617	0.097125	0	0	0	0
194	333823	3641731	0	0.0685	0.03525	0.087	0.02175
195	335616	3642683	0	0	0.018	0.199	0.04975
196	336873	3641815	0.04913	0.07788	0.083	0.176	0.044
197	334635	3640723	0.0585	0.05913	0	0	0
198	337938	3640695	0.07825	0.044	0.03425	0	0
199	337911	3642094	0.124	0	0.092	0	0
200	335645	3641926	0.05288	0.0305	0.0335	0	0
201	341637	3641535	0	0.0885	0	0	0
202	342644	3640246	0.09888	0.001875	0.03025	0	0
203	344156	3640247	0.0635	0.02388	0	0	0
204	348833	3640976	0	0.07575	0.06888	0.148	0.037

205	349250	3640135	0	0.03175	0.04825	0	0
206	346143	3639463	0.08388	0.052875	0.0285	0	0
207	347683	3640610	0.08413	0	0.09725	0	0
208	348553	3640164	0	0.0115	0.02913	0.0675	0.016875
209	346479	3642022	0.0385	0.07425	0.08525	0	0
210	345332	3640584	0.10825	0.1065	0	0	0

Appendix: B

Appendix: B: Summarised the result of Euclidean distance for the field points (210) by using fuzzy c-means method

Sample	East	North	Urban	Vegetation	wood land	Grazing land	Bare area
1	301847	3631819	0.04425	0.0365	0.1165	0.0625	0.025
2	302491	3632155	0.04175	0.02125	0.0745	0	0.099
3	303834	3631818	0	0.0545	0.13875	0.03075	0.05175
4	304480	3631008	0.04025	0.088	0.0455	0.06725	0.0145
5	306691	3632967	0.11413	0.02875	0.05275	0.02675	0.003375
6	308175	3630784	0	0.12775	0.04	0.06975	0.01775
7	309741	3633639	0.04125	0.04175	0.0465	0	0.03875
8	306944	3632240	0.11975	0.09375	0.0625	0	0.03625
9	309266	3630660	0.044	0.067125	0.0125	0	0.10513
10	307978	3631483	0	0.05175	0.04975	0	0.001
11	312262	3634117	0.033	0	0.04075	0	0.00375
12	313327	3633219	0.11425	0.0335	0.02075	0.03025	0.0295
13	315202	3635488	0.02725	0	0	0.03775	0.0685
14	312293	3633472	0.0285	0.038	0.0065	0	0
15	312794	3632829	0.01425	0.03525	0.0625	0.08275	0
16	311171	3632324	0	0.0795	0.069	0.03775	0.0275
17	313674	3631631	0.0385	0	0.06575	0	0.02725
18	319040	3635629	0.0175	0.02675	0.049	0	0.06075
19	318170	3630783	0	0.01175	0.00975	0.03675	0.03625
20	315259	3630588	0	0.039	0	0.14575	0.10625
21	320523	3637000	0.1055	0.0265	0	0.03	0.044
22	322427	3638315	0.0395	0	0.095	0.03025	0.08675
23	323183	3637140	0.0405	0.01938	0	0	0.057625
24	326767	3638985	0.0155	0.02975	0.027	0	0.01375
25	325703	3633946	0	0.05425	0	0	0.055
26	328949	3630335	0.029	0.01625	0.04575	0	0
27	330043	3637533	0.09825	0	0.10975	0.033	0.02225
28	321475	3634395	0.14825	0.0625	0.125	0.0385	0

29	328195	3633919	0.0865	0.047	0.09375	0	0.04375
30	321867	3632294	0.05388	0.06875	0.0375	0.03025	0.049875
31	331414	3639239	0.12475	0.05	0	0.04725	0.02725
32	331133	3635461	0.05	0	0.106	0	0.0515
33	332004	3635461	0.1135	0.03125	0.08025	0.04575	0.01875
34	338470	3635262	0.06975	0.05	0.02675	0	0.09375
35	335810	3639212	0.05775	0.0275	0	0.0095	0.04
36	339088	3632155	0.0575	0.01425	0.035	0	0.0375
37	335587	3637169	0.0595	0.05775	0.031	0	0.03125
38	333823	3636523	0.10275	0	0.0445	0	0.05775
39	334495	3634199	0	0	0.065	0	0.06375
40	334355	3631007	0	0.0405	0.01975	0	0.02125
41	340459	3639157	0.13475	0.07325	0	0.03425	0.0245
42	344883	3638875	0.0345	0	0.03075	0	0.06525
43	349223	3637336	0.076	0.084	0.039	0.0315	0.0625
44	350259	3635962	0.09675	0.019375	0.00563	0	0.11125
45	348412	3633500	0.05	0	0.163	0.0275	0.083
46	349167	3631371	0	0.028	0	0.03625	0.067
47	341523	3637927	0.0515	0	0.01888	0.025	0.05938
48	341804	3633277	0	0.1375	0.0325	0.0575	0.0425
49	343708	3636663	0.00375	0.1	0	0.033	0.0625
50	344575	3634982	0	0.05	0	0.08575	0.033
51	350903	3638315	0	0.03025	0.08675	0	0.05425
52	351573	3637447	0.090625	0.02288	0.06875	0	0
53	352693	3636441	0	0.08025	0	0.094	0.1755
54	357818	3634059	0	0	0.075	0.0795	0
55	358940	3632491	0.05	0.0475	0.0075	0.01	0
56	356056	3632407	0.0775	0.025	0.127	0	0.01875
57	352135	3631170	0	0.04325	0.04275	0.0395	0.05
58	354373	3632295	0	0.03263	0.032375	0	0
59	357761	3631314	0	0.0785	0	0.0785	0.00125
60	352245	3634397	0	0.02388	0.01525	0	0.004625
61	302548	3627899	0	0.04825	0.02575	0.041	0.06075
62	308062	3628149	0	0.0275	0	0.19425	0.1635
63	301511	3625128	0	0.11425	0.0305	0.0445	0.03825
64	306998	3626639	0	0	0	0.124	0.1205
65	308818	3625238	0	0.07325	0.075	0.001	0
66	305907	3623951	0	0.03575	0.16625	0.025	0.1045
67	308148	3621571	0	0.06	0	0.1325	0.0725
68	303053	3621712	0	0.10725	0	0.07325	0.033
69	306103	3625908	0	0.03425	0.05175	0.0855	0
70	304926	3627059	0.0785	0.017	0	0.036	0.025

71	312766	3628096	0.1615	0.025	0.05	0	0.0855
72	315457	3627503	0	0.06975	0	0.05425	0.12475
73	318925	3626470	0	0.16975	0	0.09175	0.0725
74	311536	3626051	0	0.095	0.08025	0.05	0.05775
75	315258	3622160	0.03025	0	0.076	0	0.042
76	318002	3624875	0	0.03525	0.12675	0	0.09025
77	319488	3623812	0.04825	0.0115	0.03225	0	0
78	313942	3625155	0	0.0685	0	0.02525	0.0405
79	310612	3621545	0	0.04675	0.038	0.142	0.05325
80	316661	3628794	0	0.11075	0	0.05775	0.05175
81	321561	3628881	0	0.0595	0.13675	0.0765	0
82	323604	3628684	0.09575	0.05	0	0	0.0455
83	328223	3627900	0	0.1615	0	0.075	0.08
84	328110	3623083	0	0	0.09975	0	0.0985
85	327271	3620871	0	0.04175	0	0.10625	0.06275
86	325254	3621628	0	0.12425	0	0.054	0.07
87	323632	3625658	0.0395	0.03625	0	0	0.0735
88	321951	3624734	0	0.075	0	0.1625	0.0875
89	322932	3622021	0	0.11425	0	0.11625	0
90	325478	3625127	0.04725	0.00125	0	0.07775	0.0325
91	332254	3629608	0.067	0.00925	0	0	0.07325
92	338332	3629327	0	0.0385	0.11925	0.0805	0
93	338640	3627703	0	0.101	0	0.13475	0.03025
94	335588	3628039	0.05775	0.036	0.06675	0	0.0445
95	336146	3626753	0.05	0.11325	0	0.06075	0
96	334998	3621626	0	0.05775	0	0.07225	0.131
97	332728	3623386	0	0.0575	0	0.1335	0.07325
98	331442	3626164	0.06225	0	0.00425	0	0.0655
99	338358	3623560	0	0	0	0.08138	0.080875
100	335161	3625040	0	0	0.07075	0.0455	0.025
101	340597	3629578	0	0.034375	0	0.07813	0.0425
102	344322	3629606	0	0.074875	0.1	0	0.023125
103	349082	3627871	0	0.141	0	0.0765	0.0625
104	348550	3625768	0	0	0.1385	0	0.134
105	346452	3623783	0	0	0	0.09625	0.09275
106	342559	3623083	0	0	0	0.06738	0.066375
107	340598	3626359	0	0	0.13	0.09025	0.03825
108	344799	3627003	0	0	0.047125	0.082	0.034625
109	346057	3624428	0.032	0.14375	0	0.10975	0
110	342392	3625406	0	0.09375	0.08575	0.17875	0
111	351071	3628208	0	0	0	0.11413	0.113125
112	357511	3630223	0	0.116625	0.12288	0	0

113	353029	3628973	0	0.1555	0	0.15525	0
114	358551	3627059	0	0	0.11163	0.109125	0
115	356560	3622943	0.05	0	0.11775	0.06425	0
116	354963	3621096	0	0	0.03	0.09675	0.131
117	354009	3626918	0	0	0.143125	0.14913	0
118	346453	3621323	0.05	0.15875	0	0.1045	0
119	350734	3624314	0	0.05513	0.054125	0	0
120	350260	3620787	0	0.07625	0	0.036125	0.035375
121	304060	3619672	0	0.104	0.101	0	0
122	307670	3619974	0	0.05	0	0.125	0.075
123	308513	3618436	0	0	0.13138	0.131375	0
124	302463	3617428	0	0.15475	0.04675	0.1045	0
125	308239	3616392	0	0.058	0	0.16975	0.108
126	300757	3613845	0	0.14025	0.1125	0.025	0
127	307615	3613705	0	0.101	0	0.095	0.0075
128	305119	3616138	0	0	0.11775	0.117	0
129	305067	3614094	0	0	0.061125	0.06238	0
130	304814	3618406	0	0.102	0	0	0.1015
131	310163	3619219	0	0.09025	0	0.05513	0.03763
132	310893	3618240	0	0	0.09575	0.05225	0.037
133	312571	3619136	0	0.025	0	0.11875	0.14375
134	319458	3618491	0	0.12775	0	0.126	0
135	315568	3617371	0.06788	0.02575	0.03025	0	0.011125
136	318448	3615102	0	0	0.07038	0.034625	0.03575
137	312681	3616081	0	0.045	0	0.142	0.09675
138	313187	3615274	0	0.1145	0.0375	0.14625	0
139	309997	3613676	0	0.068125	0.04513	0.024	0
140	315228	3613508	0	0.16025	0	0.1585	0
141	321474	3619471	0	0	0.116625	0.12138	0
142	321839	3618600	0	0.0785	0.025	0	0.106
143	324947	3619891	0.03	0.142	0.03025	0.0745	0
144	328135	3614068	0	0.1275	0	0.069	0.05725
145	323880	3616530	0	0	0	0.1515	0.148
146	323715	3613310	0	0.101	0.11063	0.01388	0.019
147	320383	3614345	0.081875	0.08488	0	0	0
148	325114	3617989	0.03025	0.142	0.05	0	0.06075
149	321112	3617400	0.05875	0.0565	0	0	0.00175
150	323070	3618436	0	0.0535	0.05275	0.16875	0.0615
151	330716	3614460	0	0.0495	0	0.1045	0.05075
152	331021	3616112	0.14888	0.121625	0.02425	0	0
153	332734	3620229	0.11325	0.14225	0	0.02725	0
154	339366	3613283	0.08025	0.0955	0.02125	0.03425	0

155	338609	3619135	0	0.1805	0.1095	0	0.0675
156	333094	3617061	0	0	0.15038	0.145125	0
157	337238	3618294	0	0.07838	0.062875	0	0.01425
158	334970	3616111	0	0.03	0	0.08925	0.12
159	337380	3615635	0.081875	0.026	0.11038	0	0
160	336429	3618604	0	0.10788	0.02175	0.084375	0
161	341383	3619219	0	0	0.06675	0.13375	0.06625
162	342474	3617036	0	0	0.13325	0.0525	0.0745
163	346369	3618742	0	0.019	0	0.14738	0.128125
164	345527	3616925	0.028	0.1645	0	0.133	0
165	342810	3614319	0.03625	0.05775	0.08213	0.10163	0.088
166	349252	3617792	0.04725	0	0.05275	0.07525	0.17825
167	348046	3616837	0	0.076	0.020375	0.09938	0
168	348607	3614152	0	0.0455	0.14013	0.062875	0.03025
169	346449	3613481	0.073625	0.062	0	0.01388	0
170	344713	3616672	0	0.10838	0.04688	0.03075	0.122
171	350260	3619528	0	0	0.0855	0.06913	0.01988
172	350847	3618155	0	0.05	0.1295	0.045	0.03425
173	357008	3619441	0	0.14463	0.025	0.087375	0.0315
174	359023	3618967	0	0.058	0	0.166	0.10725
175	357846	3615215	0	0	0.12288	0.094875	0.025
176	349726	3615830	0	0	0.058	0.11663	0.057125
177	355244	3615774	0	0	0.15213	0.107625	0.04075
178	353731	3618185	0	0.0425	0	0.039875	0.08588
179	350339	3614624	0	0.08213	0.03775	0.080125	0.0375
180	354123	3613873	0	0.07575	0.04025	0.0375	0
181	328756	3641200	0	0.0335	0.049	0.0525	0.13675
182	329008	3641144	0.1805	0.105	0.0495	0	0.025
183	328755	3641339	0.129875	0.14113	0	0	0.01
184	329147	3641534	0.10713	0.0585	0.08775	0	0.04038
185	329176	3641927	0.142	0.028	0	0.033	0.08025
186	329595	3641143	0.12513	0.03625	0.0635	0	0.024625
187	328922	3641562	0.04513	0.04988	0	0.044	0.05075
188	329819	3641367	0.10838	0.057625	0	0	0.0495
189	329483	3641534	0.05313	0	0	0	0.052375
190	328978	3641311	0.050375	0.0625	0.02175	0	0.01013
191	330154	3641060	0.04975	0.10675	0.075	0.0745	0
192	330826	3641032	0.11425	0.025	0.0525	0.03625	0
193	332701	3641617	0.121875	0	0	0	0.12288
194	333823	3641731	0	0.10725	0.0385	0.025	0.04275
195	335616	3642683	0	0	0	0.039	0.04225
196	336873	3641815	0.05238	0.10563	0.0855	0.07	0
197	334635	3640723	0.08	0.07813	0	0	0.00688

198	337938	3640695	0.02825	0.00325	0.03025	0	0
199	337911	3642094	0.143	0	0.07775	0	0.065
200	335645	3641926	0.08288	0.0125	0.035	0	0.060125
201	341637	3641535	0	0.085	0.025	0	0.1115
202	342644	3640246	0.10213	0.02013	0.03025	0	0.08825
203	344156	3640247	0.04725	0.08438	0	0	0.035625
204	348833	3640976	0	0.0775	0.06563	0.05	0.06213
205	349250	3640135	0	0.0375	0.02125	0	0.05725
206	346143	3639463	0.05163	0.022875	0.0225	0	0
207	347683	3640610	0.06213	0	0.05775	0	0.003125
208	348553	3640164	0	0.01525	0.04538	0.029875	0
209	346479	3642022	0.05	0.07075	0.069	0	0.04975
210	345332	3640584	0.11	0.05	0.0585	0	0

Appendix: C

Appendix: C: Summarised the result of Confusion index by using fuzzy set method

Pixel	Class					Maximum Membership Class	Second Highest	Confusion index
	Urban	Vegetation	Wood-land	Grazing land	Bare area			
1	0.103	0.189	0.673	0	0.032	0.673	0.189	0.280
2	0.256	0.036	0.387	0	0.321	0.387	0.321	0.829
3	0	0.076	0.216	0.053	0.651	0.651	0.216	0.331
4	0.112	0.372	0.215	0.185	0.11	0.372	0.215	0.577
5	0.265	0.473	0.147	0	0.112	0.473	0.265	0.560
6	0	0.365	0.312	0.143	0.175	0.365	0.321	0.879
7	0.2	0.021	0.654	0.029	0.095	0.654	0.2	0.305
8	0.741	0	0.132	0.073	0.121	0.741	0.132	0.177
9	0.053	0.742	0	0	0.132	0.742	0.132	0.178
10	0	0.217	0.564	0	0.214	0.564	0.217	0.384
11	0	0.234	0.217	0.121	0.547	0.547	0.234	0.427
12	0.389	0.286	0.083	0.121	0.118	0.389	0.286	0.735
13	0	0	0.297	0.372	0.321	0.372	0.321	0.862
14	0.093	0.723	0.1	0	0.074	0.723	0.1	0.138

15	0.142	0.642	0	0.212	0	0.642	0.212	0.330
16	0	0.167	0.304	0.151	0.376	0.376	0.304	0.808
17	0.086	0.378	0.176	0	0.359	0.378	0.359	0.949
18	0.456	0.104	0.294	0	0.138	0.456	0.294	0.644
19	0	0.605	0.291	0.103	0	0.605	0.291	0.480
20	0	0	0	0.365	0.632	0.632	0.365	0.577
21	0.479	0.097	0	0.221	0.203	0.479	0.221	0.461
22	0.286	0	0.38	0.121	0.213	0.38	0.286	0.752
23	0.178	0.194	0	0	0.618	0.618	0.194	0.313
24	0.794	0.102	0	0	0.101	0.794	0.102	0.128
25	0	0.189	0	0	0.804	0.804	0.189	0.235
26	0	0.748	0.247	0	0	0.748	0.247	0.330
27	0.583	0	0.217	0.167	0.032	0.583	0.217	0.372
28	0.811	0	0	0.187	0	0.811	0.187	0.230
29	0.032	0.658	0.109	0	0.2	0.658	0.109	0.165
30	0.117	0.167	0.109	0.054	0.543	0.543	0.167	0.307
31	0.357	0.217	0	0.179	0.246	0.357	0.217	0.607
32	0.128	0.089	0.279	0	0.504	0.504	0.279	0.553
33	0.387	0	0.286	0.11	0.216	0.387	0.286	0.739
34	0.134	0.169	0.687	0	0	0.687	0.134	0.195
35	0.105	0.613	0	0.038	0.24	0.613	0.24	0.391
36	0	0.186	0.712	0	0.092	0.712	0.186	0.261
37	0.462	0.427	0	0	0.103	0.462	0.427	0.924
38	0.567	0	0.134	0	0.298	0.567	0.298	0.525
39	0	0	0.398	0	0.593	0.593	0.398	0.671
40	0	0.342	0.185	0	0.465	0.465	0.342	0.735
41	0.365	0.457	0	0.132	0.041	0.457	0.365	0.798
42	0.659	0	0.105	0	0.225	0.659	0.225	0.341
43	0.479	0.038	0.187	0.264	0.032	0.479	0.264	0.551

44	0.321	0.512	0	0	0.167	0.512	0.321	0.626
45	0	0.187	0.487	0.091	0.232	0.487	0.232	0.476
46	0	0.131	0	0.54	0.329	0.329	0.131	0.398
47	0.105	0	0.101	0.043	0.748	0.748	0.105	0.140
48	0	0.654	0.059	0.176	0.105	0.654	0.176	0.269
49	0.103	0.257	0	0.029	0.608	0.608	0.257	0.422
50	0	0	0	0.564	0.432	0.564	0.432	0.765
51	0	0	0.654	0	0.342	0.654	0.342	0.522
52	0.564	0.267	0.165	0	0	0.564	0.267	0.473
53	0	0.213	0	0.484	0.298	0.484	0.298	0.615
54	0	0	0.374	0.521	0.102	0.521	0.374	0.717
55	0	0.601	0.171	0.112	0.106	0.601	0.171	0.284
56	0.213	0.1	0.342	0	0.341	0.342	0.341	0.997
57	0	0	0	0.285	0.712	0.712	0.285	0.400
58	0	0.714	0.279	0	0	0.714	0.279	0.390
59	0	0.431	0	0.453	0.106	0.453	0.431	0.951
60	0	0.534	0.163	0	0.3	0.534	0.163	0.305
61	0	0.342	0	0.654	0	0.654	0.342	0.522
62	0	0.215	0	0.453	0.326	0.453	0.326	0.719
63	0	0.584	0	0.216	0.198	0.584	0.216	0.369
64	0	0.116	0	0.478	0.403	0.478	0.403	0.843
65	0	0.101	0.176	0.723	0	0.723	0.176	0.243
66	0	0	0.367	0	0.631	0.631	0.367	0.581
67	0	0	0	0.294	0.695	0.695	0.294	0.423
68	0	0.253	0	0.743	0	0.743	0.253	0.340
69	0	0	0.321	0.679	0	0.679	0.321	0.472
70	0.215	0.514	0.045	0.223	0	0.514	0.223	0.433
71	0.432	0	0.151	0	0.416	0.432	0.416	0.962
72	0	0.264	0	0.459	0.267	0.459	0.267	0.581

73	0	0.543	0.115	0.342	0	0.543	0.342	0.629
74	0	0.176	0	0.712	0.102	0.712	0.176	0.247
75	0.214	0	0.121	0	0.663	0.663	0.214	0.322
76	0	0.141	0.368	0	0.487	0.487	0.368	0.755
77	0.2	0.663	0.032	0	0.104	0.663	0.104	0.156
78	0	0.456	0.065	0.101	0.374	0.456	0.374	0.820
79	0	0.187	0.144	0.563	0.106	0.563	0.187	0.332
80	0	0.385	0	0.127	0.479	0.479	0.385	0.803
81	0	0	0.694	0.306	0	0.694	0.306	0.440
82	0.329	0	0.148	0	0.517	0.517	0.329	0.636
83	0	0.432	0.165	0.101	0.301	0.432	0.301	0.696
84	0	0	0.594	0	0.395	0.594	0.395	0.664
85	0	0.211	0.059	0.376	0.344	0.376	0.344	0.914
86	0	0.549	0	0.102	0.341	0.549	0.341	0.621
87	0.621	0.142	0	0	0.236	0.621	0.236	0.380
88	0	0.543	0	0.35	0.103	0.543	0.103	0.189
89	0	0.561	0	0.432	0	0.561	0.432	0.770
90	0.276	0.103	0.211	0.302	0.107	0.302	0.276	0.913
91	0.216	0.107	0.058	0	0.615	0.615	0.216	0.351
92	0	0.183	0.564	0.248	0	0.564	0.248	0.439
93	0	0.534	0	0.358	0.105	0.534	0.358	0.670
94	0	0.82	0.17	0	0	0.82	0.17	0.207
95	0	0.766	0	0.227	0	0.766	0.227	0.296
96	0	0	0	0.289	0.707	0.707	0.289	0.408
97	0	0.112	0	0.478	0.402	0.478	0.402	0.841
98	0.369	0	0.163	0	0.465	0.465	0.369	0.793
99	0	0	0	0.459	0.541	0.541	0.459	0.848
100	0	0	0.771	0.125	0.1	0.771	0.125	0.162
101	0	0.105	0	0.365	0.528	0.528	0.365	0.691

102	0	0.587	0.158	0	0.251	0.587	0.251	0.427
103	0	0.691	0	0.306	0	0.691	0.306	0.442
104	0	0	0.496	0	0.5	0.5	0.496	0.992
105	0	0	0	0.432	0.563	0.563	0.432	0.767
106	0	0	0	0.665	0.331	0.665	0.331	0.497
107	0	0	0.443	0.551	0	0.551	0.443	0.803
108	0	0	0.376	0.297	0.326	0.376	0.326	0.867
109	0.128	0.341	0	0.531	0	0.531	0.341	0.642
110	0	0	0.325	0.673	0	0.673	0.325	0.482
111	0	0	0	0.118	0.876	0.876	0.118	0.134
112	0	0.589	0.411	0	0	0.589	0.411	0.697
113	0	0.453	0	0.543	0	0.543	0.453	0.834
114	0	0	0.214	0.785	0	0.785	0.214	0.272
115	0.196	0	0.279	0.523	0	0.523	0.279	0.533
116	0	0	0.09	0.453	0.453	0.453	0.09	0.198
117	0	0	0.632	0.368	0	0.632	0.368	0.582
118	0.154	0.354	0	0.487	0	0.487	0.354	0.726
119	0	0.763	0.118	0.117	0	0.763	0.118	0.154
120	0	0.376	0	0.421	0.2	0.421	0.376	0.893
121	0	0.443	0.556	0	0	0.556	0.443	0.796
122	0	0.118	0	0.539	0.342	0.539	0.342	0.634
123	0	0	0.379	0.621	0	0.621	0.379	0.610
124	0	0.367	0.187	0.436	0	0.436	0.367	0.841
125	0	0.184	0	0.438	0.378	0.438	0.378	0.863
126	0	0.379	0.62	0	0	0.379	0.62	1.635
127	0	0.553	0	0.223	0.22	0.553	0.223	0.403
128	0	0	0.276	0.723	0	0.723	0.276	0.381
129	0	0	0.432	0.563	0	0.563	0.432	0.767
130	0	0.467	0	0	0.531	0.531	0.467	0.879

131	0	0	0	0.517	0.476	0.517	0.476	0.920
132	0	0	0.654	0.339	0	0.654	0.339	0.518
133	0	0	0	0.619	0.38	0.619	0.38	0.613
134	0	0.438	0	0.552	0	0.552	0.438	0.793
135	0.458	0.214	0.063	0	0.263	0.458	0.263	0.574
136	0	0	0.267	0.732	0	0.732	0.267	0.364
137	0	0.311	0	0.467	0.22	0.467	0.311	0.665
138	0	0.367	0.154	0.475	0	0.475	0.367	0.772
139	0	0.714	0.102	0.176	0	0.714	0.176	0.246
140	0	0.354	0	0.638	0	0.638	0.354	0.554
141	0	0	0.442	0.557	0	0.557	0.442	0.793
142	0	0.437	0.115	0	0.445	0.445	0.437	0.982
143	0.127	0.538	0	0.328	0	0.538	0.328	0.609
144	0	0.447	0	0.254	0.296	0.447	0.296	0.662
145	0	0	0	0.386	0.613	0.613	0.386	0.629
146	0	0.538	0.152	0.3	0	0.538	0.152	0.282
147	0.683	0.182	0	0	0.132	0.683	0.182	0.266
148	0	0.532	0.178	0	0.29	0.532	0.178	0.334
149	0.138	0.633	0	0	0.22	0.633	0.138	0.218
150	0	0	0.236	0.438	0.326	0.438	0.326	0.744
151	0	0.215	0	0.459	0.31	0.459	0.215	0.468
152	0.475	0.523	0	0	0	0.523	0.475	0.908
153	0.52	0.48	0	0	0	0.52	0.48	0.923
154	0.375	0.124	0.031	0.47	0	0.375	0.124	0.330
155	0	0.376	0.354	0	0.27	0.376	0.354	0.941
156	0	0	0.265	0.73	0	0.73	0.265	0.363
157	0	0.312	0.63	0	0.057	0.63	0.312	0.495
158	0	0.09	0	0.376	0.532	0.532	0.376	0.706
159	0.532	0.201	0.263	0	0	0.532	0.263	0.494

160	0	0.328	0	0.667	0	0.667	0.328	0.491
161	0	0	0.254	0.576	0.17	0.576	0.254	0.440
162	0	0	0.432	0.101	0.467	0.467	0.432	0.925
163	0	0	0	0.329	0.67	0.67	0.329	0.491
164	0	0.417	0	0.576	0	0.576	0.417	0.723
165	0	0.253	0.156	0.231	0.352	0.352	0.253	0.718
166	0.121	0	0.184	0.347	0.345	0.347	0.345	0.994
167	0	0.432	0.354	0.211	0	0.432	0.354	0.819
168	0	0	0.276	0.654	0.065	0.654	0.276	0.422
169	0.523	0.165	0	0.312	0	0.523	0.312	0.596
170	0	0.386	0	0	0.613	0.613	0.386	0.629
171	0	0	0.423	0.387	0.186	0.423	0.387	0.914
172	0	0	0.316	0.547	0.137	0.547	0.316	0.577
173	0	0.349	0	0.521	0.126	0.521	0.349	0.669
174	0	0.247	0	0.263	0.49	0.263	0.247	0.939
175	0	0	0.574	0.423	0	0.574	0.423	0.736
176	0	0	0.253	0.321	0.42	0.321	0.253	0.788
177	0	0	0.318	0.513	0.163	0.513	0.318	0.619
178	0	0.174	0	0.587	0.237	0.587	0.237	0.403
179	0	0.178	0.131	0.569	0.121	0.569	0.178	0.312
180	0	0.742	0.167	0.03	0.06	0.742	0.167	0.225
181	0	0	0.235	0.216	0.548	0.548	0.235	0.4288
182	0.369	0.42	0.204	0	0	0.369	0.204	0.552
183	0.792	0.203	0	0	0	0.792	0.203	0.256
184	0.211	0	0.33	0	0.459	0.459	0.211	0.459
185	0.543	0	0	0.132	0.321	0.543	0.321	0.591
186	0.254	0.132	0.231	0	0.369	0.369	0.254	0.688
187	0.154	0.385	0	0	0.453	0.453	0.385	0.849
188	0.449	0.473	0	0	0.078	0.473	0.449	0.949

189	0.528	0	0.123	0	0.341	0.528	0.341	0.645
190	0.657	0.104	0.087	0	0.147	0.657	0.147	0.223
191	0.225	0.276	0.243	0.253	0	0.276	0.253	0.916
192	0.511	0.221	0.065	0.194	0	0.511	0.221	0.432
193	0.576	0	0	0	0.416	0.576	0.416	0.722
194	0	0.476	0.141	0.087	0.291	0.476	0.291	0.611
195	0	0	0.072	0.199	0.721	0.721	0.199	0.276
196	0.116	0.376	0.332	0.176	0	0.376	0.332	0.882
197	0.734	0.076	0	0	0.19	0.734	0.076	0.103
198	0.187	0.676	0.137	0	0	0.676	0.187	0.276
199	0.254	0	0.368	0	0.376	0.376	0.368	0.978
200	0.351	0.128	0.134	0	0.386	0.386	0.351	0.909
201	0	0.354	0	0	0.645	0.645	0.354	0.548
202	0.167	0.32	0.121	0	0.392	0.392	0.167	0.420
203	0.121	0.342	0	0	0.53	0.342	0.121	0.353
204	0	0.303	0.287	0.148	0.258	0.303	0.287	0.947
205	0	0.123	0.432	0	0.442	0.442	0.432	0.977
206	0.102	0.774	0.114	0	0	0.774	0.114	0.147
207	0.476	0	0.389	0	0.126	0.476	0.389	0.817
208	0	0.296	0.321	0.38	0	0.321	0.296	0.922
209	0.154	0.328	0.341	0	0.176	0.341	0.328	0.961
210	0.567	0.426	0	0	0	0.567	0.426	0.751

Appendix: D

Appendix: D: Summarised the result of Confusion index by using fuzzy c-means method

Pixel	Class					Maximum Membership Class	Second Highest	Confusion index
	Urban	Vegetation	Wood-land	Grazing land	Bare area			
1	0.073	0.104	0.716	0	0.1	0.716	0.104	0.145
2	0.167	0.165	0.298	0	0.354	0.354	0.298	0.841
3	0	0.218	0.195	0.123	0.457	0.457	0.218	0.477
4	0.089	0.273	0.182	0.269	0.183	0.273	0.269	0.985
5	0.231	0.365	0.211	0.107	0.076	0.365	0.231	0.632
6	0	0.239	0.285	0.279	0.196	0.285	0.279	0.978
7	0.54	0.167	0.189	0	0.095	0.54	0.189	0.35
8	0.854	0	0	0	0.145	0.854	0.145	0.169
9	0.176	0.456	0.2	0	0.142	0.456	0.176	0.385
10	0	0.543	0.324	0	0.121	0.543	0.324	0.596
11	0.132	0	0.587	0	0.265	0.587	0.265	0.451
12	0.543	0.134	0.083	0.121	0.118	0.543	0.134	0.246
13	0.234	0	0	0.276	0.476	0.476	0.276	0.579
14	0.364	0.348	0.276	0	0	0.364	0.348	0.956
15	0.432	0.234	0	0.331	0	0.432	0.331	0.766
16	0	0.432	0.276	0.151	0.14	0.432	0.276	0.638
17	0.154	0	0.487	0	0.359	0.487	0.359	0.737
18	0.43	0.232	0.196	0	0.132	0.43	0.232	0.539
19	0	0.453	0.289	0.103	0.145	0.453	0.289	0.637
20	0	0.156	0	0.167	0.675	0.675	0.167	0.247
21	0.578	0.106	0	0.12	0.176	0.578	0.176	0.304
22	0.342	0	0.38	0.121	0.153	0.38	0.342	0.9
23	0.213	0.235	0	0	0.543	0.543	0.235	0.432
24	0.438	0.256	0.108	0	0.18	0.438	0.256	0.584
25	0	0.467	0	0	0.53	0.53	0.467	0.881

26	0.116	0.315	0.567	0	0	0.567	0.315	0.555
27	0.643	0	0.186	0.132	0.036	0.643	0.186	0.289
28	0.843	0	0	0.154	0	0.843	0.154	0.182
29	0.346	0.438	0	0	0.2	0.438	0.346	0.789
30	0.097	0.1	0.15	0.121	0.512	0.512	0.121	0.236
31	0.376	0.2	0	0.189	0.234	0.376	0.234	0.622
32	0.2	0	0.326	0	0.456	0.456	0.326	0.714
33	0.296	0	0.321	0.183	0.2	0.321	0.296	0.9221
34	0.654	0.2	0.143	0	0	0.654	0.2	0.305
35	0.731	0.14	0	0.038	0.09	0.731	0.14	0.191
36	0.23	0.432	0.235	0	0.1	0.432	0.235	0.543
37	0.512	0.356	0.124	0	0	0.512	0.356	0.695
38	0.589	0	0.178	0	0.231	0.589	0.231	0.392
39	0	0	0.365	0	0.63	0.63	0.365	0.579
40	0	0.287	0.421	0	0.29	0.421	0.29	0.688
41	0.211	0.543	0	0.137	0.098	0.543	0.211	0.388
42	0.487	0	0.127	0	0.386	0.487	0.386	0.792
43	0.554	0.164	0.156	0.126	0	0.554	0.164	0.296
44	0.387	0.265	0.165	0	0.18	0.387	0.265	0.684
45	0.2	0	0.348	0.11	0.332	0.348	0.332	0.954
46	0	0.112	0	0.145	0.732	0.732	0.145	0.198
47	0.456	0	0.237	0.1	0.2	0.456	0.237	0.519
48	0	0.45	0.13	0.23	0.17	0.45	0.23	0.511
49	0.265	0.1	0	0.132	0.5	0.5	0.265	0.53
50	0	0.2	0	0.657	0.132	0.657	0.2	0.304
51	0	0.121	0.653	0	0.217	0.653	0.217	0.332
52	0.675	0.221	0.1	0	0	0.675	0.221	0.327
53	0	0.321	0	0.376	0.298	0.376	0.321	0.853
54	0	0	0.55	0.432	0	0.55	0.432	0.785

55	0.2	0.31	0.28	0.21	0	0.31	0.28	0.903
56	0.31	0.1	0.367	0	0.2	0.367	0.31	0.844
57	0	0.173	0.171	0.342	0.3	0.342	0.3	0.877
58	0	0.432	0.567	0	0	0.567	0.432	0.761
59	0	0.564	0	0.311	0.12	0.564	0.311	0.551
60	0	0.342	0.311	0	0.331	0.342	0.331	0.967
61	0	0.432	0.103	0.211	0.243	0.432	0.243	0.562
62	0	0.11	0	0.223	0.654	0.654	0.223	0.340
63	0	0.543	0.122	0.178	0.153	0.543	0.178	0.327
64	0	0	0	0.254	0.732	0.732	0.254	0.346
65	0	0.543	0.2	0.254	0	0.543	0.254	0.467
66	0	0.143	0.21	0.1	0.543	0.543	0.21	0.386
67	0	0.24	0	0.22	0.54	0.54	0.24	0.444
68	0	0.321	0	0.543	0.132	0.543	0.321	0.591
69	0	0.113	0.543	0.342	0	0.543	0.342	0.629
70	0.436	0.318	0	0.144	0.1	0.436	0.318	0.729
71	0.354	0.1	0.2	0	0.342	0.354	0.342	0.966
72	0	0.279	0	0.342	0.376	0.376	0.342	0.909
73	0	0.321	0	0.367	0.29	0.367	0.321	0.874
74	0	0.12	0.321	0.3	0.231	0.321	0.3	0.934
75	0.121	0	0.321	0	0.543	0.543	0.321	0.591
76	0	0.141	0.243	0	0.611	0.611	0.243	0.397
77	0.432	0.421	0.129	0	0	0.432	0.421	0.974
78	0	0.476	0	0.101	0.412	0.476	0.412	0.865
79	0	0.187	0.152	0.432	0.213	0.432	0.213	0.493
80	0	0.432	0	0.231	0.332	0.432	0.332	0.768
81	0	0.238	0.453	0.306	0	0.453	0.306	0.675
82	0.367	0.2	0	0	0.432	0.432	0.367	0.849
83	0	0.354	0	0.3	0.32	0.354	0.32	0.903

84	0	0	0.476	0	0.519	0.519	0.476	0.917
85	0	0.167	0	0.45	0.376	0.45	0.376	0.835
86	0	0.378	0	0.341	0.28	0.378	0.341	0.902
87	0.342	0.23	0	0	0.419	0.419	0.342	0.816
88	0	0.3	0	0.35	0.35	0.35	0.35	0.857
89	0	0.832	0	0.16	0	0.832	0.16	0.192
90	0.436	0.12	0	0.311	0.12	0.436	0.311	0.713
91	0.232	0.213	0	0	0.543	0.543	0.232	0.427
92	0	0.154	0.523	0.322	0	0.523	0.322	0.615
93	0	0.654	0	0.211	0.121	0.654	0.211	0.322
94	0.231	0.356	0.233	0	0.178	0.356	0.233	0.654
95	0.2	0.547	0	0.243	0	0.547	0.243	0.444
96	0	0.231	0	0.289	0.476	0.476	0.289	0.607
97	0	0.23	0	0.216	0.543	0.543	0.23	0.423
98	0.376	0	0.108	0	0.512	0.512	0.376	0.734
99	0	0	0	0.237	0.761	0.761	0.237	0.311
100	0	0	0.342	0.432	0.225	0.432	0.342	0.791
101	0	0.325	0	0.25	0.42	0.42	0.325	0.773
102	0	0.612	0.1	0	0.28	0.612	0.28	0.457
103	0	0.436	0	0.306	0.25	0.436	0.306	0.701
104	0	0	0.321	0	0.661	0.661	0.321	0.485
105	0	0	0	0.365	0.621	0.621	0.365	0.587
106	0	0	0	0.543	0.453	0.543	0.453	0.834
107	0	0	0.23	0.611	0.153	0.611	0.23	0.376
108	0	0	0.376	0.297	0.326	0.376	0.326	0.867
109	0.128	0.3	0	0.564	0	0.564	0.3	0.531
110	0	0	0.157	0.84	0	0.84	0.157	0.186
111	0	0	0	0.231	0.765	0.765	0.231	0.301
112	0	0.654	0.321	0	0	0.654	0.321	0.490

113	0	0.378	0	0.621	0	0.621	0.378	0.608
114	0	0	0.116	0.874	0	0.874	0.116	0.132
115	0.2	0	0.154	0.632	0	0.632	0.2	0.316
116	0	0	0.12	0.387	0.476	0.476	0.387	0.813
117	0	0	0.76	0.216	0	0.76	0.216	0.284
118	0.2	0.24	0	0.543	0	0.543	0.24	0.441
119	0	0.342	0.654	0	0	0.654	0.342	0.522
120	0	0.32	0	0.332	0.329	0.332	0.329	0.990
121	0	0.334	0.654	0	0	0.654	0.334	0.510
122	0	0.2	0	0.5	0.3	0.5	0.3	0.6
123	0	0	0.287	0.713	0	0.713	0.287	0.402
124	0	0.256	0.187	0.543	0	0.543	0.256	0.471
125	0	0.232	0	0.321	0.432	0.432	0.321	0.743
126	0	0.189	0.7	0.1	0	0.7	0.189	0.27
127	0	0.654	0	0.12	0.22	0.654	0.22	0.336
128	0	0	0.154	0.843	0	0.843	0.154	0.182
129	0	0	0.432	0.563	0	0.563	0.432	0.767
130	0	0.467	0	0	0.531	0.531	0.467	0.879
131	0	0.361	0	0.342	0.287	0.361	0.342	0.947
132	0	0	0.367	0.459	0.148	0.459	0.367	0.799
133	0	0.1	0	0.6	0.3	0.6	0.3	0.5
134	0	0.239	0	0.754	0	0.754	0.239	0.316
135	0.541	0.103	0.121	0	0.232	0.541	0.232	0.428
136	0	0	0.156	0.701	0.143	0.701	0.156	0.222
137	0	0.18	0	0.432	0.387	0.432	0.387	0.895
138	0	0.167	0.1	0.71	0	0.71	0.167	0.235
139	0	0.71	0.132	0.154	0	0.71	0.154	0.216
140	0	0.234	0	0.759	0	0.759	0.234	0.308
141	0	0	0.654	0.327	0	0.654	0.327	0.5

142	0	0.564	0.1	0	0.326	0.564	0.326	0.578
143	0.12	0.432	0.121	0.298	0	0.432	0.298	0.689
144	0	0.365	0	0.276	0.354	0.365	0.354	0.969
145	0	0	0	0.269	0.717	0.717	0.269	0.375
146	0	0.654	0.12	0.132	0.076	0.654	0.132	0.201
147	0.765	0.223	0	0	0	0.765	0.223	0.291
148	0.121	0.432	0.2	0	0.243	0.432	0.243	0.562
149	0.265	0.476	0	0	0.243	0.476	0.265	0.556
150	0	0.214	0.211	0.325	0.246	0.325	0.246	0.756
151	0	0.198	0	0.332	0.453	0.453	0.332	0.732
152	0.217	0.674	0.097	0	0	0.674	0.217	0.321
153	0.453	0.431	0	0.109	0	0.453	0.431	0.951
154	0.321	0.118	0.165	0.387	0	0.387	0.321	0.829
155	0	0.278	0.438	0	0.27	0.438	0.278	0.634
156	0	0	0.211	0.768	0	0.768	0.211	0.274
157	0	0.249	0.689	0	0.057	0.689	0.249	0.361
158	0	0.12	0	0.357	0.52	0.52	0.357	0.686
159	0.765	0.104	0.121	0	0	0.765	0.121	0.1581
160	0	0.256	0.087	0.65	0	0.65	0.256	0.393
161	0	0	0.267	0.465	0.265	0.465	0.267	0.574
162	0	0	0.342	0.21	0.423	0.423	0.342	0.808
163	0	0.076	0	0.223	0.7	0.7	0.223	0.318
164	0.112	0.342	0	0.532	0	0.532	0.342	0.642
165	0.145	0.231	0.109	0.156	0.352	0.352	0.231	0.656
166	0.189	0	0.211	0.301	0.287	0.301	0.287	0.953
167	0	0.554	0.269	0.165	0	0.554	0.269	0.485
168	0	0.182	0.127	0.564	0.121	0.564	0.182	0.322
169	0.732	0.127	0	0.132	0	0.732	0.132	0.180
170	0	0.254	0	0.123	0.613	0.613	0.254	0.414

171	0	0	0.342	0.411	0.233	0.411	0.342	0.832
172	0	0.2	0.232	0.43	0.137	0.43	0.232	0.539
173	0	0.234	0.1	0.537	0.126	0.537	0.234	0.435
174	0	0.232	0	0.211	0.554	0.554	0.232	0.418
175	0	0	0.321	0.567	0.1	0.567	0.321	0.566
176	0	0	0.232	0.221	0.541	0.541	0.232	0.428
177	0	0	0.204	0.618	0.163	0.618	0.204	0.330
178	0	0.17	0	0.597	0.219	0.597	0.219	0.366
179	0	0.109	0.151	0.633	0.1	0.633	0.151	0.238
180	0	0.803	0.089	0.1	0	0.803	0.1	0.124
181	0	0.134	0.196	0.21	0.453	0.453	0.21	0.463
182	0.278	0.42	0.198	0	0.1	0.42	0.278	0.661
183	0.832	0.123	0	0	0.04	0.832	0.123	0.147
184	0.134	0.234	0.351	0	0.276	0.351	0.276	0.786
185	0.432	0.112	0	0.132	0.321	0.432	0.321	0.743
186	0.187	0.145	0.254	0	0.411	0.411	0.254	0.618
187	0.132	0.238	0	0.176	0.453	0.453	0.238	0.525
188	0.254	0.543	0	0	0.198	0.543	0.254	0.467
189	0.6	0	0	0	0.397	0.6	0.397	0.661
190	0.764	0	0.087	0	0.147	0.764	0.147	0.192
191	0.176	0.198	0.3	0.298	0	0.3	0.298	0.993
192	0.543	0.1	0.21	0.145	0	0.543	0.21	0.386
193	0.675	0	0	0	0.321	0.675	0.321	0.475
194	0	0.321	0.154	0.1	0.421	0.421	0.321	0.762
195	0	0	0	0.156	0.831	0.831	0.156	0.187
196	0.103	0.265	0.342	0.28	0	0.342	0.265	0.774
197	0.82	0	0	0	0.16	0.82	0.16	0.195
198	0.387	0.487	0.121	0	0	0.487	0.387	0.794
199	0.178	0	0.311	0	0.51	0.51	0.311	0.609

200	0.231	0.2	0.14	0	0.428	0.428	0.231	0.539
201	0	0.34	0.1	0	0.554	0.554	0.34	0.613
202	0.154	0.232	0.121	0	0.478	0.478	0.232	0.485
203	0.564	0.1	0	0	0.33	0.564	0.33	0.585
204	0	0.31	0.3	0.2	0.189	0.31	0.3	0.967
205	0	0.1	0.54	0	0.354	0.54	0.354	0.655
206	0.231	0.654	0.09	0	0	0.654	0.231	0.353
207	0.564	0	0.231	0	0.2	0.564	0.231	0.409
208	0	0.311	0.256	0.432	0	0.432	0.311	0.719
209	0.2	0.342	0.276	0	0.176	0.342	0.276	0.807
210	0.56	0.2	0.234	0	0	0.56	0.234	0.417

Appendix: E

Appendix: E: Summarised the Membership from the field compared with membership of classification image by using fuzzy set method.

Urban field	Urban classification	Vegetation field	Vegetation classification	Woodland field	Woodland classification	Grazing land field	Grazing land classification	Bare land field	Bare land classification
0.25	0.103	0.25	0.189	0.25	0.673	0.25	0	0	0.032
0	0.256	0.25	0.036	0	0.387	0	0	0.75	0.321
0	0	0	0.076	0.75	0.216	0	0.053	0.25	0.651
0.25	0.112	0.625	0.372	0	0.215	0	0.185	0.125	0.11
0.6875	0.265	0.25	0.473	0	0.147	0	0	0.0625	0.112
0	0	0.75	0.365	0.125	0.312	0	0.143	0.125	0.175
0.375	0.2	0	0.021	0.375	0.654	0	0.029	0.25	0.095
0.375	0.741	0.375	0	0.25	0.132	0	0	0	0.121
0	0.053	0.1875	0.742	0.25	0	0	0.073	0.5625	0.132
0	0	0.75	0.217	0.125	0.564	0	0	0.125	0.214
0	0	0	0.234	0.75	0.217	0	0	0.25	0.547
1	0.389	0	0.286	0	0.083	0	0.121	0	0.118
0.125	0	0	0	0	0.297	0.125	0.372	0.75	0.321
0.25	0.093	0.5	0.723	0.25	0.1	0	0	0	0.074
0.375	0.142	0.375	0.642	0.25	0	0	0.212	0	0
0	0	0.75	0.167	0	0.304	0	0.151	0.25	0.376
0	0.086	0	0.378	0.75	0.176	0	0	0.25	0.359
0.5	0.456	0.125	0.104	0	0.294	0	0	0.375	0.138
0	0	0.5	0.605	0.25	0.291	0.25	0.103	0	0
0	0	0	0	0	0	0.75	0.365	0.25	0.632
1	0.479	0	0.097	0	0	0	0.221	0	0.203
0.5	0.286	0	0	0	0.38	0	0.121	0.5	0.213
0.375	0.178	0.3125	0.194	0	0	0	0	0.3125	0.618
0.5	0.794	0.375	0.102	0	0	0	0	0.125	0.101
0	0	0.25	0.189	0	0	0	0	0.75	0.804
0	0	0.25	0.748	0.75	0.247	0	0	0	0
0.25	0.583	0	0	0.625	0.217	0	0.167	0.125	0.032
0.25	0.811	0.25	0	0.5	0	0	0.187	0	0
0	0.032	0.25	0.658	0.375	0.109	0	0	0.375	0.2
0.3125	0.117	0.375	0.167	0	0.109	0	0.054	0.3125	0.543
0.875	0.357	0	0.217	0	0	0	0.179	0.125	0.246
0	0.128	0	0.089	0.75	0.279	0	0	0.25	0.504
0.75	0.387	0.125	0	0	0.286	0	0.11	0.125	0.216
0.375	0.134	0	0.169	0.25	0.687	0	0	0.375	0
0.5	0.105	0.25	0.613	0	0	0	0.038	0.25	0.24
0	0	0.375	0.186	0.375	0.712	0	0	0.25	0.092

0.75	0.462	0.125	0.427	0	0	0	0	0.125	0.103
1	0.567	0	0	0	0.134	0	0	0	0.298
0	0	0	0	0.625	0.398	0	0	0.375	0.593
0	0	0.125	0.342	0.5	0.185	0	0	0.375	0.465
0.75	0.365	0.25	0.457	0	0	0	0.132	0	0.041
0.625	0.659	0	0	0.25	0.105	0	0	0.125	0.225
0.25	0.479	0.5	0.038	0	0.187	0	0.264	0.25	0.032
0	0.321	0.1875	0.512	0.1875	0	0	0	0.625	0.167
0	0	0	0.187	1	0.487	0	0.091	0	0.232
0	0	0	0.131	0	0	0	0.54	1	0.329
0.25	0.105	0	0	0.3125	0.101	0	0.043	0.4375	0.748
0	0	1	0.654	0	0.059	0	0.176	0	0.105
0.25	0.103	0.5	0.257	0	0	0	0.029	0.25	0.608
0	0	0	0	0	0	1	0.564	0	0.432
0	0	0	0	1	0.654	0	0	0	0.342
0.3125	0.564	0.3125	0.267	0.375	0.165	0	0	0	0
0	0	0	0.213	0	0	0	0.484	1	0.298
0	0	0	0	0.25	0.374	0.75	0.521	0	0.102
0	0	0.5	0.601	0.25	0.171	0.25	0.112	0	0.106
0	0.213	0	0.1	0.875	0.342	0	0	0.125	0.341
0	0	0	0	0	0	0.5	0.285	0.5	0.712
0	0	0.5625	0.714	0.4375	0.279	0	0	0	0
0	0	0.25	0.431	0	0	0.625	0.453	0.125	0.106
0	0	0.4375	0.534	0.25	0.163	0	0	0.3125	0.3
0	0	0.625	0.342	0	0	0.375	0.654	0	0
0	0	0	0.215	0	0	1	0.453	0	0.326
0	0	1	0.584	0	0	0	0.216	0	0.198
0	0	0	0.116	0	0	0.75	0.478	0.25	0.403
0	0	0.25	0.101	0.5	0.176	0.25	0.723	0	0
0	0	0	0	0.875	0.367	0	0	0.125	0.631
0	0	0	0	0	0	0.75	0.294	0.25	0.695
0	0	0.75	0.253	0	0	0.25	0.743	0	0
0	0	0.25	0	0.75	0.321	0	0.679	0	0
0.75	0.215	0.25	0.514	0	0.045	0	0.223	0	0
1	0.432	0	0	0	0.151	0	0	0	0.416
0	0	0	0.264	0	0	0.125	0.459	0.875	0.267
0	0	1	0.543	0	0.115	0	0.342	0	0
0	0	0.5	0.176	0	0	0.5	0.712	0	0.102
0	0.214	0	0	0.625	0.121	0	0	0.375	0.663
0	0	0	0.141	0.75	0.368	0	0	0.25	0.487
0.625	0.2	0.375	0.663	0	0.032	0	0	0	0.104
0	0	0.75	0.456	0	0.065	0	0.101	0.25	0.374

0	0	0	0.187	0	0.144	1	0.563	0	0.106
0	0	0.875	0.385	0	0	0	0.127	0.125	0.479
0	0	0	0	1	0.694	0	0.306	0	0
0.75	0.329	0	0	0	0.148	0	0	0.25	0.517
0	0	1	0.432	0	0.165	0	0.101	0	0.301
0	0	0	0	0.875	0.594	0	0	0.125	0.395
0	0	0	0.211	0	0.059	0.875	0.376	0.125	0.344
0	0	0.875	0.549	0	0	0.125	0.102	0	0.341
0.5	0.621	0.375	0.142	0	0	0	0	0.125	0.236
0	0	0	0.543	0	0	1	0.35	0	0.103
0	0	0.375	0.561	0	0	0.625	0.432	0	0
0.625	0.276	0.125	0.103	0	0.211	0	0.302	0.25	0.107
0.5	0.216	0.25	0.107	0	0.058	0	0	0.25	0.615
0	0	0	0.183	1	0.564	0	0.248	0	0
0	0	0.25	0.534	0	0	0.75	0.358	0	0.105
0	0	0.5	0.82	0.5	0.17	0	0	0	0
0	0	1	0.766	0	0	0	0.227	0	0
0	0	0	0	0	0	0	0.289	1	0.707
0	0	0	0.112	0	0	0.75	0.478	0.25	0.402
0.625	0.369	0	0	0.125	0.163	0	0	0.25	0.465
0	0	0	0	0	0	0.5625	0.459	0.4375	0.541
0	0	0	0	0.625	0.771	0.25	0.125	0.125	0.1
0	0	0.1875	0.105	0	0	0.5625	0.365	0.25	0.528
0	0	0.3125	0.587	0.5	0.158	0	0	0.1875	0.251
0	0	1	0.691	0	0	0	0.306	0	0
0	0	0	0	0.875	0.496	0	0	0.125	0.5
0	0	0	0	0	0	0.75	0.432	0.25	0.563
0	0	0	0	0	0	0.8125	0.665	0.1875	0.331
0	0	0	0	0.75	0.443	0.25	0.551	0	0
0	0	0	0	0.1875	0.376	0.625	0.297	0.1875	0.326
0	0.128	0.875	0.341	0	0	0.125	0.531	0	0
0	0	0.375	0	0.5	0.325	0.125	0.673	0	0
0	0	0	0	0	0	0.6875	0.118	0.3125	0.876
0	0	0.1875	0.589	0.8125	0.411	0	0	0	0
0	0	1	0.453	0	0	0	0.543	0	0
0	0	0	0	0.5625	0.214	0.4375	0.785	0	0
0	0.196	0	0	0.625	0.279	0.375	0.523	0	0
0	0	0	0	0	0.09	0	0.453	1	0.453
0	0	0	0	0.1875	0.632	0.8125	0.368	0	0
0	0.154	0.875	0.354	0	0	0.125	0.487	0	0
0	0	0.5625	0.763	0.4375	0.118	0	0.117	0	0
0	0	0.625	0.376	0	0	0.1875	0.421	0.1875	0.2

0	0	0.75	0.443	0.25	0.556	0	0	0	0
0	0	0	0.118	0	0	1	0.539	0	0.342
0	0	0	0	0.8125	0.379	0.1875	0.621	0	0
0	0	0.875	0.367	0	0.187	0.125	0.436	0	0
0	0	0	0.184	0	0	1	0.438	0	0.378
0	0	0.75	0.379	0.25	0.62	0	0	0	0
0	0	0.25	0.553	0	0	0.5	0.223	0.25	0.22
0	0	0	0	0.625	0.276	0.375	0.723	0	0
0	0	0	0	0.1875	0.432	0.8125	0.563	0	0
0	0	0.875	0.467	0	0	0	0	0.125	0.531
0	0	0	0	0	0	0.5625	0.517	0.4375	0.476
0	0	0	0	0.75	0.654	0.25	0.339	0	0
0	0	0	0	0	0	0.125	0.619	0.875	0.38
0	0	0.75	0.438	0	0	0.25	0.552	0	0
0.8125	0.458	0	0.214	0	0.063	0	0	0.1875	0.263
0	0	0	0	0.4375	0.267	0.5625	0.732	0	0
0	0	0	0.311	0	0	1	0.467	0	0.22
0	0	0.625	0.367	0.25	0.154	0.125	0.475	0	0
0	0	0.4375	0.714	0.3125	0.102	0.25	0.176	0	0
0	0	0.875	0.354	0	0	0.125	0.638	0	0
0	0	0	0	0.1875	0.442	0.8125	0.557	0	0
0	0	0.25	0.437	0	0.115	0	0	0.75	0.445
0	0.127	1	0.538	0	0	0	0.328	0	0
0	0	0.875	0.447	0	0	0	0.254	0.125	0.296
0	0	0	0	0	0	0.875	0.386	0.125	0.613
0	0	0.25	0.538	0.5625	0.152	0.1875	0.3	0	0
0.4375	0.683	0.5625	0.182	0	0	0	0	0	0.132
0	0	1	0.532	0	0.178	0	0	0	0.29
0.5	0.138	0.25	0.633	0	0	0	0	0.25	0.22
0	0	0	0	0	0.236	1	0.438	0	0.326
0	0	0	0.215	0	0	0.75	0.459	0.25	0.31
0.8125	0.475	0.1875	0.523	0	0	0	0	0	0
0	0.52	1	0.48	0	0	0	0	0	0
0	0.375	0.5	0.124	0.25	0.031	0.25	0.47	0	0
0	0	1	0.376	0	0.354	0	0	0	0.27
0	0	0	0	0.8125	0.265	0.1875	0.73	0	0
0	0	0.5625	0.312	0.4375	0.63	0	0	0	0.057
0	0	0	0.09	0	0	0	0.376	1	0.532
0.4375	0.532	0	0.201	0.5625	0.263	0	0	0	0
0	0	0.6875	0.328	0	0	0.3125	0.667	0	0
0	0	0	0	0	0.254	1	0.576	0	0.17
0	0	0	0	0.875	0.432	0	0.101	0.125	0.467

0	0	0	0	0	0	0.8125	0.329	0.1875	0.67
0	0	1	0.417	0	0	0	0.576	0	0
0	0	0	0.253	0.4375	0.156	0.5625	0.231	0	0.352
0	0.121	0	0	0	0.184	0	0.347	1	0.345
0	0	0.25	0.432	0.1875	0.354	0.5625	0.211	0	0
0	0	0	0	0.6875	0.276	0.3125	0.654	0	0.065
0.4375	0.523	0.375	0.165	0	0	0.1875	0.312	0	0
0	0	0.6875	0.386	0.1875	0	0	0	0.125	0.613
0	0	0	0	0	0.423	0.6875	0.387	0.3125	0.186
0	0	0	0	0.75	0.316	0.25	0.547	0	0.137
0	0	0.8125	0.349	0	0	0.1875	0.521	0	0.126
0	0	0	0.247	0	0	0.875	0.263	0.125	0.49
0	0	0	0	0.8125	0.574	0.1875	0.423	0	0
0	0	0	0	0	0.253	0.6875	0.321	0.3125	0.42
0	0	0	0	0.8125	0.318	0.1875	0.513	0	0.163
0	0	0	0.174	0	0	0.4375	0.587	0.5625	0.237
0	0	0.4375	0.178	0	0.131	0.3125	0.569	0.25	0.121
0	0	0.5	0.742	0.25	0.167	0.25	0.03	0	0.06
0	0	0	0	0	0.235	0	0.216	1	0.548
1	0.369	0	0.42	0	0.204	0	0	0	0
0.3125	0.792	0.6875	0.203	0	0	0	0	0	0
0.5625	0.211	0	0	0	0.33	0	0	0.4375	0.459
1	0.543	0	0	0	0	0	0.132	0	0.321
0.6875	0.254	0	0.132	0	0.231	0	0	0.3125	0.369
0.3125	0.154	0.4375	0.385	0	0	0	0	0.25	0.453
0.6875	0.449	0.3125	0.473	0	0	0	0	0	0.078
0.8125	0.528	0	0	0	0.123	0	0	0.1875	0.341
0.5625	0.657	0.25	0.104	0	0.087	0	0	0.1875	0.147
0.375	0.225	0.625	0.276	0	0.243	0	0.253	0	0
1	0.511	0	0.221	0	0.065	0	0.194	0	0
0.1875	0.576	0	0	0	0	0	0	0.8125	0.416
0	0	0.75	0.476	0	0.141	0	0.087	0.25	0.291
0	0	0	0	0	0.072	0	0.199	1	0.721
0.3125	0.116	0.6875	0.376	0	0.332	0	0.176	0	0
0.5	0.734	0.3125	0.076	0	0	0	0	0.1875	0.19
0.5	0.187	0.5	0.676	0	0.137	0	0	0	0
0.75	0.254	0	0	0	0.368	0	0	0.25	0.376
0.5625	0.351	0.25	0.128	0	0.134	0	0	0.1875	0.386
0	0	0	0.354	0	0	0	0	1	0.645
0.5625	0.167	0.3125	0.32	0	0.121	0	0	0.125	0.392
0.375	0.121	0.4375	0.342	0	0	0	0	0.1875	0.53
0	0	0	0.303	0.5625	0.287	0	0.148	0.4375	0.258

0	0	0.25	0.123	0.625	0.432	0	0	0.125	0.442
0.4375	0.102	0.5625	0.774	0	0.114	0	0	0	0
0.8125	0.476	0	0	0	0.389	0	0	0.1875	0.126
0	0	0.25	0.296	0.4375	0.321	0.3125	0.38	0	0
0	0.154	0.625	0.328	0	0.341	0	0	0.375	0.176
1	0.567	0	0.426	0	0	0	0	0	0

Appendix: F

Appendix: F: Summarised the Membership from the field compared with membership of classification image by using fuzzy c-means method.

Urban field	Urban classification	Vegetation field	Vegetation classification	Woodland field	Woodland classification	Grazing land field	Grazing land classification	Bare land field	Bare land classification
0.25	0.073	0.25	0.104	0.25	0.716	0.25	0	0	0.1
0	0.167	0.25	0.165	0	0.298	0	0	0.75	0.354
0	0	0	0.218	0.75	0.195	0	0.123	0.25	0.457
0.25	0.089	0.625	0.273	0	0.182	0	0.269	0.125	0.183
0.6875	0.231	0.25	0.365	0	0.211	0	0.107	0.0625	0.076
0	0	0.75	0.239	0.125	0.285	0	0.279	0.125	0.196
0.375	0.54	0	0.167	0.375	0.189	0	0	0.25	0.095
0.375	0.854	0.375	0	0.25	0	0	0	0	0.145
0	0.176	0.1875	0.456	0.25	0.2	0	0	0.5625	0.142
0	0	0.75	0.543	0.125	0.324	0	0	0.125	0.121
0	0.132	0	0	0.75	0.587	0	0	0.25	0.265
1	0.543	0	0.134	0	0.083	0	0.121	0	0.118
0.125	0.234	0	0	0	0	0.125	0.276	0.75	0.476
0.25	0.364	0.5	0.348	0.25	0.276	0	0	0	0
0.375	0.432	0.375	0.234	0.25	0	0	0.331	0	0
0	0	0.75	0.432	0	0.276	0	0.151	0.25	0.14
0	0.154	0	0	0.75	0.487	0	0	0.25	0.359
0.5	0.43	0.125	0.232	0	0.196	0	0	0.375	0.132
0	0	0.5	0.453	0.25	0.289	0.25	0.103	0	0.145

0	0	0	0.156	0	0	0.75	0.167	0.25	0.675
1	0.578	0	0.106	0	0	0	0.12	0	0.176
0.5	0.342	0	0	0	0.38	0	0.121	0.5	0.153
0.375	0.213	0.3125	0.235	0	0	0	0	0.3125	0.543
0.5	0.438	0.375	0.256	0	0.108	0	0	0.125	0.18
0	0	0.25	0.467	0	0	0	0	0.75	0.53
0	0.116	0.25	0.315	0.75	0.567	0	0	0	0
0.25	0.643	0	0	0.625	0.186	0	0.132	0.125	0.036
0.25	0.843	0.25	0	0.5	0	0	0.154	0	0
0	0.346	0.25	0.438	0.375	0	0	0	0.375	0.2
0.3125	0.097	0.375	0.1	0	0.15	0	0.121	0.3125	0.512
0.875	0.376	0	0.2	0	0	0	0.189	0.125	0.234
0	0.2	0	0	0.75	0.326	0	0	0.25	0.456
0.75	0.296	0.125	0	0	0.321	0	0.183	0.125	0.2
0.375	0.654	0	0.2	0.25	0.143	0	0	0.375	0
0.5	0.731	0.25	0.14	0	0	0	0.038	0.25	0.09
0	0.23	0.375	0.432	0.375	0.235	0	0	0.25	0.1
0.75	0.512	0.125	0.356	0	0.124	0	0	0.125	0
1	0.589	0	0	0	0.178	0	0	0	0.231
0	0	0	0	0.625	0.365	0	0	0.375	0.63
0	0	0.125	0.287	0.5	0.421	0	0	0.375	0.29
0.75	0.211	0.25	0.543	0	0	0	0.137	0	0.098
0.625	0.487	0	0	0.25	0.127	0	0	0.125	0.386
0.25	0.554	0.5	0.164	0	0.156	0	0.126	0.25	0
0	0.387	0.1875	0.265	0.1875	0.165	0	0	0.625	0.18
0	0.2	0	0	1	0.348	0	0.11	0	0.332
0	0	0	0.112	0	0	0	0.145	1	0.732
0.25	0.456	0	0	0.3125	0.237	0	0.1	0.4375	0.2
0	0	1	0.45	0	0.13	0	0.23	0	0.17

0.25	0.265	0.5	0.1	0	0	0	0.132	0.25	0.5
0	0	0	0.2	0	0	1	0.657	0	0.132
0	0	0	0.121	1	0.653	0	0	0	0.217
0.3125	0.675	0.3125	0.221	0.375	0.1	0	0	0	0
0	0	0	0.321	0	0	0	0.376	1	0.298
0	0	0	0	0.25	0.55	0.75	0.432	0	0
0	0.2	0.5	0.31	0.25	0.28	0.25	0.21	0	0
0	0.31	0	0.1	0.875	0.367	0	0	0.125	0.2
0	0	0	0.173	0	0.171	0.5	0.342	0.5	0.3
0	0	0.5625	0.432	0.4375	0.567	0	0	0	0
0	0	0.25	0.564	0	0	0.625	0.311	0.125	0.12
0	0	0.4375	0.342	0.25	0.311	0	0	0.3125	0.331
0	0	0.625	0.432	0	0.103	0.375	0.211	0	0.243
0	0	0	0.11	0	0	1	0.223	0	0.654
0	0	1	0.543	0	0.122	0	0.178	0	0.153
0	0	0	0	0	0	0.75	0.254	0.25	0.732
0	0	0.25	0.543	0.5	0.2	0.25	0.254	0	0
0	0	0	0.143	0.875	0.21	0	0.1	0.125	0.543
0	0	0	0.24	0	0	0.75	0.22	0.25	0.54
0	0	0.75	0.321	0	0	0.25	0.543	0	0.132
0	0	0.25	0.113	0.75	0.543	0	0.342	0	0
0.75	0.436	0.25	0.318	0	0	0	0.144	0	0.1
1	0.354	0	0.1	0	0.2	0	0	0	0.342
0	0	0	0.279	0	0	0.125	0.342	0.875	0.376
0	0	1	0.321	0	0	0	0.367	0	0.29
0	0	0.5	0.12	0	0.321	0.5	0.3	0	0.231
0	0.121	0	0	0.625	0.321	0	0	0.375	0.543
0	0	0	0.141	0.75	0.243	0	0	0.25	0.611
0.625	0.432	0.375	0.421	0	0.129	0	0	0	0

0	0	0.75	0.476	0	0	0	0.101	0.25	0.412
0	0	0	0.187	0	0.152	1	0.432	0	0.213
0	0	0.875	0.432	0	0	0	0.231	0.125	0.332
0	0	0	0.238	1	0.453	0	0.306	0	0
0.75	0.367	0	0.2	0	0	0	0	0.25	0.432
0	0	1	0.354	0	0	0	0.3	0	0.32
0	0	0	0	0.875	0.476	0	0	0.125	0.519
0	0	0	0.167	0	0	0.875	0.45	0.125	0.376
0	0	0.875	0.378	0	0	0.125	0.341	0	0.28
0.5	0.342	0.375	0.23	0	0	0	0	0.125	0.419
0	0	0	0.3	0	0	1	0.35	0	0.35
0	0	0.375	0.832	0	0	0.625	0.16	0	0
0.625	0.436	0.125	0.12	0	0	0	0.311	0.25	0.12
0.5	0.232	0.25	0.213	0	0	0	0	0.25	0.543
0	0	0	0.154	1	0.523	0	0.322	0	0
0	0	0.25	0.654	0	0	0.75	0.211	0	0.121
0	0.231	0.5	0.356	0.5	0.233	0	0	0	0.178
0	0.2	1	0.547	0	0	0	0.243	0	0
0	0	0	0.231	0	0	0	0.289	1	0.476
0	0	0	0.23	0	0	0.75	0.216	0.25	0.543
0.625	0.376	0	0	0.125	0.108	0	0	0.25	0.512
0	0	0	0	0	0	0.5625	0.237	0.4375	0.761
0	0	0	0	0.625	0.342	0.25	0.432	0.125	0.225
0	0	0.1875	0.325	0	0	0.5625	0.25	0.25	0.42
0	0	0.3125	0.612	0.5	0.1	0	0	0.1875	0.28
0	0	1	0.436	0	0	0	0.306	0	0.25
0	0	0	0	0.875	0.321	0	0	0.125	0.661
0	0	0	0	0	0	0.75	0.365	0.25	0.621
0	0	0	0	0	0	0.8125	0.543	0.1875	0.453

0	0	0	0	0.75	0.23	0.25	0.611	0	0.153
0	0	0	0	0.1875	0.376	0.625	0.297	0.1875	0.326
0	0.128	0.875	0.3	0	0	0.125	0.564	0	0
0	0	0.375	0	0.5	0.157	0.125	0.84	0	0
0	0	0	0	0	0	0.6875	0.231	0.3125	0.765
0	0	0.1875	0.654	0.8125	0.321	0	0	0	0
0	0	1	0.378	0	0	0	0.621	0	0
0	0	0	0	0.5625	0.116	0.4375	0.874	0	0
0	0.2	0	0	0.625	0.154	0.375	0.632	0	0
0	0	0	0	0	0.12	0	0.387	1	0.476
0	0	0	0	0.1875	0.76	0.8125	0.216	0	0
0	0.2	0.875	0.24	0	0	0.125	0.543	0	0
0	0	0.5625	0.342	0.4375	0.654	0	0	0	0
0	0	0.625	0.32	0	0	0.1875	0.332	0.1875	0.329
0	0	0.75	0.334	0.25	0.654	0	0	0	0
0	0	0	0.2	0	0	1	0.5	0	0.3
0	0	0	0	0.8125	0.287	0.1875	0.713	0	0
0	0	0.875	0.256	0	0.187	0.125	0.543	0	0
0	0	0	0.232	0	0	1	0.321	0	0.432
0	0	0.75	0.189	0.25	0.7	0	0.1	0	0
0	0	0.25	0.654	0	0	0.5	0.12	0.25	0.22
0	0	0	0	0.625	0.154	0.375	0.843	0	0
0	0	0	0	0.1875	0.432	0.8125	0.563	0	0
0	0	0.875	0.467	0	0	0	0	0.125	0.531
0	0	0	0.361	0	0	0.5625	0.342	0.4375	0.287
0	0	0	0	0.75	0.367	0.25	0.459	0	0.148
0	0	0	0.1	0	0	0.125	0.6	0.875	0.3
0	0	0.75	0.239	0	0	0.25	0.754	0	0
0.8125	0.541	0	0.103	0	0.121	0	0	0.1875	0.232

0	0	0	0	0.4375	0.156	0.5625	0.701	0	0.143
0	0	0	0.18	0	0	1	0.432	0	0.387
0	0	0.625	0.167	0.25	0.1	0.125	0.71	0	0
0	0	0.4375	0.71	0.3125	0.132	0.25	0.154	0	0
0	0	0.875	0.234	0	0	0.125	0.759	0	0
0	0	0	0	0.1875	0.654	0.8125	0.327	0	0
0	0	0.25	0.564	0	0.1	0	0	0.75	0.326
0	0.12	1	0.432	0	0.121	0	0.298	0	0
0	0	0.875	0.365	0	0	0	0.276	0.125	0.354
0	0	0	0	0	0	0.875	0.269	0.125	0.717
0	0	0.25	0.654	0.5625	0.12	0.1875	0.132	0	0.076
0.4375	0.765	0.5625	0.223	0	0	0	0	0	0
0	0.121	1	0.432	0	0.2	0	0	0	0.243
0.5	0.265	0.25	0.476	0	0	0	0	0.25	0.243
0	0	0	0.214	0	0.211	1	0.325	0	0.246
0	0	0	0.198	0	0	0.75	0.332	0.25	0.453
0.8125	0.217	0.1875	0.674	0	0.097	0	0	0	0
0	0.453	1	0.431	0	0	0	0.109	0	0
0	0.321	0.5	0.118	0.25	0.165	0.25	0.387	0	0
0	0	1	0.278	0	0.438	0	0	0	0.27
0	0	0	0	0.8125	0.211	0.1875	0.768	0	0
0	0	0.5625	0.249	0.4375	0.689	0	0	0	0.057
0	0	0	0.12	0	0	0	0.357	1	0.52
0.4375	0.765	0	0.104	0.5625	0.121	0	0	0	0
0	0	0.6875	0.256	0	0.087	0.3125	0.65	0	0
0	0	0	0	0	0.267	1	0.465	0	0.265
0	0	0	0	0.875	0.342	0	0.21	0.125	0.423
0	0	0	0.076	0	0	0.8125	0.223	0.1875	0.7
0	0.112	1	0.342	0	0	0	0.532	0	0

0	0.145	0	0.231	0.4375	0.109	0.5625	0.156	0	0.352
0	0.189	0	0	0	0.211	0	0.301	1	0.287
0	0	0.25	0.554	0.1875	0.269	0.5625	0.165	0	0
0	0	0	0.182	0.6875	0.127	0.3125	0.564	0	0.121
0.4375	0.732	0.375	0.127	0	0	0.1875	0.132	0	0
0	0	0.6875	0.254	0.1875	0	0	0.123	0.125	0.613
0	0	0	0	0	0.342	0.6875	0.411	0.3125	0.233
0	0	0	0.2	0.75	0.232	0.25	0.43	0	0.137
0	0	0.8125	0.234	0	0.1	0.1875	0.537	0	0.126
0	0	0	0.232	0	0	0.875	0.211	0.125	0.554
0	0	0	0	0.8125	0.321	0.1875	0.567	0	0.1
0	0	0	0	0	0.232	0.6875	0.221	0.3125	0.541
0	0	0	0	0.8125	0.204	0.1875	0.618	0	0.163
0	0	0	0.17	0	0	0.4375	0.597	0.5625	0.219
0	0	0.4375	0.109	0	0.151	0.3125	0.633	0.25	0.1
0	0	0.5	0.803	0.25	0.089	0.25	0.1	0	0
0	0	0	0.134	0	0.196	0	0.21	1	0.453
1	0.278	0	0.42	0	0.198	0	0	0	0.1
0.3125	0.832	0.6875	0.123	0	0	0	0	0	0.04
0.5625	0.134	0	0.234	0	0.351	0	0	0.4375	0.276
1	0.432	0	0.112	0	0	0	0.132	0	0.321
0.6875	0.187	0	0.145	0	0.254	0	0	0.3125	0.411
0.3125	0.132	0.4375	0.238	0	0	0	0.176	0.25	0.453
0.6875	0.254	0.3125	0.543	0	0	0	0	0	0.198
0.8125	0.6	0	0	0	0	0	0	0.1875	0.397
0.5625	0.764	0.25	0	0	0.087	0	0	0.1875	0.147
0.375	0.176	0.625	0.198	0	0.3	0	0.298	0	0
1	0.543	0	0.1	0	0.21	0	0.145	0	0
0.1875	0.675	0	0	0	0	0	0	0.8125	0.321

0	0	0.75	0.321	0	0.154	0	0.1	0.25	0.421
0	0	0	0	0	0	0	0.156	1	0.831
0.3125	0.103	0.6875	0.265	0	0.342	0	0.28	0	0
0.5	0.82	0.3125	0	0	0	0	0	0.1875	0.16
0.5	0.387	0.5	0.487	0	0.121	0	0	0	0
0.75	0.178	0	0	0	0.311	0	0	0.25	0.51
0.5625	0.231	0.25	0.2	0	0.14	0	0	0.1875	0.428
0	0	0	0.34	0	0.1	0	0	1	0.554
0.5625	0.154	0.3125	0.232	0	0.121	0	0	0.125	0.478
0.375	0.564	0.4375	0.1	0	0	0	0	0.1875	0.33
0	0	0	0.31	0.5625	0.3	0	0.2	0.4375	0.189
0	0	0.25	0.1	0.625	0.54	0	0	0.125	0.354
0.4375	0.231	0.5625	0.654	0	0.09	0	0	0	0
0.8125	0.564	0	0	0	0.231	0	0	0.1875	0.2
0	0	0.25	0.311	0.4375	0.256	0.3125	0.432	0	0
0	0.2	0.625	0.342	0	0.276	0	0	0.375	0.176
1	0.56	0	0.2	0	0.234	0	0	0	0