Land Use / Land Cover Change Detection: an Object Oriented Approach, Münster, Germany

Thesis
Master of Science in Geospatial Technologies

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Institute for Geoinformatics
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Abstract

Land use / land cover (LULC) change detection based on remote sensing (RS) data has been established as an indispensible tool for providing suitable and wide-ranging information to various decision support systems for natural resource management and sustainable development. LULC change is one of the major influencing factors for landscape changes. There are many change detection techniques developed over decades, in practice, it is still difficult to develop a suitable change detection method especially in case of urban and urban fringe areas where several impacts of complex factors are found including rapid changes from rural land uses to residential, commercial, industrial and recreational uses. Although these changes can be monitored using several techniques of RS application, adopting a suitable technique to represent the changes accurately is a challenging task. There are a number of challenges in RS application for analysis of LULC change detection. This study applies object-oriented (OO) method for mapping LULC and performing change detection analysis using post-classification technique.

This study consists of four major parts. The first part is implementing the OO method for mapping the LULC of the study area based on three consecutive satellite images: Landsat TM (1990), Landsat ETM+ (2000) and ASTER (2005). Principal component analysis (PCA) and image fusion are used to enhance the change assessment. Secondly, classification accuracy is another section of interest since the aim of this work is to accurately characterize the LULC changes. Due to unavailability of ground truth or reference data obtained at the time of image acquisition, the error matrix for accuracy is utilized supplied by the Definiens software based on training samples. An alternative method of accuracy assessment has also been adopted from the concept of the CORINE Land Cover (CLC) 2000 programme to justify the accuracy more robustly. The third part of this study focuses on LULC change detection analysis based on three classified LULC layers from (multi-temporal) images of 1990, 2000 and 2005. There are many methods of LULC change detection amongst which the post-classification comparison method has been implemented for this study. The fourth and final part is an additional chapter focusing on OO classification of very high resolution (aerial) image and its accuracy assessment based on a high quality existing reference layer. The study area is the Münster “Rieselfelder” (sanctuary) and its surroundings which covers some fringe area of Münster city, Germany and covers an area of 100 km square. Even though the study area contains some part of the Münster city urban fringe area, it can be considered as rural area as a whole.

The present study exhibits a great potential for accurate LULC change detection using object oriented image classification method using moderate to high resolution satellite images. It also shows us some technical steps that can influence the accuracy or enhance the change assessment. Although the preliminary results in this work seem to be promising, more study in this regard is required to improve classification results by utilizing OO method using very high resolution (VHR) satellite imagery in future.

Key Words: Land Use/ Land Cover (LULC), Change Detection, Remote Sensing, Object Oriented, Accuracy Assessment, Landsat, ASTER, Post Classification Method, Segmentation.

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Abbreviations

ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
CLC	Corine Land Cover
DGK	Deutsche Grundkarte
EEA	European Environmental Agency
ETM+	Enhanced Thematic Mapper Plus
FCC	False Colour Composite
GCP	Ground Control Point
HPF	High Pass Filter
IHS	Intensity-Hue-Saturation
IRS	Indian Remote Sensing
LULC	Land Use / Land Cover
LWIR	Long Wave Infrared
MF	Membership Function
MMU	Minimum Mapping Unit
MS	Multispectral
MSS	Multispectral Scanner
NASA	National Aeronautics and Space Administration
NN	Nearest Neighbour
OIF	Optimum Index Factor
OO	Object Oriented
Pan	Panchromatic
PC	Principal Component
PCA	Principal Component Analysis
RS	Remote Sensing
SNN	Standard Nearest Neighbour
SWIR	Short Wave Infrared
TM	Thematic Mapper
TTA Mask	Training and Test Area Mask
UTM	Universal Transverse Mercator
VNIR	Visible and Near Infra-Red
WGS 84	World Geodetic System 1984
WiFS	Wide Field Sensor

1 Introduction

Land use / land cover (LULC) changes are affected by human intervention and natural phenomena such as agricultural demand and trade, population growth and consumption patterns, urbanization and economic development, science and technology, and other factors (Research on Land use change & Agriculture, International Institute for Applied Systems Analysis, 2007). As a consequence, information about LULC is essential for any kind of natural resource management and action planning. Timely and precise information about LULC change detection of earth's surface is extremely important for understanding relationships and interactions between human and natural phenomena for better management of decision making (Lu *et al.*, 2004). There is a continuing demand for accurate and up-to-date LULC information for any kind of sustainable development programme where LULC serves as one of the major input criteria. As a result, the importance of properly mapping LULC and its change as well as updating it through time has been acknowledged by various research workers for decision making activities; as for example, application of land cover change in urban environment by Deng *et al.*, (2005) and land cover dynamic monitoring by Sobrino & Raissouni, (2000).

1.1 Problem Definition

The application of remote sensing (RS) for extracting LULC information has been exploited since the advent of optical satellite systems. Various improvement and techniques have been developed through past decades with the development of RS technology. Many change detection techniques have been developed and utilized by several research workers. Due to the importance of monitoring LULC change, research of change detection techniques is an active field and several new methods are emerging regularly. Recent advancement of RS with wide-ranging spectral and higher spatial resolution of satellite images and repetitive coverage, this research field of change detection has been growing strongly. Coupled with the availability of historical RS data, the reduction in data acquisition and processing as well as higher spatial, spectral and temporal resolution, the application of RS has great impact on growing development of change detection techniques (Rogan & Chen, 2004).

Successful use of RS for LULC change detection largely depends on an adequate understanding of the study area, the satellite imaging system and the various information extraction methods for change detection in order to fulfill the aim of the present study (Yang & Lo, 2002). Extracting meaningful LULC change information from satellite data using various techniques has been performed and established by a large number of authors. However, it is still sometimes appeared difficult in practice to select a good change detection method. Moreover, the choice of methods depends on the RS data available, the performed time limit and the objective of the study. The determination of suitable LULC change detection techniques from the various methods is a problem in the present research. There are a number of challenges in applying suitable set of techniques from change detection considering a series of dynamic factors ranging from selection of input data and their classification algorithm, to accuracy assessment to the ultimate aim of the study. Most of them were discussed by Lu *et al.*, 2004. However, change detection methods have their own merits (and demerits as well) and no single method has been proven as optimal to all cases. In the present study, investigating the efficacy of preferred change detection methods, selected based on existing case studies, availability of resources and target of the work, to fulfill the objectives is one of the major challenges.

1.2 Research Objectives

To address the above mentioned problem, the primary aim of the study is to identify change detection of land use / land cover (LULC) in the study area with emphasis on:

- Object oriented (OO) classification of three consecutive satellite images from the study area.
- Accuracy assessment to judge the applicability of OO classification method in this case study and to ensure the accurate change detection.
- Identify the LULC changes in the study area during the time periods of 1990 to 2000 and 2000 to 2005 as well as 1990 to 2005 using post-classification method.
- Perspective view on aerial image classification using OO method for LULC change & accuracy assessment based on the existing reference layer.

1.3 Research Questions

The following research questions can be made in order to fulfill the above mentioned objectives of the present research work:

- Can the LULC Changes in the study area be assessed using the applied satellite images?
- How effective is the OO method for image classification in the context of the present study?
- Is there a relationship between this advanced method of classification and the resolution of images?
- Does the application of Principal Component Analysis (PCA) improve the accuracy of classification?
- Is the method of accuracy assessment using the error matrix based on samples in the Definien software environment well enough for the accuracy assessment?
- How can an alternative method of accuracy assessment be used to strengthen the justification of accuracy for the derived classification?
- What are the LULC changes in the study area in three time periods considering the aspects of aerial extent?
- How suitable is the use of the aerial image for the present context and how effective is the accuracy assessment based on the existing reference layer.

1.4 Scope of the Work

The present research is not completely free of limitation. First of all, considering the technical aspects of the satellites images used are restricted to certain spatial and spectral resolution. The effectiveness of the OO method has a great impact on the resolution. Secondly, for accuracy assessment, a true high quality reference data or ground truth data with the same number of classes was not available. Thirdly, due to time limitations, the choice of data, aerial extent of study area and number of methodologies used are also restricted.

1.4 Thesis Outline

The thesis outline can be divided into seven chapters (fig.- 1.4.1). This chapter primarily gives the aim of the present research work. The rest of the thesis is arranged as follows: Chapter 2 is for the literature review where related research wok has been discussed. This chapter shows how the application of remote sensing is utilized for the LULC change detection study and briefly reviews various existing techniques and their advantages through several case studies. After this chapter, a workflow has been proposed for the present work. Chapter 3 is allocated for the description of study area and data used for the whole work. Chapter 4 illustrates the methodologies used in detail with focus on object oriented methods for image classification after image preprocessing, enhancement and fusion. Then the several approach used for classification is introduced and briefly described as well as provided the result with accuracy assessment by the classification software.

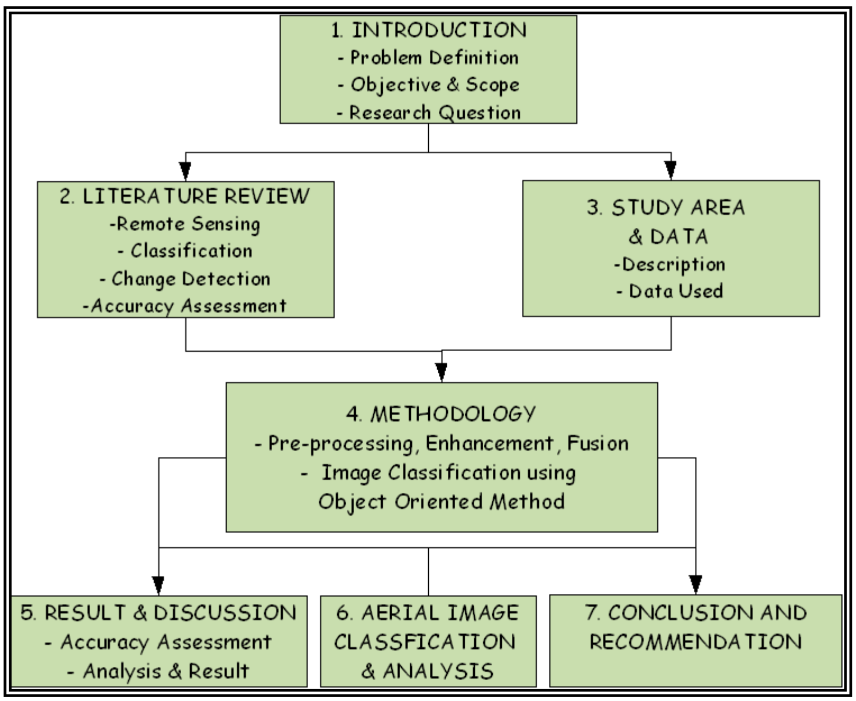


Fig.- 1.4.1: Flow diagram of thesis outline

An alternative method of accuracy assessment is proposed in Chapter 5 along with detailed analysis and discussion of result of LULC change detection. The discussion is provided in detail in relation to the objectives. Chapter 6 adds to the present study a focus on aerial image classification and its accuracy assessment based on existing reference data. Chapter 7 concludes the research work and recommends the future work.

2 Literature Review

Over the past decades, Remote Sensing (RS) has played a large role in studying land use / land cover (LULC) change detection. LULC change detection studies are becoming demanding tasks with the availability of a suite of wide range sensors operating at various imaging scales and scope of using various techniques as well as increasing avenues for monitoring effective and accurate LULC change. Considerable research has been directed at the various components of LULC change including the accuracy assessment which is drawing an equal attention by scientists nowadays. The literature review looks into the following aspects considering the objective of the present study.

2.1 Remote Sensing As a Tool for Change Detection

"*Remote Sensing is the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with object, area, or phenomenon under investigation*" (Lillesand and Kiefer, 1987). It provides a large variety and amount of data about the earth surface for detailed analysis and change detection with the help of various spaceborne and airborne sensors. It presents powerful capabilities for understanding and managing earth resources. RS have been proven to be a very useful tool for LULC change detection (Matinfar, Sarmadian, Panah, Heck, 2007).

A large number of change detection techniques have been developed since the advent of the orbital system (Lillestrand 1972). Weismiller *et al.* (1977) have used various RS techniques for evaluating change detection for coastal zone environments. In 1980, Byrne, Crapper and Mayo have shown that Landsat multispectral data can be used to identify LULC changes very effectively.

Change detection and monitoring involve the use of several multi-date images to evaluate the differences in LULC due to various environmental conditions and human actions between the acquisition dates of images (Singh 1989). Successful use of satellite RS for LULC change detection depends upon an adequate understanding of landscape features, imaging systems, and methodology employed in relation to the aim of the analysis (Yang & Lo, 2002). Various RS data products over time have often been incorporated into historical land use information (Acevedo, Foresman, & Buchanan, 1996; Clarke, Parks & Crane, 2002; Meaille & Wald, 1990).

With the availability of historical RS data, the reduction in data cost and increased resolution from satellite platforms, RS technology appears poised to make an even greater impact on monitoring land-cover and land-use change (Rogan & Chen, 2004). In general, change detection of LULC involves the interpretation and analysis of multi-temporal and multi-source satellite images to identify temporal phenomenon or changes trough a certain period of time. RS data are the primary source for change detection in recent decades and have made a greater impact on urban planning agencies and land management initiatives (Yeh and Li 1999, Yang and Lo 2002, Rogan and Chen 2004).

2.2 Classification Method

Classifying the satellite images to extract the land use / land cover theme is the one of the major steps in this type of study. Classification is the process of assigning classes to the pixels in images. Moreover, successful utilization of remotely sensed data for LULC studies demands careful selection of an appropriate data set and image processing technique(s) (Lunetta, 1998). The most common image analysis for extracting LULC is digital image classification. Sabins (1997) explains that image classification techniques are most generally applied to the spectral data of a single-date image or to the varying spectral data of a series of multi-date images. The complexity of image classification techniques can range from the use of a simple threshold value for a single spectral band to complex statistically based decision rules that operate on multivariate data. The purpose of image classification is to label the pixels in the image with the real information (Jensen & Gorte, 2001). Through classification of RS image, thematic maps such as the LULC can be obtained (Tso and Mather, 2001). Classification involves labelling the pixels as belonging to particular classes using the spectral data available.

There are two broad types of classification procedure and each finds application in processing of RS image. One is referred to as supervised classification and the other one is unsupervised classification. These can be used as alternative approaches but are often combined into hybrid methodologies using more than one method (Richards and Jia, 2006). Both the supervised and unsupervised classification methods used for classifying various multispectral images are based on so called traditional pixel-based method which has been played a great importance for classifying low resolution images. On the other hand, when using new generation images, characterized by a higher spatial and spectral resolution, it is still difficult to obtain satisfactory result (Lewinski and Zaremski, 2004).

With the advancement of RS technology, a new concept of classification technique-object oriented method has been emerged. Advantages of this method are meaningful statistic and texture calculation, an increased uncorrelated feature space using shape (e.g. length, number of edges, etc.) and topological features (neighbor, super-object, etc.), and the close relation between real-world objects and image objects (Definiens User Guide, 2006). This relation improves the value of the final classification unlike the traditional pixel-based approaches (Benz *et al.*, 2004). Context techniques assume that the spectral response and the neighbour pixels are highly correlated and thus efficient when compared with those techniques used previously for images with medium spatial resolution (Whiteside & Ahmad, 2005). Object oriented method is a new concept, allows the integration of a wide field of different object features such as spectral values, shape, and texture. Such classification techniques incorporate contextual and semantic information, image object attributes and relationship among different image objects (Laliberte *et al.* 2004; Gitas *et al.*, 2004). Several studies investigated the capability of satellite imagery, including Landsat TM and ETM+, to perform change detection analysis (Owojori and Xie, 2005).

2.3 Change Detection Technique

Although coarse-spatial resolution meteorological satellite data have been available since the 1960s, civilian RS of the Earth's surface from space at medium spatial resolutions (i.e. <250 m) only began in 1972 with the launch of the first of a series of Landsat Satellites (Rogan & Chen, 2004). Since then a large numbers of change detection techniques have been developed after the launching of Landsat orbital system as described in the article titled "Techniques for Change Detection" by Lillestrand in 1972. Many methods of change detection have been developed to detect land cover change (Lambin & Ehrlich, 1997; Mas, 1999; Singh, 1989), but by far the most popular has been the utilization of post classification comparison method. In spite of the numerous evaluations of these techniques (Weismiller *et al.* 1977; Singh 1989; Stow, 1990), no standard techniques have yet been adopted (Macleod and Congalton 1998) for all cases. Although the development of RS technology has been developed dramatically within last few years, examples of effective LULC change detection studies remain relatively rare (Loveland *et al.*, 2002; Rogan *et al.*, 2004).

Numerous researchers have addressed the problem of accurately monitoring LULC change in wide applications with greater success (Muchoney and Haack, 1994; Chan *et al.*, 2001). One of the most definite reasons is that a wide variety of digital change detection techniques and algorithm have been developed and manipulated over last few decades commensurate with the fast-pace advancement of RS technology with spatial, spectral, thematic and temporal properties. They can be broadly divided into two which are pre-classification spectral change detection or post-classification methods (Nelson 1983, Pilon *et al.* 1988, Singh 1989). The simplest rule separates LULC changes that are categorical versus those that are continuous (Abuelgasim *et al.*, 1999). Basically, the detection of categorical and continuous changes are also known as post-classification and pre-classification method respectively.

In case of post classification change detection, two multi-temporal images are classified separately and labelled with proper attributes. The area of change is then extracted through the direct comparison after obtaining the classification results (Colwell and Weber 1981, Howarth and Wickware 1981). With the post-classification methods basic issues are the accuracies of the component classifications and more subtle issues associated with the sensors and data preprocessing methods (Khorram, 1999). Though it avoids the difficulties in change detection, it has significant limitations because the comparison of land cover classifications for temporal images does not allow the detection of subtle changes within land cover classes (Macleod and Congalton, 1998). Owojori and Xie (2005) have shown the example of post classification in the study demonstrated the potential for accurate LULC change assessment with advanced atmospheric correction and object-oriented image analysis using medium resolution satellite data (Landsat TM).

Pre-classification technique, where changes occur in the amount or concentration of some attribute that can be continuously measured (Coppin and Bauer, 1996). Image differencing (one of the most common pre-classification methods) is the most commonly used change detection algorithm (Singh, 1989). It involves subtracting one date of imagery from a second date that has been precisely registered to the first. According to recent research, image differencing emerges to perform generally better than other methods of pre-classification change detection (Coppin & Bauer, 1996). Maryna Rymasheuskaya (2007) in recent study has proved that both image differencing and post-classification comparison confirms their ability to be used for detecting land cover changes over northern Belarusian landscapes. The presented study allows estimating the amount of changes occurred at the study area. Fig.- 2.3.1 is showing the used general sequence of land cover change detection (taken from Rymasheuskaya, 2007).

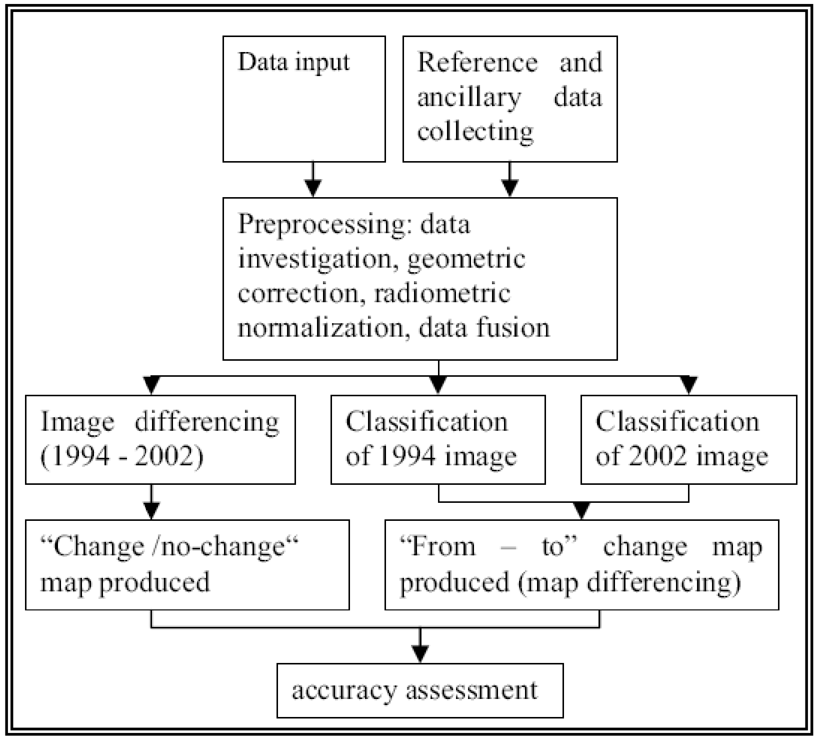


Fig.- 2.3.1: Land cover change detection workflow for Belarus (Maryna Rymasheuskaya, 2007)

Spectral change detection technique is also considered as pre-classification category where the conception is about spectral signature change of the affected land surface through certain period of time. The largest number of change-detection techniques are considered as spectral change category, such as image differencing, image ratioing, vegetation index differencing, principal-component analysis (PCA) and change vector analysis (CVA) (Deng *et al.*, 2008). Despite many factors affecting the selection of suitable change-detection methods, image differencing, PCA, and post-classification are, in practice, the most commonly used methods (Lu *et al.* 2004). Principal component analysis (PCA) has been proven as efficient and basic economical technique for change detection in most cases (Byrne *et al*. 1980; Fung and LeDrew, 1988). According to Byrne *et al.* (1980), PCA has provided an effective way of identifying areas in which change has occurred between two four-channel multispectral images (Maldonado *et al.*, 2002). In 2005, Deng *et al.* adopted the technique of combining PCA with interactive supervised classification to detect changes. The method of combining PCA and supervised classification is common practice to detect temporal changes with satisfying results (Xlago, 1998; Li & Ye, 2004; Eastman & Filk, 1993).

Other not so common change detection techniques in the category of spectral change detection are Change vector analysis and composite analysis. Change vector analysis (CVA) (Malila, 1980) involves the calculation of two change features (magnitude and direction of change) based on a multi-temporal dataset. Composite analysis (CA) is often performed in change detection applications (Yuan and Elvidge, 1998). This approach involves compositing all desired bands into a multi-date layer stack (the layer stack may contain raw or enhanced image data). Supervised or unsupervised classification is then performed on the data set to obtain the desired number of output classes (Rogan & Chen, 2004).

2.4 Accuracy Assessment

Accuracy assessment is an essential and most crucial part of studying image classification and thus LULC change detection in order to understand and estimate the changes accurately. It is important to be able to derive accuracy for individual classification if the resulting data are to be useful in change detection analysis (Owojori and Xie, 2005). Another part that is continuing to get increased attention by research workers is classification accuracy (Lillesand et al, 2004). The post-classification method for LULC change detection has dependency on the accuracy of individual classification results (Foody, 2002). Furthermore the change map of two multi-date classifications of LULC often reveals accuracies similar to the product of multiplying the accuracies of each individual classification (Stow *et al.*, 1980; Mas, 1999). Error in the individual classifications may also be confused with change detection (Khorram, 1999) – which must lead to misinterpret about the actual change in reality. Sometimes it is quite impossible to get ground truth or referenced data for assessing accuracy for the classified result from the historical image data.

As a consequence of these and other issues, the estimation of the accuracy of a change product is a substantially more difficult and challenging task when compare to the assessment of the accuracy of a single image classification (Congalton & Green, 1999). There is no single and appropriate method for assessing the accuracy of change detection products. The most common and popular method for accuracy assessment for LULC is the error matrix or confusion matrix method which can be further used for change detection accuracy assessment (Foody, 2002). The elements of change detection confusion matrix also used for showing individual from/to class change scenarios (Congalton & Green, 1999; Khorram, 1999). The related assessment elements include overall accuracy, producer accuracy, user accuracy, and kappa coefficient. Previous studies provided the meanings and methods of calculation for these statistical elements for judging the accuracy (Congalton 1991, Congalton and Green 1999, Foody 2002).

The two approaches to assess accuracy using this method are – random sampling or using referenced data. Bock *et al.* (2005) have shown the use of random sampling method for accuracy assessment by means of error matrix based on stratified and randomly selected points across the classified image. Instead of purely random method, stratified random sampling is usually recommended so that the sampling points are fairly spread in each LULC change class (Congalton 1991). He also gave suggestion about the number of sample size- a collection of minimum 50 samples for each class. On the other hand, accuracy assessment with error matrix using reference data requires a high-accuracy LULC data with the same number of classes which is sometime difficult to obtain. Stanislaw Lewinski in the research studies of land use classification of ASTER image (2005) and applying fused Landsat data to object oriented classification (2006) have proposed the accuracy assessment can be performed using a method of visual interpretation according to the way adopted by CORINE Land Cover (CLC) 2000 project. The interpreter edits the edges of objects and the codes of classes directly on the screen displaying the vector database and the satellite image in the background. "*As a result of interpretation, a so-called change layer was obtained, which provided information about the correctness of the classification*" (Lewinski, 2006).

2.5 Summary

The studies from various literature of related work revealed that the use of RS application is a key instrument for studying LULC change detection. However, a careful selection of RS data has to be stipulated considering the scope and type of actual work. With rapid advancement of RS techniques, a bunch of classification techniques have been developed as well. Those can be primarily grouped into two broad types which are tradition pixel based method and advance object oriented method. The preference of employing them is fairly driven by the resolution of RS data. Evolution of RS technology also accelerated the growing development of various change detection techniques which are implemented through case studies. The case studies in this regard have greatly influenced the development of new techniques. However, it has not been established any single technique as optimum and best. Every techniques are useful and having a balance between pros and cons. Because of impacts of complex factors and objectives, different researchers often arrived at different conclusion about which the efficacy of various methods. Accuracy assessment is also a part of good change detection research work. Moreover, it can be mentioned that accuracy assessment itself is an active field of research nowadays. The chapter briefly reviews the background and methods for various accuracy assessments that are most commonly used and recommended. In summary, the chapter discusses about several aspects (fig.- 2.5.1) of related work for LULC change detection.

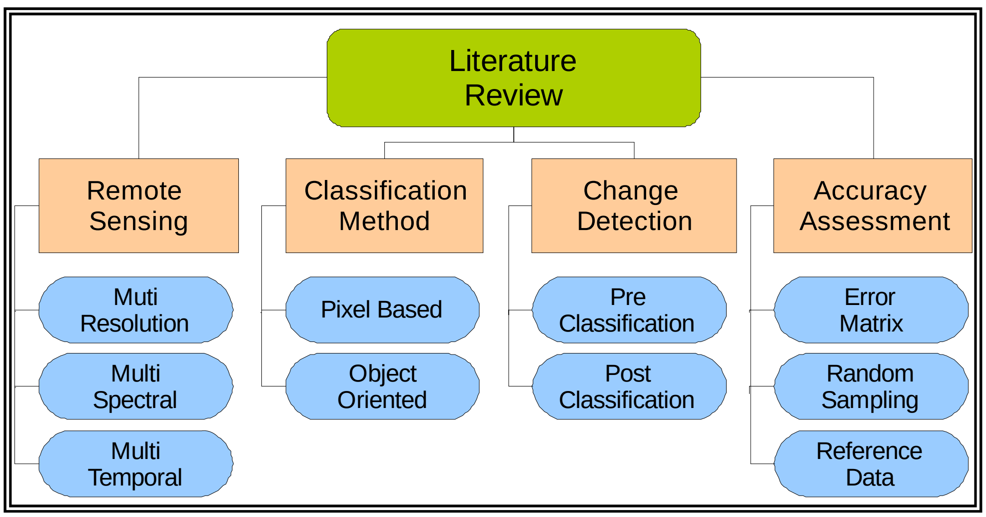


Fig.- 2.5.1: Literature review summary

3 Study Area and Data

This chapter describes the area and data used for the study. At first, a short description of the study area is given to demonstrate the characteristics of the area in terms of geography, land use / land cover and general narrative. Then, it illustrates about the technical details of the various data used for the proposed study.

3.1 Study Area

The study area lies in the region (Bundesländer) of Nordhein-Westfalen, close to the city of Munster (fig- 3.1.1) in Germany. The study area covers a part of the Münster city urban area. The study area is situated in the northern part of the state (source: Stadt Münster).

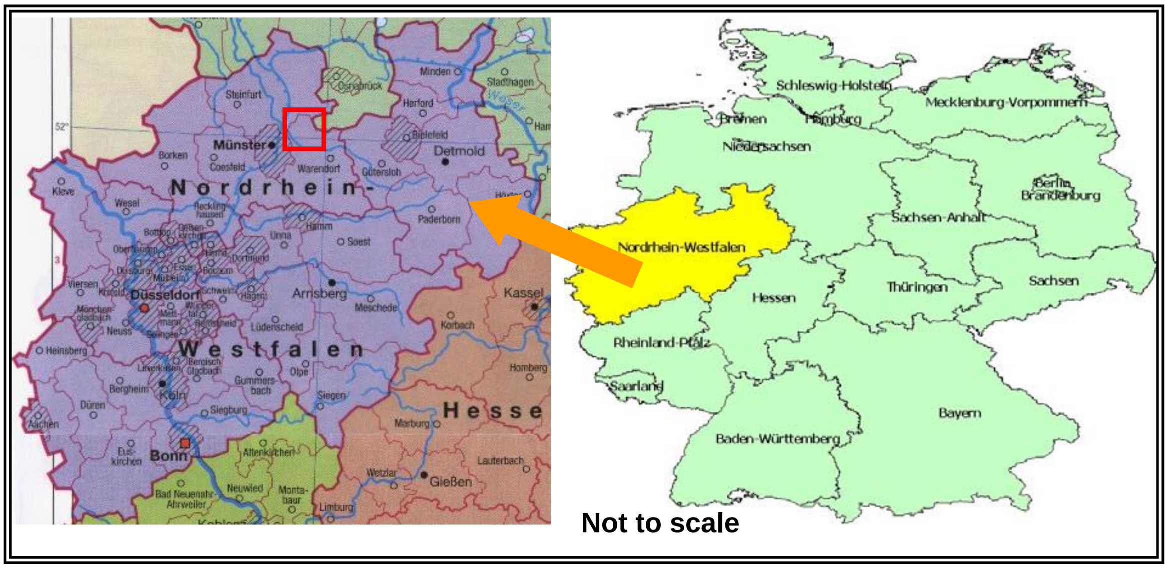


Fig.- 3.1.1: The map showing the study area (red square in left side map)

The geographical co-ordinate of the area under study is between 52 01 15.72 N to 51 55 58.23 N and 7 33 18.38 E to 7 42 12.24 E. The study was performed on the subset of images covering an area of 100 km2. The area of interest has been chosen after a visual examination of the study area which is a 10 km X 10 km square area based on which all the full scene images have been subset (fig.- 3.1.2).

"A well known saying in Münster is *"Entweder es regnet oder es läuten die Glocken. Und wenn beides zusammen fällt, dann ist Sonntag"* ("Either it rains or the church bells ring. And if both occurs at the same time, it's Sunday."), but in reality the rainfall of the area is approximately 744 mm per year – which is the average rainfall in Germany. The impression of Münster as a rain-laden city depends not on the absolute amount of rainfall but on the above-average number of rainy days with relatively little rainfall" (source: Wikipedia).

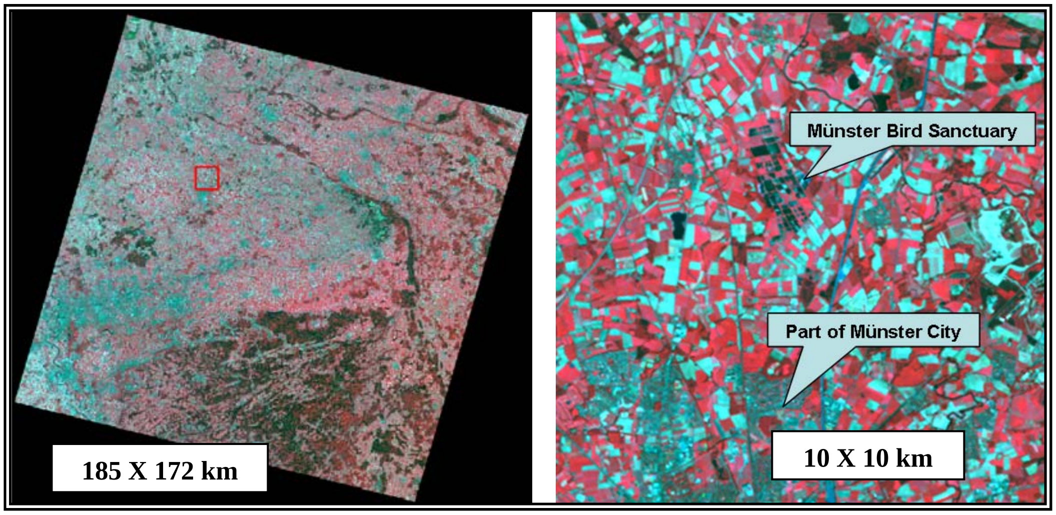


Fig.- 3.1.2: Full scene of Landsat TM Image (band 4,3,2) with area of interest (marked as red square) and the study area after subset (right).

The study area can be considered as rural-urban fringe area. In the southern part, it is mostly covered by part of Münster city and its surroundings while the rest part is dominated by rural and agricultural land use / land cover. The study area has a bird sanctuary (Rieselfelder), located about 6 km north of the Münster city. This man-made wetland on the former "Verrieselungsflächen" (agricultural land) has an important resting and molting place for migratory birds. Viewed from the air sanctuary provide a picture of a large lakes with over 130 individual ponds (fig.- 3.1.3). The division of the zone is clear. In the northern part, the original checkerboard-like parceling are extensively prominent. The southern part boasts "naturerlebnisgebiet". Both areas are European bird reserve, as protected Natura 2000 network for the conservation of Europe's natural heritage (source: EU-Vogelschutzgebiet Rieselfelder Münster).

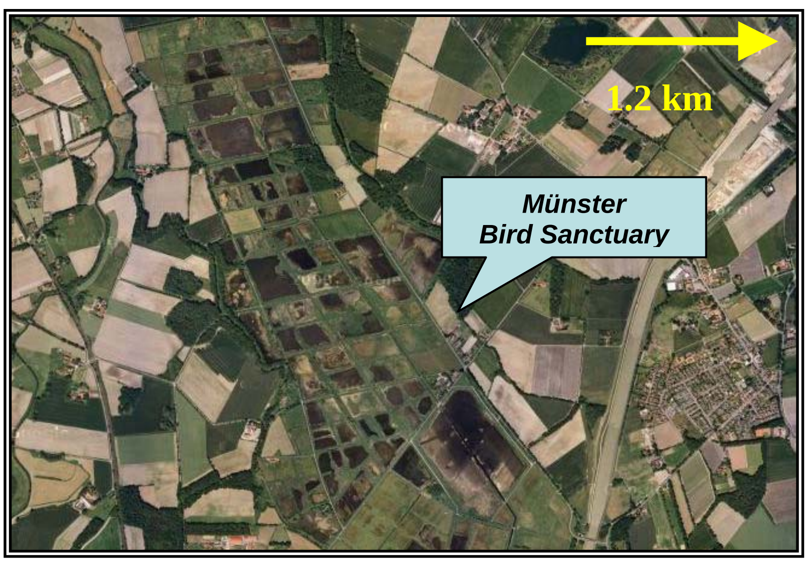


Fig. - 3.1.3: The Münster Bird Sanctuary and its surrounding area (Source: Google Imagery)

3.2 Data

Several types of data, have been used for this research work, are listed in the table 3.2.1. The data used can be subdivided into remote sensing data and ancillary data. Both satellite images and aerial image have been used for remote sensing application. Among ancillary data, the Germans basic maps at a scale of 1: 5000 (DGK 5) for the study area are mainly used. Apart from this, some vector data have also been used from different sources.

Table- 3.2.1: Data used for the purpose of study

RS Data	***Date of Acquisition***	***Band /Colour***	***Resolution***	***Source***
Landsat TM	25 May, 1989	Multi-spectral	30 m	**IVV Geowissenschaften** (University of Münster)
Landsat ETM+	15 May, 2000	Multi-spectral & Panchromatic	30 m (MS) 15 m(Pan)	**IVV Geowissenschaften** (University of Münster)
ASTER	2 April, 2005	Multi-spectral	15m (VNIR)	**IVV Geowissenschaften** (University of Münster)
Aerial Photo	2006	True Colour	10 cm	**IVV Geowissenschaften** (University of Münster)
Anciallary Data	***Date***	***Format***	***Scale***	***Source***
DGK 5	1987	GeoTiff	1:5000	**IVV Geowissenschaften** (University of Münster)
Bundesläander, Stadt Layer	2001-2002	Shapefile	1:5,000,000	Exercise data (University of Münster)
CLC 2000	2000	Shapefile	1:100000	European Environment Agency
Rieselfelder data	2007	Shapefile	1:5000	Vermessungs-und Kata-steramt (Stadt Münster)

3.2.1 Landsat Data

The Landsat images used for the study are from two Landsat operations. The Landsat TM imagery is part of Landsat 5 mission, launched in March 1, 1984 by NASA. And the Landsat ETM+ images are part of Landsat 7 mission, launched on April 15, 1999 *(source, NASA web).*

Table- 3.2.1.1: Bands of Landsat TM (left) and ETM+ (right) (source, NASA web)

Band	**µm**	**Resolutionn**	**Band**	**µm**	**Resolutionn**
1	0.45-0.52	30 m	1	0.45-0.515	30 m
2	0.52-0.60	30 m	2	0.525-0.605	30 m
3	0.63-0.69	30 m	3	0.63-0.69	30 m
4	0.76-0.90	30 m	4	0.75-0.90	30 m
5	1.55-1.75	30 m	5	1.55-1.75	30 m
6	10.4-12.5	120 m	6	10.4-12.5	60 m
7	2.08-2.35	30 m	7	2.09-2.35	30 m
-	-	-	8	0.52-0.9	15 m

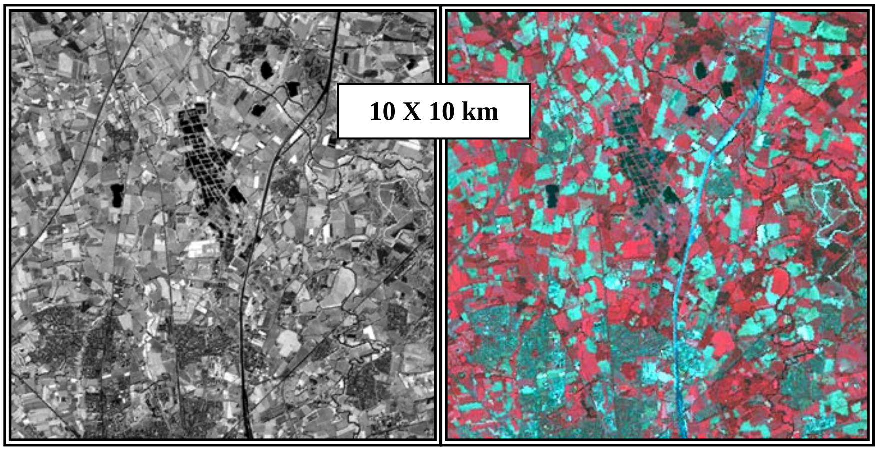


Fig.- 3.2.1.1: Landsat ETM+ Pan (Left) and MS, band 432 (Right) of the study area

The technical details of Landsat TM and Landsat ETM+ bands have been provided in the table-3.2.1.1.For other specification; refer to the official portal of Landsat (Landsat Program, NASA web). The Landsat TM image of the study area is shown in fig.- 3.1.2

3.2.2 Aster Data

ASTER (Advanced Spaceborne Thermal Emission and Reflection Radiometer) is an RS imaging instrument on Terra, a satellite launched in December 1999 as part of NASA's Earth Observing System (EOS). ASTER is a collaborative project between NASA, Japan's Ministry of Economy, Trade and Industry (METI) and Japan's Earth Remote Sensing Data Analysis Center (ERSDAC). ASTER is being used to obtain detailed maps of earth surface features (study area on ASTER, fig.- 3.2.1.2).

ASTER consists of three separate instruments, each operating in different spectral region, using a separate optical system. These subsystems are the visible and near infrared (VNIR), the Short Wave Infrared (SWIR) and the Thermal Infrared (TIR) respectively. The present study is only concerned for VNIR subsystem which has 15 m ground resolution (table- 3.2.2.1) (source: ASTER, NASA Web).

Table- 3.2.2.1: Technical specification of ASTER satellite (source: NASA web)

Characteristic	VNIR
Bands	Band 1: 0.52 - 0.60 µm & Band 2: 0.63 - 0.69 µm (Nadir looking), Band 3: 0.76 - 0.86 µm (Nadir & Backward looking)
Ground Resolution	15 m
Data Rate (Mbits/sec)	62
Cross-track Pointing (deg./km)	±24/60
Swath Width (km)	±318
Detector Type	Si
Quantization (bits)	8

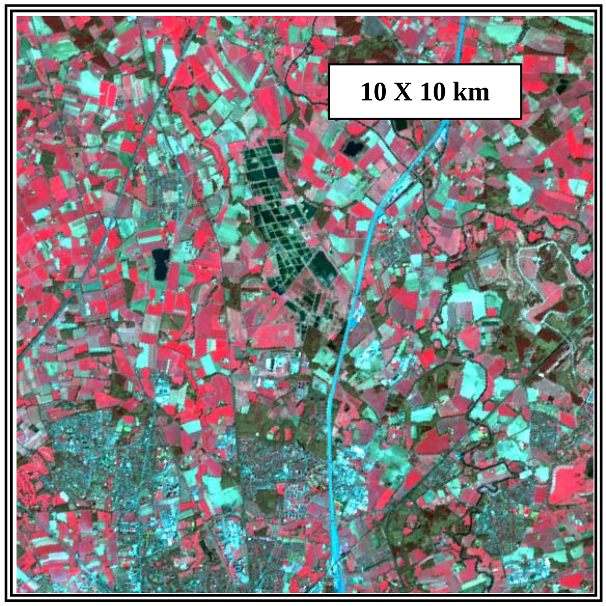


Fig.- 3.2.1.2: ASTER MS Data (Band 3,2,1) of the study area

3.2.3 Aerial Photo

One aerial photo from 2006 has also been used for the classification of the land use / land cover. The aerial photo is having 10 cm resolution mainly covers the Münster sanctuary and its adjacent area to some extent. The aerial photo covering the whole study area was not available. The aerial photo came in both GeoTiff and MrSID format. Moreover, aerial photograph were split into several part which have been mosaicked later on.

3.2.4 Ancillary Data

In general, ancillary data are used for various purposes including geometric correction of the remote sensing data and extraction of some base layers like road, railways, contour etc. In the present study, three types of such data have been used.

The German basic maps (DGK 5) on scale of 1:5000 have been primarily used for geometric correction. The DGK 5 is the basis of topographic maps in North Rhine-Westphalia. The scale of 1:5000 permits a largely complete and faithful description of the ground surface in its natural human activity is influenced by manifestations. The DGK 5 is suitable mainly for planning large-scale tasks and as a basis for thematic surveys. Applications include, for example road planning and management, administration, transportation, housing and others (source: Landesvermessungsamt, Nordhein-Westfalen).

Some thematic layers have been used for delineating the study area, creating the area of interest (AOI) and for some other references. Those layers are mainly administrative boundaries (Bundesläander) of Germany, cities of Germany in shapefile format. All those thematic are capable of importing into GIS software for having proper reference system with required non-spatial attribute data. These data from other sources than remote sensing have been used to aid in the classification, to assist in image processing and to populate metadata as well. Most importantly, a detailed LULC data (rieselfelder) from survey and cadastre, Stadt Münster was available for the accuracy assessment of aerial image classification.

It is very important to mention about CORINE land cover (CLC) data has been used for the present study. CLC is a data of the European environmental landscape based on interpretation of satellite images. It provides comparable digital maps of land cover for each country for much of Europe (European Environment Agency Web, 1995-2009). The classification nomenclatures used here have been adopted from CORINE for better acceptability and easy use. These datasets were frequently used as training site, wherever required, for the classification of LULC. Those datasets are downloadable for the study area in shapefile format. The scale of all output products of CLC is set to 1:100000, facilitating the detection of essential features of the terrain by means of satellite images (Spot, Landsat MSS and TM) and their representation. The detailed technical description and methodology about the data can be found from official portal of CORINE.

It is also worthy mention that Google map and Google earth were frequently using whenever some confusion arose regarding the decision of land use / land cover type. As we know Google Maps is a free web mapping service application and technology provided by Google. It is also a source of high-resolution satellite images for most urban and rural areas. A related product is Google earth - is a virtual globe, map and geographic information programme. It maps the earth by the superimposition of images obtained from satellite imagery, aerial photography and GIS 3D globe (source: Wikipedia). It is quite useful to use to check the classified data from remote sensing images using Google earth programme. The derived land use / land cover data can easily be overlaid upon high resolution images used by Google earth in order to check and compare the classified images.

4 The Methodology

In this chapter, a general sketch of the methodology adopted has been described. The present research is a framework of digital image processing using a case study to meet the expected result in order to solve the specified research problems. Towards this approach, information extraction using digital image processing using remote sensing (RS) data has been adopted. There are several techniques exist for improved information extraction from various sources of RS from simple visual interpretation of aerial photographs to complex automatic digital interpretation using various developed classification procedures. These techniques are directly influenced by several technical factors – resolution and type of the image, target information to be extracted, objective the study and accuracy requirements are worthy mentioned. Object oriented method for image classification along with required preprocessing; enhancement and post-classification analysis for change detection have been utilized for the whole study. The following sections are devoting to describe the various steps (fig.- 4.1) of the present work.

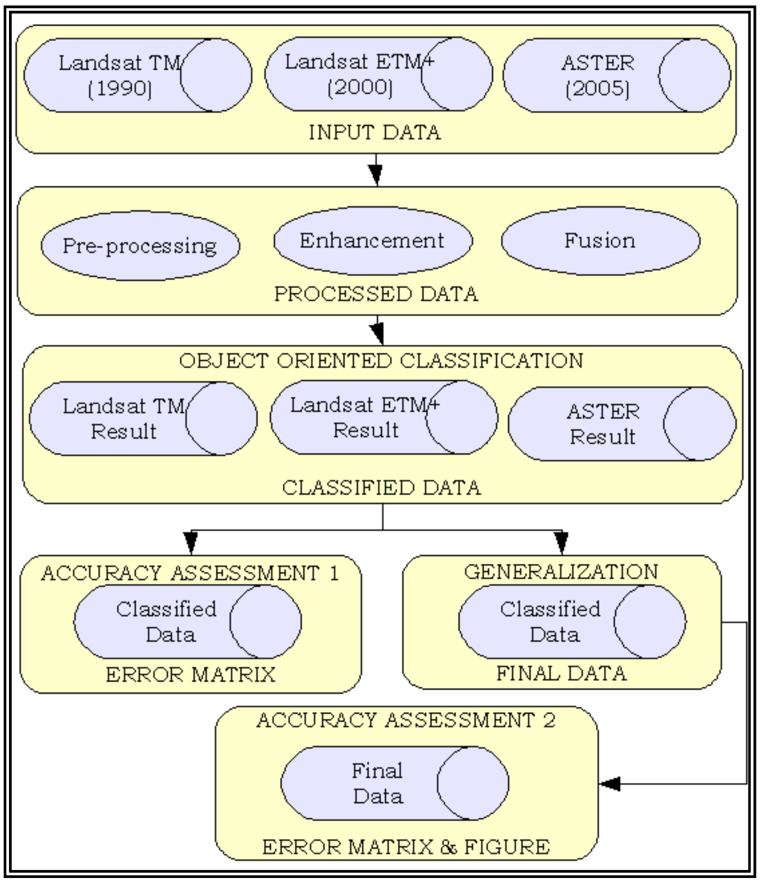


Fig.- 4.1: Workflow Diagram for proposed methodology

However, this chapter does not include the methodology for the study of aerial image classification and its accuracy assessment based on existing reference layer (land use / land cover from Survey and Cadastre, Stadt Münster). Chapter 6 is provided for implementing this work including methodology and result.

4.1 Pre-processing

Before performing the classification of the RS data, it is important to pre-process the data to correct the error during scanning, transmission and recording of the data. It refers to the functions which are frequently performed to improve geometric and radiometric qualities of the images. Typically, the pre-processing steps are (i) radiometric correction to compensate the effects of atmosphere (ii) geometric correction i.e. registration of the image to make it usable with other maps or images of the applied reference system , and (iii) noise removal to remove any type of unwanted noise due to the limitation of transmission and recording processes.

In this study, the radiometric correction has not been adopted due to the following reasons (i) first of all, the data for this study were already corrected to some extent (fig.- 4.1.1). From the histogram, it is noticed that all bands have ‘offsets’ from zero which is acceptable except for the case of Band 6 (Band 6 will not be exploited for the classification later on). (ii) For radiometric correction or normalization, calibrated data is required to achieve the higher accuracy (iii) most importantly; radiometric correction is obligatory only when image differencing is used for change detection analysis.

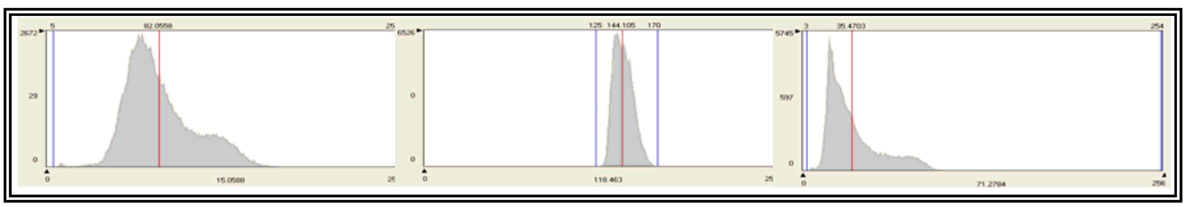


Fig.- 4.1.1: Three bands (band 5, 6 & 7 respectively) with histograms of Landsat TM

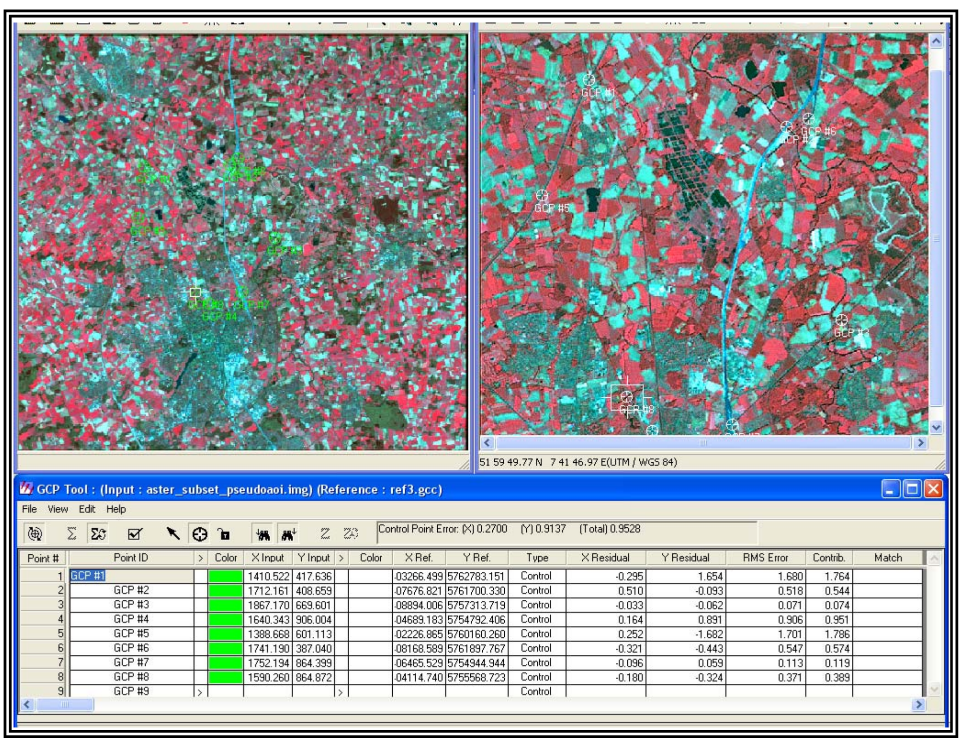


Fig.- 4.1.2: Two image windows (ASTER and Fused Landsat) with GCP Tool

In the present study all the datasets except the ASTER image and the German basic maps (DGK 5) were geometrically corrected by the source in UTM WGS 84 system. The ASTER image has been geo-referenced to the other datasets in UTM WGS 84 system using image to image registration method. The Landsat ETM+ fused image has been used as a reference image in this case. During registration, initially 4 ground control points (GCP) were used from the Landsat image but finally 8 GCPs have been used to improve the positional accuracy and the root mean square was 0.371 (fig.- 4.1.2). During resampling nearest neighbour algorithm was used as it has advantages of preserving the pixel value or nearest pixel value of the original image which is useful for further image classification. The German basic maps were corrected using the same reference system but in different way. The GCP has been collected from the map itself as it has some cross-points with known latitude / longitude value.

After close examination of all the datasets and their image statistics and histogram, there were no noise or image pixel dropout, primarily because those might be removed by the data centre who delivered the data to the source. However, all the images have been enhanced its quality in terms of visual appealing which is described in the next section under image enhancement.

4.2 Image Enhancement

Image enhancement involves the technique to increase the visual distinction of the features or classes in the image. This step alters the pixel value of the image and therefore image enhancement is followed after the pre-processing step is completed. The choice of enhancement technique depends upon the features to be used for extracting from the image. The most commonly used one is the simple contrast stretching which has also been adopted in this study. This step has been considered and proved to increase effectively the overall contrast of the image elements by accomplishing few simple steps. There are several methods for contrast stretching as well. After performing those methods on the complete dataset, it has been found that linear stretching and histogram equalization are the suitable ones for this purpose.

Almost all image processing software have the facility of performing contrast stretching and those are nearly the same with some subtle differences in the way they follow the procedure. ENVI has been used in this case for having interactive stretching which allows real-time visualization of the image and its histogram together. At first, Landsat TM (multispectral) has been chosen for enhancement and ‘Linear 2%’ method was applied (fig.- 4.2.1). Although the contrast of the image has been improved, it was not visibly distinguishable. After that, histogram equalization was applied which improved the image significantly (fig.- 4.2.2).

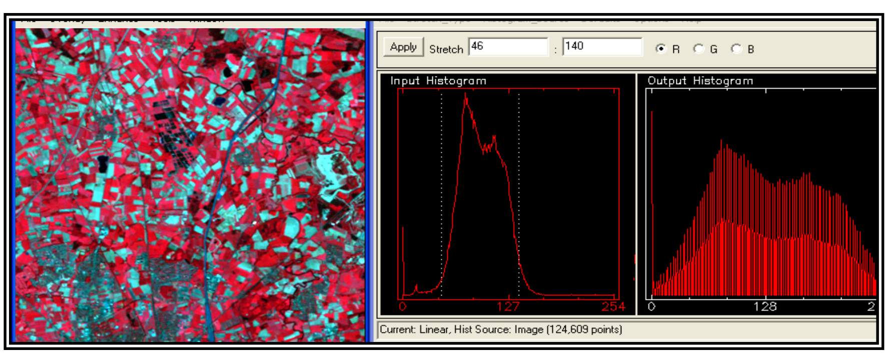


Fig.- 4.2.1: Input Landsat TM image with histogram after contrast stretching (Linear 2%)

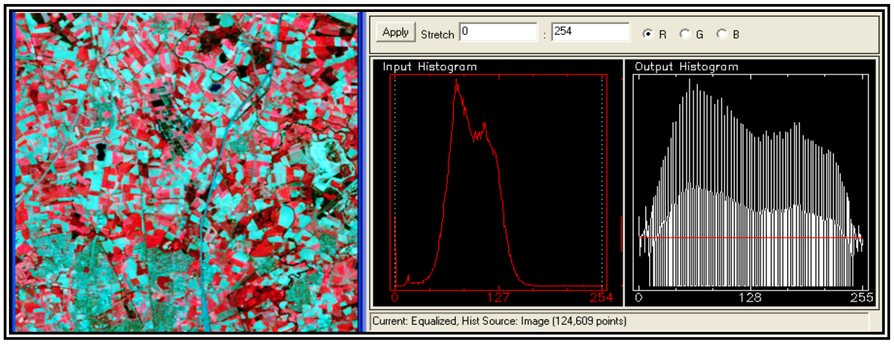


Fig.- 4.2.2: Histogram (R-band) after contrast stretching (Histogram Equalization)

After finishing the contrast enhancement of the Landsat TM image, the same methods were followed for rest of the datasets. It has been decided to use histogram equalization method for enhancement since it is supposed to be best for this case study. A histogram equalization stretch assigns the image values to the display levels on the basis of their frequency of occurrence (Lillesand & Kiefer, 1987). As it can be easily seen form the previous figures (fig.- 4.2.1 and 4.2.2), more display values are assigned to the frequently occurring portion of the histogram which consequently increased the radiometric quality of the image.

4.3 Image Fusion (Resolution Merge)

Image fusion is the spatial enhancement technique to make the best use of different complementary information from multi-source and multi-temporal imagery. A multi-spectral image can be fused with a higher resolution panchromatic (pan) image to create the high resolution multi-spectral (MS) image. The technique of fusing MS image with pan one is most popular and widely used to increase the resolution. The resulting fused image will have more information than the input image. This is common practice in almost all kind of LULC studies especially when high resolution MS data are unavailable due to various limitations.

Before running the fusion, it has to be kept in mind that both images should have registered in a common reference system and they should matched one-to-one without any displacement of the same features within the images. To ensure (although they were geometrically corrected) this, two images were displayed in the same image window and took advantage of the tool sets of swipe, blend and flicker which are the dedicated tools for comparing two superimposed layers of images. After visual inspection, they were found acceptable for image fusion further.

Various techniques of image fusion (sometimes called merging or sharpening) have been developed by scientist and software vendors. The most common are IHS (Intensity-Hue-Saturation), HPF (High Pass Filter), Colour Normalized (Brovey), PC (Principal Component) Spectral, Gram-Schmidt Spectral, Wavelet etc. Examples of using those methods have been found in various literature and case studies – in every cases, analyst have their own logic to use specific type of image fusion. However, after consulting several literature and books, it has been originated that the most widely used and affective methods in this purpose are IHS (Intensity-Hue-Saturation) and HPF (High Pass Filter) image fusion. However, PC method has not been adopted since it has been applied as an enhancement for better classification later on.

Both methods offered by ERDAS Imagine have been selected for the datasets of Landsat ETM+ multispectral and Pan images. Moreover, the IHS method is known as modified IHS in ERDAS Imagine (ERDAS Field Guide, 2005). This tool provides an implementation of "The Modified IHS Method for Fusing Satellite Imagery," proposed by Siddiqui, 2003. Normally, the limitation of a method based on IHS processing is that it can only process three bands at a time (because of using the RGB to IHS method). "*However, the color consistency is so good that this implementation of the approach enables images with more than three bands to be merged by running multiple passes of the algorithm and merging the resulting layers*" (ERDAS Tour Guide, 2006). The HPF resolution merge function also allows merging high-resolution pan data with lower resolution MS data. The process involves applying high pass filter (HPF) on the high resolution PAN data before merging it with multispectral data.

As mentioned before, both modified IHS and HPF methods have been used to combine the Landsat ETM+ multispectral and pan data and produced excellent fused images. Sometimes more pre-processing steps are required before merging especially when the images are from different satellites and not from the same date. The images used are both from the same satellite and of same time which was the one of the great advantage to get accurate fused image. In both cases, the steps followed are more or less the same except the resampling technique. In case of modified IHS method, there are three techniques for resampling like nearest neighbour, bilinear interpolation and cubic convolution whereas there is no option for choosing resampling technique in HPF method. It is to be noted that in case of modified IHS method, bilinear interpolation is chosen as it was advised in the software manual that if the ratio of high resolution to low resolution is 2:1 (for example, Landsat 15m Pan to Landsat 30m multispectral), then bilinear interpolation is a reasonable compromise of image quality and speed of processing (ERDAS Tour Guide, 2006).

The following diagram (fig.- 4.3.1) shows the two outputs images from the IHS and the HPS fusion. After displaying them in two image windows for visual comparison, both of them provide sharper than input multispectral image at a first glance. But after close examination, the result of IHS method is sharper than the other one. Moreover, the texture in the resultant image of modified IHS is more vivid especially if look into the urban area (lower part of the image). Since the image has been used for object oriented classification where texture is one element for classification and having more sharpness and contrast the image from modified IHS fusion technique was considered for use initially for the study.

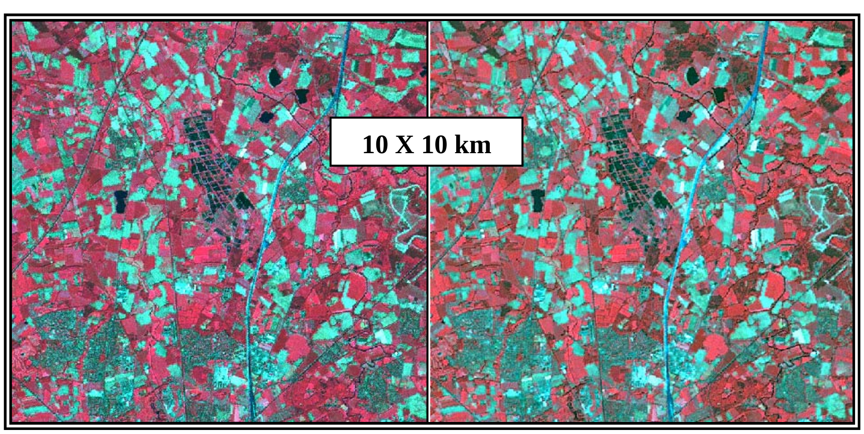


Fig.- 4.3.1: Two resultant image from modified IHS (L) and HPF (R) fusion technique

Although modified IHS method was found to be considered best suited for the fusion in this case, another alternative method of fusion technique has been adopted for improving the quality. As suggested by Lewinski *(2006)*, the fusion of Landsat ETM+ multispectral and panchromatic data by PANSHARP algorithm is an obvious choice because other methods achieved result depending on the skills of the operating person. The power of PANSHARP lies in the simplicity of its algorithm and its versatility. It is an algorithm newly developed by PCI Geomatica based on thorough studies and analyses of existing fusion algorithms and fusion effects for applying the automatic image fusion algorithm to increase the resolution of multispectral (colour) image data by using a high resolution panchromatic (B&W) image. It is to be noted that for best results, the input image channels have to be selected in such a way that the multispectral bands cover as close as possible the frequency range of the high resolution panchromatic image (Geomatica help tool, PCI Geomatica 9). As a consequence, band 2, 3 & are chosen for fusion with panchromatic band for better result (fig.- 4.3.2)

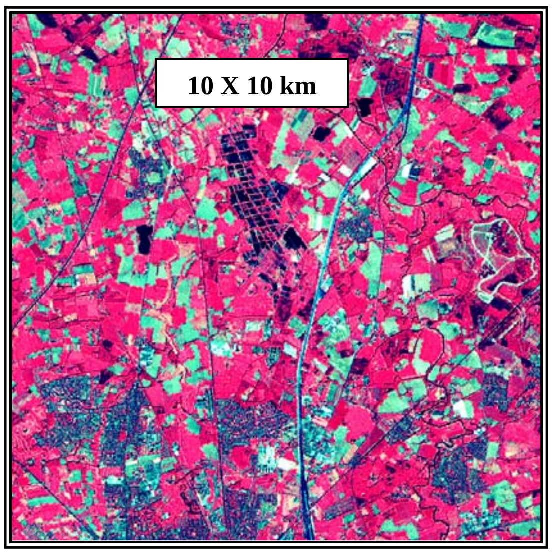


Fig.- 4.3.2: The resultant image (pansharp band 4,3,2) from PANSHARP fusion technique

After performing the fusion, three new channels were obtained which are PANSHARP 2, PANSHARP 3 and PANSHARP 4 to combine FCC image (fig.- 4.2.2). After visual examine with previously fused images by IHS and HPF methods, this fused image was considered to use for image classification subsequently.

4.4 Image Classification for Land use / Land cover

Image classification is the most widely used technique in various remote sensing applications for extraction of target thematic information. In the context of present study, the land use / land cover (LULC) is the main 'theme' which is to be extracted using a suitable classification method for LULC change detection. Basically, image classification is a mapping process to generalize the image pixels into meaningful groups each resembling different land category (Jensen, 1995). The process requires an optimum and specifically designed classification algorithm for precise application purpose because it largely varies depending upon the type and objective of the work.

Typical method for RS image classification is so called pixel based method in which the classifier considers different pixel values and group them into classes solely based on their spectral properties. This practice is based on conventional statistical techniques such as supervised and unsupervised classification where the classes are supervised by analyst and are not supervised (i.e. fully automatic based on spectral values) respectively. The expediency of traditional pixel based image classification often proves very effective especially in case of low and medium resolution satellite images, e.g.- Landsat MSS, IRS WiFS etc. The CORINE programme of European LULC database is good example where visual interpretation technique has been adopted instead of traditional pixel based method to obtain accurate result. But with increasing availability of various high resolution (both spatial and spectral) data (e.g.- Quickbird, IKONOS, Cartosat etc.), a new generation of classification technique, object oriented (OO) classification has been emerged which has proved to obtain result with full satisfaction (Lewinski, 2005).

The object oriented method is a newly developed image classification techniques considering not only the spectral information of the image but also shape, texture, contextual and semantic information (Owojori & Xie, 2005). It also considers relationship within different image objects. This method mostly resembles the visual interpretation technique. This new technique for image classification is assumed as more efficient when compared with those techniques used previously for low and medium resolution images. The reason behind such reality is that the automatic classifiers previously used neglects the important information of the image like texture, shape, context which are considered in the object oriented technique for creating meaningful objects of different category.

The object oriented method for image classification has been adopted in the present study considering the spatial and spectral resolution of the imagery used and for expectation of acceptable result. The commercially available software for OO classification method is Definiens Professional which has been used for entire classification using three satellite images. In the present study, the Professional is exploited to show how it can be used for OO classification to extract LULC more effectively. The following section delivers the basic concepts for such classification techniques and important steps which are to be followed to perform the required information extraction of LULC.

4.4.1 Object Oriented Classification using Definiens Professional

Definiens Professional (previously called eCognition) offers the cutting-edge technology for OO classification methods with wide-ranging image analysis tools. Before proper utilization of the software, it is most important to understand the basic concepts of the OO classification using this software. The software offers various tools for precise classification of image depending upon the type, scale and level of classification. Expert knowledge of the system helps to opt for the suitable approach and thus largely influence the classification result.

As an importance, the workflow (fig.- 4.1.1.1) used for the classification in the present study should be understood. The workflow followed here has been developed from the user manual of the software (eCognition Professional User Guide, 2004) according to the purpose. The following major steps are included for the classification scheme:

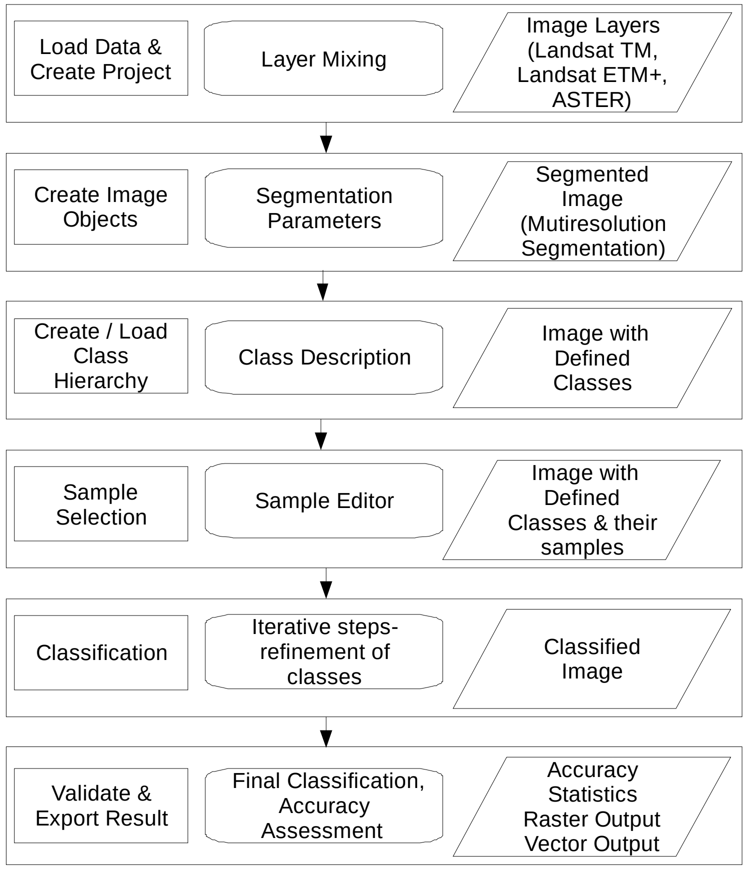


Fig.- 4.1.1.1: Workflow for OO classification using Definiens Professional

<u>I. Segmentation</u>: The image is segmented to create meaningful objects .The object size is adjusted by the 'scale' parameter which has to be mentioned before the segmentation process. It is possible to get image objects resembling those in the visual interpretation technique by applying correct scale factor. The quality of segmentation is decisive for outcome of subsequent classification- so it is most important step and sometimes, manual editing might be required to ensure accurate image objects (Lewinski, 2005 & 2006). Hence, the shape of the segmented image objects is determined by the following parameters (Definiens Professional User Guide, 2006) (fig.- 4.4.1.2):

- Weight of Image channels - It is used to give weight to different channels of the image which influences the segmentation. The weight is related to the type of images. In most cases, equal weights are given especially when only three channels are used, e.g. – Quickbird. In this case (fig.- 4.1.1.2), channel 4 of ASTER image is given no weight since it will not be used for the segmentation.
- Scale – Scale parameter is the most important to regulate the object size. The default size is 10. But, in most case, it is required to increase if the larger objects are required. The size of the objects increases with higher scale.
- Colour and Shape – These are the composition of homogeneity criteria and they are mutually exclusive. The higher the colour the less shape criterion influences the size of image objects.

- Smoothness and Compactness - These are the composition of homogeneity criteria and mutually exclusive like colour and shape.
- Level – It is used to mention the levels which directly influence the size of the objects.

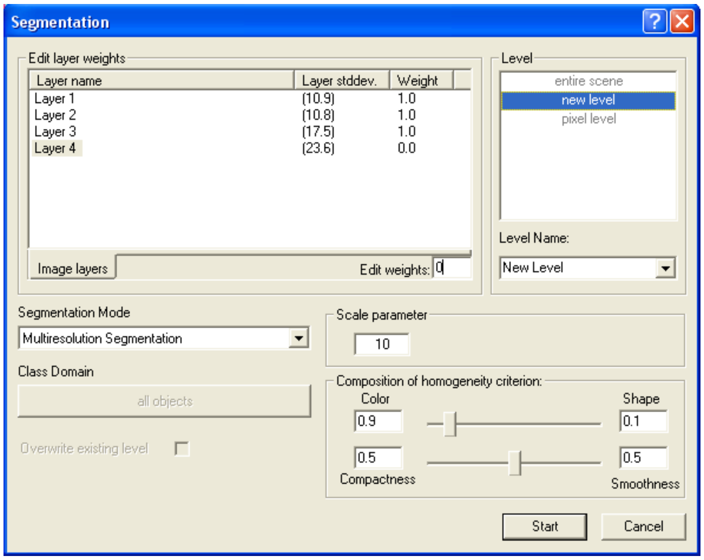


Fig.- 4.1.1.2: Segmentation parameters for creating objects

However, although the quality of classification largely depends on the segmentation process which is influenced by those parameters but there is no created rule for choosing suitable segmentation criteria. The suitable criteria or parameters for different land cover can be achieved through trial and error process and by expert knowledge or previous experiences. The parameters used for the entire classification of the present study have been selected after trying the combination of several parameters. Parameter(s) used for one land cover might not be strong for another land cover. As for example, for artificial lake, higher value of shape should be consider where as colour is the primary criteria to distinct between water and forest. If only one level of segmentation is used where all land category are to be defined at once, in that cases those parameters are chosen such a way that fulfils the conditions for all land classes at optimum level. Manual object editing might be needed to refine the result of segmentation process which, in turn, improves the subsequent classification.

II. <u>Classification</u>: This classification process is based upon the fuzzy set theory, used in the nearest neighbour method of classification and in the membership function (TSo & Mather, 2001). So, there are two classification techniques available in the software – nearest neighbour classifier which assigns class based on minimum distance measures and membership function in which classes are precisely described based on expert knowledge. Using the nearest neighbour classifier which is similar to supervised classification, training samples are required prior to the classification. On the other hand, the classification using membership function required good practical knowledge about the objects and the attributes used to define membership function for separation of classes. The nearest neighbour is quite easier compare to membership function method as it demands very good knowledge about the attributes of the image objects. But, membership function is more advanced and sometimes performing more effectively than nearest neighbour. Either one of the methods or both together can be used depending on the preferences, nature of images and expected accuracy of the outcome.

The Definiens offers some features which are used for class description. Those features can be utilized using both techniques. But, some features are only restricted to membership function (fig.- 4.1.1.3). The most commonly used features are (Baatz *et al.*, 2004):

- Object features :
  - Layer values of image bands (Mean, S.D., Mean Difference etc.)
  - Shape of objects (Area, Perimeter, Length/Width etc.)
  - Texture (GLCM Statistics, Layer value texture etc.)
  - Hierarchy (Level, Number of neighbours etc.)

- Class-related features:
  - Relations to neighbour objects
  - Relations to sub objects
  - Relations to super objects
  - Relations to classification

- Scene features:
  - Class-related (Number of classified objects, area etc.)
  - Scene-related (Number of pixels, Number of objects etc.)

- Logical terms:
  - Operators for building expression and including more than one expression in the class description (And, Or, Not etc.)

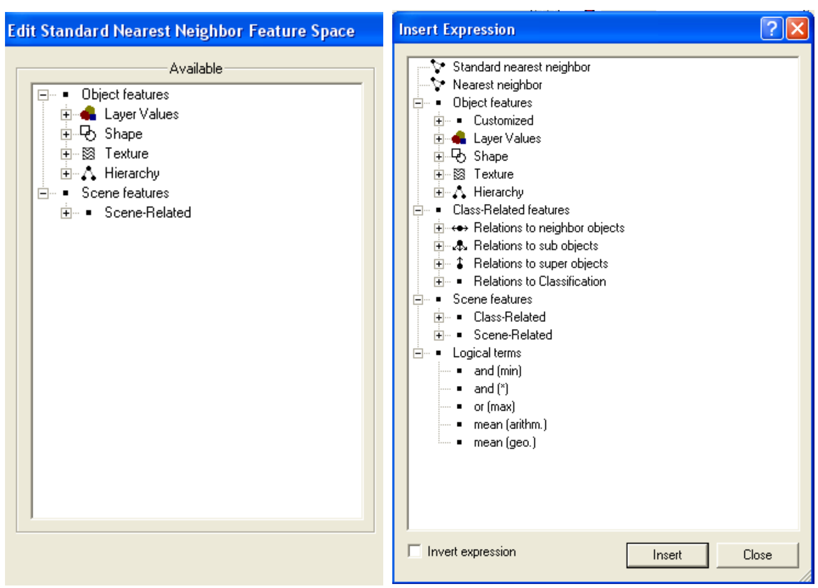


Fig.- 4.1.1.3: Features used for Nearest Neighbour (L) and Membership Function (R)

Layer values are most common feature used for almost every classification – it concerns about the pixel value of each image channel. Mean Layer value is most widely used (especially for nearest neighbour technique) for differentiating dissimilar features based on spectral values. Using layer value of one single band is also quite common to further refinement for separation of classes using membership function. As for example, NIR band has higher spectral value for vegetation when compare to other classes. So the layer value of band NIR can help to separate vegetation using membership function.

Texture is another most important feature for describing classes. Texture is used in this purpose calculating grey level co-occurrence matrix (GLCM) after *Harallic* (1973) which shows the information about pixel grey –level (Shamaoma, 2005). A wide variety of GLCM features are available amongst which GLCM dissimilarity, homogeneity and entropy are most common. These features are vital to describe or separate classes which are having different texture. As for example, both urban and industrial areas have almost same spectral reflectance whereas urban areas are highly textured and thus can easily be separate out from industrial areas using GLCM dissimilarity feature of texture properties.

Class-related feature is also another aspect for defining classes based on relationship between neighbour objects, sub or super objects and classified objects as well. The software provides enormous number of features for describing different classes accurately at higher level. Few of them have been mentioned here which are most common and found relevant to the present study. All of them have been explained by the Definiens professional 5 user guide (2006) in more detail. Though exploiting all or most of them is out of the scope of present work. However, some of them have been used for the purpose of present work and their uses have been pointed out on the following section wherever applicable.

III. Accuracy Assessment: The Definiens Professional use accuracy assessment methods to produce statistical outputs which can be used to check the quality of the classification results. This is based on an error matrix (also known as confusion matrix) which compares on class-by-class basis classification data with known reference data. A known reference data such as thematic layer with same number of classes is required for this type of accuracy assessment. Obtaining such a reference data is quite difficult in most cases. To avoid this, the software introduced four possible ways for accuracy assessment which have been established quite functional. Those methods are based on (Definiens Professional 5 User Guide, 2006):

- Classification Stability
- Best Classification Result
- Error Matrix based on TTA Mask
- Error Matrix based on Samples

The last two methods are mostly applied for accuracy assessment using this software. Although the accuracy assessment within this software is not vigorous since it is used training sample as a reference but the assessment have been considered as fair enough by various scientist and research workers. However, other approaches of accuracy assessment can be implemented further to support the internal accuracy assessment of this software and to enhance the value of the classification for the user.

4.4.2 Land use / Land cover: Principles & Nomenclature

Land use illustrates how a piece of land is used (such as for agriculture, industry etc.) and Land cover depicts the materials or resources (vegetation, buildings etc.) (Sabins, 1997). The classification system should recognize both of them. With the various advantages of RS methods for LULC mapping over ground surveys due to faster and easy interpretation for large area, availability of wide-ranging data, less expensive, timely and accurate mapping possibilities, it has some limitation as well. Those limitations should be kept in mind before handling LULC mapping task. The most important facts in this regard are:

- Different type of LULC category may not be easily distinguishable on the images available for the work.
- The level of classification may not serve the objective of the work
- It may be difficult to recognize the definitive examples of land category on the images as those definitions of category are on theory.
- The classification output has a limitation in terms of scale and minimum mapping unit (This factor fairly depends on the spatial resolution of remote sensing images and level of classification)

Considering these practical issues, the RS data has important implications on classification nomenclature, mapping unit and scale of the output. With the spatial resolution of 30 meter (Landsat TM) to 15 meter (ASTER), the image can not portray all the objects on the earth surfaces. There must be some limitation as per sensor capabilities. The objects can be easily distinguished when they are larger than the one pixel in image and spectrally look different. With the lower resolution of satellite images, only the broad classes can be mapped. It seems that the nomenclature has to be adopted according to the sensor capabilities which are merely difficult and incorrect way of building LULC nomenclature.

The nomenclature followed for the present work has been taken from CORINE CLC Nomenclature (Lima, 2005). The following actuality did work to take this decision:

- The spatial and spectral resolution of the images used for the present work overlaps with those of images used for CORINE program.
- Building a new nomenclature is difficult and may raise some questions regarding applicability. Moreover, the CORINE nomenclature has been established and the definitions of classes are readily available.
- There are always some problems and uncertainties arise especially for mapping those classes which have subtle distinct boundary between classes. The definition of those classes also makes confusion. The existing nomenclature with definition and practical explanation can help to minimize theses uncertainties.
- Most importantly, one of the objectives in this study is efficacy of OO method for classification and LULC change detection following the same nomenclature which has been used for LULC database using visual interpretation of remote sensing images.

The CORINE has multilevel classification system possessing three levels (table- 4.2.2.1). All classes which are present only in the study area are shown. Actually, the nomenclature has been modified from CORINE nomenclature applicable for the study area – the classes which are not present in the study area have been simply removed. Considering the time limitation of the present work and uncertainties, the present work is limited to the second level of classification which has 10 classes in total. Moreover, in this study area, most classes in second level have only one adjacent class in third level – the use of nomenclature up to second level is highly justified. Third level has 14 classes in the area under study. For complete nomenclature and their definition, refer to the CORINE nomenclature in methodology guidebook (Lima, 2005).

Besides nomenclature, the classification principles require minimum mapping unit (MMU) smaller than patches of classified pixels which will be merged into neighbouring larger patches.

The MMU here is 4 ha. The selection of MMU is not random. According to CORINE guideline (European Commission Web), the minimum mapping unit was 4 ha for the output form the image with 30 meter resolution like Landsat TM and ETM+ multispectral. But for the images with higher resolution (15 m for Landsat ETM+ Pan and ASTER), the MMU could be set to 1 ha which was not chosen to avoid detect LULC changes inaccurately. The linear feature of the width of less than 100 meter have also been generalized and merged into the larger pixels.

The spatial resolution not only determines the MMU but also the scale of output from the images. However, the MMU is directly linked to the scale. The relationship between these parameters and the resolution of image is quite difficult to perceive and sometimes look complex but these parameters should be set carefully and logically before performing the classification. The scale of the all output set to 1:100000 which indicate that the accuracy of the classification has to be judged on that scale. This scale is related to the legibility of the printed maps.

Table- 4.4.2.1: LULC Nomenclature for the Study Area (Modified from Luma, 2005)

Level 1	Level 2	Level 3
Agricultural areas	Arable land	Non-irrigated arable land
	Heterogeneous agricultural areas	Complex cultivation patterns
		Land principally occupied by agriculture, with significant areas of natural vegetation
	Pastures	Pastures
Artificial surfaces	Artificial, non-agricultural vegetated areas	Green urban areas
		Sport and leisure facilities
	Industrial, commercial and transport units	Industrial or commercial units
	Urban fabric	Continuous urban fabric
Forest and semi natural areas	Forests	Broad-leaved forest
		Coniferous forest
		Mixed forest
	Scrub and/or herbaceous vegetation associations	Natural grasslands
Water bodies	Inland waters	Water bodies
Wetlands	Inland wetlands	Inland marshes

4.4.3 Classification of Landsat TM Image (1989)

The classification of the Landsat TM (multispectral) image was performed by Definiens Professional software using object oriented (OO) method. The same workflow (fig- 4.1.1.1) was used for all the images. The satellite image was taken on May, 1989 which not an optimum period for LULC classification. This image has been selected due to lack of images of other season and most importantly, the image was completely cloud free. The image has seven channels in total. All channels could be used for classification – this is not obligatory and sometime confuses analyzer to differentiate classes. Some of them have been used for input channels for classification after consulting with the statistical reports (see the table- 4.4.3.1)

Table - 4.4.3.1: Spatial Statistics for the Landsat TM Image

Correlation	Band1	Band2	Band3	Band4	Band5	Band6	Band7
Band1	1.000000	0.954136	0.919301	-0.208809	0.765758	0.465843	0.813484
Band2	0.95413	1.00000	0.95620	-0.16993	0.817356	0.337569	0.852892
Band3	0.919301	0.956208	1.000000	-0.358326	0.831938	0.215240	0.923354
Band4	-0.20880	-0.16993	-0.358326	1.000000	-0.031682	0.196938	-0.309648
Band5	0.76575	0.817356	0.831938	-0.031682	1.000000	0.222525	0.925752
Band6	0.465843	0.337569	0.215240	0.196938	0.222525	1.000000	0.152028
Band7	0.813484	0.852892	0.923354	-0.309648	0.925752	0.152028	1.000000
Std Dev.	11.510202	7.200868	12.224598	24.980550	26.942254	12.944463	20.142771

Although these statistical parameters are strong enough for choosing correct bands for image segmentation and subsequent classification, optimum index factor (OIF) is frequently used for selection of best combination of image channels. Prinz (1996) applied the use of OIF to select suitable bands of TM image. The OIF for TM image has been calculated based on the following algorithm (modified from Prinz, 1996):

$$\text{OIF} = \Sigma\sigma(i)/\Sigma|r(i)|$$

Where $\Sigma\sigma(i)$ denotes the Sum of standard deviations of the bands in combination and $\Sigma|r(i)|$ denotes the Sum of the absolute values of the correlation co-efficient between any two of the three bands being evaluated.

After calculating OIF value for all possible band combination, the OIF has been given rank. The highest value has rank 1 and so on (table- 4.4.3.2). The colour composite of band 432 was selected (although the ranking is not the highest) as it builds standard FCC. It is interesting to note that the natural color composite has the lowest OIF value. However, from the OIF values, it is evident that band 5 & 7 are present in first three combination. As a consequence, those bands were considered for image segmentation. Band 1 was not considered although it is the member of best possible combination because of lower standard deviation when compare to band 5 & 7. Further, band 1 has a narrow band width, very low standard deviation and low co-variance values with bands 4 and 5. However, after consulting statistical parameters and visual inspection of all band combination, the combination of band 432 found suitable for the present study and band 5 &7 were chosen additionally during segmentation step.

However, different combinations of input channels have been used for different steps. The combination of input channels for segmentation was not the same as for classification steps.

Table – 4.4.3.2: OIF value with rank for possible band composition of TM Image

Rank	***Band Combination***	$\Sigma\sigma(i)$	$\Sigma\lvert r_{(i)}\rvert$	***OIF***
1	145	63.433006	1.006232	63.04014
2	245	59.123672	1.018968	58.02309
3	457	72.065575	1.267082	56.87523
4	345	64.147402	1.221946	52.4961
5	147	56.633523	1.331932	42.51983
6	247	52.324189	1.33247	39.26857
7	347	57.347919	1.591328	36.03777
8	124	43.69162	1.33286	32.78035
9	134	48.71535	1.486427	32.77346
10	234	44.406016	1.484464	29.91384
11	157	58.595227	2.504994	23.39136
12	357	59.309623	2.681044	22.12184
13	257	54.285893	2.596	20.91136
14	135	50.677054	2.516989	20.134
15	125	45.653324	2.537236	17.99333
16	235	46.36772	2.605502	17.79608
17	137	43.877571	2.656139	16.51931
18	127	38.853841	2.620506	14.82685
19	237	39.568237	2.732454	14.48084
20	123	30.935668	2.829639	10.93273

I. Segmentation: Careful attention is required in this stage to improve the quality of classification. During the segmentation, several segmented objects or region were created based on several adjustable criteria. Since there is no clear rule for appending those parameters during segmentation process, several tests have been attempted through trial and error technique to achieve best functional parameters for that image segmentation. The following parameters (table- 4.4.3.3) were used for this segmentation. Segmentation was performed using five image channels and the study area was divided into 1018 objects of consistent shapes. The applied parameters were competent to separate the objects correctly including linear features. However, the edges of each object were carefully examined and in few cases they have been manually edited and merged into larger objects for better representation and classification afterwards. Finally, total 833 objects were kept for classification.

Application of channels 2, 3 and 4 in segmentation process is justified as those are the channels for standard FCC image. Channels 5 and 7 have been used additionally for high standard deviation and lower correlation between other channels. The performed trial attempts for segmentation indicated that the inclusion of channels 5 and 7 increase the precision of segmentation.

Table- 4.4.3.3: Segmentation parameters for Landsat TM classification

Level	Channels	Scale	Color	Shape	Compactness	Smoothness	Number of Objects
1	2,3,4,5,7	15	0.6	0.4	0.7	0.3	833

II. <u>Classification</u>: After the proper segmentation, the classification took place. At the very beginning of classification, a class hierarchy consisting of required classes following the nomenclature has been created and thus a set of ten classes has been defined using suitable color code (fig.- 4.4.3.1). These ten classes are the level 2 classes from the nomenclature mentioned before (see section 4.4.2). For the identification of different classes both standard nearest neighbour (SNN.) and membership method (parametric criteria) were used. Initially, all classes were defined using SNN algorithm using mean function of image channels. The separation of classes has further been refined by using several membership functions or criteria. Each class was assigned different criteria after inspecting the image object information of the each object of corresponding class (fig.- 4.4.3.1).

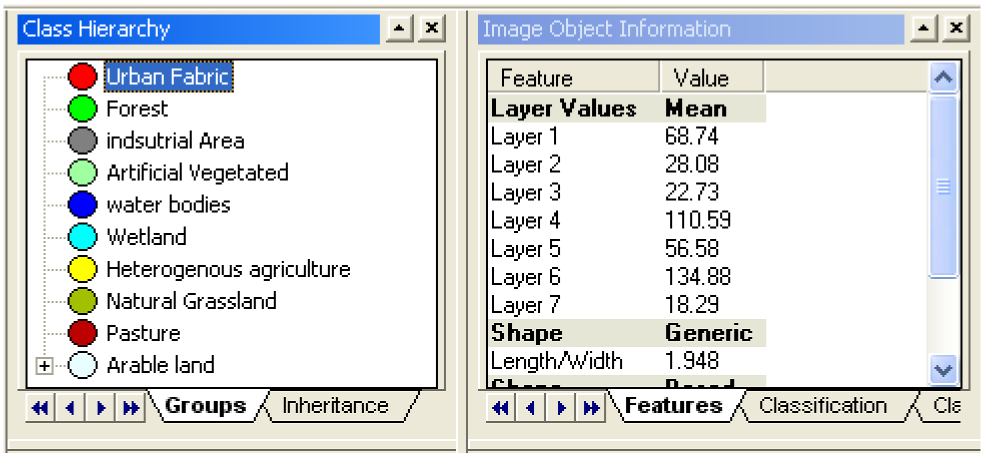
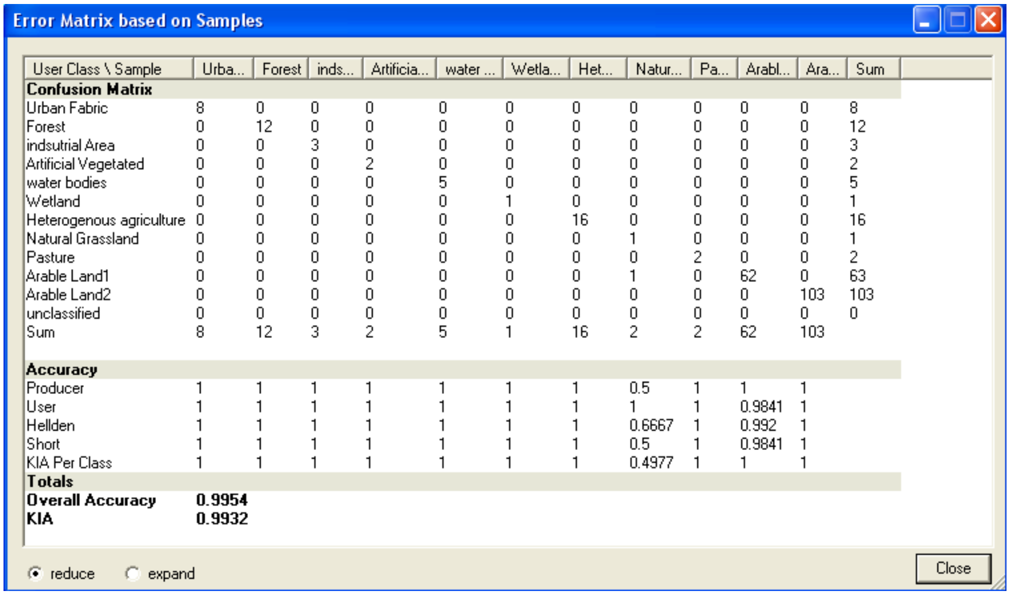


Fig.- 4.4.3.1: Class hierarchy (L) for TM image & image object information (R)

The membership functions were used for accurate separation between classes. Before that, some samples, as in case of traditional supervised classification, have been collected from training site based on knowledge and reference data. The CORINE land cover from 1990 (CLC 1990) has been considered as reference data for sample collection in some cases wherever confusion occurs. The training samples have been collected as much as possible for representing the range of spectral and spatial properties of a particular class. It has to be considered that selecting an overwhelming number of training samples would cause poor performance during classification. It is also true that some classes have mixed pixels which caused confusion between classes. The sample selection information tool helps to understand this confusion. The sample navigation has been used to minimize the mixed pixel problem.

However, it is nearly impossible to avoid the problems of mixed pixels completely. As a result, some classes have been misinterpreted. As a consequence, the process of classification involved the membership function (MF) together with SNN to further purify the separation of classes. Various features have been used for membership functions which all are listed in the table 4.4.4.1. The selection of those parametric criteria for each class description was not random. Each type of classes has some exclusive properties of shape, texture, contextual and semantic information which have been exploited through membership function for better classification result. Finally, an expected accurate result has been achieved and all the classes were correctly described. The classified image obtained as a result of the OO classification was generalized afterwards considering the minimum mapping unit of 4 ha.

III. Accuracy Assessment: In order to evaluate the result of classification, an error matrix was generated by the Definiens software based on samples collected for the classification (fig.-4.4.3.2). The classification has high accuracy with 99% of both overall accuracy and kappa value. In most classes, producer and user accuracy is 100% except for natural grassland and arable land. The detailed discussion about the classification result was provided in the next chapter along with another additional accuracy assessment for all classification. The accuracy assessment in this way is the easiest way and fair enough. In every cases of object oriented classification using Definiens professional, the user relies on the accuracy assessment in this way. However, since the accuracy assessment here is based on known given samples (which were considered as accurate as taken from reference data), it is restricted to the knowledge of analyst who has taken the samples. Therefore, another method of accuracy assessment was also performed for each classification to ensure the quality of change detection of LULC.



User Class \ Sample	Urba...	Forest	inds...	Artificia...	water ...	Wetla...	Het...	Natur...	Pa...	Arabl...	Ara...	Sum
Confusion Matrix												
Urban Fabric	8	0	0	0	0	0	0	0	0	0	0	8
Forest	0	12	0	0	0	0	0	0	0	0	0	12
indsutrial Area	0	0	3	0	0	0	0	0	0	0	0	3
Artificial Vegetated	0	0	0	2	0	0	0	0	0	0	0	2
water bodies	0	0	0	0	5	0	0	0	0	0	0	5
Wetland	0	0	0	0	0	1	0	0	0	0	0	1
Heterogenous agriculture	0	0	0	0	0	0	16	0	0	0	0	16
Natural Grassland	0	0	0	0	0	0	0	1	0	0	0	1
Pasture	0	0	0	0	0	0	0	0	2	0	0	2
Arable Land1	0	0	0	0	0	0	0	1	0	62	0	63
Arable Land2	0	0	0	0	0	0	0	0	0	0	103	103
unclassified	0	0	0	0	0	0	0	0	0	0	0	0
Sum	8	12	3	2	5	1	16	2	2	62	103	
Accuracy												
Producer	1	1	1	1	1	1	1	0.5	1	1	1	
User	1	1	1	1	1	1	1	1	1	0.9841	1	
Hellden	1	1	1	1	1	1	1	0.6667	1	0.992	1	
Short	1	1	1	1	1	1	1	0.5	1	0.9841	1	
KIA Per Class	1	1	1	1	1	1	1	0.4977	1	1	1	
Totals												
Overall Accuracy	**0.9954**											
KIA	**0.9932**											

Fig.- 4.4.3.2: Classification accuracy (Error Matrix) of the Landsat TM Image.

4.4.4 Classification Landsat ETM+ Image (2000)

This section presents the methodology of OO classification of Landsat ETM+ satellite image using fused multispectral (MS) and panchromatic (Pan) data. The usefulness of fused MS and Pan data has been assessed based on Landsat ETM+ acquired on May, 2000. Although this season gives cloudless images, it is not the optimum period of acquiring an image for the purpose of LULC classification. In spring season, the vegetation has a high quantity of chlorophyll content which, therefore, decreases the spectral diversity between classes of green character like artificial vegetation, grassland, forest etc. The same workflow has been pursued for the classification with some minor changes in segmentation step and in classification step.

I. Segmentation: Segmentation of Landsat ETM+ image was preceded by, the same way as followed in case of Landsat TM image previously, an analysis of particular channels and their spatial statistics particularly standard deviation and correlation coefficients. The statistics reports have not been listed here due to limitation of space. Although the OIF value of the combination 432 (OIF ranking-5) is lower than some others but it is found visually superior than others. Image channel 2, 3 & 4 (fused) were selected for image segmentation with same parameter (see table- 4.4.3.1) used previously for the Landsat TM image except the image channels and number of image objects. Please note that the number of image object is not a parameter for segmentation rather the result of segmentation applying those parameters. However, the number of objects is directly controlled by the segmentation parameter indeed.

Finally, the total number of segmented objects was 3419 which has been reduced to 2913 after visual examination of edges for each object and editing them accordingly to merge some redundant smaller objects. The performed trials before the final segmentation process indicated that the use of fused of MS and Pan data sufficiently increased the precision of segmentation when compare to MS data only.

II. Classification: The same set of image channels (fused 2, 3 & 4) have been used for classification as well. Besides the statistics report of image channels, two other facts assisted to select those bands although other bands (fused 5 & 6) are having higher standard deviation – (a) the combination band 2, 3 & 4 produce the standard FCC using which identification of classes is easy (b) the multispectral band 2, 3 & 4 cover the frequency range of the high resolution panchromatic image and thus giving better fusion result in those bands.

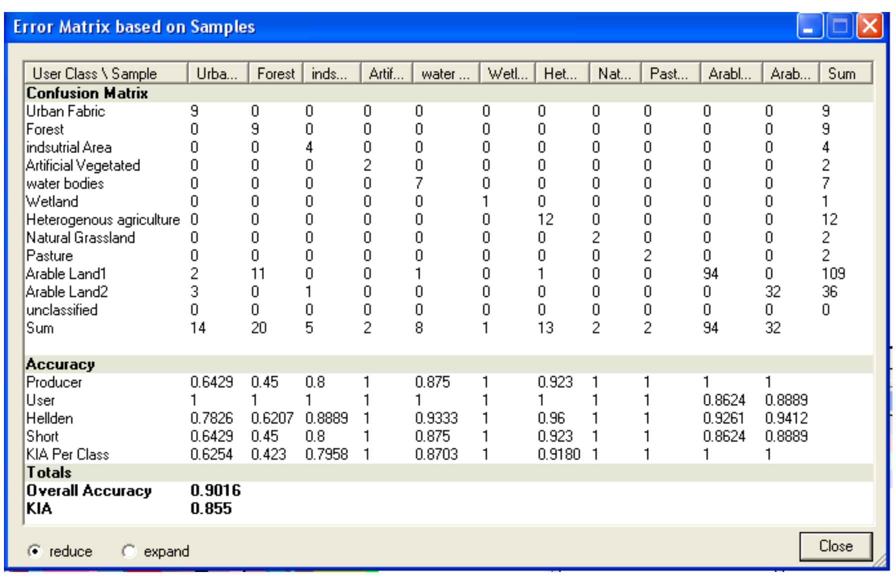
The same class hierarchy (from TM image classification) has been imported to this classification instead of creating a new. But the class description for all has been deleted immediately. Because a new set of classification algorithm is quite obvious because this image is spectrally different from the previous image. The previously collected samples for TM image have been imported here as ‘TTA mask’ which saved some time and helped to collect the samples more efficiently. However, this strategy for using TTA mask was very effective but has to be careful to avoid wrong sample collection. Because the spectral difference, texture and shape of objects are not exactly the same as both images. As a result, chances of collecting wrong samples were quite high. To avoid this problem, each sample have been deleted first and then recollected again. Moreover, a set of CORINE land cover (CLC 2000) data from the year 2000 have also been considered as reference layer for sample collection while necessary.

After the sample collection and classification using SNN method, some classes required to be identified accurately. Several parametric criteria (table- 4.4.4.1) using MF was used further. The specification of those parameters is highly correlated with their shape, texture and semantic information of different objects consisting of classes. After classification, it is still noticeable some misinterpreted classes which had to be generalized considering the minimum mapping unit (MMU). Actually, some linear feature has been recognized wrong as sample were not collected for those features intentionally. Those linear features have a width of less than MMU and thus had to be incorporated into neighboring larger pixels. However, those features have been removed subsequently as a result of generalization.

III. Accuracy Assessment: The presented classification shows the following accuracy showing the error matrix based on training samples (fig.- 4.4.4.1). Original samples were deleted and new samples were declared before creating the error matrix to ensure the credibility of accuracy assessment. The overall accuracy is over 90% with a slightly lower kappa index which around 85%. Please note that the class arable land has two subclasses which also portrayed accuracy parameters separately in the error matrix.

Table- 4.4.4.1: Classification methods for TM & Fused Image

Serial No.	***Class***	***Classification Method (TM)***	***Classification Method (Fused Image)***
1	Urban Fabric	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon), GLCM Dissimilarity (all direction)
2	Forest	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon), Length (L) /Width (W)
3	Industrial or Commercial & Transport Units	1. SNN	1. SNN 2. MF: Perimeter (Polygon), GLCM Dissimilarity (all direction)
4	Artificial, non-agricultural Vegetated Areas	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon), GLCM Dissimilarity (all direction)
5	Inland Waters	1. SNN	1. SNN 2. MF: Perimeter (Polygon), L/W
6	Inland Wetlands	1. SNN	1. SNN 2. MF: Length/Width
7	Heterogenous Agricultural Areas	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon)
8	Scrub and /or herbaceous vegetation associations	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon)
9	Pasture	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon)
10	Arable Land	1. SNN (2 subclasses)	1. SNN (2 subclasses) 2. MF: Perimeter (Polygon) (1 subclass)


Error Matrix based on Samples

User Class \ Sample	Urba...	Forest	inds...	Artif...	water ...	Wetl...	Het...	Nat...	Past...	Arabl...	Arab...	Sum
Confusion Matrix												
Urban Fabric	9	0	0	0	0	0	0	0	0	0	0	9
Forest	0	9	0	0	0	0	0	0	0	0	0	9
indsutrial Area	0	0	4	0	0	0	0	0	0	0	0	4
Artificial Vegetated	0	0	0	2	0	0	0	0	0	0	0	2
water bodies	0	0	0	0	7	0	0	0	0	0	0	7
Wetland	0	0	0	0	0	1	0	0	0	0	0	1
Heterogenous agriculture	0	0	0	0	0	0	12	0	0	0	0	12
Natural Grassland	0	0	0	0	0	0	0	2	0	0	0	2
Pasture	0	0	0	0	0	0	0	0	2	0	0	2
Arable Land1	2	11	0	0	1	0	1	0	0	94	0	109
Arable Land2	3	0	1	0	0	0	0	0	0	0	32	36
unclassified	0	0	0	0	0	0	0	0	0	0	0	0
Sum	14	20	5	2	8	1	13	2	2	94	32	
Accuracy												
Producer	0.6429	0.45	0.8	1	0.875	1	0.923	1	1	1	1	
User	1	1	1	1	1	1	1	1	1	0.8624	0.8889	
Hellden	0.7826	0.6207	0.8889	1	0.9333	1	0.96	1	1	0.9261	0.9412	
Short	0.6429	0.45	0.8	1	0.875	1	0.923	1	1	0.8624	0.8889	
KIA Per Class	0.6254	0.423	0.7958	1	0.8703	1	0.9180	1	1	1	1	
Totals												
Overall Accuracy	**0.9016**											
KIA	**0.855**											

reduce expand Close

Fig.- 4.4.4.1: Error matrix for the classification derived from ETM+ fused image

4.4.5 Classification of Landsat ETM+ PC Image (2000)

Based on the analysis of the result and errors signified by error matrix, an alternative method of classification has been proposed by incorporating principal component analysis (PCA) which has been proved as an efficient and basic technique for LULC change detection. There are many ways to apply PCA technique for classification of LULC and its change discovery. In the present study, a PC image has been generated from the Landsat ETM+ fused image. The technique of combining PCA with OO classification was adopted in this study.

PCA is a common statistical technique rotating the axes of multidimensional image space in the direction of maximum variance (Lillesand & Kiefer, 2004). As it can be perceived from the spatial statistics of the image, there is an extensive inter-band relationship which is frequently encountered a problem for image classification. As a result, most bands of the image essentially convey the same information. PCA technique is used to reduce such redundancy in multispectral bands for better identification of classes during classification. The bands of PCA data are non-correlated and independent, and are often more interpretable than the source data (Sabins, 1997).The technique applied here can be considered as enhancement of image prior to the actual classification. However, it is not always advisable to pursue this technique for all kind of LULC classification as it changes the spectral behavior (colour) of the image which might arise some difficulties for analyst during classification due to inability to interpret confidently as in case of standard FCC or true color images. The attempt has been made to justify the application of PCA as an alternative method of classification.

I. Principal Component Image: Prior to the classification, four components have been created using ERDAS Imagine from fused ETM+ image. Those components have been both visually and statistically analyzed for selecting appropriate image channels for the subsequent classification. The following verdict can be made after examining the statistical reports (table- 4.4.5.1) and the first four PC components of the image (fig.- 4.4.5.1):

- The first two components have majority of data variance (over 90%) with higher standard deviation and virtually explain all of the variance in the image.
- The fourth component has least information amongst four channels.
- The first three components are suitable for as input channels for further classification.

Table- 4.4.5.1: Statistical reports for four pc components of fused ETM+ image

Basic Stats	***Min***	***Max***	***Mean***	***Stdev***
PC1	13.7749	506.1572	131.1964	50.4431
PC2	-9.0809	283.9471	106.7742	26.1807
PC3	-302.9237	-0.0184	-58.809	14.3726
PC4	-73.2478	51.4185	-12.4673	5.5809
Covariance	***PC1***	***PC2***	***PC3***	***PC4***
PC1	2544.5099	28.2478	1.7601	-0.5859
PC2	28.2478	685.427	3.4845	-0.3444
PC3	1.7601	3.4845	206.5708	0.0705
PC4	-0.5859	-0.3444	0.0705	31.1469

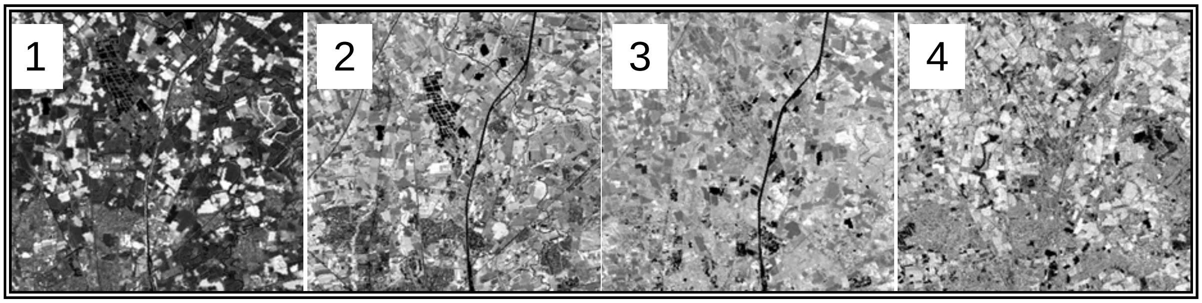


Fig.- 4.4.5.1: Four PC components of ETM+ fused image (1-4)

Principal component (PC) images for classification are normally treated as if they were normal image. So, any three components have to be combined to color composite (CC) image. However, after combining first three components (PC1, PC2 and PC3), the CC image somehow looks dull and shows weak spectral variance between target classes (fig.- 4.4.5.2). An alternative CC (fig.- 4.4.5.2) using PC1, PC2 and PC4 have been generated for using with the classification as it shows adequate amount of spectral difference between classes.

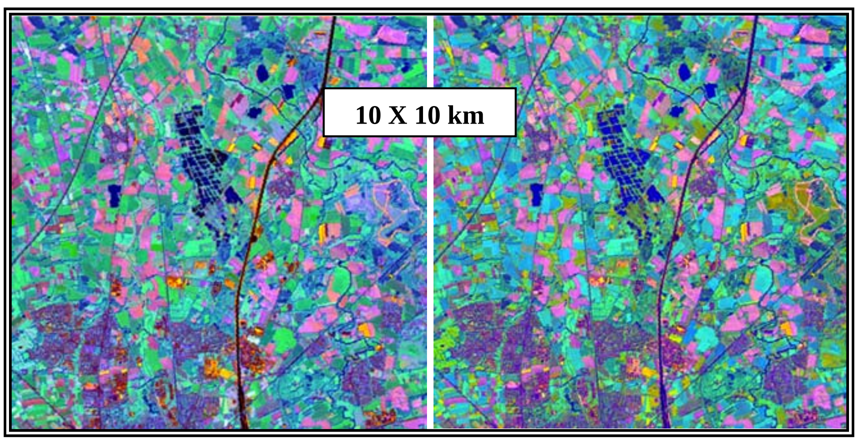


Fig.- 4.4.5.2: Colour composite using PC 1, 2, 3 (L) and PC 1, 2, 4 (R)

For the PC image, OIF vales have been calculated for all possible combination (table- 4.4.5.2). However, only first 4 bands were considered because of high standard deviation. It is evident from the table below is that the combination 134 is best in term of OIF ranking. However, it has low value of sum of standard deviation ($\Sigma\sigma(i)$). The second-ranked was also not selected because of absent of band 1 which has most data variance. As a consequence, the combination of band 124 (it has also higher value of $\Sigma\sigma(i)$) was selected for further classification.

Table- 4.4.5.2: OIF value with rank for possible band composition of TM Image

Rank	GBTM	$\Sigma\sigma(i)$	$\Sigma\|r(i)\|$	OIF
1	134	70.39665	0.005388	13065.45
2	234	46.13417	0.012496	3691.915
3	124	82.20474	0.025828	3182.776
4	123	90.99637	0.033078	2750.963

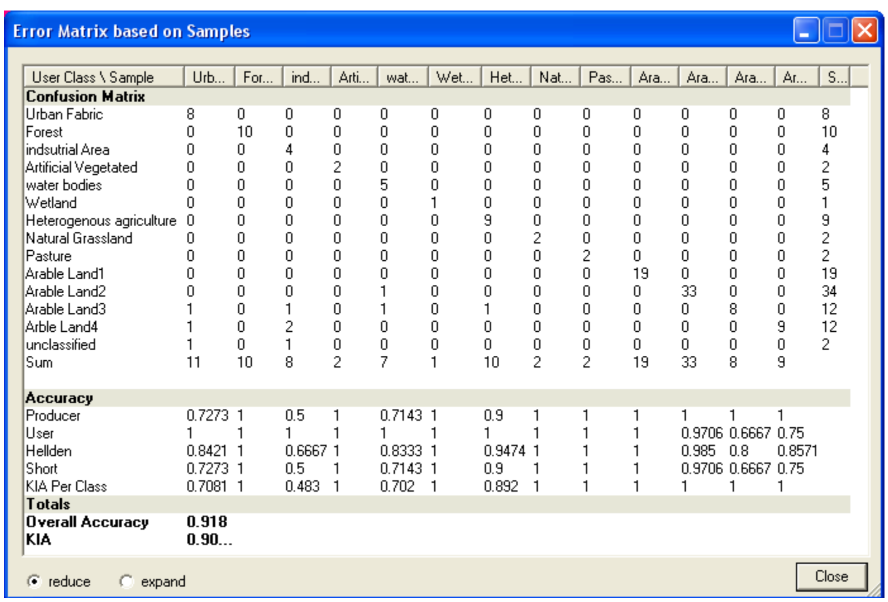
II. <u>Segmentation</u>: The image segmentation parameters for PC image have been deviated slightly from those previous parameters. The parameters used before would have created too many objects in one class in some cases. As a consequence, the parameters have been modified accordingly (see table - 4.4.5.3).

Table- 4.4.5.3: Segmentation parameters for PC Image classification

Level	Channels	Scale	Color	Shape	Compactness	Smoothness	Number of Objects
1	1,2,4	25	0.6	0.4	0.7	0.3	1382

III. <u>Classification</u>: The classification of PC image was performed with the partial help of the classification of fused image earlier. The class hierarchy and sample as TTA mask were imported to this classification. The samples collected for fused image helps to understand the spectral and textural information of classes in the PC image. Moreover, the CLC 2000 layer has contribution during collection of samples as well before classification using SNN method. However, it is to be noted that due to complete unusual spectral characteristics when compare to normal image, a new set of parametric criteria have been developed for using membership function (table- 4.4.6.1).

III. <u>Accuracy Assessment</u>: The classification achieved a higher accuracy (fig.- 4.4.5.3). The error matrix was generated using the same practice followed in case of fused ETM+ image classification where training samples were deleted and a new set of samples were collected which does not cover the area of training samples so that the comparison between two error matrix from two successive classification could be justified.


Error Matrix based on Samples

User Class \ Sample	Urb...	For...	ind...	Arti...	wat...	Wet...	Het...	Nat...	Pas...	Ara...	Ara...	Ara...	Ar...	S...
Confusion Matrix														
Urban Fabric	8	0	0	0	0	0	0	0	0	0	0	0	0	8
Forest	0	10	0	0	0	0	0	0	0	0	0	0	0	10
indsutrial Area	0	0	4	0	0	0	0	0	0	0	0	0	0	4
Artificial Vegetated	0	0	0	2	0	0	0	0	0	0	0	0	0	2
water bodies	0	0	0	0	5	0	0	0	0	0	0	0	0	5
Wetland	0	0	0	0	0	1	0	0	0	0	0	0	0	1
Heterogenous agriculture	0	0	0	0	0	0	9	0	0	0	0	0	0	9
Natural Grassland	0	0	0	0	0	0	0	2	0	0	0	0	0	2
Pasture	0	0	0	0	0	0	0	0	2	0	0	0	0	2
Arable Land1	0	0	0	0	0	0	0	0	0	19	0	0	0	19
Arable Land2	0	0	0	0	1	0	0	0	0	0	33	0	0	34
Arable Land3	1	0	1	0	1	0	1	0	0	0	0	8	0	12
Arble Land4	1	0	2	0	0	0	0	0	0	0	0	0	9	12
unclassified	1	0	1	0	0	0	0	0	0	0	0	0	0	2
Sum	11	10	8	2	7	1	10	2	2	19	33	8	9	
Accuracy														
Producer	0.7273	1	0.5	1	0.7143	1	0.9	1	1	1	1	1	1	
User	1	1	1	1	1	1	1	1	1	1	0.9706	0.6667	0.75	
Hellden	0.8421	1	0.6667	1	0.8333	1	0.9474	1	1	1	0.985	0.8	0.8571	
Short	0.7273	1	0.5	1	0.7143	1	0.9	1	1	1	0.9706	0.6667	0.75	
KIA Per Class	0.7081	1	0.483	1	0.702	1	0.892	1	1	1	1	1	1	
Totals														
Overall Accuracy	**0.918**													
KIA	**0.90...**													

reduce expand Close

Fig.- 4.4.5.3: Error matrix for the classification of ETM+ fused PC image

4.4.6 Classification of ASTER Image (2005)

Final classification was performed based on ASTER satellite image. This image also was from spring season which caused less spectral difference between classes especially those belong to so called 'green' classes due to high level of chlorophyll content. However, careful segmentation of the satellite image which has been next classified using SNN and customized MF was able to classify the image precisely.

I. <u>Segmentation</u>: Since the available image for the study was restricted to 3 VNIR channels, there was no requirement for using functions to select best set of channels for the classification. By default, three VNIR channels were used for segmentation and classification subsequently. Channel 3, 2 & 1 were used to combine to produce standard FCC composite image. It is, in fact, to be noted that those three channels have higher standard deviation value and data variance in the image. The segmentation parameters remain unchanged from the Landsat TM image (see table – 4.4.3.1). Those parameters were applied on channel 1, 2 & 3 with full weight and the number of created objects was 1781 which have eventually been reduced to 1442 using manual editing of objects for fine-tuning.

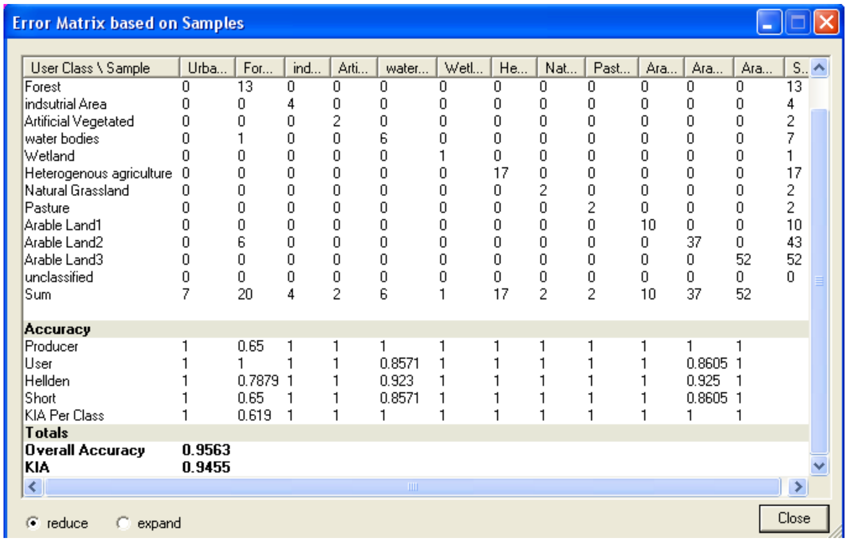
II. <u>Classification</u>: The classification of this image was 'smooth' when compare to previous image. In the phase of training site selection, very few samples were good enough for the classification. An aerial photo of 10 cm resolution from the part of study area was also considered for sample collection whenever it requires. There were not so much confusion between classes – mixed pixels problem between classes were much less than those cases of previous image classification. However, in case of class of 'Arable Land', spectral difference was very high- as a result; three subclasses were required to define the classes accurately. Moreover, membership function (for criteria, table – 4.4.6.1) was required to separate few misinterpreted classes just after the SNN function.

III. <u>Accuracy Assessment</u>: The error matrix for the classification derived from the ASTER image has proved an acceptable level of high accuracy (fig.- 4.4.6.1). However, some rectification should be made after this classification by means of generalization which has been attempted further. This step has been discussed in the next chapter along with an alternative procedure of accuracy assessment after finalizing the classification output. The concept of adopted method of accuracy assessment was taken from CLC 2000 programme (Lima, 2005) where a change layer is created by visual interpretation of the same image used for the corresponding image and editing the classified image accordingly (Lewinski, 2005). Then, this obtained change layer has been used for checking accuracy of performed classification.

The method of accuracy assessment based on existing reference layer has also been attempted in chapter 6. This chapter is a approaching a perspective outlook on the classification of high resolution aerial image and its accuracy assessment based on existing reference layer (rieselfelder land cover data). However, this method of accuracy assessment could also be applied in case of the classification from these three satellite images if corresponding reference layer were available for that purpose.

Table- 4.4.6.1: Land use / Land cover classes and classification methods for ASTER

Serial No.	***Class***	***Classification Method (Fused PC)***	***Classification Method (ASTER)***
1	Urban Fabric	1. SNN 2. MF: Area (including inner polygons)	1. SNN 2. MF: Perimeter (polygon)
2	Forest	1. SNN 2. MF: Area (including inner polygons)	1. SNN 2. MF: Perimeter (polygon)
3	Industrial or Commercial & Transport Units	1. SNN 2. MF: Area (including inner poly), Mean Layer 1	1. SNN 2.MF: GLCM Dissimilarity (all direction)
4	Artificial, non-agricultural Vegetated Areas	1. SNN 2. MF: Area (including inner polygons)	1. SNN 2. MF: Perimeter (polygon),
5	Inland Waters	1. SNN 2. MF: Mean Layer 4, Length/Width	1. SNN 2. MF: GLCM Dissimilarity (all dir), Perimeter (polygon)
6	Inland Wetlands	1. SNN 2. MF: Mean Layer 4, Length/Width	1. SNN 2. MF: Perimeter (polygon)
7	Heterogenous Agricultural Areas	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon)
8	Scrub and /or herbaceous vegetation associations	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: Perimeter (Polygon)
9	Pasture	1. SNN 2. MF: Perimeter (Polygon)	1. SNN 2. MF: GLCM Dissimilarity (all dir), Perimeter (polygon)
10	Arable Land	1. SNN (4 subclasses)	1. SNN (3 Subclasses)


Error Matrix based on Samples

User Class \ Sample	Urba...	For...	ind...	Arti...	water...	Wetl...	He...	Nat...	Past...	Ara...	Ara...	Ara...	S...
Forest	0	13	0	0	0	0	0	0	0	0	0	0	13
indsutrial Area	0	0	4	0	0	0	0	0	0	0	0	0	4
Artificial Vegetated	0	0	0	2	0	0	0	0	0	0	0	0	2
water bodies	0	1	0	0	6	0	0	0	0	0	0	0	7
Wetland	0	0	0	0	0	1	0	0	0	0	0	0	1
Heterogenous agriculture	0	0	0	0	0	0	17	0	0	0	0	0	17
Natural Grassland	0	0	0	0	0	0	0	2	0	0	0	0	2
Pasture	0	0	0	0	0	0	0	0	2	0	0	0	2
Arable Land1	0	0	0	0	0	0	0	0	0	10	0	0	10
Arable Land2	0	6	0	0	0	0	0	0	0	0	37	0	43
Arable Land3	0	0	0	0	0	0	0	0	0	0	0	52	52
unclassified	0	0	0	0	0	0	0	0	0	0	0	0	0
Sum	7	20	4	2	6	1	17	2	2	10	37	52	
Accuracy													
Producer	1	0.65	1	1	1	1	1	1	1	1	1	1	
User	1	1	1	1	0.8571	1	1	1	1	1	0.8605	1	
Hellden	1	0.7879	1	1	0.923	1	1	1	1	1	0.925	1	
Short	1	0.65	1	1	0.8571	1	1	1	1	1	0.8605	1	
KIA Per Class	1	0.619	1	1	1	1	1	1	1	1	1	1	
Totals													
Overall Accuracy	**0.9563**												
KIA	**0.9455**												

reduce expand Close

Fig.- 4.4.6.1:Error matrix for the classification of ASTER image

5 Result and Discussion

This chapter includes final classification results and an alternative method of accuracy assessment as well as detailed discussion about the achieved result. As it has been mentioned before, a generalization technique was adopted for all the classification results. Sometimes a classified result contains data that is erroneous or irrelevant to the analysis at hand or is more detailed than it requires. For instance, if a dataset is derived from the classification of a satellite image, it may contain many small and isolated areas that are misclassified or are too detailed for the present purpose. In the present case study, some classes were below the minimum mapping unit. As a consequence, generalization using ArcGIS was performed for all classification result to assign those small classified areas to relevant larger classes and to dissolve the boundary between same classes.

5.1 Accuracy Assessment

Before using the classification result from satellite images for change detection, it is important to test the result against any reference data or ground truth data. In some cases, if the satisfaction is not up to the mark, the classification needs to be repeated or updated (Shamaoma, 2005). The most common way of accuracy assessment for any application of remote sensing is creating an error matrix or confusion matrix (Foody, 2002) which has been used in the previous chapter.

An alternative method of assessing the accuracy of classification was executed besides the method of error matrix method by Definiens Professional. The purpose of approaching error matrix method is to derive final accuracy or reliability figures by means of independent and more accurate data. This method of creating error matrix based on reliable reference data has also been followed in case of aerial image classification in the next chapter. Some non-spatial statistics such as producer accuracy, user accuracy, overall accuracy and kappa coefficient were generated from error matrix. Although these measures are in widespread use, but none of these statistics explicitly considers the spatial distribution of misclassification. The method adopted here is to show the spatial distribution of classification errors, and which presents the user with a visual indication of the reliability of classification. Having an outstanding result of statistics (value), the spatial distribution of error for each class might not be the same for entire study area. Looking at the spatial distribution of the errors can help to refine the classification process further whenever necessary. It shows the specific class or polygon that needs to be classified again.

The determination of the spatial distribution of the errors in LULC classification is carried out by directly comparing classification with their respective reference classification maps (change layer). Those reference layers have been created by visual interpretation of corresponding images according to the way suggested in case of the CLC 2000 project (Lima, 2005). The classification result (raster) was converted into vector. Next the analyst examined the classification with displaying the images in the background and edited the edges of polygons and attributes of classes whenever required for correctness. As result of interpretation, a different layer (sometimes, it is called change layer) has been obtained for each classification (Lewinski, 2005). This obtained change layer was used as a reference layer to show the spatial distribution of error for all the classification results.

For this phase of accuracy check, two approaches were used. First error maps (or images) were generated for visual comparison of errors by subtracting the classified layer from obtained change layer. The error image for each case has three attributes mainly- correctly labelled, incorrectly labelled and unrecognized. The workflow for the method of accuracy assessment is given below (fig.- 5.1.1)

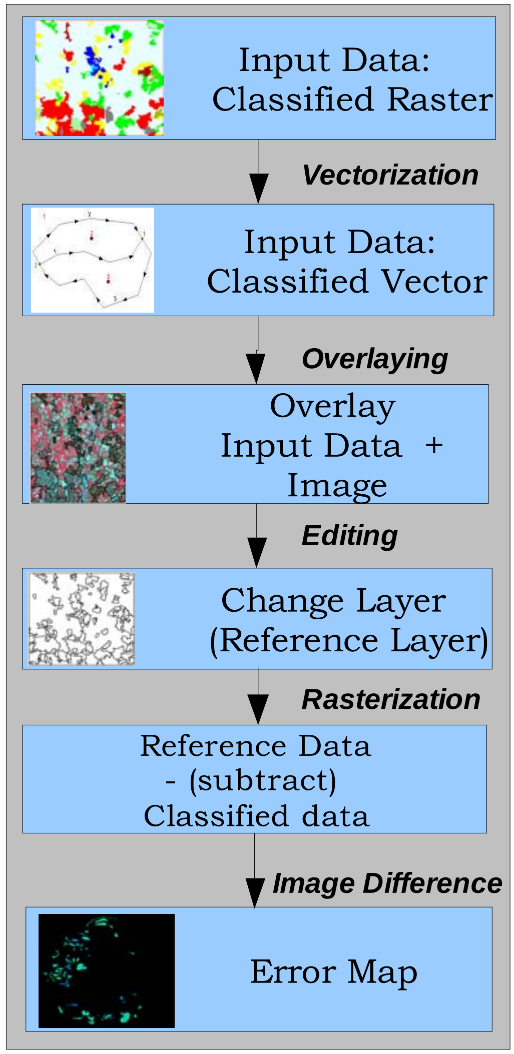


Fig.- 5.1.1: Workflow diagram for accuracy assessment

Four sets of error images were generated (Fig.- 5.1.2 & 5.1.3) for four cases of classification by the same way of image subtraction using raster calculator in ArcGIS Spatial Analyst. The consequential error image show those pixels (or classes) which are having different value in classified image from corresponding reference data image. This way the error image gives three types of value (or attributes) which can be described as correctly labelled which are classified as correct class, incorrectly labelled which are classified as different class i.e. misinterpretation and unrecognized which could not be classified.

Apart from visual impression of spatial distribution of error, a comprehensive quantitative assessment is always an advantage of accuracy check. The same way, it has been approached for error matrix, could be followed here. However, there were some technical difficulties in this regard. In the previous case, the error matrix has been generated by Definiens professional software after the final classification. The software can not import any external shapefile (the final classification result after generalization) and generate the error matrix. It has also been attempted with ENVI but failed as ENVI needs the used file in ENVI classification format. Other software like ERDAS Imagine and PCI Geomatica create error matrix based on sampling method which was not considered here. To avoid these difficulties, simple calculations have been made to show the percentage of those errors in each case (table- 5.1.1 & 5.1.2).

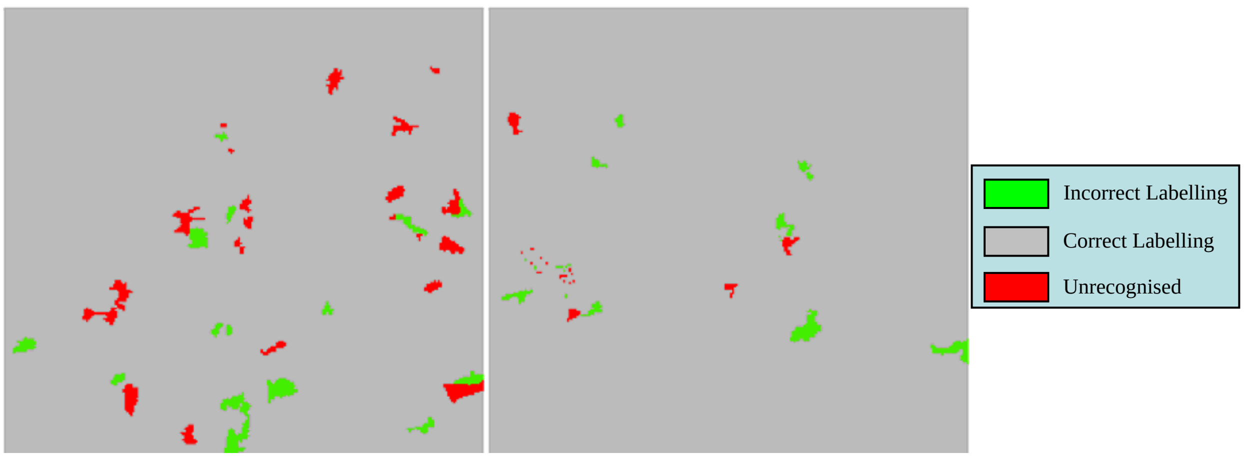


Fig.- 5.1.2: Error map for the classification of Landsat Fused, 2000 (L) & its PC Image (R)

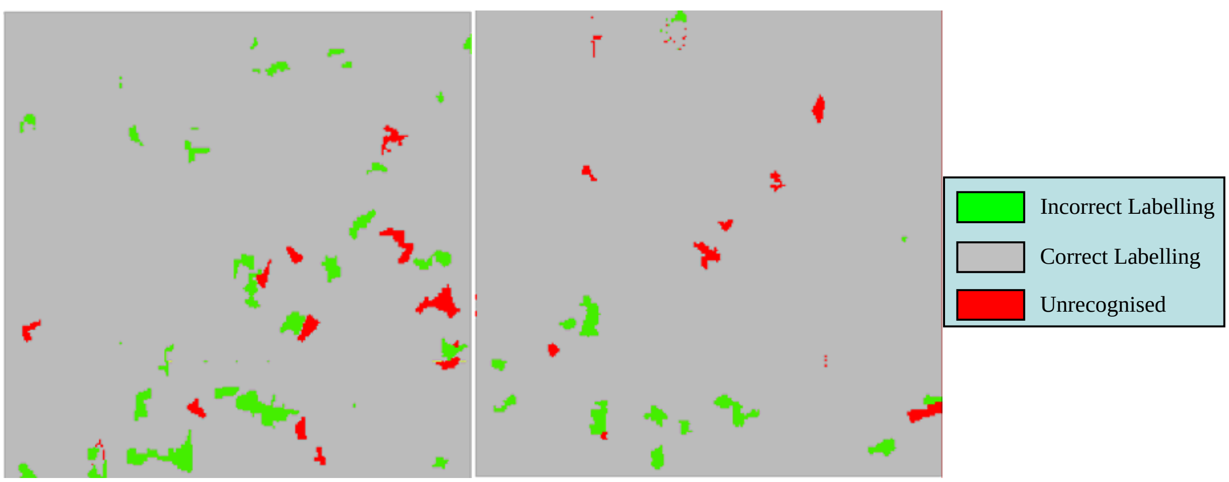


Fig.- 5.1.3: Error map for classification of Landsat TM, 1990 (L) & ASTER Image, 2005 (R)

There are mainly two types of errors in the classification – (i) incorrect labelling which refers to misinterpretation or attribute of class is given wrong, (ii) unrecognized which refers that the classification was unable to detect or identify certain polygon of some classes. Actually, in broad sense, there is no error under this type as there were no unclassified pixels in the classification. But the class which has been classified as 'Arable Land' instead of some other classes is considered as unrecognized. On the other hand, the class which has been classified wrongly as some other classes excluding the class of arable land is considered as incorrect labelling.

Table- 5.1.1: Percentage of error for the classification of TM and ASTER images

Accuracy for TM Classification				Accuracy for ASTER Classification	
Error Type	***Error (sq.m)***	***Error (%)***		***Error (sq.m)***	***Error (%)***
Correct	96470459.9654	95.87		98116798.6943	97.96
Incorrect	2893630.722	2.88		1355766.6263	1.3536
Unrecognized	1260830.7487	1.25		687498.6793	0.6864

Table- 5.1.2: Percentage of error for the classification of fused and fused PC images

Accuracy for Fused Classification				Accuracy for Fused PC Classification	
Error Type	***Error (sq.m)***	***Error (%)***		***Error (sq.m)***	***Error (%)***
Correct	97270794.0988	96.93		99308408.4158	98.96
Incorrect	1364832.2849	1.36		773940.1898	0.77
Unrecognized	1719688.6789	1.71		272966.4570	0.27

Some inferences can be drawn from the observation of error maps and the percentage of different types of errors as well from the error matrix created in the previous chapter. It is highly noticeable that the spatial distributions of error vary from one to other. Some of the contributing reasons for such discrepancy can be explained as follows:

- Most importantly the error in case of classification of fused and ASTER images are quite less when compare to others. It proves the advantage of higher spatial resolution which directly affects the quality of LULC classification. However, the error for the classification of Landsat TM image is very less as shown by error matrix (fig.-4.4.3.2). As a consequence, this statement is not true only when we consider the error statistics in error matrix.

- Although the resolution of Landsat fused image is higher than Landsat TM, but the classification result from both of them have almost same amount of error. However, the unrecognized error is even more in case of fused image. The enhanced image of fusion techniques distorts multi-spectral information contains in the original image, which reduces the spectral difference between land cover to be classified. The pixel value is not stable within the same land cover class.

- On the other hand, fused PC image gives far better result when compare to the fused image. This is probably due to higher data variance of images within first two components which further improves the spectral difference between land cover classes.

- The higher accuracy of fused PC classification, compare to ASTER image, shows that not only the spatial resolution but also spectral difference enhances the classification accuracy.

- The accuracy check in this case yields very high, which supports the accuracy assessment by creating error matrix.

- It is to be noted that one of the reason for achieving high accuracy in the present study is presence of very few classes and most part of the study area covers one major land cover which is 'arable land'. The higher number of classes and detailed classification nomenclature (level 3 & 4) increase the probability of lower accuracy which is not the case here.

It is to be noted that some of the conclusion drawn above, can only be strongly justified if some differences in result are noticed statistically. The error matrix method could not be followed here due to some difficulties discussed before. As consequences, some statistical measurement (overall, producer and user accuracy with kappa index) is highly desirable in future. However, the error matrix created for each classification method in the previous chapter indicates that the results are statistically different which supports the most of statement above. But the justification of high error in Landsat TM image classification as shown by the error map (fig.-5.1.3) and calculation of error percentage (table- 5.1.1) is not supported by the error matrix (fig.-4.4.3.2)

5.2 Classification Result

Since the change detection method adopted here is completely dependent of individual classification, it is imperative to display the classification result from each classification method. These results from all the classifications have further been used for calculation of change detection information.

Two approaches were used to show the result. At first, the classified images have been displayed immediately after the classification (fig.- 5.2.1). It is to be noted that those classified images are the primary result of classification before generalization using ArcGIS. Secondly, the classification output (as vector, after generalization) has been overlaid with corresponding image. The classes have been shown as polygon vector in different colour according to the legend. This technique was followed to show the result along with fact how accurately the polygon of each class follows the same group of pixels defining the corresponding class. This is a visual impression of the classification result, which should not be considered explicitly for accuracy judgment.

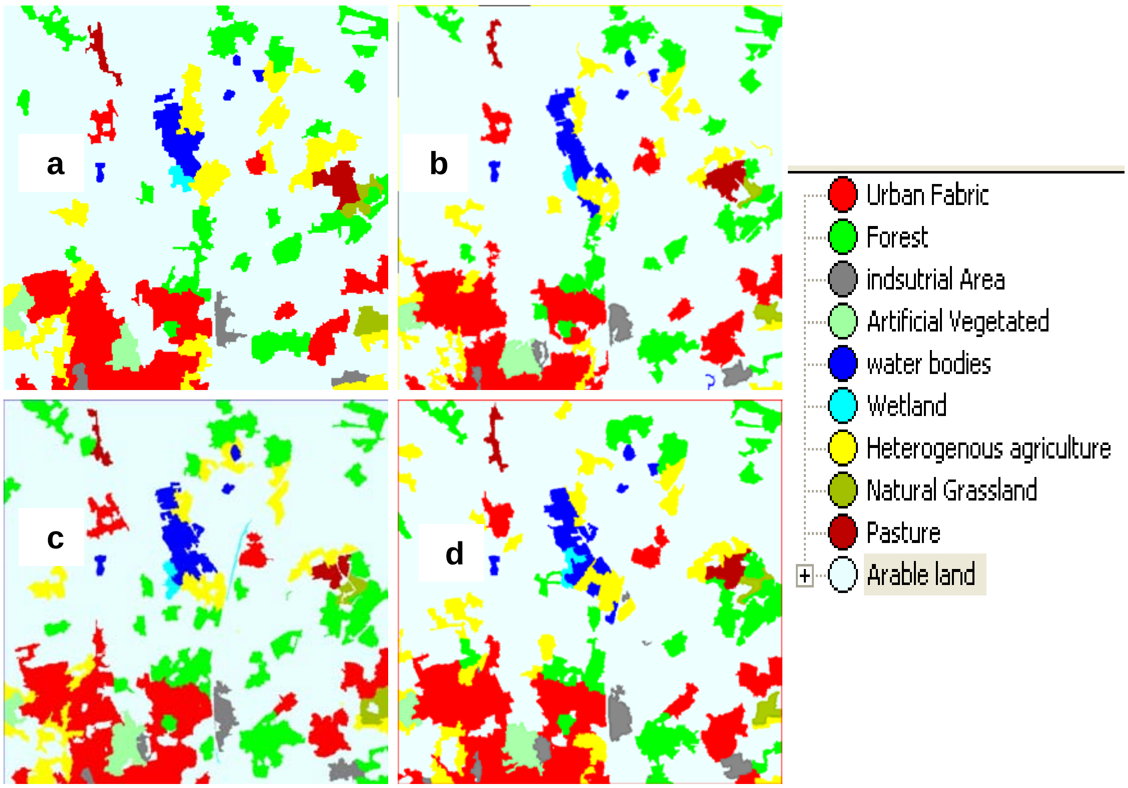


Fig.- 5.2.1 (a-d): Classified images derived from TM, Fused, Fused PC & ASTER images

It is to be noted that the classification result could be laid over German basic maps (DGK 5) which has not been done for several valid reasons:

- The scale of DGK 5 map is 1:5000 whereas the classified output is on 1:100000 as per CORINE nomenclature.
- Although those basic maps can refer to some land cover classes but it can not be compared with classification having land cover which are not described by DGK 5 map.
- The DGK 5 map is too detail to read when it is used as overlay with derived classification result.
- The canal and river channels shown by DGK 5 could not be classified in the present classification studies as those were below the minimum mapping unit.
- Most importantly, the DGK 5 maps are not from the same time period of acquisition time of those images.

As a consequence, the same image has been chosen for displaying the classification results overlaying with them. The classification results have been shown in the following figures (fig.- 5.2.2 and 5.2.3 respectively). From the figures, it is clearly evident that each polygon correctly describes the different patches indicating land cover classes. However, this is not a precise indication of accuracy. But the technique of displaying result in this manner includes some visual impression to the reader for comparison with the accuracy statistics. Secondly, area of each class has been provided in the following table (table- 5.3.1) which has been placed together with the change detection results.

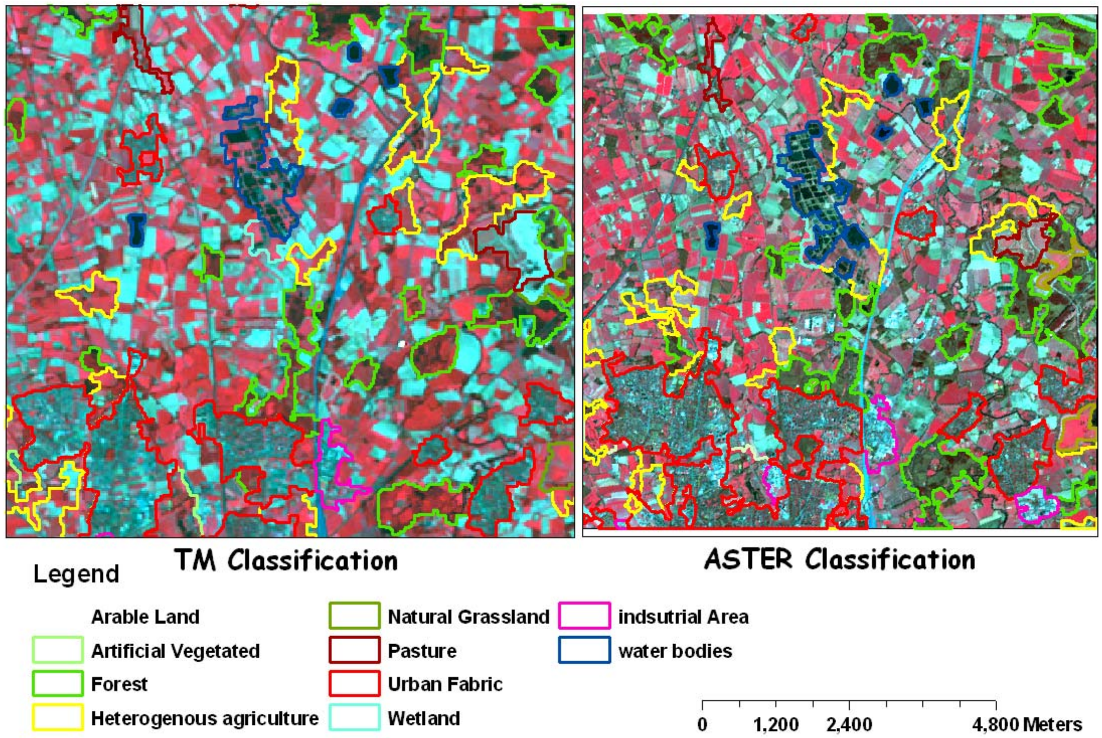


Fig.- 5.2.2: Classification result from Landsat TM and ASTER images

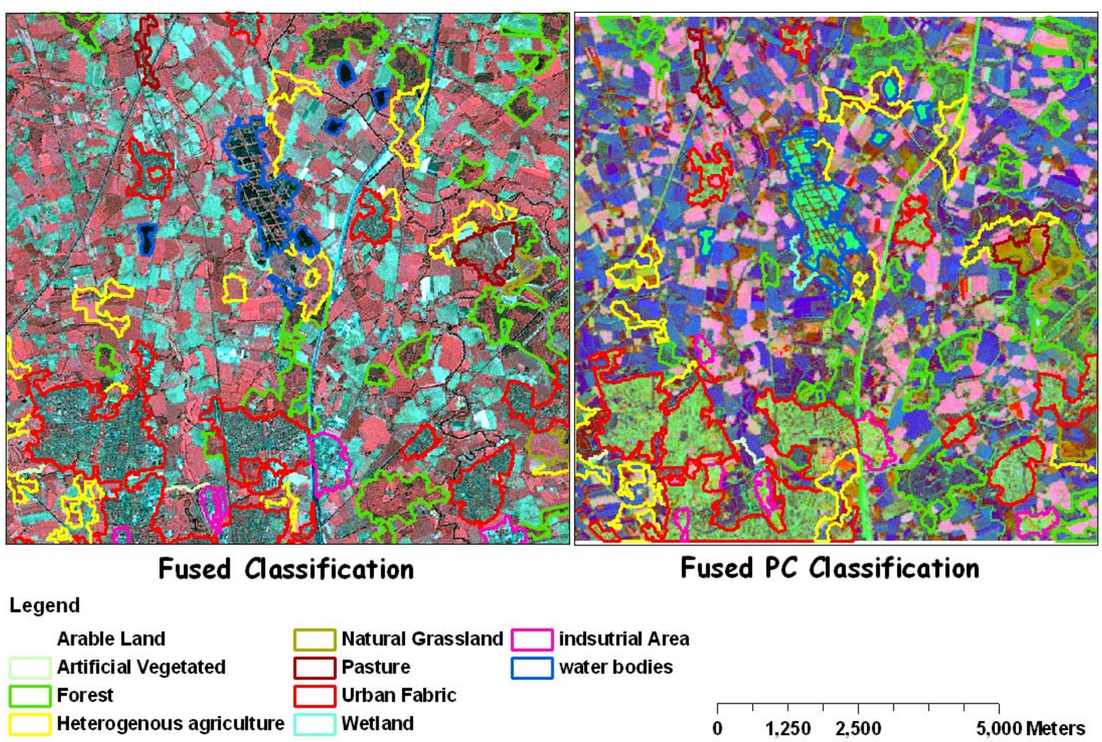


Fig.- 5.2.3: Classification result from Fused and Fused PC images

5.3 Change Detection

Post classification change detection method was applied for the present study. The post classification method is the most widely used and has been adopted here for following reasons:

- The accuracy of change detection is dependent on the accuracy of individual classification which can be reclassified or updated easily whenever necessary.
- Pre-classification method provides the change information by attribute of "change or no change" only.
- To avoid the problems those arise due to different properties of multi-source images and due to co-registration since each image have been classified independently.
- Individual classification of time-series images produced a historical set of LULC data which can be used for some other applications as well.

The method of post classification consists in overlaying the classified images, using the cross operation, to be compared for change detection. The cross operation using two classified images from different time allows the interpreter to know the extent and nature of changes in LULC – transition between different land cover classes and corresponding area of change. Since the final change classes resulting from cross operation are quite numerous and time consuming as well as slight difference in co-registration between data might result misinterpretation of changes, it has been decided to confine the change analysis to the perspective of area change for each class where area of each class have been calculated individually to show the area change for each class. Moreover, the study is more focused on suitability of applied change detection method instead the result of change detection.

The detail change detection analysis has been provided in the table- 5.3.1 and 5.3.2. However, it is to be noted that the classification result from fused image (marked red in the table) has not been considered as the result from fused PC image producing better result. The classification result indicates that the study area is mostly covered by arable land as the mainstay of majority of the region is farming. The area covers by a relatively higher amount of forest, settlement (urban fabric) and heterogeneous agriculture. The land cover classes such as water bodies and wetlands are mainly confined to the sanctuary. However, few scattered water bodies are also noticed away from the sanctuary as well. Most importantly, it is to be noted that the classification result does not classify canal and rivers which are below the minimum mapping unit. This is also true for road and transport network which have been considered under the class of urban fabric. However, the roads and street, apart from those are within the settlement patch, are generalized to the nearest larger pixel according to the rule of minimum mapping unit. So, it is quite obvious the change detection in relatively smaller class (level 3 and higher) is not considered in the study.

Table- 5.3.1: Classification Result (1990, 2000 and 2005)

Class	Area (km²) 1990	Area (km²) 2000	Area (km²) 2005	Area (km²) 2000
Arable Land	70.00	67.89	66.80	71.57
Artificial Vegetated	1.23	1.51	1.30	1.17
Forest	7.50	9.11	8.80	7.41
Heterogenous Agriculture	6.50	5.65	5.70	4.70
Natural Grassland	0.90	0.81	0.65	0.52
Pasture	1.10	0.83	0.90	0.90
Urban Fabric	10.30	10.68	12.22	10.74
Wetland	0.25	0.25	0.25	0.16
Industrial Area	0.98	1.40	1.50	1.16
Water bodies	1.60	2.23	2.24	2.03
Total Area	100.36	100.36	100.36	100.36

Table- 5.3.2: Status of LULC Change Detection

Class	Change (1990-2000)		Change (2000-2005)		Change (1990-2005)	
	Area (km²)	**(%)**	**Area (km²)**	**(%)**	**Area (km²)**	**(%)**
Arable Land	-2.11	-2.10	-1.09	-1.09	-3.20	-3.19
Artificial Vegetated	+0.28	+0.28	-0.21	-0.21	+0.07	+0.07
Forest	+1.61	+1.60	-0.31	-0.31	+1.30	+1.30
Heterogenous Agriculture	-0.85	-0.85	+0.05	+0.05	-0.80	-0.80
Natural Grassland	-0.09	-0.09	-0.16	-0.16	-0.25	-0.25
Pasture	-0.27	-0.27	+0.07	+0.07	-0.20	-0.20
Urban Fabric	+0.38	+0.38	+1.54	+1.53	+1.92	+1.91
Wetland	No Change	No Change	No Change	No Change	No Change	No Change
Industrial Area	+0.42	+0.42	+0.10	+0.10	+0.52	+0.52
Water bodies	+0.63	+0.63	+0.01	+0.01	+0.64	+0.64
Total	6.64	6.62	3.54	3.53	8.90	8.87

The result of the change detection analysis exhibits significant changes of LULC in the study area in three different periods (from 1990 to 2000, from 2000 to 2005 and 1999 to 2005). The most interesting fact is that the rate of change for different time period is quite consistent (0.6 to 0.7% per year). There is no change in area for the class of wetland through time, however, a small of change in aerial extent have been noticed after cross-operation between results. In all other classes, changes have been noticed but in some cases changes are too small- which can be generalized as "no change". As for example, change in water bodies for the time period of 2000-2005; the change is 0.01% which is very negligible, thus can be considered as "no change". Actually, this observable fact is sometimes the effect of automatic classification. The polygon of one particular class does not follow exactly the same way between multi-date images. But this is not the case in visual interpretation where analyst keep the classification result from previous images as background layer when interpreting another temporal image of the same study area to check the change in real-time interpretation and thus update the land cover classes in the present image.

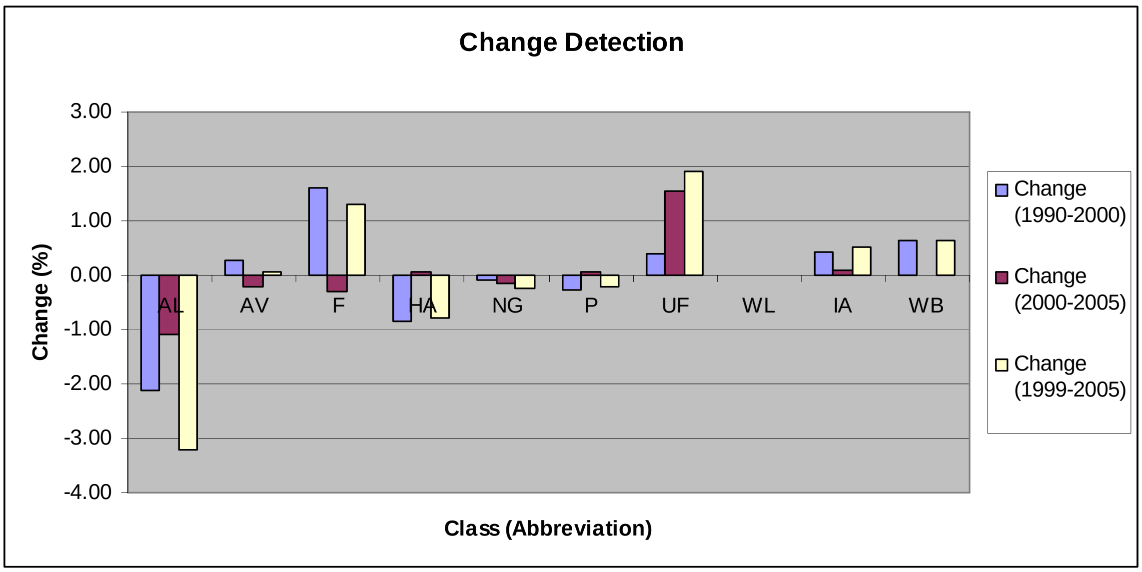


Fig.- 5.3.1: Change in area of different land use / land cover classes

The class of urban fabric has been increased through time; it is highly noticeable between the time period of 2000 and 2005. This is the same truth for industrial area but most rises took place between the time period of 1990 and 2000. Some new industries have been identified in the classification of 2000 image. Farming land witnesses a small amount of decrease both in case of arable land and heterogeneous agriculture except 0.5% increase of heterogeneous agriculture in the period of 2000 and 2005. A complete picture of the LULC change of the study area has been given above (fig.- 5.3.1). The minus value indicates decrease in area whereas plus indicates for area increase.

6 Aerial Image Classification & Analysis

This chapter is an additional count to the study which is based upon object oriented classification of an aerial image. The primary intention for this part of study is to provide a perspective view on land use / land cover (LULC) classification of very high resolution image and its accuracy assessment based on an existing high quality reference data. An aerial image with 10 cm resolution covering the part of study area was available for the study. A detailed LULC layer from Survey & Cadastre, Stadt Münster (rieselfelder) was available for the accuracy assessment. The rieselfelder data is a very comprehensive LULC data which has been classified by visual interpretation based on high resolution images. As a consequence, the data can be highly used for the accuracy assessment of the classification of aerial image.

I. Segmentation: The original image (with 10 cm resolution) was over 3 GB which is huge and demands very high configured machine and high processing time. To avoid this problem, the image has been down sampled to reduce the resolution (1.5m) for better handling. It avoids creating too many objects within the same class as well. The final segmentation was completed after several attempts (trial and error method) as the aerial image is different from the previous satellites images in terms of spatial and spectral resolution. Due to higher spatial resolution, it requires higher scale for the segmentation parameters which has been listed in table- 6.1.

Table- 6.1: Segmentation parameters for Aerial Image classification

Level	Channels	Scale	Color	Shape	Compactness	Smoothness	Number of Objects
1	1,2,3	55	0.8	0.2	0.5	0.5	1361

II. Classification: After proper segmentation, a new class hierarchy has been created for this image. The same CORINE nomenclature is followed. However, the data used for accuracy assessment is not based on CORINE nomenclature. As a consequence, the classes for that have been assigned according to the CORINE programme so that it can be used for this classification. It is important to note that the class definition for this data is different from CORINE and thus can not be directly comparable. As for example, the ‘water bodies’ class of CORINE has been considered as wetlands in rieselfelder data. The training samples were collected considering this fact. In total, 9 classes have been identified amongst which some classes have two subclasses as those classes have diverse spectral behavior. Both the standard nearest neighbour (SNN) and membership function (MF) were used for the classification. Apart from the different membership functions used previously for previous images, use of a new function – GLCM entropy has been introduced here. This entropy function have been found as very useful for separation of forest from scrub and pasture classes.

III. Accuracy Assessment: Although the classified result has some misinterpreted classes but overall it shows very good result having overall accuracy of 97.22% with kappa value of 0.9638 when the error matrix has been created based on collected samples.

For the accuracy assessment of aerial image classification, an alternative concept (which is different from as the classification of satellite images) was proposed. Instead of creating changed (reference) layer by visual interpretation, an existing reference layer from survey and cadastre department of Stadt Münster (rieselfelder) has been used. Before using that layer, a visual inspection has been carried out for checking and editing as per requirement. The data has very detailed (up to level four) LULC classification- as a result, it is not compatible for the accuracy assessment. Each class has been assigned to level 2 of CORINE nomenclature so that it can directly be used for the assessment.

Another set of error (confusion) matrix has been generated based on this rieselfelder data considering it as TTA mask. Hence, the error matrix shows very good result but a substantial amount of error also persists in some classes. This error is more apparent (maximum when compare to other classes) in class 'urban fabric', which was quite obvious. Before explaining the reason, it is to be noted that that class mainly here refers to road and transport network (in the rieselfelder layer) which had to be included under urban fabric as per CORINE nomenclature (in level 2). So, the resolution of the image (1.5m) was not adequate for identifying the roads which demands very high resolution image. Moreover, it is nearly impossible to create the image objects as same as the way visual interpretation can deliver. Apart from the urban fabric, the class 'scrub (and / or herbaceous vegetation associations)' has high error too. This is due to the confusion between scrub and pasture as those classes have almost same spectral behavior and textural characteristics. Most importantly, the rieselfelder data is not from the same year as the aerial image. There should have some changes between land cover in two datasets. Moreover, the rieselfelder data has been co-registered with the aerial image, which has created some geometric error as well. However, the rieselfelder is the most recent data but could be used for accuracy with classification of aerial image from the year 2006.

Table- 6.2: Confusion matrix for the classification of aerial image, 2006 based on TTA mask using reference data (rieselfelder)

User \ Referenc...	Arable Land	Artificial vegetated	Forest	Industrial...	Inland waters	Pastures	Scrub	Urban fabric	Inland wetlands	Sum
Confusion Matrix										
Arable Land	627904	158	9760	204	362	34798	6580	18875	53218	751859
Artificial vegetated	32	1549	0	0	0	221	0	23	0	1825
Forest	20537	0	234348	0	4588	14411	2034	7330	5601	288849
Industrial areas	5682	0	825	10883	161	221	403	3026	137	21338
Inland waters	747	52	852	221	32232	215	5725	383	914	41341
Pastures	50086	730	3603	377	176	203134	2898	7957	27960	296921
Scrub	13245	0	1500	549	2905	6797	23711	1762	1139	51608
Urban fabric	24212	146	1248	55	282	11658	4774	56171	35591	134137
Inland wetlands	157423	0	6203	583	169	30694	1428	21458	603219	821177
unclassified	2533	99	706	28	279	1100	545	209	168	5667
Sum	902401	2734	259045	12900	41154	303249	48098	117194	727947	
Accuracy										
Producer	0.6958	0.5666	0.9047	0.8436	0.7832	0.6699	0.4930	0.4793	0.8287	
User	0.8351	0.8488	0.8113	0.51	0.7797	0.6841	0.4594	0.4188	0.7346	
Hellden	0.7591	0.6795	0.8555	0.6357	0.7814	0.6769	0.4756	0.4470	0.7788	
Short	0.6118	0.5146	0.7474	0.4660	0.6413	0.5116	0.312	0.2878	0.6377	
KIA Per Class	0.5583	0.5662	0.8917	0.8422	0.7794	0.6236	0.4819	0.4487	0.7404	
Totals										
Overall Accuracy	**0.7426**									
KIA	**0.6565**									

From the analysis of classification result (fig.- 6.1) and overall accuracy assessment, the following points are evident:

- The classification achieved an acceptable amount of accuracy. Although the overall accuracy is below 85%, but this obvious as both data are not from the same year and thus it is not directly comparable.

- The automatic classification in object oriented approach can save the time of visual interpretation but can not replace it especially when the level of accuracy and that of classification have to be very high.
- Utilize of existing reference data for accuracy assessment seems better when compare to the concept of visual interpretation where the result is driven by analyst knowledge and influence.
- The use of existing reference data for accuracy assessment has some limitation as well, as for example- class definition and level of class as well as date of creating the database have to be same.
- To ensure the concrete accuracy, a reference data from the same time frame is essential which can assure whether the classification has to be repeated. In the present case scenario, the error matrix based on reference data can not suggest to repeat the classification as the reference data is not directly comparable (for different time of creation and different nomenclature).
- As a consequence, since the accuracy based on samples is much higher, the result has to be considered as accurate for further use.

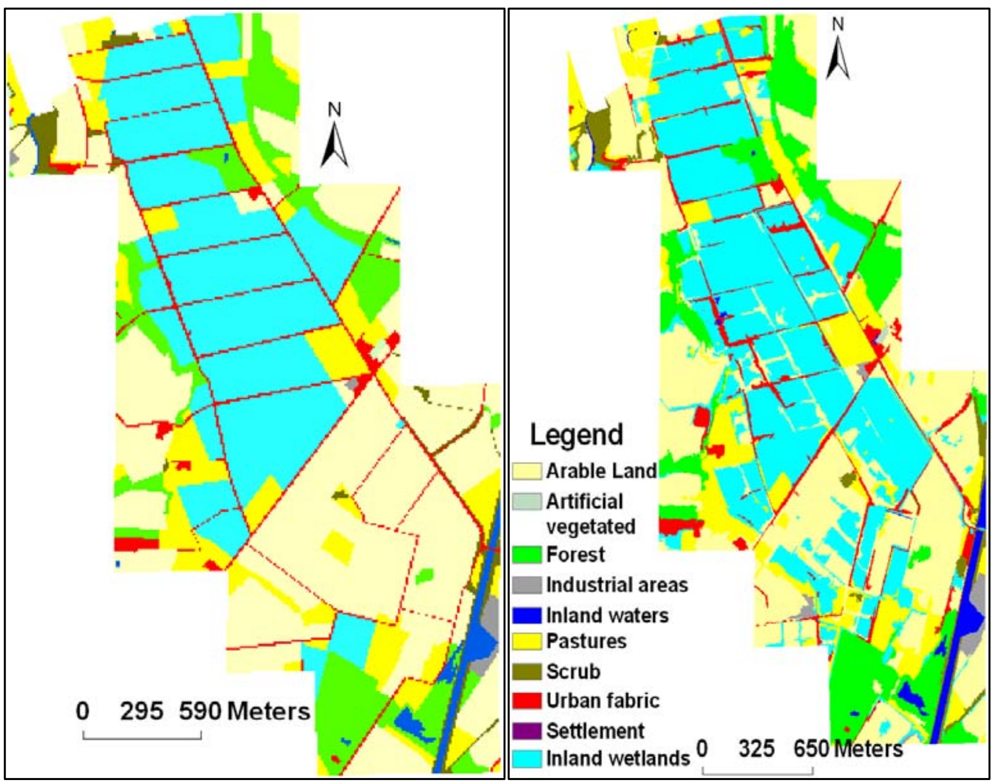


Fig.- 6.1: Reference data (rieselfelder) (L) and classification result from aerial image (R)

7 Conclusion and Recommendation

The purpose of the present work is to develop an effective method for accurate land use / land cover (LULC) change detection with special emphasis on object oriented classification of three temporal images of the study area. The study has also revealed the usefulness of various remote sensing data and analysis techniques in the context of LULC change detection. Referring to the methodology adopted in this study, several conclusions can be drawn for assessing the productivity of this research work and for using them as actuality in case of performing the work in same line of approach in future. Those conclusions are the result of successful completion of the research work considering the data availability, time and objectives of present work. Although the results form the work is very promising, the conclusion drawn here is driven by an experience of diverse result. However, those conclusions are precisely proficient to answer the research question made before conducting the research work. Conclusions are discussed in a hierarchy manner in order to address the research questions. At the end, some recommendations have been pointed out for improvements in future.

7.1 Conclusion

Despite many factors controlling the selection of suitable change detection approach from wide ranging methods, the used approach in the present study proved very effective to fulfill the objectives with successful implementation. To support this viewpoint, the following conclusions can be illustrated as observed from the analysis of the result:

a) The classification result clearly shows that the employ of used satellite images were very helpful for extracting LULC for change detection considering the level of classification (CORINE nomenclature, level 2). It is nonetheless to state that there is a great impact of spatial resolution (and spectral resolution as well) on any kind of remote sensing (RS) application. This impact of resolution was also evident in this study. The classification accuracy was fairly related to the resolution of image. As a result, the ASTER & PC image gives better accuracy. However, the classification accuracy was much higher than the acceptable accuracy (85%) in every classification. The classification from aerial image shows better result in the logic that it identified the classes in more detail especially the linear features (roads and canals).

b) The study explores a successful use of the object oriented (OO) approach for LULC change detection. The OO method for the classification of LULC and its change detection has proven very efficient as it offers multiple tools and features considering textural, contextual and semantic information of the images. Although the OO method seems to be effective for high resolution images, it proved effective also for the satellite images like Landsat TM. However, it is to be mentioned that the OO methods using medium and high resolution are not very effective for detailed mapping considering the level 3 and 4 of classification nomenclature where more 'small classes' have to be identified clearly. This is the possible reason why the classes below minimum mapping unit (like canal and roads) could not be identified in this study.

(c) The use of principal component analysis (PCA) was demonstrated to be satisfactory for improving the change information. The accuracy assessment methods of both error matrix and visual interpretation revealed that the use of the PC image has greatly influenced the classification result. According to the error matrix report, the PC image produced even better result than the ASTER image. However, visual analysis does not support at this end but clearly proved the improvement of classification after applying PCA technique.

d) For the verdict of classification, the error matrix based on samples by Definiens professional software was reasonably satisfactory. However, since the matrix was created based on collected samples, there has been requirement to pursue an alternative method of accuracy assessment along with spatial distribution of error. It is important to mention that this alternative method can, in overall, justifies the accuracy statistics created by the Definiens software. In short, the tool for accuracy assessment offered by the software is technically robust. But an alternative method is always required especially when the representation of spatial distribution of error for all land cover classes in the study area have to be considered. It is easy to identify the polygons for each class which are to be corrected by re-interpretation or by repetition of classification until the require accuracy is achieved. Moreover, an additional step for accuracy assessment has strengthened the accuracy of classification result and thus ensures the accurate change detection of the study area.

e) The two classifiers in OO method - nearest neighbour (NN) and membership function (MF) have been utilized. The NN classifiers have flanged advantage because it is very fast and easy handling of class hierarchy for the classification. On the other hand, MF demanded precise class definition which needs time and knowledge about the object information but it proved to be best for separating the classes accordingly. The software allows highly refined and specialized MF for discrimination between finer classes, which in more complex case increases the accuracy even further. The membership functions customized for images must be different so that it can adapts according to the properties of images. The class hierarchy used for all classification remained same with some minor changes improved the process and saved some time as well.

f) Post classification technique has been found as suitable method for the study. This method was applied for quantitative change detection after the classification images by comparison of results. The change is quantified by differencing classification results. The technique of combining OO approach and post classification turned out better accurate result when compare to simple image difference where the change is based on “change / no change” information.

g) Application of the PC image has increased the accuracy when compare to the fused image due to high data variance in the PC components with low correlation coefficient between bands. This is a clear indication of impact of spectral resolution on the classification of image. Higher spectral resolution means high spectral difference between objects which improves the image segmentation and subsequent classification. It must be said that the classification of ASTER could be more accurate if other image channels were available additionally.

h) The approached means of studying change detection identified a significant amount of changes in three time periods. However, those changes have some inaccuracies as well. But since each classification achieved a higher level accuracy, the derived change information is acceptable. However, it is quite obvious that more accurate change information could be obtained if the ‘change layer’ for each classification would be used instead of the classification result itself. The extent and spatial pattern of class change is different in three time periods whereas the rate of change per year is almost consistent throughout time.

i) The classification result from aerial image is very promising. It shows the result as close as the land cover data from Stadt Münster (rieselfelder). This land cover data has also been successfully used as reference layer for assessing the accuracy of classification from the aerial image. The use of existing layer as reference for accuracy assessment was justified. As in case of creating change layer by visual interpretation, the analyst might be biased by the knowledge or experience of the study area. Moreover, it is very time consuming process especially when the area of study is very large (which is, however, not the case here). The classes identified by the classification of aerial images are mostly accurate but not exactly matching with the 'rieselfelder' data. Although the aerial image has been lost some detailed information due to down sampling to the resolution of 1.5 m for reducing the size of image, it has been established again that for accurate change detection and mapping of LULC, visual interpretation is still a most common valuable and effective method which can't be substituted completely.

To sum up, the present study shows a great potential for decision makers for generating accurate LULC change detection by exploiting various sources of RS and techniques towards successful implementation of sustainable development, natural resource management and safe land use planning.

7.2 Recommendations

There are several potential possibilities which are to be considered as additional strategies for further study in future upon the conclusion of present research work. Those possibilities are wide-ranging preferences including selection of source data, set of methodologies to be used and final target of the research work for a specific application. However, the recommendations pointed out here based upon the conclusion of present study, should not be considered as a complete list of prospects which can be measured for future research. A list of possible aspects in the context of present study is discussed in the following paragraphs.

a) Since the satellite technology continues to advance, the satellite images with higher spatial and spectral resolution can be utilized for future, which will not only improve the classification accuracy but also help to classify in more detail. As a consequence, the change in fine classes (level 3 or 4) can be detected easily and more accurately. Presently hyper spectral sensors are playing a great role for mapping LULC on smaller scales as having higher spectral ranges. However, it demands high data cost and tremendous storage space and thus high processing time which can limit the usage of such data for large study area. Even so, it is true that the utilization of such data in future will be able to map finer level of details more accurately allowing analysis of more subtle changes in LULC.

b) Although the present study exhibits very good result, it is important to note that misclassification and thus confusion in change detection still exist to some extent in this study. There are many factors contributed to such confusion, such as spatial, spectral, temporal properties of images, selection of methods and study area, misregistration of temporal images which are to be handled more systematically in future.

c) Using one type of image to identify all classes with equal level of high accuracy is nearly impossible. As a result, the error matrix shows different accuracies for classes. So it is quite reasonable to use different resolution images which are to be considered for different classes.

d) It is to be noted that during the segmentation of image, only one-scale image objects level was used as there were not too many classes in the study area. The software offers multi-level image segmentation which is very useful for OO classification where each level of segmentation should have homogeneous image objects by generating a network of many scale image objects. This can be applied where the number of classes are enormous and where detail level of land cover classification is essential. In case of OO approach, a classification procedure can be more complex depending upon the choice of massive membership functions and other finer tools like feature space optimization etc. It is clear that OO classification is due to receive more research attention in future.

e) Several types of land cover were considered as just one class as per CORINE nomenclature (as for example settlement and transport under urban fabric) because of avoiding confusion on separation of classes and thus reliable discrimination. It was highly necessary considering the resolution of available satellite images which were not suitable for more detail LULC mapping.

f) The combined application of principal component analysis (PCA) has been used for the study. One aspect that still needs further research in this regards by utilizing other PCA techniques, as for example spectral rotation could be applied at a lower angle or PC image differencing etc.

g) Improving the accuracy of change detection can be one of the most important aspects in future. The multiplication of error in change information should be considered. The change direction and magnitude of change will be also primary concern in this case. A LULC transition matrix between two dates will help to understand the changes among classes more precisely. An existing layer of LULC change detection (as for example, CORINE land cover change layer from 1990 to 2000) can be considered as reference layer for accuracy assessment. Particularly, this is very important with regard to the change detection of very large areas, where accuracy assessment remains a challenge for further research work.

h) Although several attempts have been made for accuracy assessment, ground truth data collection with the use of GPS technology can be a matter of thinking for future research especially in case of classification of recent images. For the historical images, some reference data can also be considered, if available for the purpose of study. Those reference data (either image or GIS database) can also be used for training sample collection.

i) Last but not the least, although post classification for the present study has been found simple and effective, several other change detection methods also can be exploited for change information which allow picking the best suited method for the corresponding research work. However, it is question of cost-benefit and time availability.

In summary, the methodological framework consisting of the combined application of remote sensing, image classification and change detection techniques promises to support the analysis of LULC change detection. However, the research is still demanding to refine that framework in a variety of different ways.

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Declaration

I declare that the submitted work has been completed by me the undersigned and that I have not used any other than permitted reference sources or materials nor engaged in any plagiarism. All references and other sources used by me have been appropriately acknowledged in the work. I further declare that the work has not been submitted for the purpose of academic examination, either in its original or similar form, anywhere else.

Münster, 2nd March, 2009

Tanmoy Das