CHANGE DETECTION OF BUILDINGS FROM HIGH RESOLUTION SATELLITE IMAGERY AND EXISTING MAP DATA USING OBJECT BASED CLASSIFICATION

NESNE TABANLI SINIFLANDIRMA İLE YÜKSEK ÇÖZÜNÜRLÜKLÜ UYDU GÖRÜNTÜLERİ VE MEVCUT HARİTA VERİLERİNDEN BİNA DEĞİŞİMLERİNİN TESPİTİ

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This work named **"CHANGE DETECTION OF BUILDINGS FROM HIGH RESOLUTION SATELLITE IMAGERY AND EXISTING MAP DATA USING OBJECT BASED CLASSIFICATION"** by **FATEMEH SAFARLOU** has been approved as a thesis for the Degree of **MASTER OF SCIENCE IN GEOMATICS ENGINEERING** by the below mentioned Examining Committee Members.

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ETHICS

In this thesis study, prepared in accordance with the spelling rules of Institute of Graduate Studies in Science of Hacettepe University,

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- all the information and documents have been obtained in the base of the academic rules
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- in case of using others Works, related studies have been cited in accordance with the scientific standards
- all cited studies have been fully referenced
- I did not do any distortion in the data set
- and any part of this thesis has not been presented as another thesis study at this or any other university.

17/08/2015

FATEMEH SAFARLOU

To my family and my husband

I love you all dearly.

ABSTRACT

CHANGE DETECTION OF BUILDINGS FROM HIGH RESOLUTION SATELLITE IMAGERY AND EXISTING MAP DATA USING OBJECT BASED CLASSIFICATION

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The automatic and accurate detection of buildings and the changes of buildings in urban environment is important for the efficient updating of geographic databases, decision makers, urban planning and management. In this study, building changes in a selected urban area in the Altındağ district of Ankara, Turkey were detected from a high resolution satellite imagery by using image to map comparison change detection technique. The data used include the WorldView2 satellite image acquired in 2010, the vector map data compiled in 2001, and DSM data generated from stereo aerial photographs taken in 2013.

The method used in the study consists of four main steps. In the first step, a multiresolution image segmentation was carried out using the multispectral image bands and DSM data in eCognition software. In the segmentation process, the parameters Scale, Shape, Compactness and Layer Weight were used. The values for these parameters were defined by trial and error analysis. In the second step, the image was initially classified using the nearest neighbour (NN) method, which was then followed by a rule-based classification. During rule-based classification, the spatial, geometrical, contextual and texure features of the image objects as well as the relations between them were considered. After performing the classification operation, the building class was masked out and a morphological opening operation was applied on building class as a post processing operation. In the third step, the accuracy assessment of the detected building class was performed by means of comparing it with the manually digitized reference data set. With this respect, true positive (TP), true negative (TN), false positive (FP), false negative (FN), building detection percentage (BDP) and quality percentage (QP) measures were computed. In addition, an error matrix was generated based on random samples and an overall accuracy was computed. In the fourth step, the building changes were detected by means of comparing the detected building class with the old vector map data. The change detection process was carried out in ArcGIS software by means of an overlay analysis. The detected changes were categorized into new buildings and demolished buildings. Moreover, the accuracy assessment of the detected changes was also carried out based on the accuracy measures same before using the change reference data set, which was generated by manually on screen digitization of the changes.

Experimental results demonstrate the effectiveness of both object-based classification and image to map change detection methods in high resolution satellite imagery. For the building class extracted through object based classification, the building detection percentage (BDP) value was computed to be 82.21%. Similarly, the BDP values for the detected changed and unchanged areas were computed to be 86.06% and 70.64%, respectively. Multiresolution segmentation and the subsequent rule based classification were found to be quite efficient for successfully detecting buildings from high resolution satellite imagery. However, the classification performance was not quite good for small and unclear buildings as well as those buildings that are surrounded by high vegetation which strongly effects the results of classification and the subsequent change detection. The use of true orthoimagery of high resolution satellite data in classification would increase the accuracy results of both building detection and the subsequent change detection. The results demonstrate that the method presented in this study can be efficiently used to detect changes of buildings and update geodatabases in urban environment.

Keywords: Change Detection, Object Based Classification, Building Detection, Geodatabase Updating

ÖZET

NESNE TABANLI SINIFLANDIRMA İLE YÜKSEK ÇÖZÜNÜRLÜKLÜ UYDU GÖRÜNTÜLERİ VE MEVCUT HARİTA VERİLERİNDEN BİNA DEĞİŞİMLERİNİN TESPİTİ

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Kentsel alanlarda binaların ve bina değişimlerinin otomatik ve doğru tespiti, coğrafi veri tabanlarının etkin güncellemesi, karar vericiler ve kent planlaması ve yönetimi için önemlidir. Bu çalışmada, Türkiye, Ankara'nın Altındağ bölgesinde seçilen kentsel bir alanda yüksek çözünürlüklü uydu görüntüsünden görüntü-harita karşılaştırması değişim belirleme yöntemi kullanılarak bina değişimleri tespit edilmiştir. Kullanılan veriler, 2010 yılında çekilmiş WorldView2 uydu görüntüsü, 2001 yılında derlenmiş vektör harita verisi ve 2013 yılı stereo hava fotoğraflarından oluşturulmuş sayısal yüzey modelini (SYM) içermektedir.

Çalışmada kullanılan yöntem dört ana adım içermektedir. İlk adımda, renkli bantlar ve SYM verisi kullanılarak, görüntünün eCognition yazılımında çok çözünürlüklü bölütlemesi yapılmıştır. Bölütleme işleminde ölçek, şekil, yoğunluk ve katman ağırlığı parametreleri kullanılmıştır. Bu parametreler için değerler deneme yanılma yöntemiyle belirlenmiştir. İkinci adımda, görüntü başlangıçta en yakın komşu yöntemiyle sınıflandırılmış olup bunu bir kural-tabanlı sınıflandırma izlemiştir. Kural-tabanlı sınıflandırma sırasında, görüntü objelerinin uzaysal, geometrik, bağlamsal ve doku özelliklerinin yanısıra, görüntü objeleri

arasındaki ilişkiler dikkate alınmıştır. Sınıflandırma işleminin gerçekleştirilmesinden sonra, bina sınıfı maskelenmiş ve bir son işlem olarak bina sınıfı üzerinde morfolojik açılma işlemi uygulanmıştır. Üçüncü adımda, manuel çizilmiş referans veri seti ile karşılaştırmak suretiyle, belirlenen bina sınıfının doğruluk değerlendirmesi yapılmıştır. Bu bağlamda, doğru pozitif, doğru negatif, yanlış pozitif, yanlış negatif, bina belirleme yüzdesi, ve kalite yüzdesi ölçüleri hesaplanmıştır. Ayrıca, rastgele örneklere dayalı bir hata matrisi oluşturulmuş ve bir genel doğruluk hesaplanmıştır. Dördüncü adımda, belirlenen bina sınıfı ile eski harita verisini karşılaştırmak suretiyle bina değişimleri tespit edilmiştir. Değişim belirleme işlemi ArcGIS yazılımında bir çakıştırma analizi vasıtasıyla gerçekleştirilmiştir. Belirlenen değişimler, yeni ve yıkılmış binalar olarak sınıflandırılmıştır. Diğer taraftan, daha önce olduğu gibi, ekranda değişimler manuel çizilerek oluşturulan referans veri seti kullanılarak, tespit edilen değişimlerin doğruluk değerlendirmesi de yapılmıştır.

Deneysel sonuçlar, nesne-tabanlı sınıflandırma ve görüntü-harita karşılaştırması değişim belirleme yöntemlerinin her ikisinin yüksek çözünürlüklü uydu görüntüleri üzerindeki etkisini göstermektedir. Nesne-tabanlı sınıflandırma ile çıkarılmış bina sınıfı için, bina belirleme yüzdesi değeri % 82.21 olarak hesaplanmıştır. Benzer şekilde, tespit edilmiş değişen ve değişmeyen alanlar için bina belirleme yüzdesi değerleri sırasıyla % 86.06 ve % 70.64 olarak hesaplanmıştır. Çok çözünürlüklü bölütleme ve sonrasında karar-tabanlı sınıflandırma, binaların yüksek çözünürlüklü uydu görüntülerinden başarılı bir şekilde belirlenmesinde, oldukça etkili bulunmuştur. Fakat, etrafı sınıflandırma ve sonrasındaki değişim belirleme sonuçlarını güçlü bir şekilde etkileyen yüksek bitki ile çevrili binaların yanısıra, küçük ve belirsiz binalar için sınıflandırma performansı çok iyi değildir. Yüksek çözünürlüklü uydu verilerinin hassas orto-görüntüsünün sınıflandırmada kullanımı halinde bina belirleme ve sonrasında değişim belirlemenin her ikisinin doğruluk sonuçlarında artış olurdu. Sonuçlar, bu çalışmada sunulan yöntemin kentsel alanlarda bina değişimlerini belirlemede ve coğrafi veri tabanlarını güncellemede etkin bir şekilde kullanılabileceğini göstermektedir.

Anahtar kelımeler: Değişim Tespiti, Nesne Tabanlı Sınıflandırma, Bina Tespiti, Coğrafi Veri Tabanı Güncelleme

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CONTENTS

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LIST OF SYMBOLS AND NOMENCLATURE

SYMBOLS

μ_{cb}	Mean vector for band b in class c

NOMENCLATURE

ANN	Artificial Neural Networks
BDBR	Building Dark Brown Roof
BDP	Building Detection Percentage
BF	Branching Factor
BLBR	Building Light Brown Roof
BRSD	Bare Soil
CD	Change Detection
DSM	Digital Surface Model
FN	False Negative
FP	False Positive
GIS	Geographic Information System
NN	Nearest Neighbor
QP	Quality Percentage
RS	Remote Sensing
SHDW	Shadow
TP	True Positive
UNCB	Under Construction Building

1. INTRODUCTION

Land use/cover in urban areas continuously change over time and geographic location. Urban is the most sensitive in land cover change. Therefore, timely and accurate detection of changes in urban areas, particularly the changes in buildings is quite essential for local and regional level planning studies in order to assess urban development trends. This is due to the fact that the planning studies should be based on accurate and up-to-date land use/cover information. Otherwise, the decisions will not reflect the reality, the outcomes of the plan will not be as desired, and the plan will not be successful in the implementation period. Therefore, urban planners and decision makers need a mechanism to detect, monitor, and analyze the changes in urban land use/cover efficiently and effectively [1]. Remote sensing is a very suitable technology to detect changes on earth surface features. With the availability of wide selection of high spatial-and-spectral resolution multispectral images in digital form and the recent advances in both high-performance computing systems and efficient algorithms, remote sensing has become a major source for change detection studies.

The change detection algorithms can be broadly divided into two categories that are image-to-image comparison or image-to-map comparison. The traditional change detection techniques are based on image-to-image comparison, in which two images acquired at two different dates are compared pixel by pixel in order to produce an image that contains changes occurred between two dates. The most widely used techniques in this category can be divided into three main groups: (i) techniques based on algebraic operations, (ii) techniques based on image classification and (iii) techniques based on transformations. Change detection techniques based on pixel-based analysis of remote sensing data have been reviewed in various publications [1], [2], [3] and [4], where the techniques have been described in detail.

In image-to-map comparison, an existing map is utilized to find areas of change from a new image. First, the image objects are extracted and then they are compared to map's objects [5], [6] and [7]. In one sense this approach is similar to post classification comparison between two images. In image to map comparison, an overlay analysis is often used to detect changes. The change areas are defined by non-intersection zones between the image and the map's objects. The difficulty in this approach is that all the objects are needed to be accurately extracted from the image. Indeed, the classification errors directly effect the correctness of the image's objects. Thus, the incorrectly detected objects as well as the missing objects would be erronously considered as changes when compared to map objects. The most commonly used technique to detect image objects from an image is automatic classification.

Traditional image classification algorithms, which operate on per-pixel base, have been commonly implemented for the low- to medium spatial resolution images but they are not quite successful on images with high spatial resolution. This is due to the fact that in high resolution imagery the intra-class spectral variability increases and this reduces the between class statistical separability in conventional per-pixel classification techniques. Thus, the classification accuracy drops and the classified output shows a salt and peper effect with pixels labeled differently from the neighbouring pixels.

Therefore, object based techniques are considered to be more appropriate for the analysis of high resolution remote sensing data [8] and [9]. The basic idea of object based classification is that first, the spatially adjacent pixels are grouped into spectrally homogenous objects, and then classification is performed on objects as the minimum processing units. One of the earliest developments of object based segmentation and classification, which was called Extraction and Classification of Homogeneous Objects (ECHO), was proposed and developed by [10].

First motivation behind this work is to use high resolution WorldView2 image integrated with DSM data for the extraction of buildings by considering spectral, spatial and contextual features of the segmented objects. Further, Density, Rectangular Fit, Length/Width and area can also help detect rules and improve the quality of classification. For example mutual relationships like border to shadow is useful in detecting the buildings and also by applying a standard deviation rule on DSM data the high objects can be separated from the lower ones. The second motivation of the study is to detect building changes occurred between the old vector map data compiled in 2001 and a high resolution satellite imagery collected in 2010. The buildings that correspond to changed areas between these two data sets are detected by means of an overlay analysis and labeled as new or demolished buildings or buildings part. Finally, the results are evaluated through different accuracy tests.

1.1. The Objectives

The objectives of this study are as follows:

- To detect changes of buildings from high resolution space imagery by means of a image-to-map comparison change detection technique.
- To extract buildings from high resolution space imagery using an object based image classification method.
- To achieve a high accuracy in building detection from high-resolution space imagery through an object based classification approach.
- To achieve a high accuracy in change detection of buildings.

1.2. Study Area and Data

1.2.1. The Study Area

The geographical coordinates of the area under study (Figure 1.1) are between 4426062.963 N to 4426777.963 N and 496231.424 E and 497361.424 E. The study was performed on the subset of an image covering an area of 201987.5 m^2. This area consists of 431 buildings. In the study area, the smallest building is about 26 m^2 in size, while the largest building is about 1700 m^2 in size. The selected study area falls within the Altındağ district of Ankara, the capital city of Turkey. The rapid urbanization rate of the Altındağ district is very suitable for the exploration of urban expansion detection through automatic change detection from high resolution satellite imagery. Furthermore, the Altındağ district is suitable and challenging for implementing the object based classification concept to extract buildings and detect changes since the area consists of various kinds of buildings with different usage, shapes, heights, rooftops and buildings under construction. In the area, most of the buildings are residential and commercial and the number of newly constructed buildings is high. The buildings in this area have rectangular shapes with light brown and dark brown colors. Most of the buildings in this place are residential buildings. Other kinds of buildings have a white color and they have much larger size than the residential buildings. Several buildings are in gray and white colors and they have rectangular shapes and are classified as buildings under construction. Therefore, these characteristics make the study area challenging for extracting buildings through object based image classification and detecting the changes of buildings using an image-to-map comparison change detection technique.

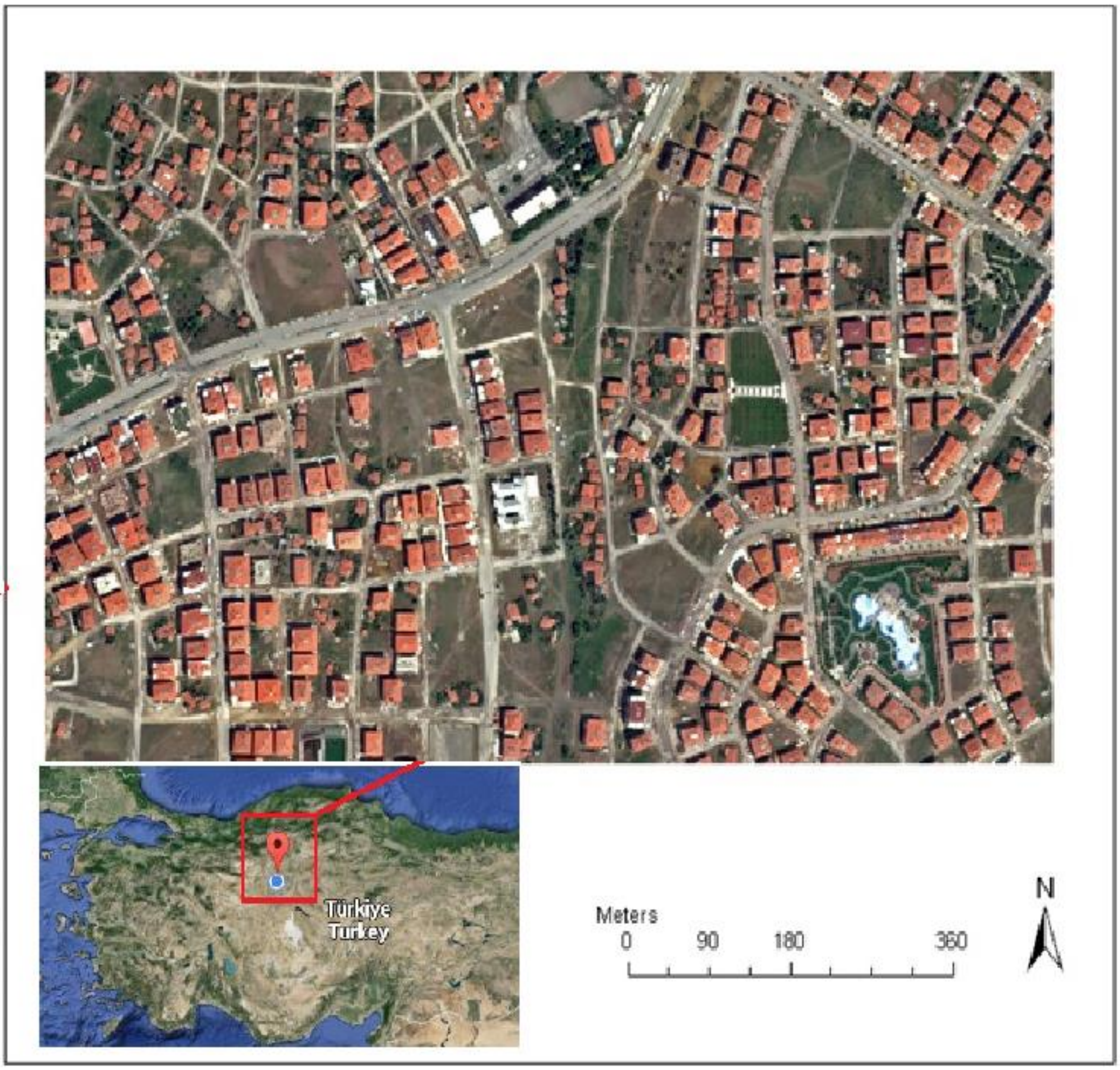


Figure 1.1. The RGB color display of the satellite imagery covering the study area

1.2.2. Data

The data used in this study include the existing vector building boundaries, the high resolution optical satellite imagery and the digital surface model (DSM). In the first step, the satellite image and DSM data were used to extract buildings and in the second step, the change detection was performed by means of comparing the detected building areas with the old vector map data. The satellite image and the existing digital map data used in this study were supplied by the Altındağ Municipality and the DSM data set was provided by the General Command of Mapping of Turkey. All data sets were in European_1950 Datum and Transverse_Mercator projection system.

The high-resolution WorldView2 image, which was acquired in 2010, was used as the raster image. The available bands of the image used were Blue, Green, and Red. Therefore, in the present case the changes of buildings were detected using the available tree bands only. The specifications of the WorldView2 satellite are given in Table 1.1.

Table 1.1. WorldView2 satellite characteristics

Spectral Resolution	Multispectral (400-1040 nm) Band1 (coastal blue) Band 2 (Blue) Band 3(green) Band 4(yellow) Band 5(red) Band 6 (red edge) Band 7 (NIR1) Band 8(NIR 2) Panchromatic
Spatial Resolution	Pan 0.5m Ms-2m
Swath Width	16.4 kilometers at nadir
Dynamic Range	11-bits per pixel
Orbit Altitude	770 kilometers

The old vector map of the year 2001 is given in Figure 1.2. In the present case, the buildings smaller than $25m^2$ were not considered. In the old vector map there were 471 buildings.

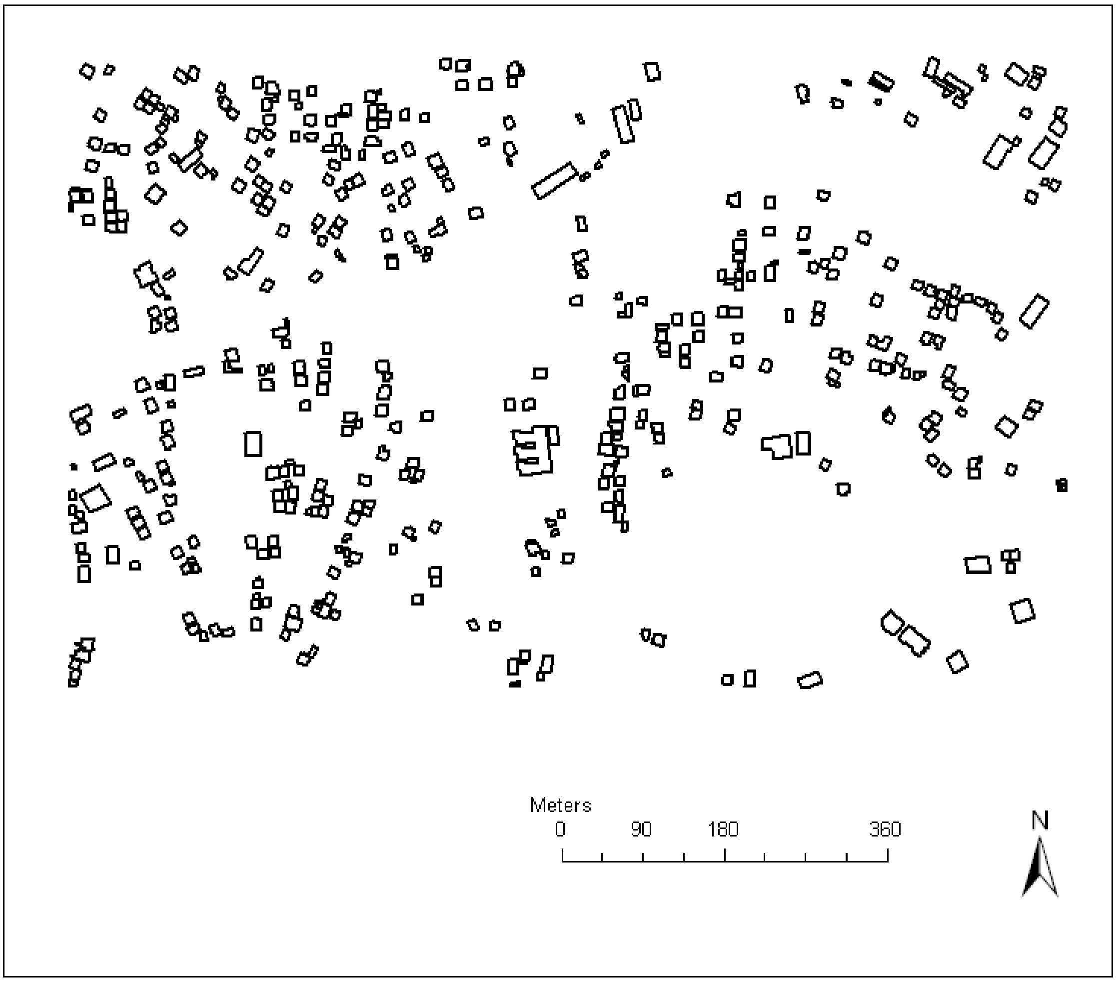


Figure 1.3. The old vector map of the year 2001

The 5m pixel size DSM was generated from overlapping aerial photographs taken in 2013 by the UltraCam Eagle camera. The flying height was 4000m. The DSM was extracted automatically using the Dense Matching method by the Match T 5.5 software. The quality of the extracted DSM was checked visually and no coarse errors were observed. In the present case, the DSM data was used to distinguish buildings from the other objects based on the height information. The extracted DSM is given in Figure 1.4.

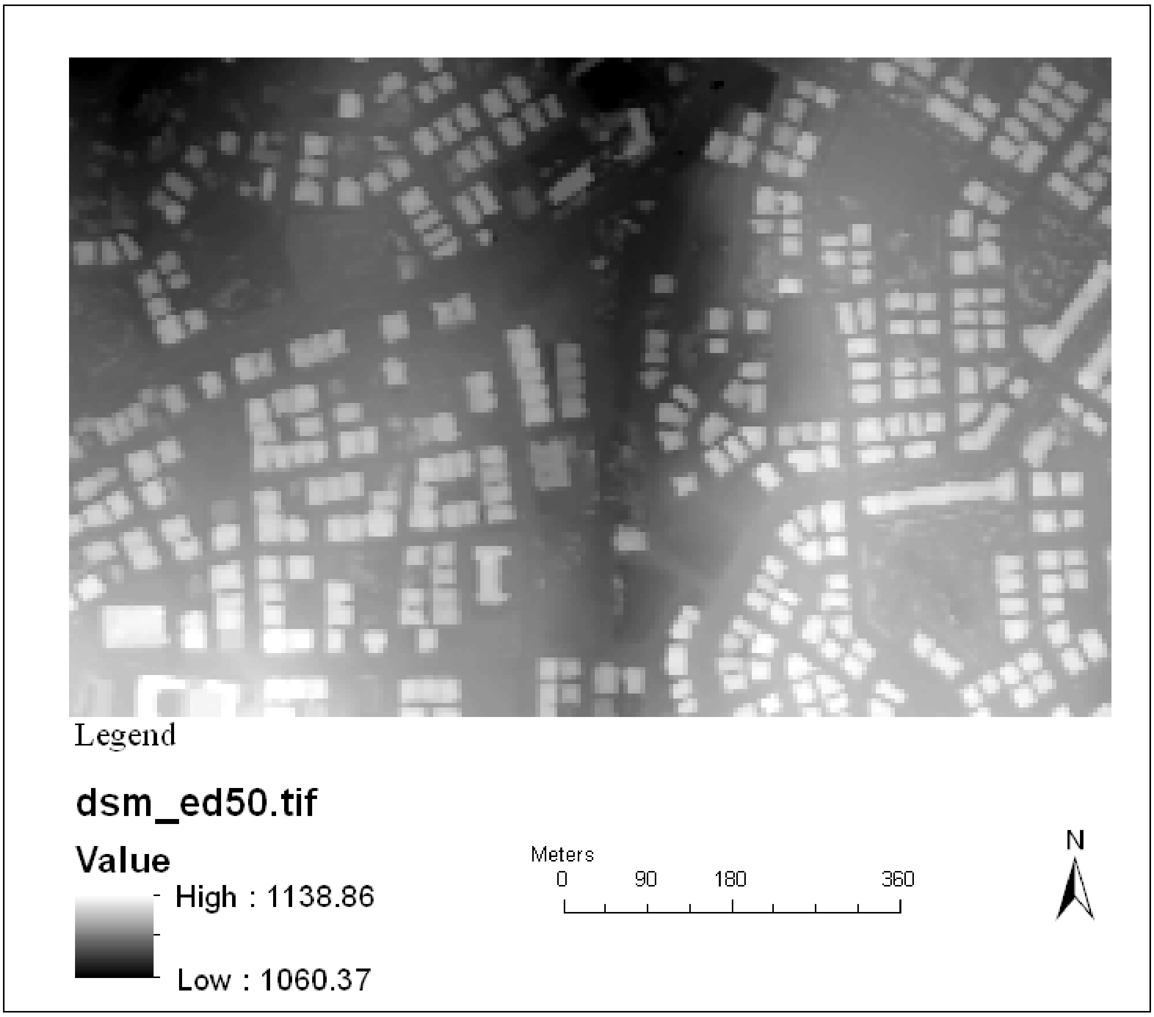


Figure 1.4. DSM data

1.3. Organization of the Thesis

The remaining parts of the thesis are organized into four chapters. Chapter 2 provides an overview of the change detection techniques and in particular on those techniques that use classified objects and old vector map data in change detection in urban areas. Chapter 3 explains the methodology used in this study, and chapter 4 presents the findings and results of this study. Finally the conclusions and recommendation for further investigations are given in chapter 5.

2. RELATED WORKS ON CHANGE DETECTION

Change detection can be defined as the process of determining areas of land cover change from the observations made at different time [1]. Changes may occur in the spatial and /or attribute characteristics of an existing feature of objects or pixels. Change detection can be effected by various elements including spatial, spectral, thematic, temporal, radiometric and atmospheric conditions, Therefore, the reliability of a change detection process depends on the correct understanding of the parameters. These parameters are related with both the sensor system and the environmental characteristics [11].

2.1. Preprocessing before Change Detection

Preprocessing before change detection is very important. The parameters related with a remote sensing system are [12];

- temporal resolution
- spectral resolution
- spatial resolution
- radiometric resolution
- environmental condition

2.1.1. Temporal Resolution

Temporal resolution specifies the revisiting frequency of a satellite sensor for a specific location. Usually, the revisit time is several days. However, some satellites can steer their sensors to observe the same area between different passes separated by a period of a few days. Thus, the actual temporal resolution of the satellite sensors depends on several conditions, which include the capabilities of satellite/sensor, the swath overlap, and the latitude [13]. In change detection, temporal resolution should be held constant. That is in order to eliminate some external effects the data of the same time of the year and of the day should be preferred when using multiple dates of images of the same geographic area. If the images taken at the same time of the day are used, diurnal sun angle effects that lead to differences in the reflectance properties in the satellite data can be eliminated. Also, seasonal sun angle and phonological vegetation differences can also be eliminated using the data taken at anniversary dates [11].

2.1.2. Spectral Resolution

Spectral resolution of a satellite sensor refers to number of spectral bands. However, the number of spectral bands is not the only aspect to define spectral resolution. Spectral resolution is also defined through the widths of the bands in which the sensor collects the reflected spectral radiance. Thus, both the number of bands and the positions of these bands and their widths in electromagnetic spectrum are important to define spectral resolution. The position of bands in the electromagnetic spectrum is also important. Therefore, the spectral characteristics of a remote sensing system include the number, width, and position of the sensor's spectral bands. A fundamental assumption of digital change detection is based on spectral difference of a pixel on two dates. Spectral resolution is the record of reflected radiant flux in spectral regions that are collected by the sensors over the area covered by a pixel [11].

2.1.3. Spatial Resolution

The spatial resolution specifies the pixel size of the satellite images covering the earth surface [13]. The size of the pixel is dependent on the sensor type and determines the resolution of the image. The resolutions of the satellite systems can be divided to Low, Medium and High. Coarse resolution having 100-500 m spatial resolution and minimum three bands spectral information availability (serving purpose from 24 Million to 7 Million scale range). Medium resolution having 50-15 m spatial resolution and minimum three band spectral information availability (serving purpose from 3.5 Million to 100,000 scale range). Fine or high resolution having better than 6 m spatial resolution either in Panchromatic mode or in Multispectral mode (serving purpose from 50,000 to 2,500 scale range). A "coarse" resolution is used to record large or global areas for climate-related enquiries, for example the radiation budget of the earth and for weather monitoring and additional applications include earth observation of land use and oceans. A course resolution METEOSAT-8 revisit the same part of the planet on every 15 min. Satellites with medium resolution such as LANDSAT 7 are used for the global observation of land surfaces. High resolution data is mainly used for smaller areas of the earth's surface. Only recently such data has become available commercially and privately. Satellites such as IKONOS, QuickBird or WorldView send data for topographic and thematic mapping of for example land use, vegetation, or as planning resources for cities. Information can also be "ordered" in advance, because the turning of the satellite sensors can reduce the repeat rates and can monitor the desired areas earlier. The higher the resolution is, the larger the degree of recognizable details on the earth's surface. If the images obtained by different sensors are used, then their data should be resampled to a uniform pixel size first. Regardless of the sensor however, the images must be applied a geometric correction. Through geometric correction, the miss registration which may very well lead to unexpected changes in the resultant image is avoided. The geometric correction of the multidate images with a root mean square error (RMSE) of less than 0.5 pixel is desired [11] and [14].

2.1.4. Radiometric Resolution

The radiometric properties of a remote sensing system are typically expressed as the number of data bits used to record the observed radiance. They also include the range of variation in brightness over which the system will be sensitive, and the signal-to-noise ratio of the sensor. The lower radiometric resolution data should be decompressed to higher resolution data in change detection process because both image must be in same radiometric range. Because of the repeated coverage of satellite images radiometric resolution is hard to maintain consist between separate images. Due to different atmospheric conditions, variations in the solar illumination angles, and sensor calibration radiometric resolution also changes. Therefore, among the various aspects of image preprocessing for land cover change detection, radiometric calibration is necessary [15].

2.1.5. Environmental Conditions

In addition to the sensor characteristics, environmental conditions, which are desired to be the same, should be understood well in change detection studies. Atmospheric condition is another factor that must be considered in change detection process. However, when using a single date image with other types of data for detecting the changes atmospheric correction is not necessary [16].

2.2. Change Detection Techniques

A detailed explanation of the change detection techniques are given by [17]. The change detection techniques can be divided into three groups: (i) Pixel-Based Methods, (ii) Object Based Methods, and (iii) Hybrid Methods.

2.2.1. Pixel Based Techniques

Task of producing highly accurate classifications often lead to unsatisfactory change detection results, especially when high-quality training sample data are not available. Post-classification comparison change detection is frequently used quantitative change detection method. The pixel based methods consider the spectral value and mostly ignore the spatial context. Most often statistical operators are used for evaluating a single pixel. Pixel-based change detection techniques can be divided into the following five categories:

- Direct Comparison
- Transformation From Image
- Classification Based Change Detection
- Machine Learning
- GIS Methods

The “Direct Comparison” category includes the methods Image Differencing, Image Ratioing, and Regression Analysis. Most of the methods in the direct comparison category are algebra based. These methods are relatively simple, but they do not provide a complete matrix of change information. In a study conducted by [18], the difference of band ratios and a threshold technique were used to identify the changed areas. [19] and [20] found that the use of visible red band was useful to detect changes in both vegetated and urban environments. It is possible to detect changes between two co-registered images through band ratioing or image differencing [21], [22] and [23]. In the image differencing method an imagery of one date is subtracted from that of another. The subtraction process generates positive and negative values in change areas and zero values in no change areas [11].

The “Transformation From Image” category includes the methods vegetation index differencing, change vector analysis (CVA), principal components analysis (PCA), tasselled cap transformation (KT), and texture analysis. These methods have an advantage that the data redundancy between the bands is reduced. However, these methods do not provide detailed change matrices. Further, it is rather difficult to interpret the changes on the transformed data sets.

The “Classification Based Change Detection” category includes the methods post-classification comparison and multi-date direct comparison. In fact, these methods are based on classified images, in which the quality and quantity of training sample data are crucial to produce high quality results. One major advantage of these methods is that they provide a matrix of change information and reduces external effects caused by atmospheric and environmental differences between multitemporal images. However, selecting high-quality and sufficiently numerous training samples for image classification is often difficult, in particular for the classification of historical images. The time consuming and difficult method [24], [25], [26], [27] and [28]. It is based on the classification of each of the multitemporal remotely sensed images. The classified images are then compared on a pixel-by-pixel basis using the matrix of change. However, all the errors in the individual dates classification maps will also be present in the final results of change detection [29]. Therefore, it is imperative that the individual classification maps are to be as accurate as possible. In the multi-date direct comparison method, the labeling process of the change classes are rather difficult and providing a complex change matrix is not possible [27].

The "Machine Learning" category includes the approaches artificial neural networks (ANN), support vector machine (SVM) and decision tree. ANN, which is non-parametric supervised algorithm, estimates data properties based on training samples. However, the size of training samples is important in teaching the network. SVM is also non-parametric and requires no assumption is made on data distribution. Further, small training data set often produces high classification accuracy. However, difficulty in selecting the best kernel function and computational time for classification can said to be the limitations. Decision tree is also non parametric and no assumption is made on data distribution. It can provide rule set for the changed and unchanged classes. However, it is sensitive the quality of training data as well as the number of samples for each class. Further, the tree may grow much larger in sizes and thus making it difficult to interpret.

The "GIS" category involves the integrated GIS and remote sensing methods and pure GIS methods. The advantage of using GIS is that different sources of data are incorporated into change detection process. However, since different sources of data are associated with different accuracies and data formats this affects the results of change detection. Most of the past change detection studies based on GIS approaches were implemented to detect changes in urban areas. This is because traditional change detection techniques often provide poor results due to the complexity of urban areas where multi-source data analysis may not be effectively utilized. Therefore, GIS functions can be conveniently used for the processing of multi-source data and they can be effectively used in performing change detection analysis on multi-source data sets.

Traditional change detection algorithms have been commonly implemented for low to medium resolution imagery but they are not quite successful for high-resolution images [30] and [31]. With the wide availability of very high resolution imagery and the rapid increase in computational capability in the last decade, the traditional pixel based methods have been abolished and it was firstly recognized by [32] and then [33] proofed that pixels are not the optimal spatial unit for representing geographical objects. The high resolution imagery often results in too many changes being detected. Known as the "salt and pepper" effect it decreases the potential accuracy of pixel based change detection approaches [34]. Another important limitation of the traditional pixel-based change detection approaches is that it is rather difficult to model the contextual information [35] and [36]. Also, pixel-based approaches lead to noisy outputs, such as isolated changed pixels or holes in the connected changed areas [37].

2.2.2. Object Based Techniques

Object based change detection techniques can be divided into the following three categories [38];

- Direct Object Change Detection (DOCD)
- Classified Object Change Detection (COCD)
- Multi Temporal/Multi Date-Object Change Detection

2.2.2.1. Direct Object Change Detection (DOCD)

This method directly compares image objects of different dates. It is similar to pixel comparisons but in this method textural or spectral (mean values and standard deviations of the bands) and geometrical properties, such as area, width, length, compactness information of the object are considered and compared to detect changes. Two approaches are used in this method. In the first approach, the objects from image at time t1 are extracted, and are assigned to or searched from image at time t2 without segmentation [39]. The advantage of this approach is that all the objects from both images are used for change detection without performing a segmentation operation on the image objects. The disadvantage of the first approach is that the changes are linked to only the objects extracted from the first image and will not provide new objects that might be created in the second image because of change. In the second approach, the segments from multitemporal images are extracted and then they are compared for detecting the changes between the same segments from different time images [34]. Whereas the first approach, this approach allows using all the objects from multitemporal images for change detection. The DOCD method is straightforward to implement and the comparison of the objects is easy. Image objects have the same geometric properties at two times and change in geometrical properties like Shape parameters, border length, size is detectable. The accuracy of the results depend on the segmentation accuracy.

2.2.2.2. Classified Object Change Detection (COCD)

In this method, “from to” change matrix is extracted. The comparison between two multi temporal map objects to identify the change based on post classification comparison is the theoretical concept of this method. In this method, the same segmentation and classification algorithm and parameters, and the same conditions should be used for both images. In the classification step, any of the classification techniques can be used. However, it is better that the classification algorithm incorporates both the spectral and textural information. Traditionally image classification is carried out on per-pixel base without considering the contextual relationships between the pixels. In other words, just the grey value and radiometric information of individual pixel is considered, other spectral information, the tone, texture, shape, context information are ignored.

In pixel based classification process, by including surrounding pixel values in the pre-defined neighborhood, a better classification can be achieved. Pixel-based approaches can have major drawbacks, however. One problem is that the spatial extent of a pixel may not match with the extent of the feature of interest. For example, one common problem is mixed pixels that represent multiple land covers leading to misclassification [32]. Another common problem and one that is less often considered, is where the object of interest is considerably larger than the pixel size [40]. The common problems with pixel-based classification noted in many previous researches, which include the speckles and salt and pepper effect with nonhomogeneous thematic maps created by the classification of isolated pixels as individual classes. Another difficulty is the selection of training samples for every image even if an additional area of the same image is to be classified. Low resolution images of urban areas have more mixed classes and thus are not useful for detail urban land cover classification.

Therefore, to overcome the high resolution problem of image classification the object based approach would be a good alternative to the traditional pixel-based methods.

Traditional pixel-based classification techniques provide results with limited reliability. The concept of object based image analysis (OBIA) was introduced about forty years ago [10]. By focusing on real-world objects, maps produced in this way may be more recognizable and directly usable by analysts [41] and [42].

The basic concept of the object based image classification is to group the adjacent pixels into spectrally homogeneous objects first, and then perform classification on objects. The objects are the basic entities within an images. Each group of pixels represent similar brightness values, and possesses an intrinsic shape and size are forming the object. This concept is known as segmentation. Human vision attends to generalize image in to homogeneous objects. [35] and [44] carried out several research studies on the segmentation methods and they divided image into space-guided spatial clustering, single-Linkage region growing, spatial clustering hybrid-Linkage region growing, centroid-Linkage region growing, and split and merge methods based algorithms.

Object based approaches provide capabilities to include texture and contextual information as well as a number of object based features in the classification operation. In addition to spectral values of the image objects, spatial properties, such as size and shape can also be explicitly utilized in the classification operation. A better concept and understanding of object oriented classification was explained in Xie lectures [45]. In total by removing the possibility of misclassifying individual pixels, object based classification can be markedly more accurate than pixel-based classification [46] and [47]. Most papers claim that object based classification has greater potential for classifying higher resolution imagery than pixel-based methods. These papers [48], [49], [50] and [51] claim that object oriented classification has greater possibilities for detecting change in higher resolution imagery.

Two main factors have triggered the development of object based classification techniques. First, the increasing capabilities of GIS technology in particular, the integration capabilities between raster and vector data sets [24] and [52] meant that image pixels could be integrated with vector objects, providing a relatively straightforward approach to perform object based classification. Second, the commercially available object based image processing systems, such as eCognition have brought object based classification concept to a mainstream audience [20].

Image segmentation and object based classification provide a tool to automatically delineate and label urban areas. The very important use of the land cover information is the temporal urban change analysis. Urban areas are exposed to more frequent changes, but due to urban heterogeneity and wide areas, measurement of physical change can never be possible or complete. However, remote sensing data, due to frequent repeat coverage or aerial photo missions, can provide such information at any desired scale, extent and temporal frequency. Detailed land cover maps derived from temporal remote sensing data are very useful for post-classification change analysis.

Post-classification change detection is a commonly used technique to produce accurate temporal changes for a variety of change analysis studies. Additionally, land cover information can also be compared and analyzed with the existing GIS database to detect changes to the urban landscape and to monitor and manage urban expansions [53], [54] and [55]. Changes can occur in the spatial and/or attribute characteristics of an existing feature of objects or pixels. Change detection can be effected by various elements including spatial, spectral, thematic, temporal, radiometric and atmospheric conditions, Therefore, the reliability of a change detection process depends on the correct understanding of the parameters. These parameters are related with both the sensor system and the environmental characteristics. In recent years, object-based image analysis tehchniques have been applied to change detection and called Object-level, Object-based, or Object-oriented Change Detection. Also, object-based methods have attracted the attention of many scholars in the related fields of study, and these methods have been considered to have the highest potential for change detection [56], [57] and [58]. Object-Based Change Detection is based on object-oriented image analysis technology. Change information can be obtained by comparing the results of segmentation and classification, or by analyzing the objects of multi date images from such aspects as spectral, texture, structure, topology, and contextual information.

Using GIS data as auxiliary information, [58] has put forward a change detection method of comparison after classification and achieved good results. When comparing the datasets domain of comparison must be defined. For instance, a vector data set provides a classified abstract illustration of landscape, while an imagery is an unclassified continuous illustration of the landscape. If data of the same nature, for example two homogeneous satellite images, are to be compared, then change detection can be performed at the data level domain (comparing the pre-processed data), while when comparing heterogeneous datasets change detection is carried out at the decision level domain (comparing the analyzed data), as some data processing (e.g., image classification, vectorization of detected features) needs to be performed before change detection.

The previous studies extracted building from images by the aid of eCognition software [39] and [59]. A System for Building Detection from Aerial Images, Monocular Building Detection presented a building extraction approach that divides the method into a low-level image processing step and a high-level feature extraction and final classification step. They use seeded-region growing algorithm to segment the entire image, then take area, mean hue angle as preselection features to reduce calculation time, finally classify based on robust features as size, form, hue angle, neighborhoods, and shadow [59], [60] and [61] gave an approach that incorporates a priori knowledge for buildings extraction multiple high-resolution images and DSM are combined to extract the urban road grid in complex, stereotypical, residential areas.

In [62] a building height considered as the most useful information source for building extraction. With removal of trees, building information was extracted. After object based classification process they used rectangle restriction to make the edge regular. They used texture filtering of multispectrally classified building to improve the accuracy of detected building in classification process. In this method, the segmentation parameters and the classification algorithm may strongly effect the change accuracy. All the thematic, geometric and topological changes are measurable and also the classification accuracy influences the change accuracy. Moreover, as data from different dates are separately classified the post-classification comparison method minimizes the problems caused by the variation in sensors, atmospheric effects, and vegetation condition between different dates and therefore, reflectance data from two dates of imagery need not be adjusted [1] and [63]. The COCD method has been mostly used in updating maps or GIS layers [17] and [64]. In a study conducted by [65] the classified objects were compared on both geometry and class membership to extract detailed change analysis on multi temporal image. [66] study the qualitative comparison of the results shows that there is a relationship between image spatial resolution, the size of objects to be classified and the accuracy of object oriented classification of building roofs. At last the paper summarizes accuracy from the four examples to show how, low spectral dimensionality, object oriented techniques are superior to the traditional pixel based methods, but still inferior to human interpretation. [38] used a set of image object features and for improve the classification result. They used seven features of objects, like basic feature of mean layers of 5 bands (Blue, Green, Red, Infrared, Pan), brightness and maximum, difference vegetation index as the Solid Adjust

Vegetation Index and Normalized Digital Surface Model (NDSM). This results can be improved by extracting feature but this strategy occupies large part of CPU.

2.2.2.3. Multi Temporal/Multi Date - Object Change Detection

Multi date images may comprise one or more co-registered panchromatic, multispectral wave band, texture and /or spectral transformation images. In this change detection technique, the segmentation and classification operations are applied directly independently to each image. First, the similar pixels are grouped into homogeneous objects through image segmentation and then, each object (polygon) is described using spectral, texture, shape and other features. Next, two segmented polygon layers from the two-date images are overlapped to create a new polygon layer, and attribute operations to each polygon in the overlapped layer are conducted to determine the thresholds and find the changed polygons [67]. The advantage of this method is that if there is miss registration or shadow effect in different dates, these may not influence the segmentation and classification results [68]. Another issue pertaining to the use of a single segmentation for all the images is that it will not provide new/different objects that might be created at different times because of change. In a study conducted by [69] a segmentation was applied to multi temporal date imagery (12-dimension comprising red, NIR and SWIR) and to detect changes the spectral properties were obtained for all objects using the Mahalanobis distance algorithm.

2.2.3. Hybrid Change Detection (HCD)

The Hybrid Change Detection (HCD) methods combine two or more methods of pixel-or object based. Therefore, the hybrid change detection methods take the advantages and disadvantages of two or more different methods. However, the final results of change, which is influenced by the different combination of pixel and object based schemas, is unclear. In a study conducted by [70], object based classification was carried out using support vector machine (SVM) classifier and a comparison was made between the detected objects and land use vector data.

3. METHODOLOGY

The flowchart of the method used in this study is shown in Figure 3.1. The method was implemented in five main steps: (i) multi-resolution segmentation, (ii) object based classification, (iii) morphological operation, (iv) change detection and (v) accuracy assessment. The multiresolution segmentation, object based classification and morphological operations were carried out using the eCognition software, while the evaluations of the results of classification and change detection were carried out using the ArcGIS software.

In the first step of the method, the high resolution image was segmented using the multiresolution segmentation technique employed by the eCognition software. After defining the classes and the class hierarchy, the nearest neighborhood classification was carried out and then, the classified output was improved by means of employing a rule-based classification. Next, the morphological opening operation was performed on the final classified image to remove imperfections. After that, the building class was masked out from the classified image and the changed buildings between the 1:1000-scale existing old digital vector map and the classified image were detected. The results of both classification and change detection were evaluated using the reference data, which were prepared in this study.

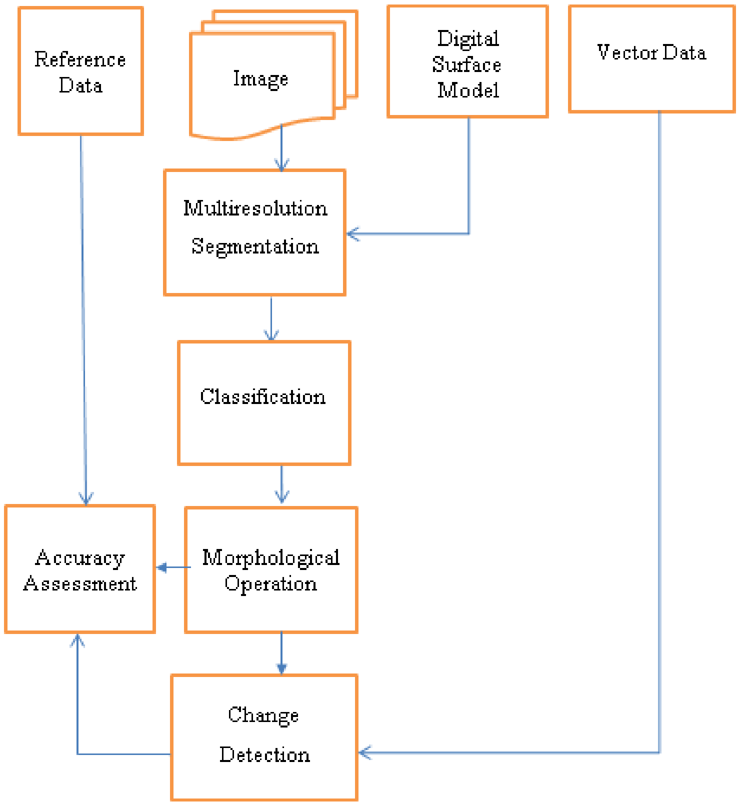


Figure 3.1. The flowchart of the methodology

3.1. Segmentation

Image segmentation is the process of dividing an image into homogeneous areas. The images are segmented on the basis of set of pixels or pixels in a region that are similar on the basis of some homogeneity criteria such as color, intensity or texture, which helps locate and identify objects or boundaries in an image [71]. Typical image segmentation involves either region merging according to a measure of homogeneity or separating objects by detecting edges using the gradients between the neighboring pixels.

Region based approaches can be divided into two categories:

- Cut-based, “top-down ” (region split and merging)
- Merged based, “bottom-up” method (region growing)

Segmentation can be carried out in both ways; from coarse to fine (top-down) and from fine to coarse (bottom-up). The idea in coarse to fine category is that the initial segmentation is performed at coarse level and then the result of this initial segmentation is used as the input for the finer level segmentation. The reverse is the case for fine to coarse segmentation approaches. For both segmentation approaches the user must define a threshold for merging or splitting.

The, “bottom-up” segmentation approach, which was also used in this study, generates a multi-scalehierarchical representation of the image. The segmentation uses several properties of image-regions including texture, average intensity and boundary. The segmentation processes successive, recursive coarsening, through which the detected segments at a level are then used to generate larger segments at the next level. With this logic, the image is segmented into fewer and fewer segments.

The multiresolution segmentation operation applied in this study is a type of “bottom up” segmentation, in which the process starts with each pixel as objects and then subsequently merged based on a specified threshold value. This approach has the capability to incorporate spectral, texture, spatial, shape, size, prior knowledge and contextual properties of the image. In this study, the multiresolution segmentation operation was carried out using eCognition software [8] and [72]. The steps followed in multiresolution segmentation using eCognition are shown in Figure 3.3. In this study, the available Blue (B), Green (G), and Red (R) image bands and a digital surface model (DSM) were used for the segmentation. To start the segmentation process, the necessary segmentation parameters were needed to be defined. In this study, the parameters Scale, Shape, Compactness, and Image Layer Weights were used in the segmentation process Figure 3.4. Of these parameters, scale determines the highest allowed heterogeneity level of the image objects and affects the average object size. The higher the scale parameter value, the larger the image objects become. The parameter Shape/Color adjusts the effect of shape vs. Color homogeneity on the generation of image objects. The higher the shape value, the less spectral homogeneity influences the object generation. The parameter Smoothness/Compactness determines the compactness or smoothness of the resulting object. With a selected shape value, the user can influence the compactness or smoothness of the final object. The parameter Image Layer Weights determines the weight of each spectral band used in segmentation. It is used to control the influence of each band on the object generation [73]. The concept of multiresolution segmentation in eCognition is represented in Figure 3.2 [74].

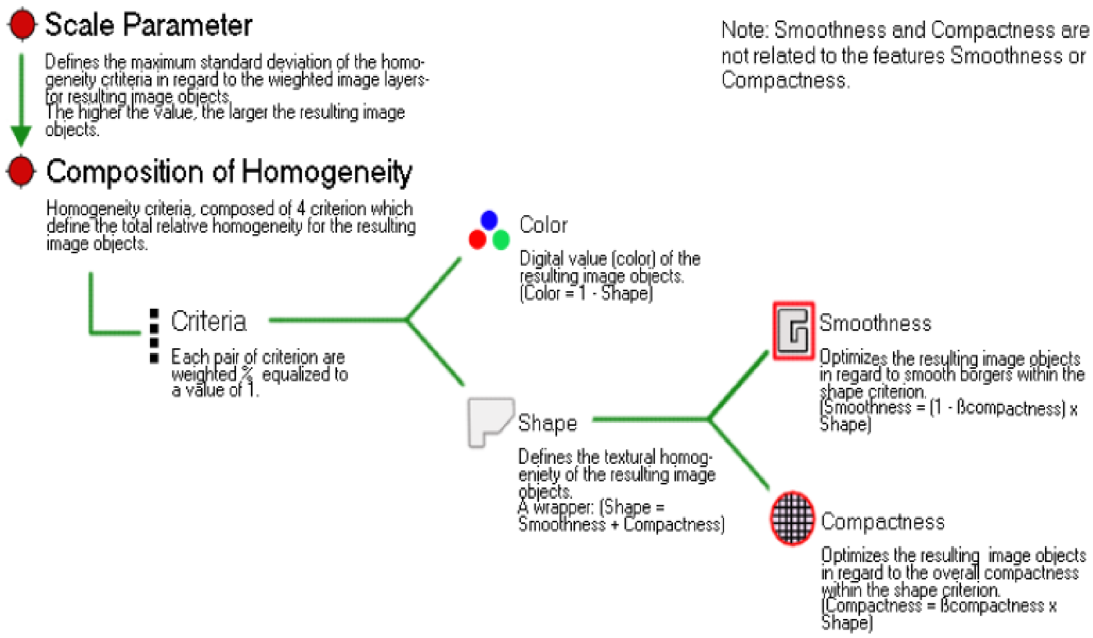


Figure 3.2. Segmentation in eCognition [74]

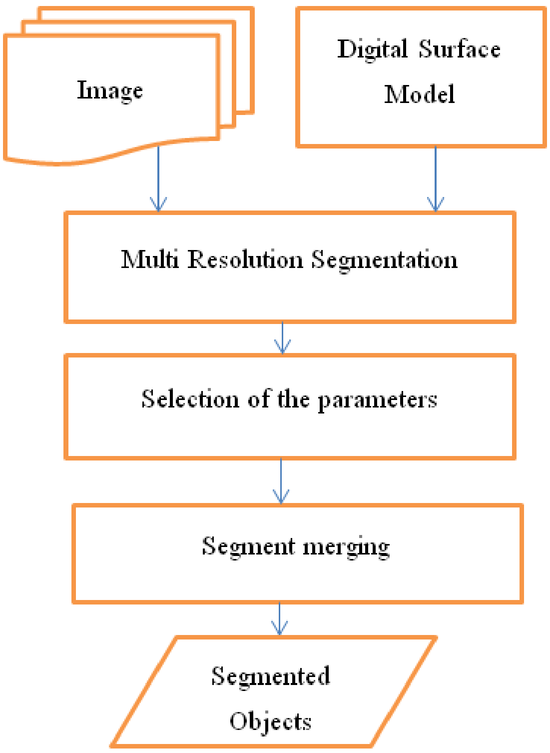


Figure 3.3. The flowchart of the segmentation process

The bands B, G, R, and DSM were weighted for the segmentation process in this way as 1, 1, 1, and 2, respectively. The DSM band was assigned a higher weight due to the fact that the buildings are vertical objects and have heights above ground. In this respect, DSM becomes a useful layer in extracting the buildings. In the study area, most of the buildings have rectangular shapes. Therefore, for the shape parameter, the maximum value (0.9 from 1) was selected as we want the segmentation results not or less influenced by the spectral values. In other words, by choosing a high value for the shape parameter the result objects would not be related to the spectral information at all. During examinations, Shape, Color, Smoothness and Compactness parameters were kept constant to show the effect of the scale parameter in the segmentation process. For the scale parameter, the values between 15 and 50 were tried. Using the values smaller and larger than 25 for the scale parameter generated segment boundaries that did not completely fit the roofs of the buildings. As it can be seen in Figure 3.5, when the small scale size (15) was used, the roofs were fragmented to many small parts, while the large scale size (50) omitted many useful details as shown in Figure 3.6. Therefore, in this study the value of 25 was used as the best fit Scale parameter for the extraction of buildings through segmentation.

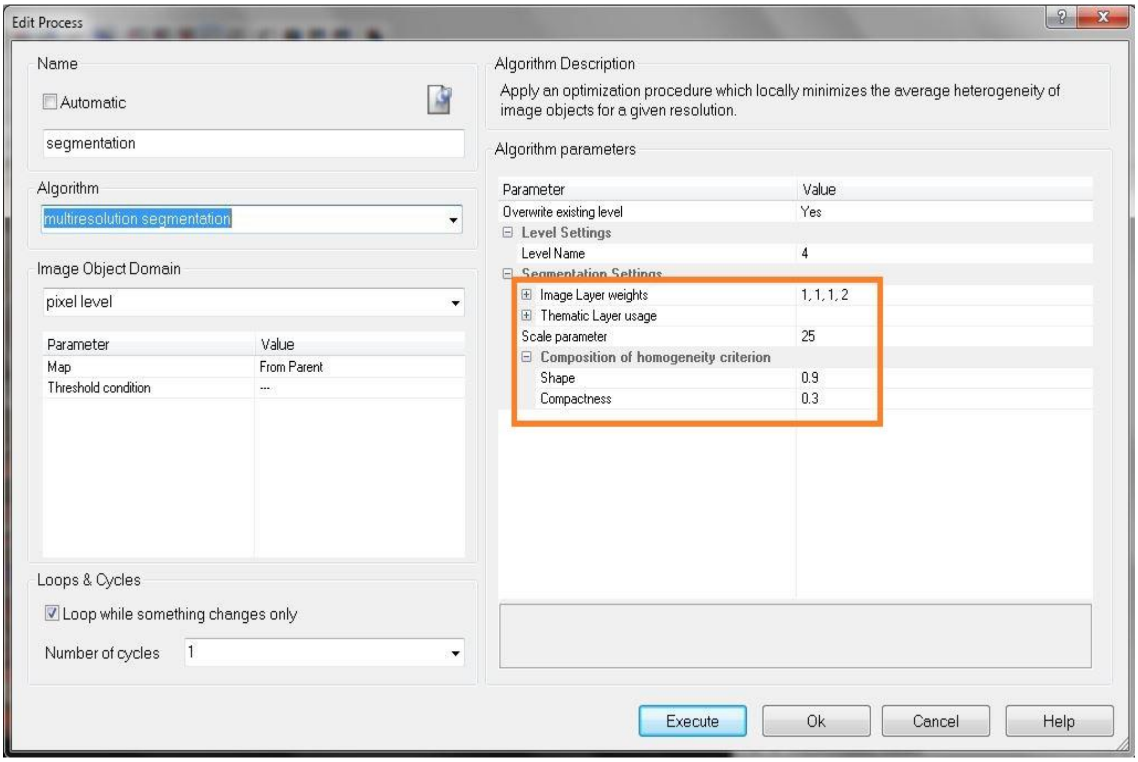


Figure 3.4. Multiresolution segmentation in eCognition

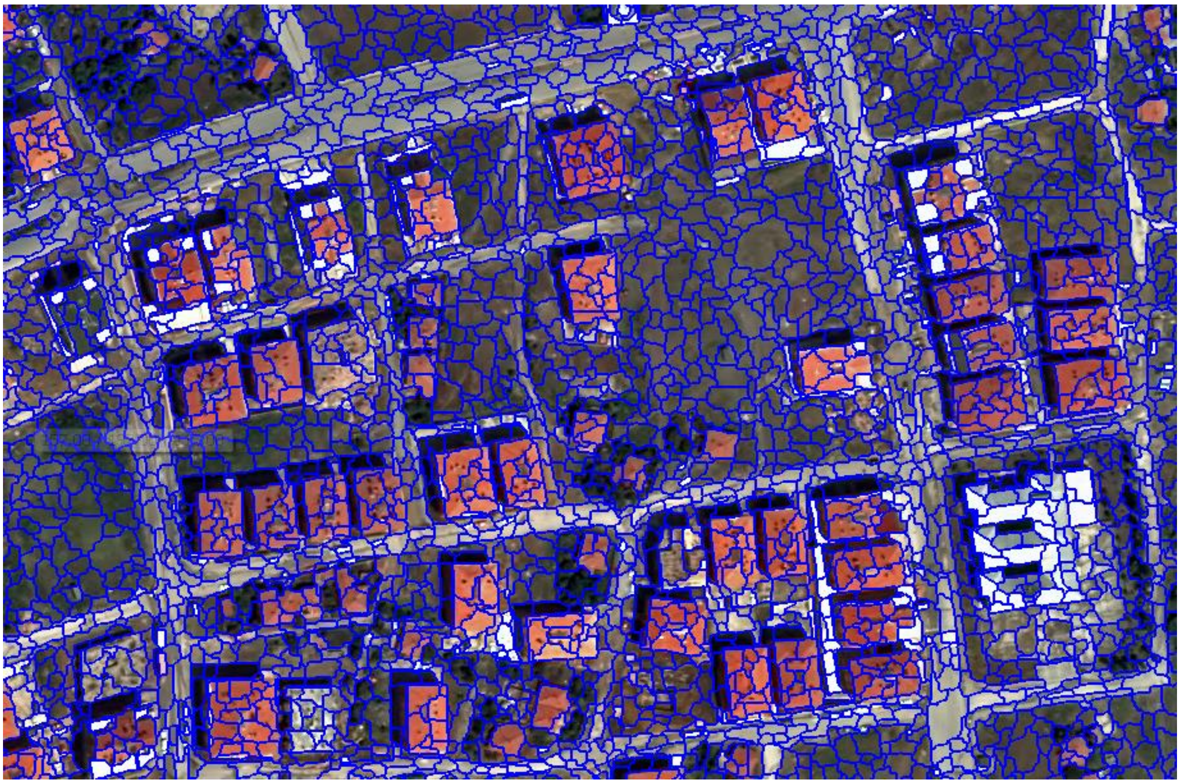


Figure 3.5. Segmentation with the scale parameter value of 15

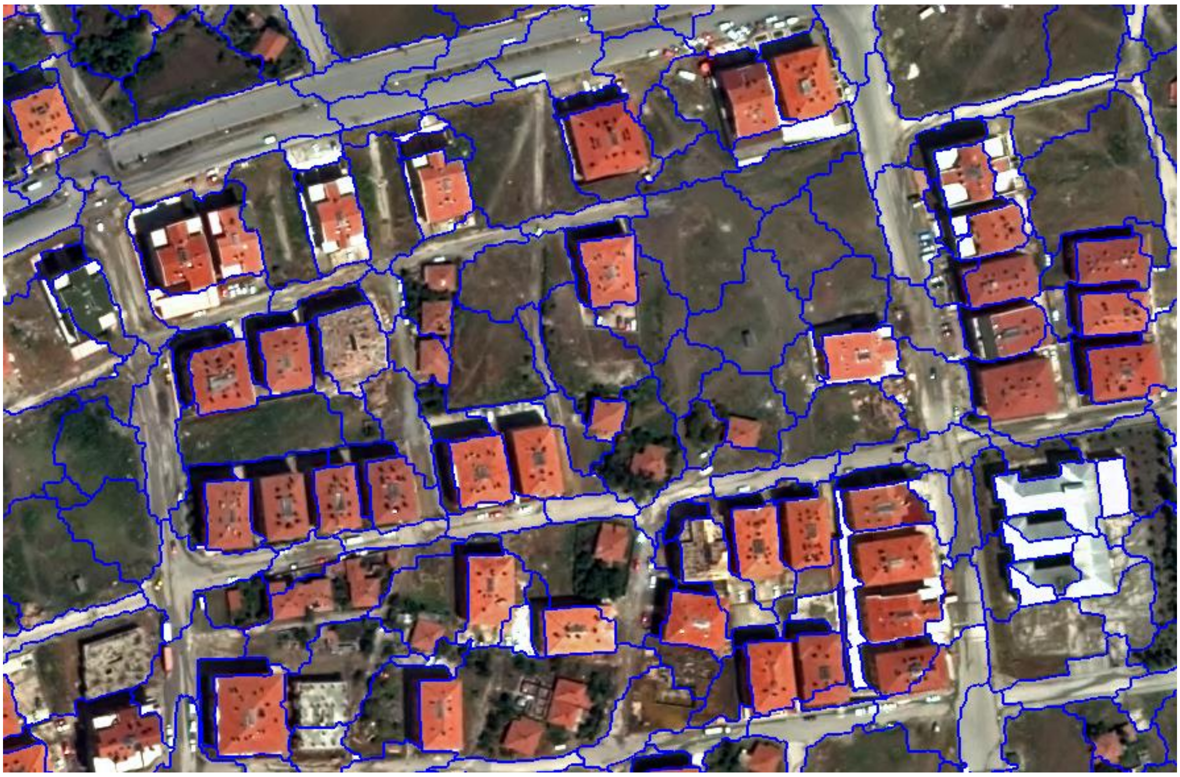


Figure 3.6. Segmentation with the scale parameter value of 50

Indeed in eCognitiontrial and error analsis is a standard approach for determining the optimum segmentation parameters to achieve high accuracy in segmentation. Further, the knowledge of the user about the image and the experience on the segmentation process also play an important role for the success of segmentation. The evaluation of the segmentation output was carried out by means of visually comparing the boundaries of the objects with the corresponding boundaries in the segmented image. To do that the segments under investigation were manually selected on the screen and their boundaries were visually checked if they match with the actual object boundaries. This is illustrated in Figure 3.7 where the boundary of a building segment, which is shown in red color in the lower left of the figure, matches quite well with the actual building boundaries.

The best fit parameter values used in this study for the extraction of urban buildings are given in Table 3.1. It should be remembered that these values may not be the best fit parameter values for all features the image contains. The output of segmentation, which is carried out using these parameter values, area shown in Figure 4.1 in the next chapter.

Table 3.1. The parameters and the parameter values used in the segmentation process for building extraction

Scale	**Image Layer weights (B, G, R,DSM)**	**Shape**	**Compactness**
25	1,1,1,2	0.9	0.3

Once the objects of the desired size are created through image segmentation, a number of features can be calculated for each object based on the Spectral, Spatial, Shape, and Texture characteristics. Many of these features may be irrelevant, correlated, and less informative to contribute to the classification. Indeed, the selection of the useful class features is a difficult and tedious process but it is very important. This analysis helps selecting a subset of important features for every class, which provides the best class separation and less overlaps to achieve better classification results. The Class Threshold value for each class can be selected from the properties table of each segment which is computed automatically.

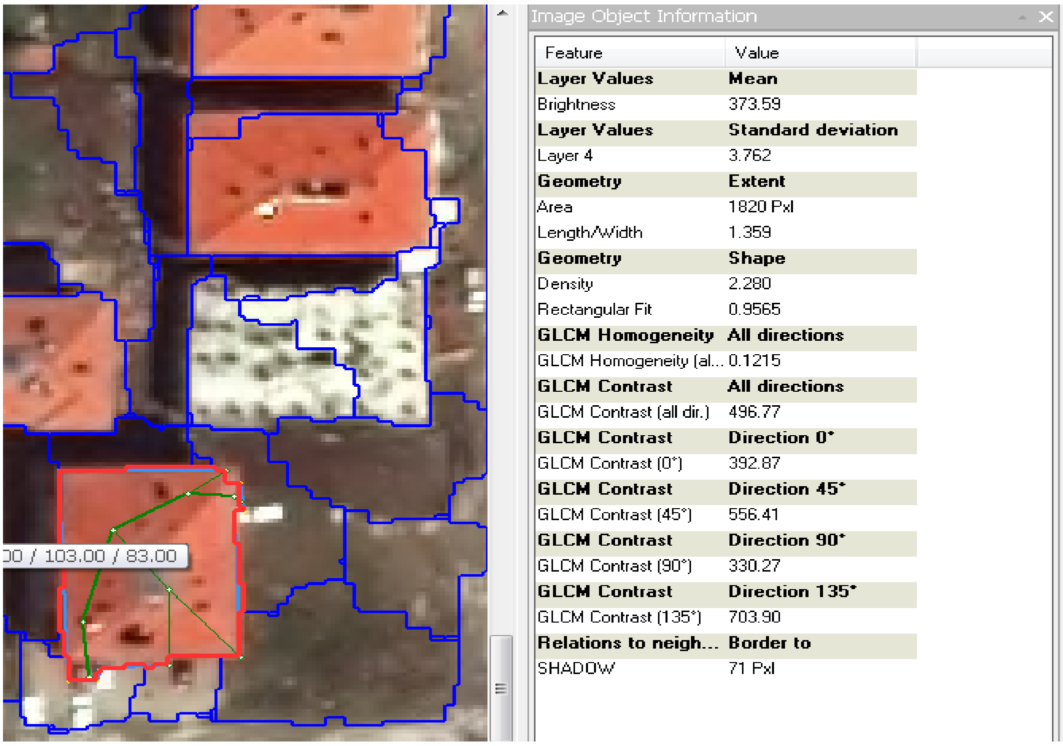


Figure 3.7. The illustration of a part of the image with the segment boundaries overlaid.

3.2. Classification

After completing the segmentation operation, the image was classified to extract the defined land cover classes. The land cover classes defined include bare soil (BRSD), building with light brown roof (BLBR), building with dark brown roof (BDBR), building with white roof (BWHR), green area (GRNA), road (ROAD), shadow (SHDW), and under construction building (UNCB) Figure 3.8.

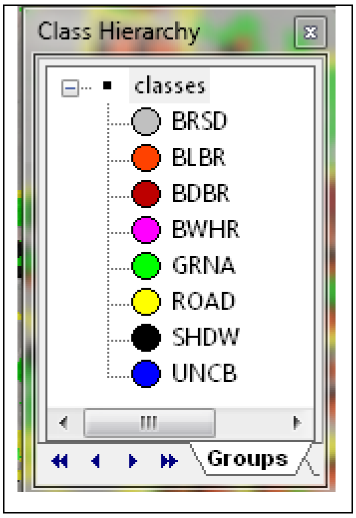


Figure 3.8. Class Hierarchy

Next, the classification operation was carried out based on the above extracted segments using their statistical properties. In the present case, a supervised classification method was used as the classification. Before performing the classification operation training samples were selected for each class. The training sample selection procedure was carried out based on the knowledge and the visual interpretation of the author. As the sampling method “simple sampling” was used. In this method each sampling unit had an equal chance for selecting. This process is easy to implement with sufficient sample size. However, difficulties may occur when the image contains one or more rare classes. Each sample object contains a number of pixels. The samples collected are called the “training sites ”. A total of 90 training sites were selected from the classes defined. Of the 90 training sites, 30 were for BLBR, 2 were for BDBL, 1 was for BWHR, 3 were for UNCB, 17 were for GRNA, 1 was for ROAD, 17 were for SHDW and 19 were for BRSD. The selected sample image objects are shown in Figure 3.9.

Figure 3.9. Sample selection

3.2.1. Nearest Neighbor (NN) Classification

The classification was carried out in two steps. First, the classification was carried out using the nearest neighbor (NN) classification method and then to improve the results a rule based classification was performed using the object features. NN classifier is non-parametric and independent of the assumption of normal distribution of the data [75]. To train the classifier sample image objects were selected for each class of interest. Then, for every unknown object, the algorithm searched for the closest sample object and assigned to the class whose sample object was the closest. Each image object was assigned to the class based on equation (3.1).

$$D_{(i,j.c)} = \sqrt{\sum_{b=1}^{n} (\mu_{cb} - X_{(i,j.c)})^2} \tag{3.1}$$

where, n is the number of bands, b is a particular band, c is a particular class, $X_{(i,j.c)}$ refers to brightness value (BV) of a candidate pixel i, j in band b, μ_{cb} is the mean vector for band b in class c, and $D_{(i,j.c)}$ is the spectral distance from pixel i, j to the mean of class c. Therefore, the NN classifier computes the Euclidean distance from the image object to be classified to the nearest sample object in n-dimensional space [76] and [77].

To improve the classification results eCognition allows to define statistics to add to the Standard NN classification. In eCognition, the object features can be added in the below given four categories:

- Image bands layer values (Mean, Standard Deviation, Mean Difference etc.),
- Object shape or geometry (Area, Perimeter, Length/Width etc.),
- Texture (GLCM Statistics, Layer value texture etc.), and
- Hierarchy and class related feature (Level, Number of neighbors etc.).

Image bands layer values are probably the most common features used in the classification process. The mean layer value is probably the most widely used feature for separating dissimilar objects based on spectral data. Texture is also an important feature to be used for describing the classes. Texture can be computed based on a grey level co-occurrence matrix (GLCM). Of the GLCM features available entropy appears to be the most common feature used and it can be applied in all directions. Area refers to total number of pixels that fall within a specific segment. Length/Width can be calculated by considering the combined length of all boundaries of the polygon. To calculate Max Diff. the minimum mean value that belongs to an object is subtracted from its maximum value. To get the maximum and minimum values the means of all layers that belong to an object are compared with each other. The features that were used in this study are given in tables Table 3.2, Table 3.3, Table 3.4 and Table 3.5. During NN classification operation the object features Area, Brightness, CLCM Entropy, Mean Layers, Standard Deviation, Length/width and Max Diff (Table 3.6) and, to improve the output of NN classification some other rules and thresholds, which were defined for the features Border to Shadow, Density, and Rectangular fit, were used (Table 3.7).

Table 3.2. Layer value [74]

Attribute	Description
Brightness	Provides spectral information for calculation
Mean Layer	In a band, the mean value of the pixels that comprise the region
Standard Deviation Layer	In a band, the standard deviation value of the pixels that comprise the region
Max Diff	Max Diff is calculated by subtracting the minimum mean value of an object from its maximum value

Table 3.3. Geometry [74]

Attribute	Description
Area	The area of a polygon, minus the area of the holes. The area is computed by the number of pixels in a segmented object.
Length/width	The total length of all boundaries of a polygon, including the boundaries of the holes.
Rectangular fit	A shape measure which represents how well the shape of a polygon is described by a rectangle. It compares the area of the polygon to the area of the oriented bounding box that enclose the polygon. For a rectangle, the rectangular fit value is 1.0, and for a non-rectangular shape it is less than 1.0. Rectangular_Fit = Area / (Major_Length * Minor_Length)
Density	For an image object, it refers to the distribution of pixels.

Table 3.4. Texture [78]

Attribute	Description
GLCM Entropy	A method of examining texture which considers pixels' spatial relationships. Figure 3.10 shows the spatial relationships of pixels, where D refers to the distance from pixel of interest.

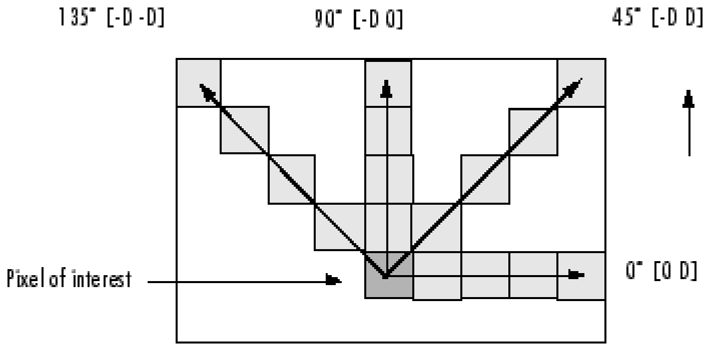


Figure 3.10. GLCM

Table 3.5. Class related feature [74]

Attribute	Description
Class-related	It is another aspect for defining classes based on relationships between the neighbor objects, sub or super objects and the classified objects. For instance, border-to defines the number of pixel edges shared with the image objects of a defined class.

Table 3.6. The features used for NN classification

Nearest Neighborhood Feature
Area
Brightness
GLCM Entropy (all Direction)
Mean Layer (1,2,3,4)
Standard Deviation (1,2,3)
Length/Width
Max.Diff

The flowchart given in Figure 3.11 shows a brief view of the NN classification process carried out in this study. After performing the NN classification, still some misclassified objects or object parts will exist and thus the results will need to be improved through a rule based classification to be performed in the next step.

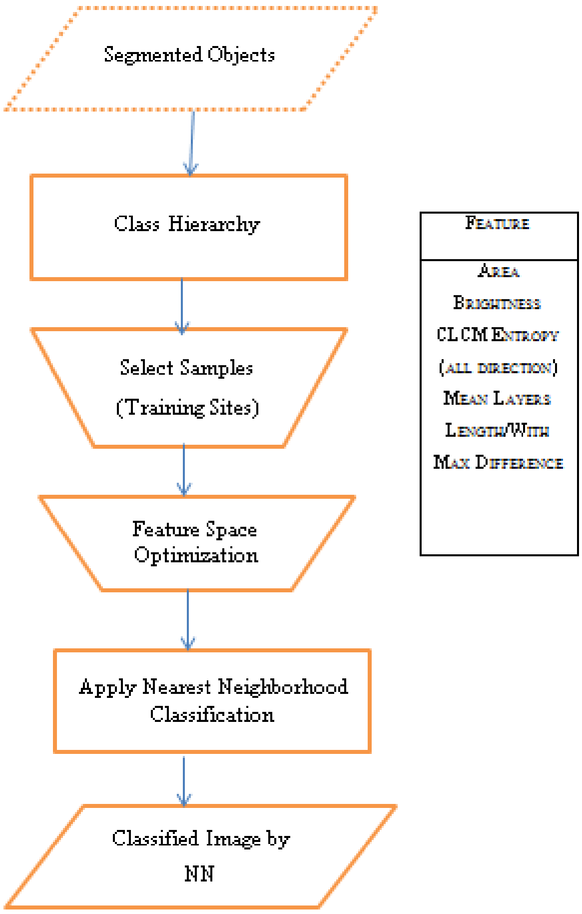


Figure 3.11. The steps followed during NN classification

3.3. Rule Based Classification

After performing the NN classification, a Rule Based classification was carried out. This is due to the fact that the NN classification has a limited capability for extracting and classifying the image objects. Therefore, this time the classification rules were considered. To calculate the important object features, the feature and statistics analysis of eCognition was used. This analysis is helpful for selecting a subset of important features for every class, providing the best class separation and less overlap in order to achieve better classification results. Rule based classification uses specific rules based upon the object characteristics to define a class. It requires the selection of object features to develop classification tools. It allows the use of Spectral, Spatial, Texture, Shape and Contextual features to form classification rules that can determine different objects. It requires expert knowledge to decide about the most appropriate object features and their combinations to form classification rules [79]. Rules are set of conditions based on feature of the objects and if they are properly assigned to classes they would improve the accuracy.

The rules can have one or more object features and they are driven from prior knowledge or through the statistics analysis of the objects. The present study focuses on the extraction of buildings in urban area. As is well known, the buildings are mainly compact and they are almost always higher than the surrounding objects. Because of this feature, the buildings cast shadows. Therefore, shadow is one of the main constituent classes that should be considered for urban land cover classification. Shadows have low brightness values and therefore, in the present case the SHDW class can be easily separated from the other classes. In other words, the adjacency information with the SHDW pixels would be a valuable feature in extracting the building class. In the case the shadow is absent, the extraction of building class is still possible by using the other features. Further, most of the buildings are rectangular in shape, their geometry is similar and they have a minimum size. Therefore, by combining these features with the color and density information of different roof types, the buildings can be correctly classified and the misclassifications occurred during the NN classification can be reduced. Roads are very different in their spectral response with each other and they can be incorrectly classified as Bare Soil (BRSD) or Under construction buildings (UNCB). To overcome this problem density of roads was considered. Roads have lower density than under construction buildings and bare soil. Roads are not completely rectangular when compared to buildings under construction. They spread in longer shapes. However, in this study the building class constitutes the most important object and different kinds of buildings are to be extracted by considering their different characteristics. For example, buildings with white roofs have a high brightness value and relatively large areas. Also, roads and buildings under construction have similar spectral values. Therefore, they can be separated by using the the density value. Considering the density values, buildings under construction have a higher density value than the roads. Also, roads do not have long borders with the cast shadows. In eCognition, all these features and the thresholds can be selected from a menu shown in Figure 3.12.

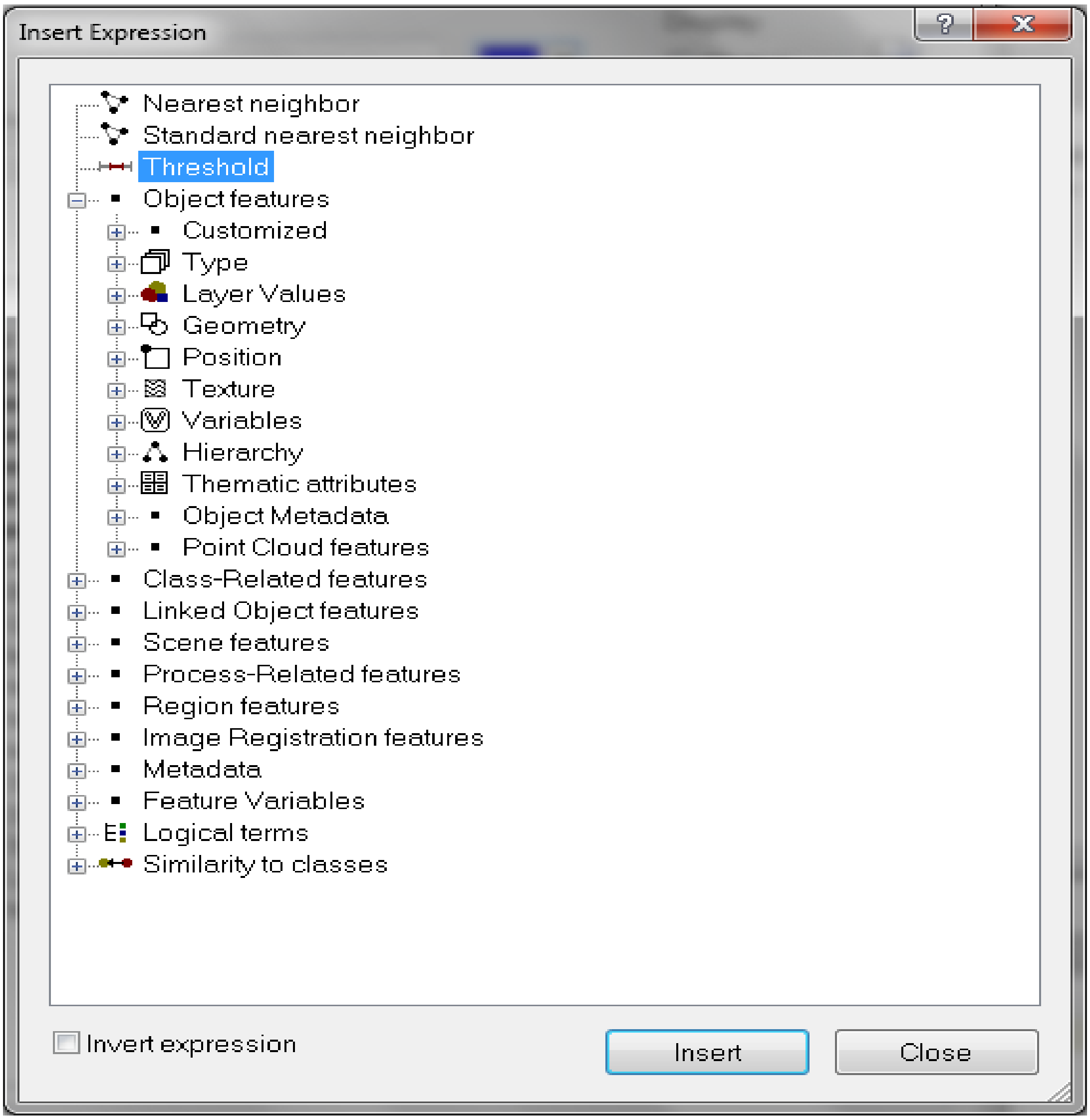


Figure 3.12. The features that exist in eCognition

The features and threshold values used for each class during rule-based classification are summarized in Table 3.7. Preferably, a minimum number of features should be used for every class to avoid computational complexity. However, multiple object features should be used to minimize between class and within-class confusions and to achieve better discrimination. After selecting the appropriate object features, the thresholds were defined to better represent the characteristics of the objects.

Table 3.7. The features and threshold values used for each class during rule based classification

Class name	Feature
BLBR	Border to Shadow >10 Pix Density >1.69 Rectangular Fit >0.6
BDBR	Border to Shadow>80 Area >800 Length/width <2 Standard deviation Layer 4 >5.3
BWR	Border to Shadow >20 Pix Area >500 Brightness >230 Standard deviation Layer 4 >4.21
UCB	Border to Shadow >50 Area >500 Density >2 Rectangular Fit >0.8
Bare Soil	
Shadow	
Road	Density <2 Rectangular Fit <0.4
Green area	

For spectrally similar and confusing classes a rule can combine a set of features. The attributes can be assigned threshod values to indicate the condition of an object. For example, if Border to Shadow is more than 2 pixels and Density is more than 1.9 and Rectangular Fit is more than 0.6, then the objects are buildings with light brown roof (BLBR). After completing the classification operation, a visual check of the results was performed and the results were improved by means of modifying or updating the class features rules, and thresholds.

3.4. Morphological Operations

Some buildings were so close to each other that during segmentation they were considered as a joint building segment. Due to the narrow and small gaps between buildings or poor shadow information close buildings were not able to be separated from each other. During segmentation some adjacent pixels to building patches with the spectral values similar to building pixels were merged with the building patches. Further, in most cases the shapes of classified buildings are not quite rectangular and the closely located buildings are merged as one building in several cases. Therefore, some of the misclassified pixels should be removed by means of a morphological opening operation.

The morphological opening operation was followed by the morphological erosion and dilation operations. The erosion and dilation operations are the fundamental morphological operations [80]. For morphological operations, the selection of both the structuring element and the kernel size of the structuring element are important. The erosion of image “I” by structuring element “K” is symbolized as $I \Theta K$. The morphological erosion process makes the objects thinner than the input image and if this process is followed by the dilation operation the image objects become thicker than the input image. The dilation of image “I” with structuring element “K” is shown as $I \oplus K$. The opening process is defined by the symbol $I \mathrm{O} K$. The equation of this process is given in equation (3.2).

$$I \mathrm{O} K = (I \Theta K) \oplus K \tag{3.2}$$

The morphological opening operation was carried out to remove thin protrusions as well as removing irregularities and thin joins between the building objects. Thus, the building patches have become slightly smaller isolated objects. The morphological opening process separated a few of the merged building patches. However, for the closely located buildings this operation did not work well and therefore, the closely located buildings remained merged Figure 4.13 in next chapter illustrates this problem. After performing the classification operation and the subsequent morphological operations, the building class was extracted and masked out from the other classes. The advantage of excluding the other classes from the building class was that further processing operations were carried out on the building class only. Figure 3.13 illustrates the flowchart of the process.

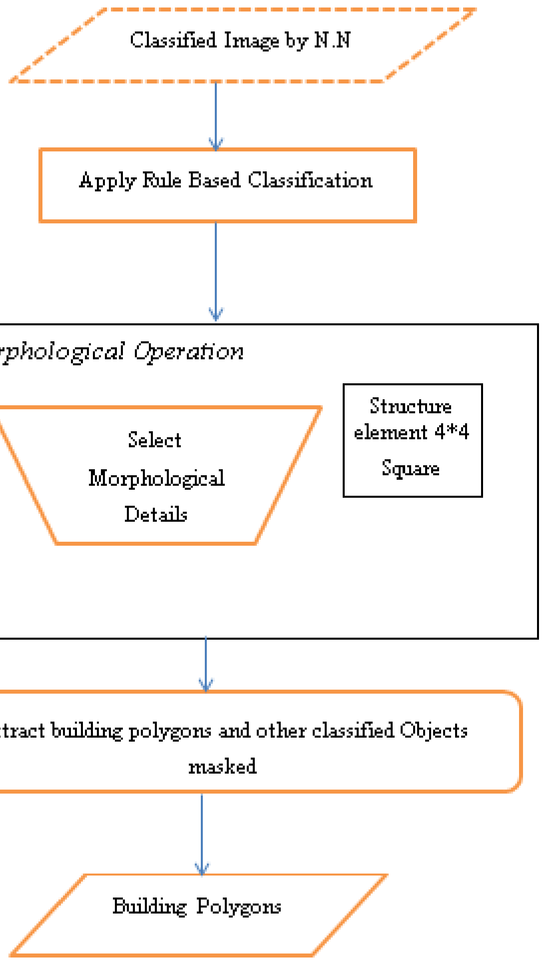


Figure 3.13. Morphological operation

3.5. Change Detection

After extracting the buildings from the image the changes of buildings or building parts were extracted by means of an overlay operation between the old vector map data and the building class which was extracted through object based image classification of the image Figure 3.14 is the flowchart of this process. The results of overlay operation shows the changed and unchanged areas. Those areas that are intersected and are the same in both data sets are considered to be the unchanged buildings or building parts. On the other word, those areas that are not intersected illustrate the changed areas Figure 3.15 and equation (3.3) illustrate this concept. The changed buildings or buildings parts can be categorized into two groups: (i) new buildings, and (ii) demolished buildings. Figure 3.16 demonstrates the changes that can occur between two data sets that belong to two different dates.

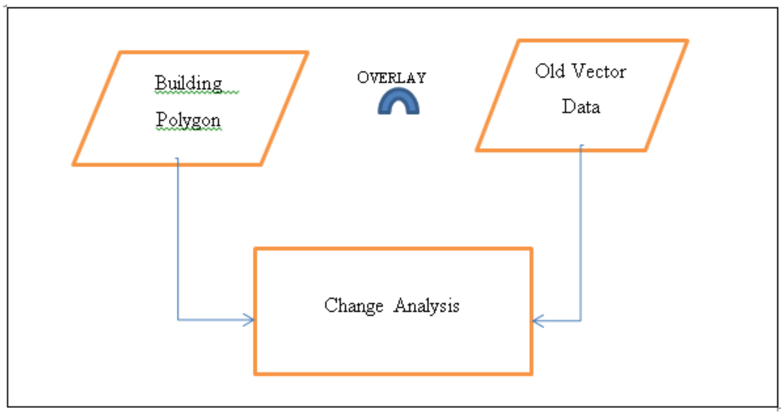


Figure 3.14. The change schema

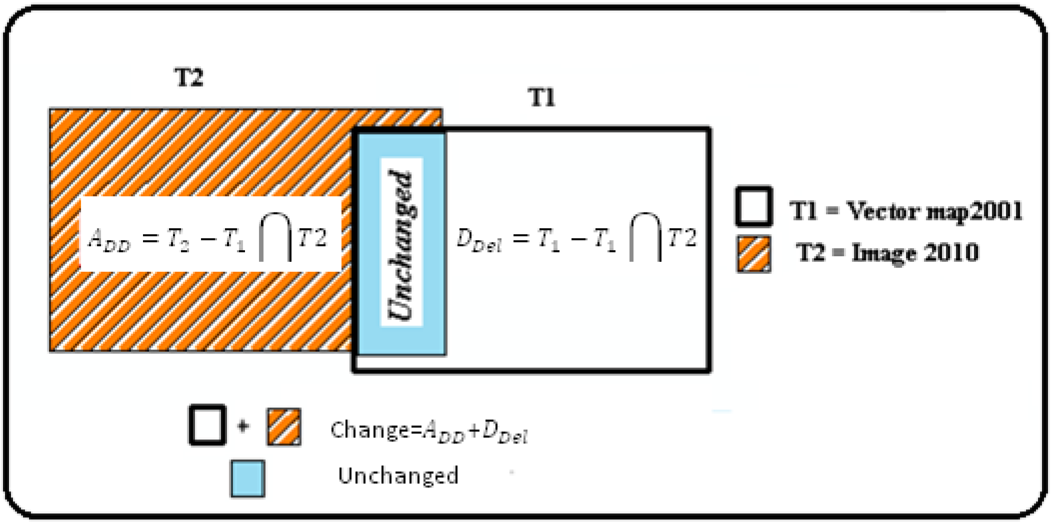


Figure 3.15. The illustration of changed and unchanged areas

$$change = A_{DD} + D_{Del}$$

$$A_{DD} = t_2 - t_1 \bigcap t_2 \qquad (3.3)$$

$$D_{Del} = t_1 - t_1 \bigcap t_2$$

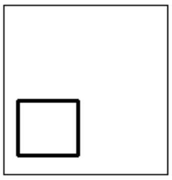
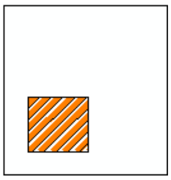
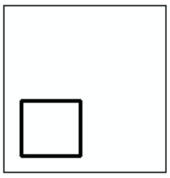
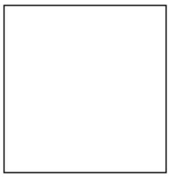
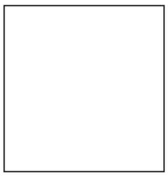
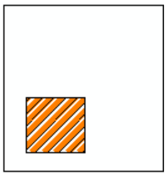
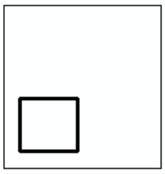
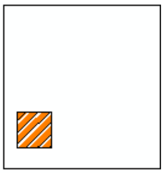
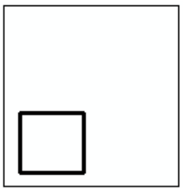
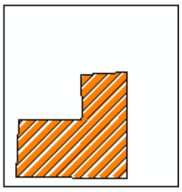
Vectormap2001 (T1)	Image2010 (T2)	Definition
a) T1 	T2 	**Unchanged buildings** Building in T1 dataset completely overlaps with the building in T2 dataset.
b) T1 	T2 	**Demolished buildings** Building in T1 dataset was demolished and does not exist in T2 dataset.
c) T1 	T2 	**New buildings** A constructed new building, which is missing in T1 dataset, appears in T2 dataset.
d) T1 	T2 	**Partially demolished** Building in T1 dataset was partially demolished and part of it exits in T2 dataset.
e) T1 	T2 	**Expanded buildings** Building in T1 dataset was expanded in T2 dataset.

Figure 3.16. Comparision of old vector map and new classified image

The detected changes must be categorized as “demolished and missed ” and “new and false detected ” changes. The buildings that exist in the classified image but missing in the old vector map data were considered as new buildings. During the classification process the other image objects were, fully or partially, classified as the building class causing false detection. These falsely detected building patches were considered as new buildings or building parts. The similar procedure was also followed for separating the demolished and missed buildings. The buildings that were in the old vector map data but missing in the classified image may not be immediately labeled as demolished buildings since the buildings may have been missed in the classification process. This obviously effects the accuracy of change. In detecting the building changes, whereas the detection through visual analysis, the automatic detection of the new and demolished buildings was difficult due to the errors in the classified image. Visual analysis can be effective for small areas however, it would be very difficult and time consuming for large areas where building density is high. The total change was obtained by the sum of new or partial new buildings and full or partial demolish buildings.

3.6. Accuracy Assessment

Accuracy assessment was performed by calculating the accuracy values for both the classified image and the detected change map. The reference data sets were generated using the ArcGIS software. To do that the new image and old vector map were displayed as superimposed on the screen and the boundaries of new buildings were delineated from the image, while the collapsed buildings were deleted. In other words, the reference data set in vector form for the accuracy assessment was prepared by means of updating the existing vector map from the new image. The old vector map was updated by deleting the demolished buildings and delineating the new buildings. During the preparation of the reference data the buildings smaller than $25m^2$ were not considered.

The change accuracy is effected by the accuracy of classification. To quantitatively evaluate the detected changes, the change reference data set was used. Reference data sets for the changed and unchanged areas were also prepared through the overlay analysis between the old vector map data and the reference data for classification in ArcGIS. The reference of the changed areas were acquired by the “Symmetrical difference” between two different dates of vector data. The change reference data set defines the none intersection areas between the old and new vector maps. The intersected areas are considered as the unchanged areas. The sliver polygons caused by the boundaries of the building patches were removed from the reference map [81] and [82].

However, one problem was that the boundaries of existing buildings in the old vector map did not quite match with the building footprints in the image. Therefore, the existing building boundaries were manually shifted so as to match with the building footprints in the image. The amount of shift was less for lower buildings than that of higher buildings and in some cases no shift was necessary. The sliver polygons caused by the boundaries of the building patches were removed from the reference map. Then, to use them in further processing operations all the building polygons were stored as a shape file (*.Shp) format of the ArcGIS software.

The accuracy values were computed by pixel-by-pixel comparing the results with the reference data sets. The result of the comparison was categorized into three cases: True Positive (TP), False Positive (FP), and False Negative (FN).

True positive (TP): The pixels that are same in both the reference data set and the results.

False Positive (FP): The pixels which are only detected by method and do not exist in the reference data. These are the pixels falsely detected by the proposed method.

False Negative (FN): The pixels which exist in reference data but are not detected by the proposed method. These are the pixels not detected by the proposed method.

Schematic representation of the study cases are shown in Figure 3.17 and the the TP, FP, and FN are illustrated in Figure 3.18.

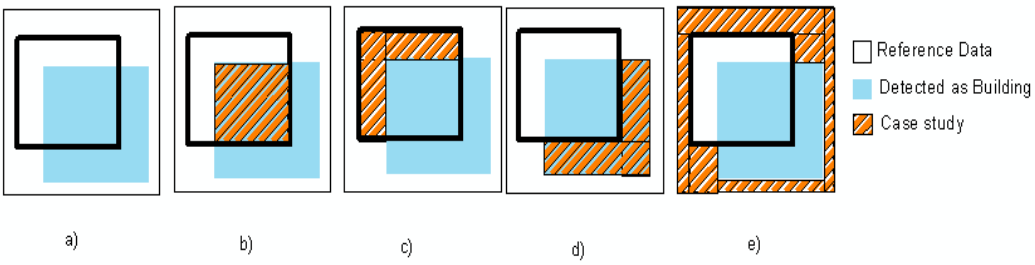


Figure 3.17. a) Detection example , b) True Positive , c) False Negative , d) False Positive , e) True Negative

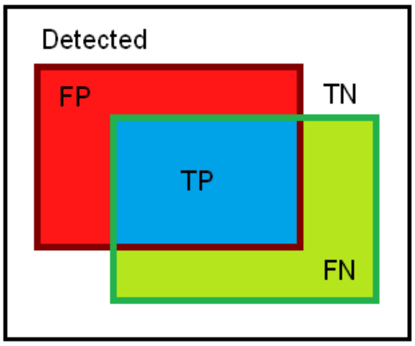


Figure 3.18. The schematic representation of TP, TN, FP and FN areas

After counting the pixels that fall into above categories, the following summary statistics were computed [83].

Branching Factor (BF): FP / TP (3.3)

Miss Factor (MF): FN / TP (3.4)

Building Detection Percentage (BDP): 100 * TP / (TP + FN)) (3.5)

Quality Percentage (QP): 100 * TP / (TP + FP + FN) (3.6)

For computing the change accuracy the quality measures correctness and compactness were used.

$$\text{Correctness} = \frac{\text{TP}}{\text{TP+FP}} \tag{3.7}$$

$$\text{Completeness} = \frac{\text{TP}}{\text{TP+FN}} \tag{3.8}$$

These measurements give us an idea about the accuracy of the detected building patches. The "Branching Factor" indicates the rate of incorrectly labeled building pixels. The "Miss Factor" describes the rate of building pixels missed. The "Building Detection Percentage" gives the percentage of building pixels correctly detected by the automatic process and the "Quality Percentage" is the overall measure of performance, which accounts for all misclassifications and describes how likely a building pixel produced by the automatic detection is true.

Correctness and Completeness are used to find the change accuracy. Correctness shows the Truly detected changed areas. In other words, correctness indicates the percentage of the detected change pixels that are overlapped with reference data. Completeness shows the percentage of change reference that were correctly detected by the proposed method. In other words, this value refers to percentage of change reference overlapped with the detected change. Correctness and completeness, which reveal the errors of commission and omission. Omission is the area that is not detected and missed area (FN) and Commission is the incorrectly detected area (FP).

4. RESULTS AND DISCUSSION

4.1. Results for Segmentation

The multiresolution segmentation process, which was applied using the parameters Scale, Shape, Compactness and Layer Weight, detected 9857 homogeny segments. The output of multiresolution segmentation of the 2010 image is given in Figure 4.1. By using different parameter values different results were generated. To obtain the best results in classification and change detection the parameters (Scale, Shape and Compactness and Layer Weight) and the parameter values were selected based on the object of interest, which is building in this study. The evaluation of the results of segmentation was carried out visually. The visual interpretation process helped find how close the segmentation results to real object boundaries. The selected best parameters and the parameter values which were defined for the detection of building boundaries with best results are given Table 3.1 in previous chapter.

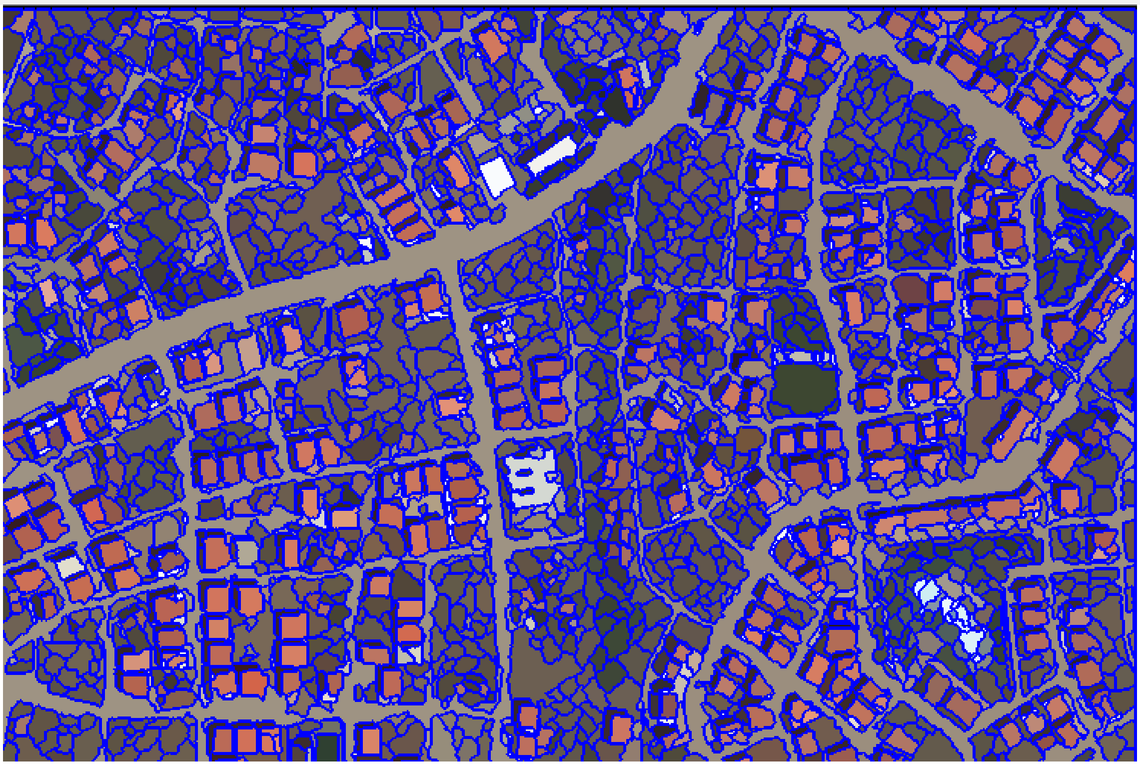


Figure 4.1. The output of multiresolution segmentation of the 2010 image

Although the best parameters were used for the segmentation process the segmented image contained various faults however. High resolution images add more useful details about the ground objects but the details make the analysis and segmentation processes harder. Buildings are complex in Structure, Shape, Geometry, Construction and Size and also they are constructed using different materials. In addition, spectral similarities between the buildings and many other urban objects, such as ROAD, BRSD, etc. were evident. A number of problems, which were found during segmentation, are listed below:

- Some inaccurate segments were caused by merging other objects with the building segments instead of reaming separate segments. For example, when the spectral reflectances of the buildings are very similar to adjacent roads the buildings have been detected partially and the corresponding building parts were merged with the roads instead of remaining as building parts and contrariwise the road segments were merged with the building segment parts. Figure 4.2 illustrates this problem with an example.
- Because of the spectral heterogeneity of the building roofs the segment boundaries did not precisely fit to roofs and thus the roofs were fragmented to small segments instead of fitting the roofs. The main reason for the fragmentation of the roofs was due to the fact that the chimneys and the shadows cast by the chimneys caused noise and holes in segmentation Figure 4.3 shows this problem with the examples.
- In some cases, buildings are very close together, the boundaries are blurred, and there is no contrast on the boundaries. Therefore, for these buildings it was not easy to separate the building image objects from each other through segmentation. Thus, the segmentation process has merged these buildings instead of splitting them into separate buildings. Figure 4.4 illustrates this problem with the examples.
- In several cases, the segments for buildings, which are small and surrounded by the trees, also contained the surrounding trees. Figure 4.5 illustrates this problems with the examples.

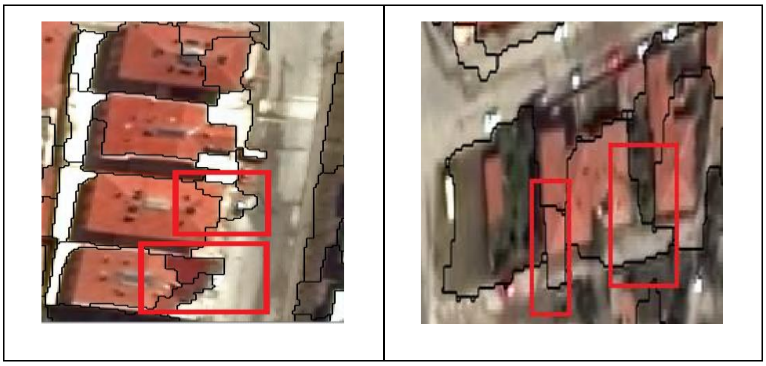


Figure 4.2. The building segments that were merged with the road segments

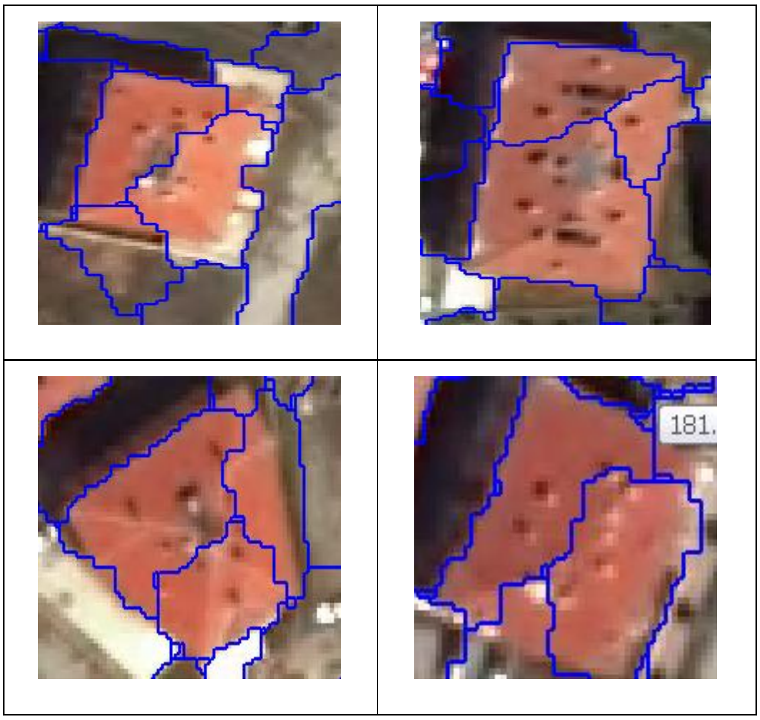


Figure 4.3. The roofs that were fragmented into small segments

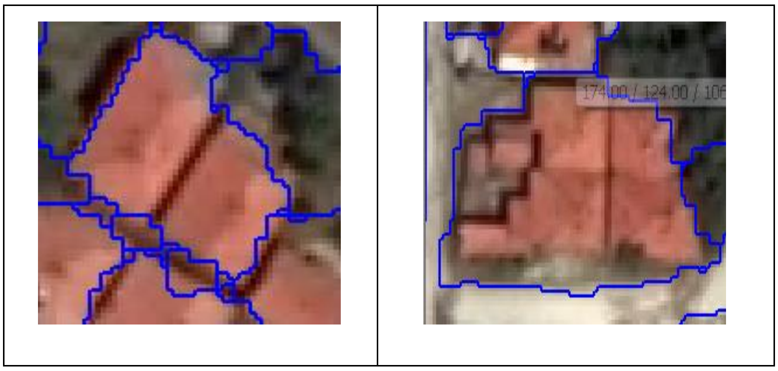


Figure 4.4. The merged segment of the adjacent roofs

Figure 4.5. Buildings surrounded by the trees

4.2. Results for Classification

As mentioned in the previous chapter, the classification was carried out by using the rules and the spectral, textural and geometrical information obtained from the segments generated for different objects. If a segment contains a high rate of pixels that belong to a specific class, then this segment potentially belongs to same class. The output of image classification is illustrated in Figure 4.6. Further processing operations were carried out on the building patches. Therefore, the other objects were masked out. The satellite image with the building class is overlaid is shown in Figure 4.7.

Figure 4.6. The classified image

The morphological image processing was performed in order to enhance the extracted building class. Therefore, this operation has increased the classification accuracy. Accuracy assessment of the classified image was carried out using two methods. In the first method, a matrix, which provides the samples selected for the training areas of the classification process, was used. The overall accuracy and the individual class accuracies are given in an error matrix in Table 4.1. The overall accuracy was computed by dividing the total number of correctly classified image objects (segments) to the total number of image objects used. The overall accuracy was computed to be 98.8%.

Figure 4.7. The satellite image with the building class is overlaid

Table 4.1. Error Matrix

Classified data		Reference Data								
		BLBR	BDBR	BWHR	UNCB	GRNA	ROAD	SHDW	BRSD	SUM
	BLBR	**30**	0	0	0	0	0	0	0	30
	BDBR	0	**2**	0	0	0	0	0	0	2
	BWHR	0	0	**1**	0	0	0	0	0	1
	UNCB	0	0	0	**3**	0	0	0	0	3
	GRNA	0	0	0	0	**17**	0	0	0	17
	ROAD	0	0	0	0	0	**1**	0	0	1
	SHDW	0	0	0	0	0	0	**17**	0	17
	BRSD	1	0	0	0	0	0	0	**18**	19
	SUM	31	2	1	3	17	1	17	18	180
Producer		0.96	1	1	1	1	1	1	1	1
User		1	1	1	1	1	1	1	1	0.94

In the second method of assessment the truly classified building patches were compared with the reference data. In this study, this comparison was made using the ArcGIS software by means of performing an overlay analysis between the reference data and the detected building patches. For the assessment, true positive (TP), false positive (FP), and false negative (FN) values were computed. Figure 4.8 shows the buildings or building parts which were detected as building in both the classified and reference data sets. In other words, these areas represent the true positive (TP) areas.

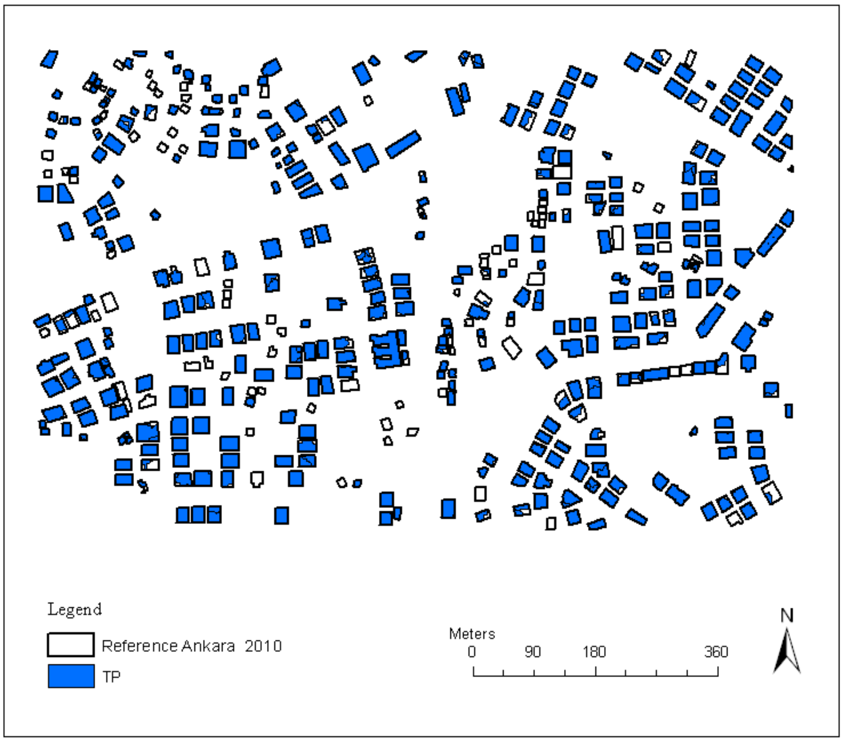


Figure 4.8. The true positive (TP) areas

The buildings which were detected through classification but they do not exist in reference vector data set are considered as false detection. Most of the misclassified areas were caused by those objects that represent similar reflectance characteristics with the buildings or during segmentation process merged with the building segments. The reference building boundaries were more generalized and crisp as they were manually digitized from the image and in the present case the buildings were considered to be rectangles or squares. However, the building outlines extracted through image classification were rather irregular as image segmentation maintains the exact building boundaries and this has caused errors in the accuracy calculations. Figure 4.9 shows the false detected buildings.

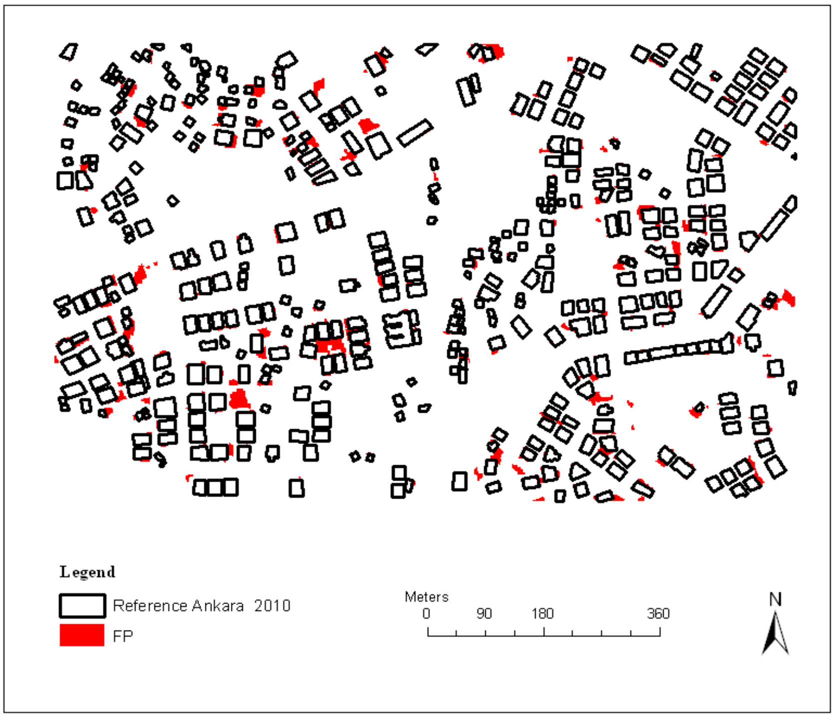


Figure 4.9. The false positive (FP) areas

The buildings that exist in the reference vector data set but missing in the classified image are considered to be missed in the classified image. These areas that are shown in Figure 4.10 refer to false negative (FN) areas and they are considered as the missed building or building parts.

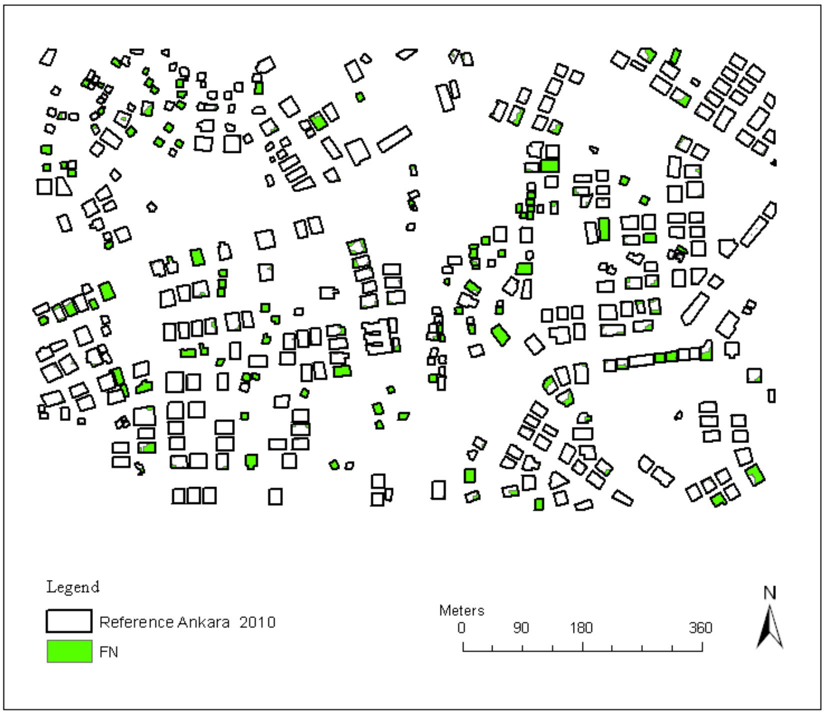


Figure 4.10. The false negative (FN) areas

The accuracy assessment results are given in Table 4.2, where “BF” refers to Branching Factor, “MF” refers to Miss Factor, “BDP” refers to Building Detection Percentage and “QP” refers to Quality Percentage. The rate of incorrectly labeled building pixels that refers to branching factor (BF) is 30%. The rate of missed building pixels (MF) during classification was computed as 21%. The range of miss factor is between 0 and 1 and for miss factor a low value is preferable. The percentage for the detected building pixels (BDP) during classification process was computed to be 82.21% and the quality percentage (QP) value was computed as 65.78%. The BDP value ranges from 0 to 100 and for BDP a high value is preferable.

Table 4.2. The BF, MF, BDP and QP values computed for the assessment of the classified image

Total classified pixels	**Total reference data pixels**	**BF**	**MF**	**BDP**	**QP**
135174	126121.5	0.30	0.21	82.21	65.78

It was observed throughout this study that the eCognition software was quite successful in the detection of large buildings. However, the classified image and the reference vector data sets did not intersect quite well for small and unclear buildings. Indeed, the small and unclear buildings were not able to be detected completely. The small size and the poor shadow information have made the detection process difficult. The shadows cast by small buildings were either not available or too thin to be detected. The inclusion of the shadow information was found to be quite necessary for correctly classifying the building segment. In Figure 4.11 the blue circles represent those buildings or building parts that were not detected through classification and make the missed buildings.

Figure 4.11. The building class with the reference data set overlaid. The blue circles illustrate those buildings or building parts that were not detected during classification

The missed buildings through classification were caused by so many reasons. Obviously, the merged and fragmented segments influence the classification results. The problems that were encountered in classification are listed below:

- Two or more separate buildings were classified as a joint building due to adjacent building segments. Morphology operators helped improve the building outlines and separated a few of the merged buildings. However, when the buildings were too close, these operation did not help much and the buildings remain merged. This case is shown in Figure 4.12 with an example.
- The fragmented segmentation of the buildings caused partial detection of the roofs in the classification process. Example cases for partially detected buildings due to fragmented segmentation are shown in Figure 4.13.
- In some cases buildings that are surrounded by high vegetation did not let to extract shadows cast by the buildings. In this study, it was assumed that buildings have a common border with their cast shadows. If this condition is not satisfied the building detection may not be possible. However, most of the small and low-height

buildings did not produce enough shadow areas and therefore this has caused a problem for the detection of buildings. Figure 4.14 illustrates this problem.

- Some building roofs are not in mono color and they contain white areas. These white areas on the roofs were segmented as separate segments and thus they were not classified as a building patch causing error in classification. This case is illustrated in Figure 4.15 with the examples.

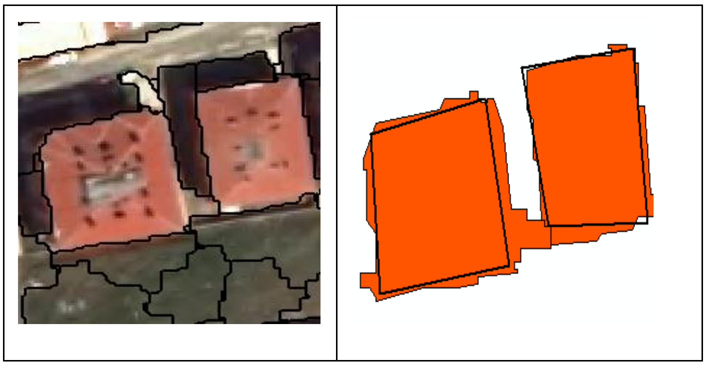


Figure 4.12. The merge of buildings in classification

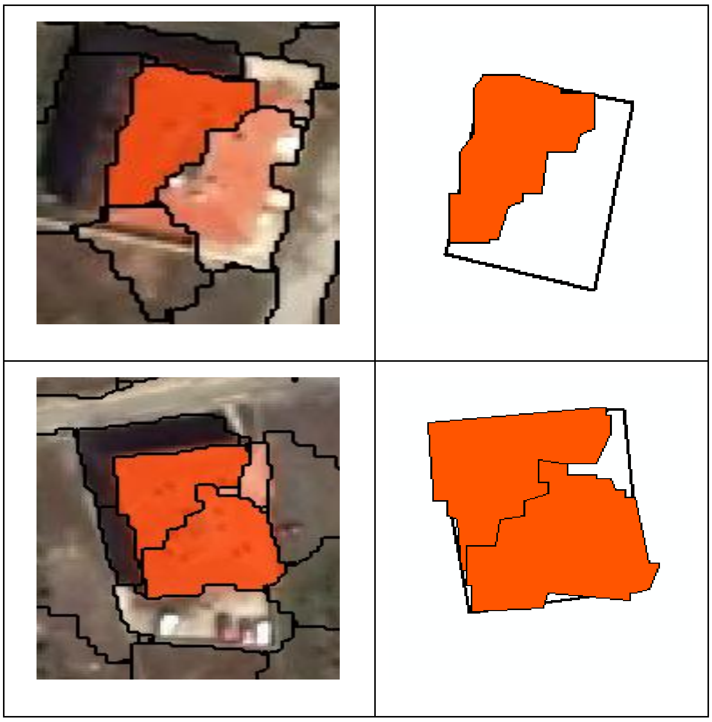


Figure 4.13. The fragmented segmentation and thus the partial detection of the roofs

Figure 4.14. The buildings that were not detected through classification due to surrounding high vegetation and low vegetation areas

Figure 4.15. Building roofs with white areas. These white areas on the roof were segmented as different image objects and they were not classified as building

4.3. Results for Change Detection

The changes between the extracted building class and the old vector data were calculated and the accuracy assessment of the detected changes were measured by means of an overlay analysis between the detected change areas and the reference data. For evaluating the accuracies of the results the same accuracy tests described above were carried out and the true positive (TP), false positive (FP), and false negative (FN) areas, which respectively show the truly detected, falsely detected and the missed changed areas were computed.

The truly detected changed areas are illustrated in Figure 4.16. As it can be seen in the figure some areas are partially or completely do not overlap with the reference data. These areas are the missed areas and are shown in Figure 4.17 as the false negative (FN) areas. Similarly, some areas were detected as the change areas by mistake and these areas are the falsely detected changed areas (Figure 4.18). The BF, MF, BDP and QP values computed for the changed areas are given in Table 4.3.

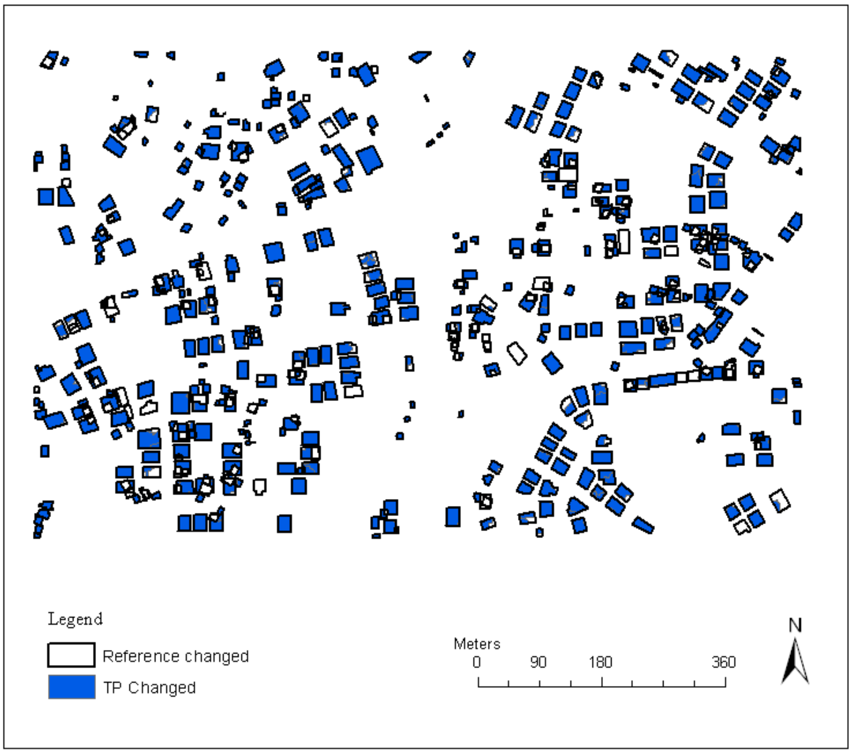


Figure 4.16. The true positive (TP) areas of Change

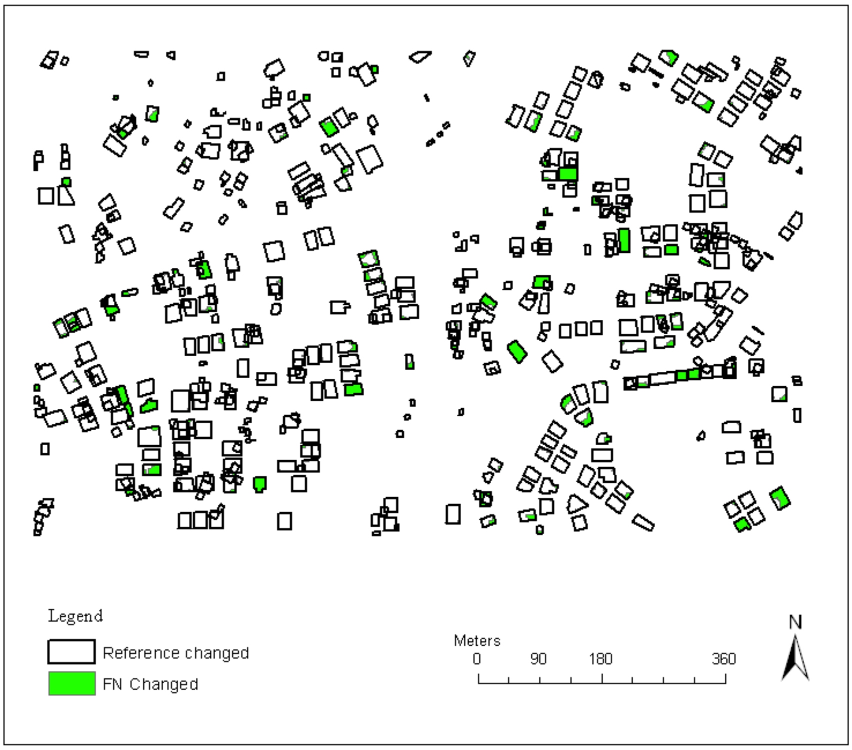


Figure 4.17. The false negative (FN) areas of change

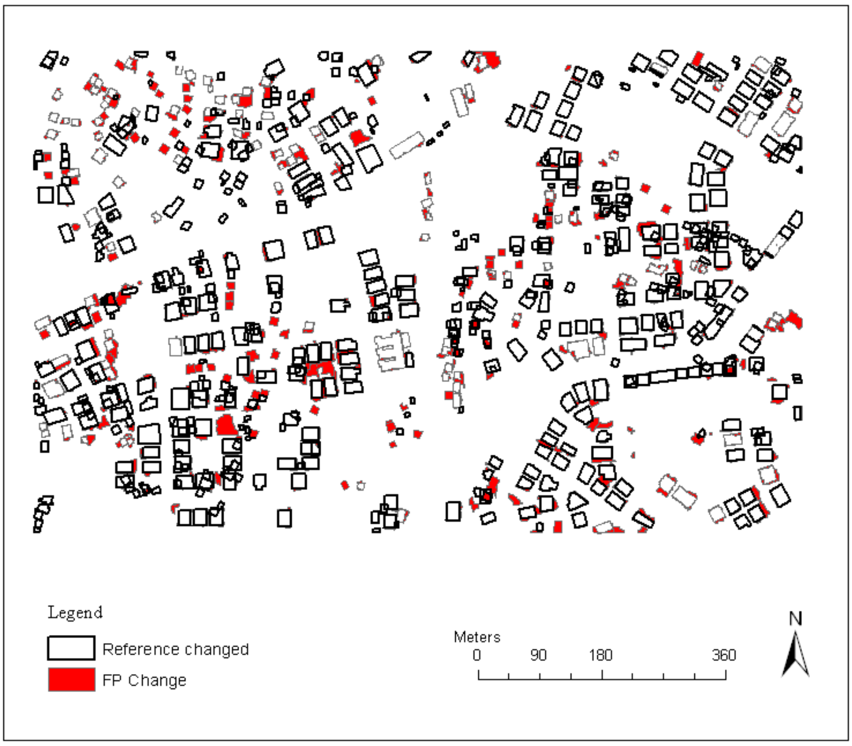


Figure 4.18. The false positive (FP) areas of Change

Table 4.3. The BF, MF, BDP and QP values computed for the changed areas

Total changed pixels	Total reference changed pixels	BF	MF	BDP	QP
130968.9	106164.4	0.43	0.16	86.06	62.76

Due to miss registration between satellite image and vector data some miss detections occurred at building boundaries in the change detection process. Therefore, due to the lack of absolute coincidence between the image and vector data sets, the small geometrical shifts were detected incorrectly as the change, while in fact they were geometric correction inaccuracies. Further, in the accuracy assessment of the detected changes the areas around the polygon boundaries were not reliable because of the manual digitization of building boundaries as reference data set. Also the misclassification due to the mixed pixels increased substantially at polygon boundaries. Further, sliver polygons that typically refer to small none overlapping areas or gaps have also resulted in errors in the change detection process. A solution would be to automatically remove the sliver polygons based on a selected threshold value. Moreover, the shifts of the roofs due to the relief displacements of the buildings have also caused problems.

Obviously classification accuracy effects the changed and unchanged areas. It was observed that most of the miss or not detected buildings were the small buildings. Some of these small buildings remained unchanged and because of that the accuracy of the unchanged areas have been computed to be lower than the changed areas. This problem is illustrated in Figure 4.19.

Figure 4.19. The falsely detected changes at the boundaries

Buildings which overlap on two data sets (the old vector data and the classified buildings from the image) are considered as the unchanged areas. The unchanged areas detected in this study are illustrated in Figure 4.20. All the necessary accuracy assessments were also carried out and the accuracy values were also calculated for the detected unchanged areas. The true positive (TP), false positive (FP) and false negative (FN) areas for unchanged are sequentially illustrated in Figures 4.21, 4.22 and 4.23. Moreover, the computed BF, MF, BDP and QP values for the unchanged areas are given in Table 4.4.

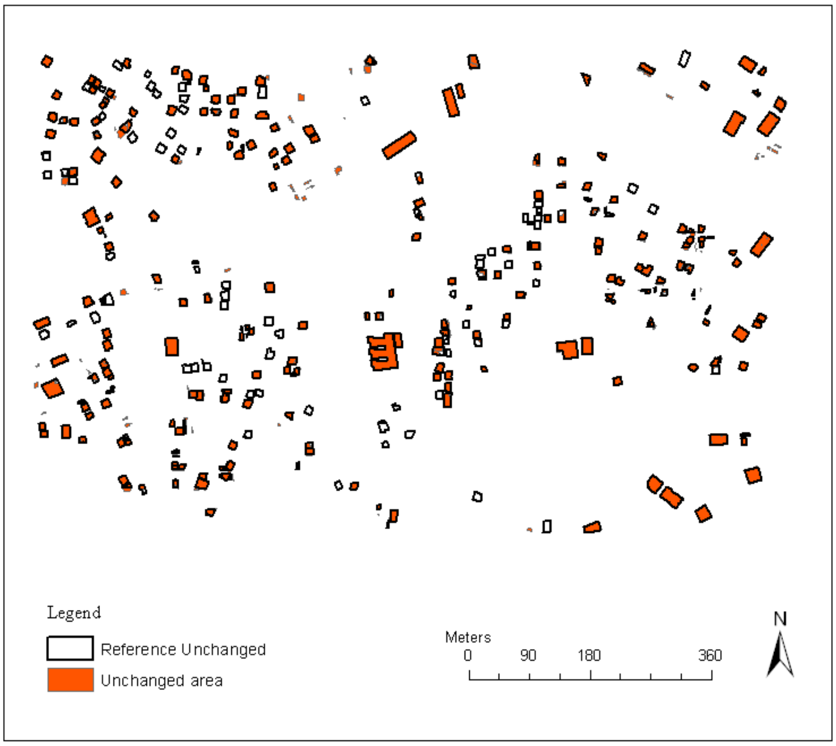


Figure 4.20. The detected unchanged areas

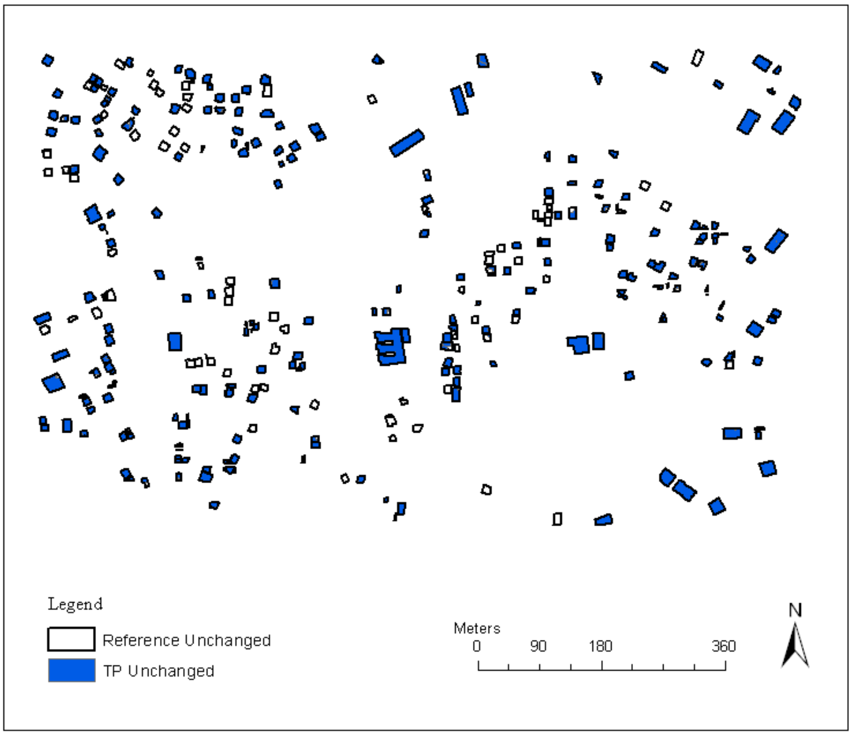


Figure 4.21. The true positive (TP) areas for unchanged

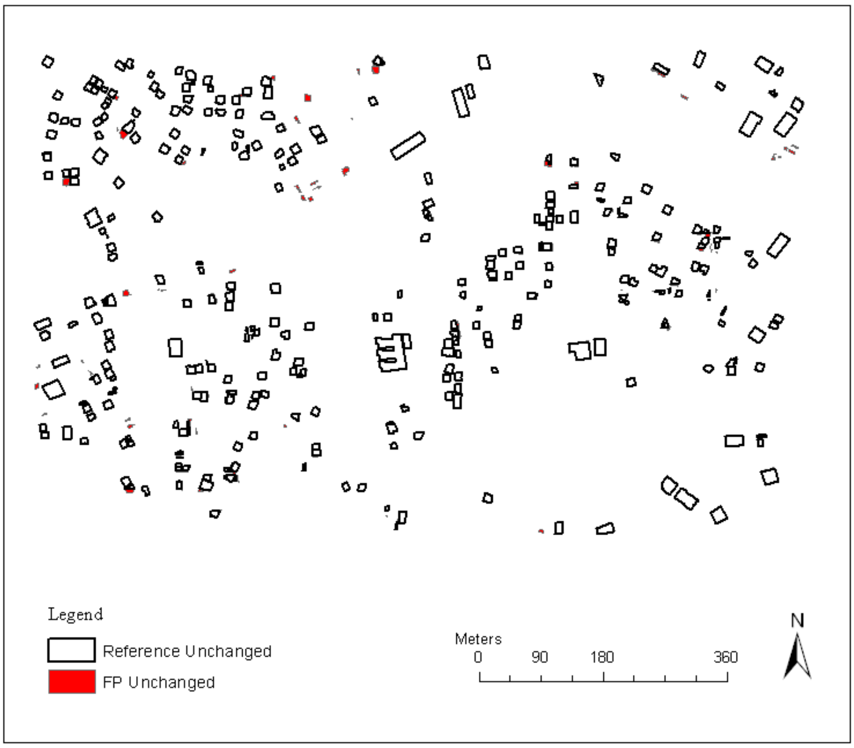


Figure 4.22. The false positive (FP) areas for unchanged

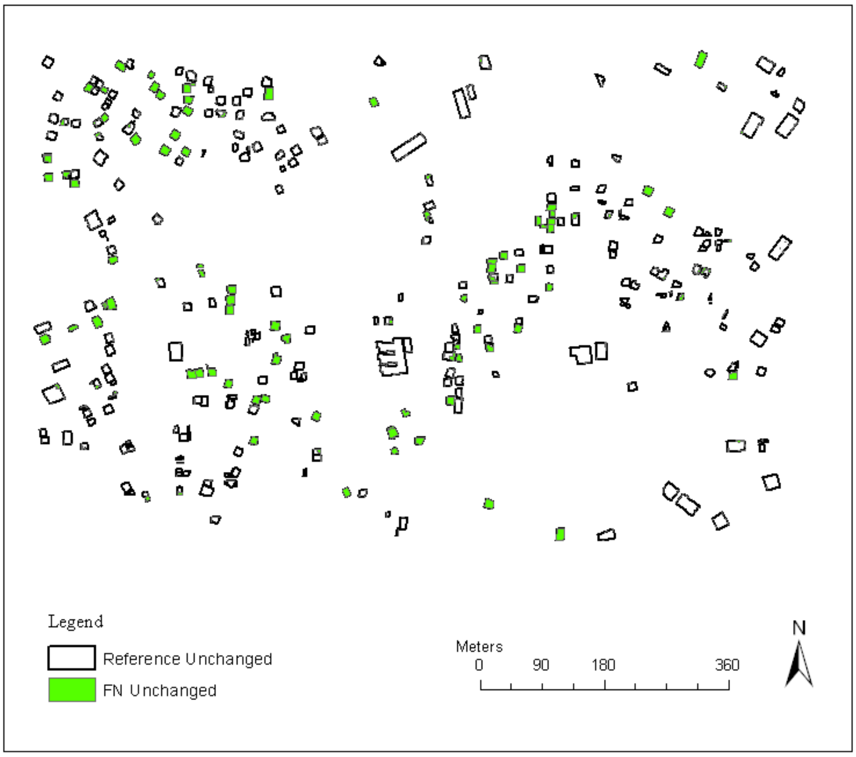


Figure 4.23. The false negative (FN) areas for unchanged

Table 4.4. The BF, MF, BDP and QP values computed for the unchanged areas

Total unchanged pixels	**Total reference unchanged pixels**	**BF**	**MF**	**BDP**	**QP**
31174	36951	0.10	0.31	76.32	70.64

The new and demolished buildings were considered as change areas. Figure 4.24 shows the detected demolished and new buildings, while Figures 4.25 and 4.26 show the results of the accuracy tests. The numerical values for these accuracy tests are given in Table 4.5.

Figure 4.24. The detected new and demolished buildings

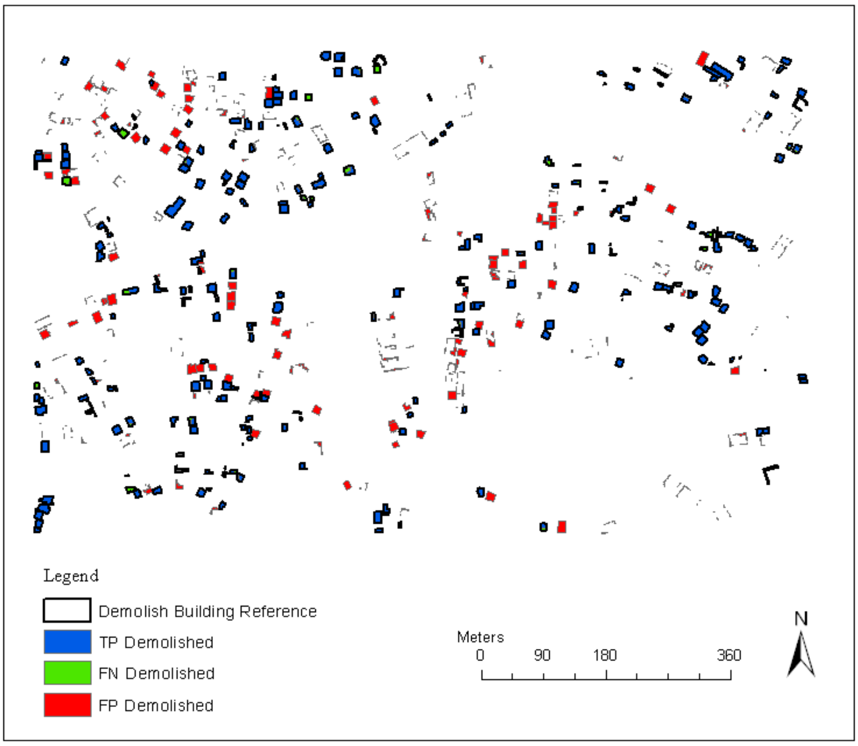


Figure 4.25. The TP, FP, and FN areas for the detected demolished buildings

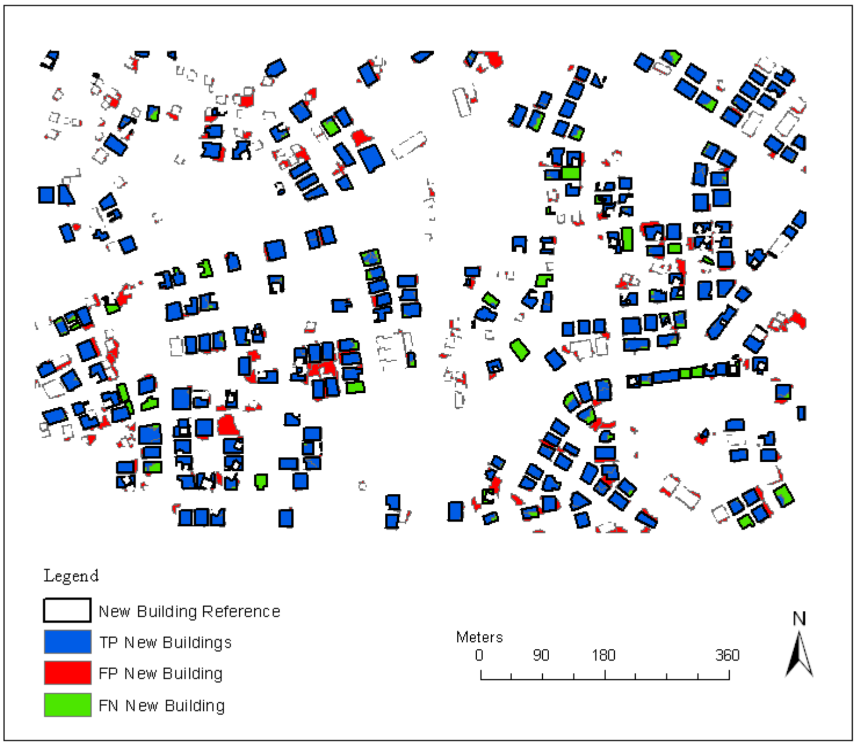


Figure 4.26. The TP, FP, and FN areas for the detected new buildings

Table 4.5. The BF, MF, BDP and QP values computed for the detected new and demolished buildings

Compactness New Building pixels	Correctness New Building pixels	BF	MF	BDP	QP
85.1	71.38	0.4	0.17	85.1	23.28

Compactness Demolished Building pixels	Correctness Demolished Building	BF	MF	BDP	QP
88.98	61.81	0.61	0.12	88.98	57.42

Several examples from buildings taken from the study area are shown in Figures 4.27, 4.28, 4.29 and 4.30. For unchanged buildings, a complete overlap is evident between the buildings from the old vector map and the building patches extracted through classification of the new image. Figure 4.27 illustrates the unchanged several buildings selected from study area. The building areas that do not exist in the old vector map data but that appear in the classified new image are considered as new buildings, which were constructed after the compilation of the old vector map. Several of the detected new buildings selected from study area are shown in Figure 4.28. Whereas new buildings, the demolished buildings are those that exist in the old vector map but disappeared in the classified new image. Figure 4.29 shows these buildings. An enlarged and completely changed area is shown in Figure 4.30. As it can be seen in Figure 4.30, a high degree of change is evident in this area between the old vector map data and the classified new image.

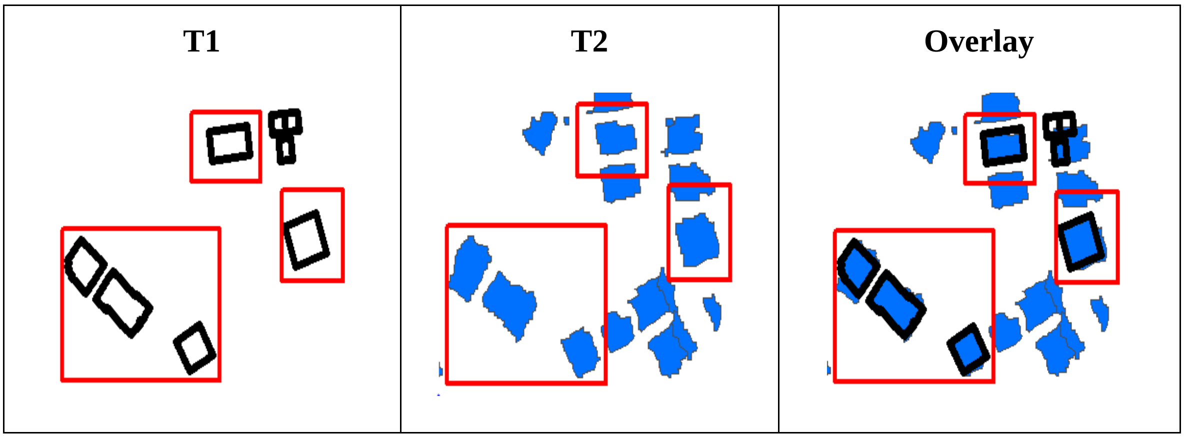


Figure 4.27. The illustration of several unchanged buildings selected from study area

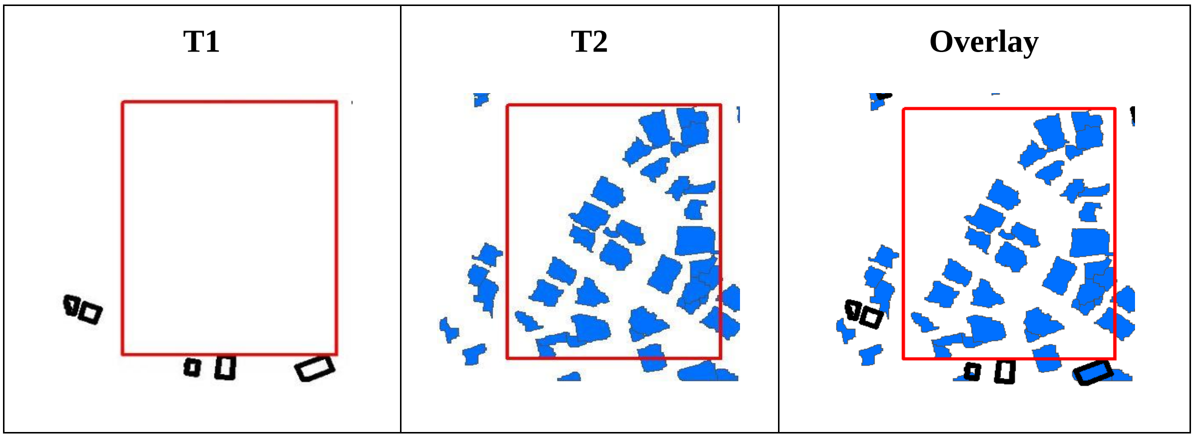


Figure 4.28. The illustration of several new buildings selected from study area

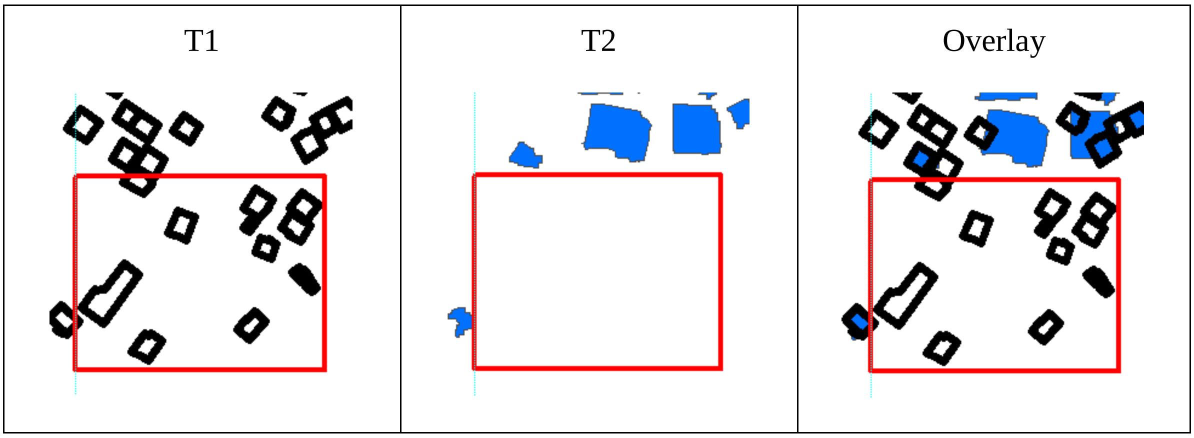


Figure 4.29. The illustration of several demolished buildings selected from study area

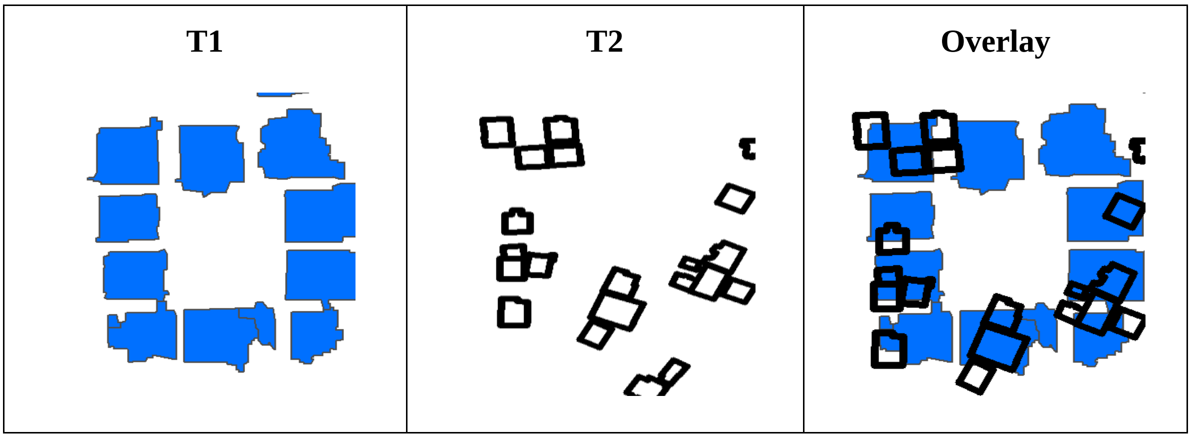


Figure 4.30. The illustration of a completely changed area selected from study area

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Conclusions

Urban areas are dynamics and detecting building changes in urban areas is very important for urban planning, management and decision making. With the availability of wide selection of high spatial and spectral resolution satellite imagery and the recent advances in computing systems the automatic detection of buildings and building changes occur in urban environment has become very important for the efficient updating of geographic databases.

In this study, a high resolution WorldView2 satellite image and an old vector map data were employed to identify building changes using the so called image to map comparison change detection method.

The method was implemented in five main steps: (i) multiresolution segmentation, (ii) object based classification, (iii) morphological operation, (iv) change detection and (v) accuracy assessment. The multiresolution segmentation, object based classification and morphological operations were carried out using the eCognition software, while the evaluations of the results of classification and change detection were carried out using the ArcGIS software.

The multiresolution segmentation operation applied in this study is a type of “bottom up” segmentation, in which the process starts with each pixel as objects and then subsequently merged based on a specified threshold value. The bands used in the segmentation process include B, G, R, and DSM, which were weighted as 1, 1, 1, and 2, respectively. The DSM band was assigned a higher weight as buildings have heights above the ground. In this respect, DSM has become a useful layer in extracting the buildings. For detecting the building segments, the parameters used include scale, compactness and shape, and the values used for these parameters were 25, 0.3 and 0.9, respectively. The best parameters and the parameter values for segmentation were found by trial and error and the segmentation results were evaluated visually.

After completing the segmentation operation, the image was classified to extract the defined land cover classes. After performing the classification operation, the building class was masked out and a morphological opening filter was applied as a post processing operation. The extracted buildings through the classification process were then used to detect the changes by means of comparing the detected building class with the old vector map data. The change and unchanged areas were detected through overlay analysis in ArcGIS software and the change areas were categorized as new buildings and demolished buildings. The results were quite satisfactory. Accuracy assessment for both classified image and the detected building changes was performed. The reference data sets used for the accuracy assessments were prepared through on screen digitization of the reference boundaries. The accuracies of the results were computed by means of pixel by pixel comparison of the results with the corresponding reference data sets. In this respect, the pixels were categorized into three classes: True Positive (TP), False Positive (FP) and False Negative (FN). After counting the pixels that fall into above categories, the Branching Factor (BF), Miss Factor (MF), Building Detection Percentage (BDP), and Quality Percentage (QP) values. Also for the detected changed accuracy, Correctness and Compactness were computed.

For the detected building class, the rate of incorrectly labeled building pixels was 30% that shows the branching factor (BF). The rate of missed building pixels (MF) was computed to be 21%. The building detection percentage (BDP) and the quality percentage (QP) were computed to be 82.21% and 65.78%, respectively. For the detected changed areas, the BF, MF, BDP and QP values were computed to be 0.43, 0.16, 86.06% and 62.76%, respectively.

The results obtained show a high efficiency of the evaluated methods for building detection when the parameters are properly adjusted and adapted to the type of urban landscape under consideration. This method can be applied to the detection of buildings for updating urban databases as well as for the inclusion of this information in urban object classification and updating of geospatial databases.

The conclusions derived from this study are as follows;

- Object based classification method was found to be quite effective for detecting the buildings from high resolution satellite images.
- It was found that three image bands (R,G,B) and a digital surface model (DSM) data were adequate to achieve good results. Buildings are mainly compact and always higher than their surroundings. Therefore, the elevations of buildings from DSM data help separate the buildings from the other low objects.
- Since the satellite image which was used in this study did not have NIR band. The extraction and separation of the vegetation class was rather difficult. Hence, the

omission of the NIR band has to some extend affected the result of segmentation which then affected the results of classification and change detection.

- It was found that true orthoimage of the high resolution imagery is necessary to decrease misclassifications during object based classification and therefore to increase the accuracies of the results of classification and change detection.
- The spectral heterogeneity on building roofs have caused the generation of fragmented segments in the segmentation process.
- The visual interpretation elements, such as Shape, Scale, Color, Texture and association between the related objects were considered in the segmentation process. By applying these features the highest possible separabilities among different classes were achieved in eCognition.
- Rectangular fit of buildings helped in the detection of building patches.
- The detection of small and/or low buildings, which do not cast enough shadow areas, was difficult, and in some cases it was impossible.
- The inclusion of the shadow information was indeed quite helpful for the detection of buildings.
- Defining the rules based on class descriptions and the selection of the appropriate thresholds are important to achieve high classification accuracy.
- It was found that morphology is necessary for improving the results of classification and change detection.
- The object-oriented method for the classification of urban area and its change detection has proven very efficient as it offers multiple tools and features considering Textural, Contextual and Semantic information of the images.
- The building detection percentage (BDP) value for the building class that was extracted through object based image classification was computed to be 82.21%. Similarly, the BDP values for the detected changed and unchanged areas were computed to be 86.06% and 70.64%, respectively.
- In the map to image comparison change detection method used in this study, the accuracy of classification directly affects the results of change detection. Therefore, a high classification accuracy is needed to be achieved.
- During change detection the boundaries of existing buildings in the old vector map did not quite match with the building footprints in the image. The existing building boundaries were needed to be manually shifted so as to match with the building

footprints in the image. The amount of shift was less for lower buildings than that of higher buildings and in some cases no shift was necessary.

- Removing the sliver polygons, which were resulted by the overlay between the old vector map data and the manually digitized building reference boundaries from the new image, was necessary to obtain a more accurate reference data for change and unchanged.

5.2. Recommendations

The recommendation regarding to possible further studies are given below;

- More accurate and up to date DSM data should be used to achieve better segmentation.
- Combination of more bands and appling them in the classification process can improve the results.
- NIR band is important for detecting the vegetation. Therefore, the inclusion of NIR band is recommended to better separate vegetation from the other classes.
- The use LIDAR based DSM data in the segmentation process is recommended to obtain more regularized and crips building outlines.

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