Object based image analysis to extract urban form from high resolution satellite image: A case study in Ahamabad City: India

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Object based image analysis to extract urban form from high resolution satellite image: A case study in Ahamabad City: India

by

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Abstract

Fast growing developing cities like Ahmadabad of India facing acute problems with urban sustainability especially with respect to urban transportation and the urban environment. Increasing pressure of urban transport triggers to deploy transport ecological footprints which have been considered as major determinants for monitoring negative impacts of this sector to environment. Urban form and urban land use information are intrinsically linked to travel pattern as well transport ecological footprints. Therefore the availability of urban form and urban land use information will make it possible to calculate the transport ecological footprints and its impacts. The urban form elements clearly are of interest to urban remote sensing component. This research aims at the application remote sensing to retrieve building footprints which will provide supports to develop urban form characteristics. However previous research proved the limitation of pixel based classification of remotely sensed images and unsuccessful to address urban form and land use information. Indeed manual photo interpretation of high resolution satellite image/aerial photography proves to be time consuming. The novelty of this research lies into experimentation of object based image analysis to extract building rooftops in the dense urban canyon using multi image.

To extract building rooftops a test site of Ahmadabad City was selected which is located in a dense urban area with the area extent around 850X 850 meters. Three different satellite images were used simultaneously to extract building footprints. Initially Cartosat Panchromatic and IRS multispectral images were merged together to produce images having better spectral properties. At later stage Google Earth mosaic image were used to extract building outlines by applying multi-resolution segmentation. The purpose of using Pan sharpened Cartosat image is to get better spectral properties which can be used to separate building rooftop from other land cover. There were also the uses of DSM to separate building rooftops form other land cover class at ground level, remarkably the DSM was generated from Cartosat stereo pair image. Before applying image segmentation and image fusion all data layers were geo-rectified by applying advanced point matching technology which generates precisely geo-rectified multiple image layers.

Theatrically there is no established image segmentation algorithm available and most of the segmentation techniques are still experimental stage. Indeed it’s uncertain to know which segmentation algorithm can efficiently address building outlines. Therefore four different image segmentation software’s (Definiens, Spring, ASTRO, Porabat) were chosen to test their quality. The both qualitative and qualitative (stand alone/empirical discrepancy method) assessment was made for all the segmented results. Quantitative assessment like average difference of areas, parameter

suggests Definiens and Spring results the best image segmentation result however data processing in SPRING is quite difficult and it does not have good feature extraction capability. Therefore Definiens segmentation results were considered for further analysis. In later stage advanced image segmentation method were applied to produce better segmentation result this includes putting weights on image layers or making selection of spectral band for better image segmentation. Image segmentation results were optimized by reducing the radiometric resolution form 8 bit to 4 bit data depth.

Different classification method was followed to optimize the classification result. To make comparison between object and pixel based classification cheese board segmentation were applied and brightness threshold value were determined for building rooftops. As usual scenario the pixel classifier produces results like salt and pepper and object classifier resituated continuous polygon. In addition with buildings some objects at ground level having similar brightness were also selected with the buildings. Later Nearest Neighbourhod(NN) classification were tested by using several land cover class. Results form NN classification visually evaluated and observed that the desired building class were not correctly classified. To have better classification of building footprints Feature Space Optimization tool were applied which also failed to retrieve the appropriate building rooftops. Efficient knowledge based rule set were developed by using three variables which includes mean brightness length and elevation. Threshold values for the three image layers were sequentially determined by changing their properties and visually checking the results. Finally the classified results were evaluated by applying overlay analysis using reference polygon. By comparing the total area difference between the reference polygons and the building rooftops there were in total 90% area matching were estimated. Whereas considering positional accuracy there was only 65% areas of classified building falls inside the reference polygon. Large amount of commission error (81%) appeared due unexpected impervious surface at ground level adjacent to buildings were misclassified as buildings.

Finally there were the discussions about the use of building rooftops to formulate urban form characteristics which can ultimately feed developing transport indicator. As most characteristics of urban from can only be measured at the city scale, however the building footprint derived in this research covers only the test site. Therefore none of the characterization was estimated in this research rather description discussions were provided which indicates how building footprints can be used to formulate urban form.

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1 Introduction

This chapter presents the research into four different sections. The first section describes the background and significance which includes the discussion about urban form, transport ecological footprints and the use of GIS and RS to derive one of the urban form Characteristics specially building rooftops. The next section is about the statement of the problems which discusses about the challenges facing cities in the developing countries as well the energy consumption by transport sector and emissions, the section also tried to relate transport ecological footprints and urban form. The next part illustrates the problems of using convention pixel based image classification techniques for urban land cover mapping as well the advantage over advanced object based classification techniques. The remaining parts include research objectives and research questions.

1.1 Background and Significance

Urban land cover mapping in the fast growing developing countries received an increasing amount of attention from urban planners and decision makers. Cities in fast growing developing countries like India is facing acute problems with urban sustainability. Ahmadabad is one of the highly urbanized City of India facing a rapid pace of development which raises the concern for urban sustainability especially with respect to urban transportation and the urban environment. Sustainable development requires close monitoring environment impacts, Ecological footprints is one of the recognized tool which can be deployed to assess the impacts (Zhang & Guidon. 2006). With the increasing importance urban transport the transport ecological footprints can be deployed for determining and monitoring the negative impacts transport sector to the environment. Urban form and urban land use information are intrinsically linked to travel pattern as well transport ecological footprints. Therefore the availability of urban form and urban land use information will help to calculate transport ecological footprints and its impacts.

There is a very complex relationship between Travel behavior, urban form and land use and a change in one significantly affects other two. Urban land use shapes the travel pattern of an urban areas (Stad and Marshall, 2002; Snellen, 2001) and ultimately transport ecological footprint. Urban form is measured using multi-dimensional approach like building density, mixed use, land-use, transit integration, urban growth patterns and location. The basic unit behind all those measures is individual dwelling or buildings. The dwelling units or buildings clearly are of interest to urban remote sensing component. In this research the use of RS and GIS came into special attention because the use of both of the technology building footprints will be extracted which will provide supports to develop urban form characteristics.

Previously sseveral approaches were made for land-cover/land-use (LCLU) mapping such as the European Environment Agency's CORINE ('Co-ordination of Information on the Environment') program (EEA, 1997) and its related efforts to create a European urban atlas (EEA, 2002). Satellite images like Landsat series are considered as a source of imagery from which consistent Land Cover and Land Use information can be extracted. However previous research proved the limitation of pixel based classification method and failed to extract urban form and land use information which can feed to extract transport ecological footprints(Zhang & Guidon. 2006). In this research building rooftops will be extracted using advanced object based classification method to support developing urban form indicators. The structure of this research is more related to the application of object based image analysis method to derive building rooftops which can characterize urban form from by using remotely sensed images.

However the most efficient way of preparing an urban land cover map is accurate recognition and classification of spatial layouts from remotely sensed data (Chen et al, 2007). To extract a detailed outline of building form satellite images requires very high resolution satellite (VHS) images either from airborne or space borne sensors. In recent years the availability and large supply of VHR mages form state of the art satellites broadens the scope of the detailed level land use mapping (Donnay *et al.*, 1999) process. Traditional methods of extracting information form VHR Airphotos relies on the Photogrammetry and image interpretation process which is very time consuming and expensive but produces reliable results (Bowden, 1975; Benz et al, 2004). In addition the availability of high speed computer and commercial image processing software significantly reduces human labour intensive photo interpretation but so far does not achieved the same level of accuracy. Most application on the extraction of urban form from satellite images is based on the use of spectral concepts which can only able to address broad land use types (Blaschke et al. 2000). It is also recognized that multi Spectral classification process failed to address individual objects in the urban canyon (Benz et al. 2004, Niebergall et al. 2007). Realizing the pros and cons of traditional photo interpretational and pixel based image classification process geospatial society decides to develop a new ways of image interpretation which can make a bridge between the two approaches (Lica, 2008; Definiens, 2008)

Whereas the complex nature of urban land use is an amalgam of socioeconomic and environmental functions. All this mixed kind of land use and function shapes urban form. The relation between urban form of a city and the recorded spectral response of an image is indirect and very complex (Barnsley, 1997). It is realized that new inferential remote sensing is required as an analysis tool for mapping precise and accurate urban land cover. This research tries to explore the use of object based image analysis (OBIA) to extract one of the major characteristics of urban form which is building rooftop. The knowledge based rule sets will be developed to classify building rooftops to particular criteria (Baatz et all, 2007). Thus focus of this research lies into experimentation of object based image analysis to extract building rooftops in the dense urban canyon. In dense urban environment the object based approach is still under experimental stage therefore more attention will be given for exploration of available object based approach to extract building rooftops.

1.2 Statement of the Problems

The rapid growth of urban areas perpetuates challenges in infrastructure development and renewal energy consumption. The adverse impact of urbanization includes Environmental threats, health costs associated with degraded air quality and fragmentation of eco-sensitive lands. The major area of concern to the policy and decision makers is energy consumption within the urban landscape. However in the complex urban environment assessing transport behavior based on solely statistical and spatial analysis and predicting energy consumption is still arguable and having limitations. It has proposed that satellite remote sensing and image classification techniques can be applied to evaluation and quantification of indicators presenting transport related energy and sustainability. It has also proved that the urban form alone from low resolution satellite image is insufficient to quantify the most indicators. Based on the case study for the city of Ahemabad, India this research gives an overview of possible application of object based image analysis to extract building rooftops which can help to characterize urban form. Previous work on pixel based classification of urban areas failed to address urban form for transport indicator development (Dalumpines, 2008). Such limitation emerged to apply an improved object based classification for delineating urban form characteristics.

Most RS application requires transferring data or images into information. Major constraints of RS application are the retrieval of required information from satellite images. Conventional approaches of feature extraction processes use multi dimensional spectral space based classification algorithms which in most situations failed to address urban objects from high resolution satellite images (Benz et al, 2004). The traditional spectral based algorithm uses pixel boundaries or rectangular areas as individual elements and ignores the contextual information or spatial properties of individual objects in the image. Individual objects in the image having homogeneity with the neighbourhood features or having continuity have not been taken into account in such algorithm; and the reason is the entire process is based only on the spectral properties which only consider the value of individual pixel. Whereas in the traditional approach of photo interpretation from very high resolution aerial photograph follows a hierarchical relationship of image interpretation methodologies using tone color as a primary element for photo-interpretation. Photo interpretation based on texture, context, and spatial configurations of urban landcover features has become very efficient and popular however it is the most labour intensive and time consuming process (Bowden *et al.*, 1975, Benz et al, 2004).

Though the availability of VHR satellite imagery increased, but the necessary tool and methodologies to retrieve information from VHR images is still in the development stage (David, 2003). Traditional pixel based classification processes failed to retrieve urban objects form VHR images due to ignoring homogeneity criteria of urban objects. It became challenging and time consuming to perform manual photo interpretation with the increasing supply of VHR images (Benz et al, 2004; Niebergall, 2007). Thus an efficient extraction of building rooftop requires a bridge between popular visual interpretation approach and digital image processing techniques (Benz et al, 2004).

Remarkably either in the case of sensor based feature extraction or in the contextual information retrieval stage the flexibility of data fusion is necessary. In most cases problems with data fusion appears while they are coming from different sources; especially the sensor based measures with raster output do not comply with digital geo information. Again a gap can be observed between theoretically available RS based information and the existing geo information base (Benz et al, 2004; Niebergall, 2007). There requires the flexibility of integrating several data layers from several source also known as multi-map data analysis. Therefore the above situation urged an expert classifier which can significantly fill the gap between those the traditional approach of photo interpretation as well the pixel based automated classification techniques in addition the data fusion process.

1.3 Objectives

The main objectives of this research is as follows

> *Application of object based image analysis to help formulating urban form characteristics from high resolution satellite imagery for Ahmadabad City*

The main objectives can be subdivided into the following three sub objectives.

- To identify object based feature extraction methods from high resolution satellite imagery.
- To extract urban object features which can characterize urban form
- To validate the extracted features using the secondary data sources

1.4 Research Questions

1. What are the urban object features that characterize urban form? Which features of urban form will be extracted and how to extract such features using object based approach?

2. What are the drawbacks of pixel based image classification? What is the methodology behind the object based classification approach? What are the advantages of using the object based classification compared to traditional pixel based classification?

3. Whether object based classification approaches are well established and if such approaches are efficient to extract features that characterize urban form, which approaches should be followed to extract features and how to evaluate several?

4. Can geometrical other shape properties of urban form features are helpful to extract to objects?

5. How the extracted urban form features will be validated?

2 Review of Literature

Literature review chapter starts with the discussion about urban form and transport ecological footprints and the means to model travel behaviour using urban form. The second part of literature review covers approaches to object based image classification and this includes image segmentation, object hierarchy development, fuzzy classification and finally knowledge based feature extraction. Third section is more detailed illustration about image segmentation which includes different image segmentation algorithms, scale space theory and blob object features. The literature review continues with the discussion about optimizing segmentation parameter and several approaches to validate the segmentation results. This followed by the means to extract building rooftops from the segmented image objects. The chapter concludes with the review on uncertainties and ambiguities on image segmentation feature extraction.

2.1 Urban form and Transport Ecological Footprints

2.1.1 Urban form

The definition of Urban from is presented in different literature in different ways. Anderson et al. 1996 explained urban form in terms of urban densities as well the location of transport infrastructure. Urban form can be relative to the location of residence, work places, shopping malls or recreational areas. Urban form can also be defined as the pattern of development in urban area including the aspects like densities, use of land the degree to which urban development is contagious or scattered at the edge (Zhang and Guidon, 2006). The characterization of urban form includes the distance of residence form the urban centres, settlement size, mixing of land uses, provision of local facilities, density of development, proximity to transport networks, availability of residential parking, road network type and neighbourhood type. The availability of high resolution satellite images and with the advancement of land cover mapping system it was perceived that all the building rooftops of an urban area could be an effective characterization of urban form. Because building rooftops are considered as the primitive measure of the following urban form characteristics like distance of residence form the urban centres, settlement size, mixing of land uses, provision of local facilities, density of development, proximity to transport networks and neighbourhood type.

2.1.2 Transport Ecological Footprints

The TEF measures and communicates in an easily-understood manner the extent of ecological impacts of transport, using a single common measure – the area of productive land and sea needed to grow the necessary raw materials and/or to assimilate the relevant wastes. TEF, often expressed in global hectares, is measured by accounting for fuel use, materials used for manufacture and maintenance of vehicles, land occupied, and vehicle emissions, following Wackernagel & Rees (1996). In terms of components, TEF combines a number of important activities that have an impact on the environment (Barrett *et al.* 2001). These include: 1) The carbon dioxide, nitrous oxide and methane emissions from the burning of petroleum; 2) The carbon dioxide emissions from the manufacture of vehicles; 3) The carbon dioxide emissions from the maintenance of vehicles; and 4) The road space and other land that is put aside for transport (i.e. car parks). All these various impacts of transport are converted into a land figure. Calculations are often performed using spreadsheets (Lewan & Simmons 2001). Thus, to calculate the TEF, data concerning fuel consumption, the energy requirements of manufacturing and maintenance, the land area occupied by roads, and distance travelled are collected.

2.1.3 Urban Form and Transport Modelling

There are large amount of literature available showing the relationship between urban form and travel characteristics (Stead and Marhsall, 2001). Much of the work originated and tested on developed countries especially in Western Europe and United States. Studies shows that urban form characteristics ranging form regional to local scale have influence on travel pattern as well to the environmental impacts of transport and therefore it is related to transport ecological footprints. The elements of urban form closely related to the TEF components, as travel pattern is related to vehicle emissions and land occupied by transport (Barrett *et al*, 2001).

Land use relates to the human activity of economic function for a specific piece of land like residential use or industrial use or it can be like natural reserve areas. Human activities shape the urban living environment which ultimately has impacts on urban form. Distribution of various activities in urban areas is responsible for making trip by urbanities. Research work conducted by Snellen(2001) summarized the empirical study which investigates the use of spatial variables to travel behaviour.

Urban areas are the complex mixture of different activities. Those activities can be perceived as four different types of land uses like residential, commercial, industrial and institutional category. In transport modelling residential areas are considered as trip origins where trips are generated and commercial, industrial and institutional areas are considered trip destinations where trips were distributed. Therefore spatial arrangements of four land use can be associated with to the travel pattern. All these in terms can be linked to vehicle fuel consumption or emission and consequently remarked as transport ecological footprints. Energy use of transport is closely related to TEF as fuel consumption is directly related with vehicle emissions.

2.2 Object Based Approach

Conventional approach of thematic mapping using digital remote sensing image is known as pixel based statistical classification. The attribute considered in pixel based classification used pixel size cell value and its position (De Kok et al. 2000; Walker, 2008). The size attribute is constant and therefore this significantly limits the freedom of analysis. In addition pixel based classification ignores size shape context aspect or image objects. By considering shape attribute and contextual information there will be a four tire classification approach (pixel size cell value and its position and contextual information) this is also known as object based image analysis(OBIA) (De Kok et al. 2000; Walker, 2008). In the case of manual human photo interpretation size shape or context information considered the basic clues (Lobo, 1997; Walker, 2008) and still it's considered as supreme analytical mean. Therefore classification methodology can be enhanced by adding the contextual information. It is possible to analyze the contextual and other relevant information of a neighbourhood cell and the result can be transferred to the central value; later cubic convulsion masks with moving window filter can be applied to the entire mage (Walker, 2008, Jain et al. 1995). With the availability of high speed computer and its processing power now this algorithm is and processing can be implemented with the desktop computer and commercially available software can be deployed to simulate the process.

2.3 Image Segmentation

Image segmentation has widely been used in the filed of mechanical engineering since 1980. Image segmentation was used by the quality controllers for checking surface or material. Even in later days several other image segmentation techniques became available and most of them are less suitable for urban land use and land cover classification (Carleer et al., 2004 Jacquin et al, 2008). Because segmentation algorithm are not specially developed for remotely sensed data and the process result huge number of possible results (Blaschke, 2005; Jacquin et al, 2008). However multi resolution land cover classification has brought some success in the remote sensing field (Jacquin et al, 2008, Baatz and Schape, 2000). The software eCognition includes all the most useful segmentation techniques (Walker,2008; Benz, 2004).

2.4 Object Hierarchy

Image objects generated form multi resolution segmentation using its different parameter can be used to formulate hierarchical network or class objects (Benz et al, 2004). Software tool can be used to prepare arbitrary level is strong hierarchical network. Each segmentation generates a construction of new level next to its upper level. In such situation an object boarder follows the boarder objects of its next level however it can be spitted into several parts which is determined by the properties of segmentation parameter. Therefore effective segmentation level can be designed serve each specific purpose. The advantage of this process is the identification of different objects at different hierarchical level; such extraction is not possible at single level (Benz at al 2004, Chen et al, 2007). One example provided by Chen, 2007 in their studies 'In this research, four, level four was generated for the delineation of bare soil in an image; level three was for differentiation between water, vegetation and non-vegetation; level two was especially for the extraction of impervious sites from non-vegetated areas and level one was mainly for the subdivision of non-vegetation land into urban areas of different densities.' The hierarchy Class and its internal linkages are presented in the following figure. The child classes inherits al the class definition rule of its parent class. Therefore its is apparent that the context information and semantics will be used to interpret the decision tree (Benz at al 2004).

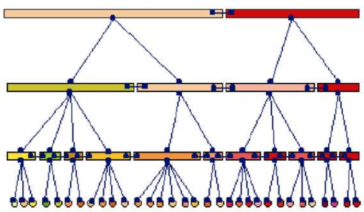


Figure 2.4: Abstract illustration of four levels Hierarchical Object Network after Benz at al, (2004).

2.5 Fuzzy classification

Fuzzy classification is known as one of the powerful probability based soft classifier. Fuzzy based classification can be applied to the previous derived segmented image. Fuzzy rule base can be developed based on different fuzzy set. Possible simplest rule can be dependent only one fuzzy set. Fuzzy rules are nested *if-else* conditions. One simplest example if feature value of x equals low then the image object will be classified to land cover w. in the flowing figure value when the object feature value equals 70 then the probability of that feature to be classified as land cover w is .4; when it s 200 then the probability to be classified as w is 0 (Benz et al, 2004).

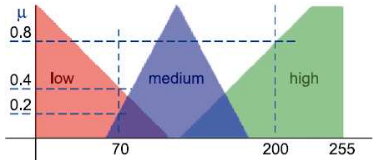


Figure2.5: Example of three fuzzy sets, after Benz et al, (2004).

Advanced fuzzy rules can be developed by combining conditional operator like 'and' 'or' and 'not'. Fuzzy rule base returns probability values of certain objects belongs to a certain category therefore probability based map can be prepared based on this method. Fuzzy classification will return membership vales with respect values with respect to land cover class; the higher the membership the better the classification. Software tools can be used to represent stability or reliability map of the image classification. In addition if several classes receives equal membership value or the membership value is low then there will be the possibility of unstable classification and further quality assurance will be required.

A threshold value for minimum membership value can be defined if certain class cannot reach the minimum threshold then it will remain unclassified (*Benz et al, 2004*). Defuzzification will be applied on the fuzzy output map to translate back to crisp value which will generate standard land cover map. The maximum membership value will be used as class assignment for crisp classification.

2.6 Knowledge based Feature Extraction

Knowledge base classification rule can deployed to extract features form each level of segmentation. The knowledge are the rule sets containing *if then* condition also known as classification rules. The knowledge base classification rules was created by Zhou (2008) to classify objects into different classes based on conditional statement is presented in the following table(Zhou, 2007).

Table2.6: Conditional statement of different land use class

Class	Parameter	Values of Features
Building	BF	BF = 1
Non-Building	BF	BF = 0
Non-Shadow	BF,B	BF = 0 & B > 30
Shadow	BF,B	BF = 0 , B <30
Missing Building	BF, B, NDVI, H	BF=0&B>30&NDVI<.08&H>=0
Bare Soil	BF, B, NDVI, H,YB	BF=0&B>30&NDVI<.08&H<3&YB>=1999
Pavement	BF, B, NDVI, H,YB	BF=0&B>30&NDVI<.08&H<3&YB<1999
Shaded Pavement	BF, B, NDVI, H	BF=0&B<30&H<2
Shaded Building	BF, B, H,RBB	BF>0 &B<30 & H>= 2 & RBB>.2

BF: A feature derived form building footprint dataset with value form 1 or 0
B: Brightness defined as channel mean value of the 3 emerge band layer
NDVI: Normalized Difference Vegetation Index
H: a feature of height derived from LIDAR data
YBB: Year of Construction
RBB: Relative Boarder to Building which is ranging form 0 and 1 (After Zhou et al,2007)

2.7 Segmentation Algorithm: Edge Based Segmentation

Edge can be addressed as the boundaries between image objects and it can be located in the places where the changes occur. Edge based segmentation tries to delineate the object boundaries. Several types of algorithm available to delineate object boundaries (Laplace filter, Sobel-operator, representativeness) and popular type of edge based segmentation proposed by Hoffman and Boehner (1999). There are several ways to derive edge form images general procedures are to apply filtering which decrease noise in the image. Another common approach is known as enhancement reveals local change in intensities. In addition edge detection can be implemented by defining threshold level which may either close gaps and delete artifacts or combine or extend line (Lang, 2006).

It was Observed that the edge based segmentation is suitable to delineate elongated objects, in this situation it can successfully addressed the boundary between homogeneous areas. In generic sense the edge segmentation check the image brightness as a function and then first derivative is generated to draw line at the edge between homogeneous regions (Lang., 2006). The process can be graphically expressed in the following ways.

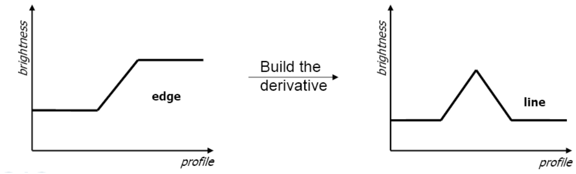


Figure 2.7: Edge detection using brightness value (Lang., 2006)

Hoffman and Boehner 1999 proposed a method of edge based segmentation which calculates representativeness of each pixel for its neighbour. Therefore the segmentation is totally dependent upon the representativeness value of each pixel. Initially pixel values are calculated by harmonic analysis of values in each spectral channel. The minima in the matrix of representativeness – typically arranged in pixel lineaments – represent spatial unsteadiness in the digital numbers. For the image segmentation, the vectorized minima of the representativeness delimit areas consisting of pixels with similar spectra properties (spatial segments). A convergence index is combined with a single-flow algorithm for the vectorisation of the representativeness minima. Standardization is performed through the calculation of a convergence index for every pixel in a 3 by 3 window (Blaschke et al., 2004; Lang., 2006)

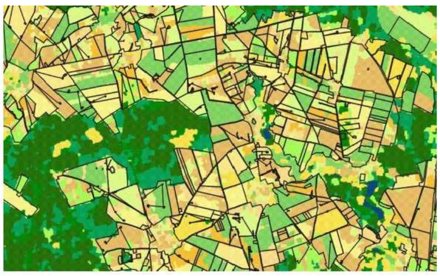
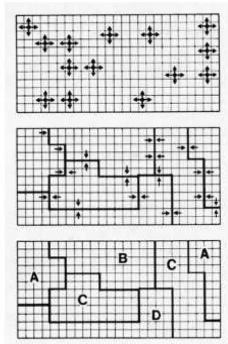


Figure2.7.1: Edge Based
Segmentation using representativeness measures (Lang., 2006)

2.8 Segmentation Algorithm: Region Growing Segmentation



Region based segmentation starts form seed point; it develops clusters of pixel and continues growing until a certain threshold is reached. The threshold is defined considering the parameter homogeneity criterion or a combination size and homogeneity. A region is allowed to grow until certain pixel is available exclusion form any of the segments and the processes stops while no more pixels are available to attribute any of the segments. The system also allows including new seeds thus the entire process repeated once again. The algorithm is dependent on a set of given seed points and have no control over the break of criteria for the growth of a region (Blaschke et al., 2002).

Kettig and Landgrebe explained the process as ECHO (Extraction and Classification of Homogeneous Objects) which searches for neighbouring objects that contains similar spectral value. If the spectral value of neighbouring pixels resembles to the core group then there is an enlargement of its group. The algorithm first searches Neighbourhood pixels (around four contagious pixels) for each group and then it tests the homogeneity of those neighbouring pixels; if the candidate pixel is not similar to its neighbours then it will be neglected. At certain time the process develop several numbers of patches and each of the patches compared to its neighbours, if there are similarities then the patches will be merged together. Patches are allowed to grow as long as they reach to the constraining patches. The process stops when all patches reach to their maximum extent. ECHO operates based on the average brightness of pixel values however it considers image texture (Campbell, 2002, p. 346).

2.9 Segmentation Algorithm: Region Merging and Splitting

In region merging and splitting techniques the image is divided into sub regions and these regions are merged or split based on their properties. In region merging the basic idea is to merge segments starting with initial regions. These initial regions may be single pixels or objects determined with help of any segmentation technique. In region splitting methods the input usually consists of large segments and these segments are divided into smaller units if the segments are not homogeneous tough. In an extreme case region splitting starts with the original image and proceeds by splitting it into rectangular sub-images. The homogeneity of these rectangles is studied and each rectangle is recursively divided into smaller regions until the homogeneity requirement is fulfilled. In both, region merging and splitting techniques, the process is based on a high number of pair wise merges or splits. The segmentation process can be seen as a crystallisation process with a big number of crystallization seeds. The requirement for the maintenance of a similar size/scale of all segments in a scene is to let segments grow in a simultaneous or simultaneous-like way (Blaschke et al., 2004).

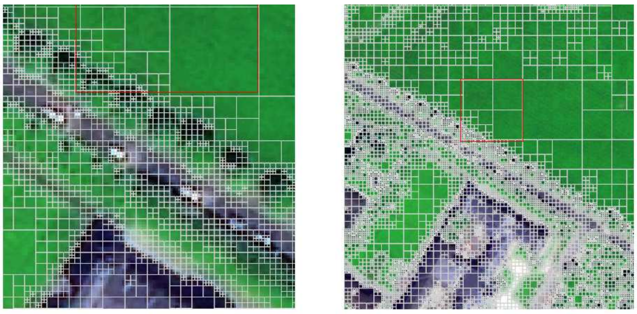
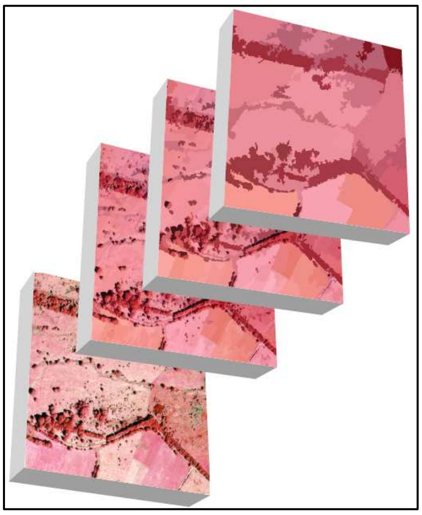


Figure 2.9: Quadtree structure in a Quickbird Image

2.10 Scale space analysis

2.10.1 Scale space theory: Scale is known as crucial aspect of image understanding. In the image analysis phase scale is predetermined based the objects of interests, pixel resolution as well users own satisfaction. The absence or occurrence of certain features depends on the determined scale. Because the same objects appears differently in different scale. Therefore the classification task and objects of interests are totally dependent upon the particular scale of interest. Remarkably to mention the basic difference between the resolution and scale; resolution refers as average area dimensions covered by pixel on the ground whereas in scale it's possible to describe magnetite or level of abstraction to which a certain phenomena can be modelled. Therefore an adequate approach of image understanding and analysis still is in different scale rather than using different resolution (Lang, 2004).



An example of multi scale concept of image analysis is presented at here which depicts the urban areas with different scale. Closer distance visualization provides single house roads buildings and other urban objects. Whereas single houses are missing after applying an enlargement of viewing distance however the neighbourhoods are still visible. Those neighbourhood areas still preserving some size shape and texture features which can be used to determine settlement type.

Figure 2.10.1: Space Scale Theory (After Lang, 2004)

According to multi scale concept for image analysis urban areas acquired by high resolution satellite image may appear in the following ways. At certain distance from image its easy to detect and recognize single houses, buildings, roads and other urban objects. However an enlargement of viewing distance causing invisible to single buildings rather different kind of settlement or neighborhood may be visible. Individual settlement and neighborhood has its own texture size and shape structure. Different kinds of objects like roads buildings gardens underlying an image shape the neighbourhood textures textures. At larger scale a city area can appear just a single entity with surrounded by forest and agriculture areas. The above scenario can be presented into three level image scales.

The following describes the multi-scale concept for analysis of an image which depicts
(1) trees, buildings and roads at a fine scale;

(2) groups of trees and groups of buildings aggregated to different settlement types at a medium scale;

(3) forest and urban area and open landscape at a coarse scale.

2.11 Scale space theory: Image Objects and Blobs

Lindberg (1994) presented a multi-scale approach of image understanding which is composed of two principle component known as Linear Scale-Space (SS) and Blob-Feature Detection. Hey et al (2002) provided a detailed non –mathematical description of those theories in remote sensing images. The concept is known as non linear approach and the primary goal of this theory is to link structures at different scale in space scale environment. Objects generated in the higher order are called 'Space Scale Bolb'. A SS multiscale representation of a signal (such as a remote sensing image of a landscape) is an ordered set of derived signals showing structures at coarser scales that constitute simplifications, i.e. smoothing, of corresponding structures at finer scales. This results in a scale-space cube or 'stack' of progressively 'smoothed' image layers, where each new layer represents convolution at an increased scale. The second SS component we use is referred to as Blob-Feature Detection (Lindberg, 1994). The primary objective of this non-linear approach is to link structures at different scales in the scale-space, to higher order objects called 'scale-space blobs' and extract significant features based on their appearance and persistence over scales. An important premise of SS is that structures which persist in scale-space are likely candidates to correspond to significant structures in the image and thus in the landscape. Within a single hyper-blob four primary types of 'bifurcation events' may exist: annihilations (A), merges (M), splits (S) and creations (C). These SS-events represent critical components of SS analysis, as scales between bifurcations are linked together forming the lifetime (Ltn) and topological structure of individual SS-blobs(Hay et al.; 2003).

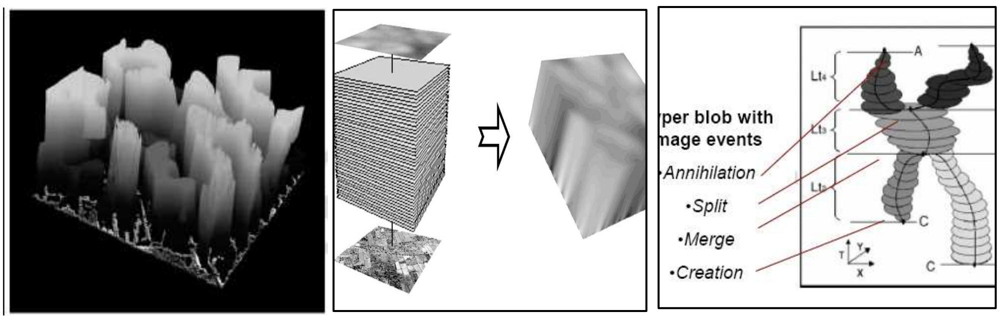


Figure 2.11: Hyper Binary blob stack composed 2D bineary Bolbs. (b) Linear scale-space 'stack'. The bottom contains finest scale and on the top coarser scale. Cube represents diffusive patter of scale space objects at margins,

After Hey (2003). A hyper-blob stack composed of 2D binary blobs. For illustration only, each binary layer has been assigned a value equal to its scale. Thus, dark values are on the bottom, while bright values are near the top.

2.12 Multi-Resolution Image Segmentation

Several successful urban land cover and land use classification (Burnett and Blaschke, 2003) follows multi-resolution segmentation and draws reliable results. However not necessarily multi-resolution segmentation always automatically bring desired and optimum result (Baatz and Schape, 2000, Walker, 2008). There requires optimization of segmentation parameter by changing the influence of shape and spectral properties of objects. In fact the segmentation technique follows region growing procedure which groups pixel or sub region into large region based on shape and spectral properties of objects.(Carleer et al., 2005, Jacquin et al.2008). It is possible to make weighting of two parameters by changing the parameter of shape and spectral properties (Baatz and Schape, 2000; Thomas et al., 2003; Willhauck, 2000). Therefore scale parameter will determine level of heterogeneity, the larger the scale smaller number of objects and bigger size of objects of (Jacquin et al; 2008, Benz et al., 2004)

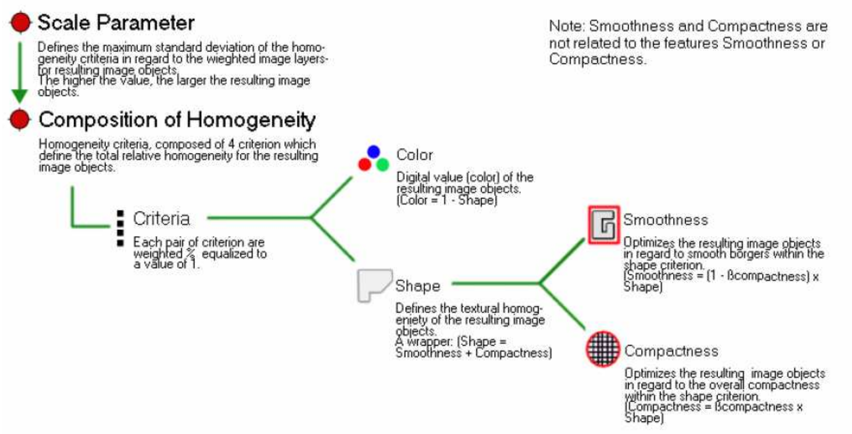


Figure2.12: Conceptual flow diagram of Multi-resolution segmentation (after Definiens, 2008)

2.13 Optimizing Segmentation Parameter

Image segmentation is a preliminary and critical step in segment-based image analysis. Its proper evaluation ensures that the best segmentation result is used in image classification. Image segmentations were carried out and the results were evaluated with an objective function that aims at maximizing homogeneity within segments and separability between neighbouring segments (Gao 2007).

Conventional attempts to image segmentation based on trial-and-error approaches (Flanders *et al*. 2003, Giada *et al*. 2003, Gitas *et al*. 2004, Gao *et al*. 2006). Recently Espindola *et al*. (2006) proposed a new method known as objective function to decide the parameter settings generate the best segmentation results, based on intersegment homogeneity and intersegment separability. The optimal segmentation reached in the highest objective function value, also resulted in the highest classification accuracy. This shows that the objective function is indeed an effective way to determine the optimal segmentations to carry out the classifications. The method is robust as it utilizes the inherent characteristics of images: variance and spatial autocorrelation, which have not been considered in image segmentation evaluation before (Pal and Pal 1993, Evans *et al*. 2002, Benz 2004).

The segmentation quality was evaluated with an objective function proposed by Espindola *et al.* (2006). The objective function combines the variance measure and the autocorrelation measure given by equation

F (V, I) = F (V) + F (I), Where *F (V)* and *F (I)* is normalized function

$$V = \sum_{i=1}^{n} a_i v_i \Big/ \sum_{i=1}^{n} a_i$$

Where v_i is the variance of a segment and a_i is its area; the calculation of Moran's I is expressed as:

$$I = \frac{n\sum_{i=1}^{n}\sum_{j=1}^{n} w_{ij}(y_i - y)(y_j - y)}{(\sum_{j=1}^{n}(y_i - y)2)(\sum_{i\neq j}\sum w_{ij})}$$

Where *n* is the total number of regions

w_{ij} is a measure of the spatial proximity
y_i is the mean grey value of region R_i
y is the mean grey value of the image.
Each weight w_{ij} is a measure of the spatial adjacency of regions R_i and R_j.
If regions R_i and R_j are adjacent, $w_{ij} = 1$.
Otherwise, $w_{ij} = 0$. (After Espindola *et al*, 2006.)
This model can be used to fuel research into optimization of what is traditionally seen as a trial-and-error approach to segmentation. This approach can be used to observe the significant effect on different segmentation parameters on the subsequent classification accuracies. It also showed that there is in fact an optimal segmentation result and the objective function is indeed an effective way to determine the optimal segmentations to carry out the classifications. Research result using the model indicates that the classification accuracy increases for optimally segmented images.

However in this study the above optimization tool was not applied and rather the conventional procedure using visual assessment were used to determine segmentation parameter.

2.14 Evaluating Segmentation Result

Table 2.14: Various evaluation method for image segmentation

Evaluations Approach	Method Type	Equation	Description
Area Fit Index (AFI) Lucieer (2004)	ED	$AFI = A_{reference\ object} - A_{Largestsegment} \ / \ A_{reference\ object}$	Address over/ under segmentation by analyzing the number of segmented and reference objects
Fragmentation (FRAG) Starters' and Gerbrands(1991)	ED	$FRAG = 1 / 1+p \ \lvert T_n - A_n \rvert^q$	
Geometric Feature Circularity *Yang et al (1995)*	ED	$Circularity = 4\varphi A/P$ Where A is area and P is perimeter	Address the shape conformity between segmentation and reference polygon (scale invariant shape features)
Geometric Features Shape Index Neubert and Meinel (2003)	ED	$Shapeindex = P / 4\sqrt{A}$ Where A is area and P is perimeter	
Empirical Evaluation Function Borostti et al (1998)	EG	$Q(I) =\{ 1/1000(N\text{-}M)\} \sqrt{R} \sum_{i=1}^{R} [e^2/1+\log A_i+(R(A_i)/ A_i)]^2$ where $N{\cdot}M$ is the size of the image I, ei is the colour error of the region i and $R(A)$ the number of regions of the size A	Address the uniformity feature within segmented regions(color deviation)
Entropy Based evolution function and a weighted disorder function Zhang et al (2004)	EG	$E = H_l (I) + H_r (I)$ Where H_l is the layout entropy and H_r is the expected region entropy of image I	Addresses the uniformity within segmented regions (luminosity) using the entropy as a criterion of disorder within a region
Fitness Function Everingham et al (2002)	A, ED	Probabilistic hull potential accuracy f(a,i) Multidimensional fitness-cost-space	Address multiple criteria and parameterization of algorithm by a probabilistic fitness/cost analysis

ED: Empirical Discrepancy Method

2.15 Feature Extraction and Rule Set Development

2.15. 1 Generic Building Mathematical Model

Ruther et al (2002) formulated generic building model which considers geometric and radiometric properties of remotely sensed images. By investigating radiometric properties of building edge form satellite image it can observed that buildings edge are continuous, having high contrast. Therefore squared sum of grey value and their derivative should be maximum. The literature also expressed about the properties of building regions or rooftops which are usually continuous and the pixel values measured over that surface almost homogeneous. The literature mathematically expressed the energy outcome form building region, it was found that the energy outcome is related the area of the building objects. The concept was mathematically expressed as follows. According to his concept it is assumed that a building in the object space consists of small building areas as primitives (analogous to pixels in the image domain, and preferably equal in size with the pixel footprint). Thus quantifying a property of a building region in the image space can be done by evaluating the property over the building primitives and summing up the property characteristic of the primitives over the entire building region.

Ruther et al (2002) also explained Building Geometric Property which tries to explain formulate mathematical expression of building geometric properly. According to their works building contains sharp turning points or high curvature. As their works originated form SNAKES dynamic model, they try to approximate the curvature line using second order derivatives of contour lines. Their work explained about the edge value of building which is modelled as high second order derivative value. In addition building outline edges are right angle to each other and often it appears right angle to each other; mathematically their works modelled the phenomena using the following expression.

$$(\,|\,(\alpha_{bi} - \alpha_{bi+1})\,|\, - 90) < T \text{ and}$$

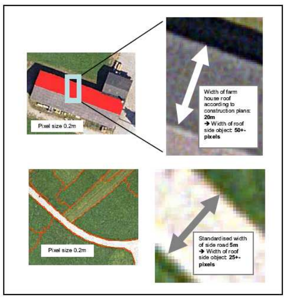
$$(\,|\,(\alpha_{bi} - \alpha_{bi+1})\,|\, - 270) < T$$

Here T is user defined threshold and α bi is the direction vector of building edge bi.

Nobrega, 2008 presented their works for Detection of road and informal settlements.
Their works criticized about the Segmentation results which may results unexpected objects due to high spectral heterogeneity dirty rooftops. The problem will be severe while increasing the color criterion of segmentation. The literature also shows the challenges of Mapping Impervious surface will enable to separate paved and unpaved areas. The both principle component 2 and segmented image can be used for this purpose. Literature suggests that principle component 2 is suitable for identifying urbanized areas. The higher the principle component 2 value the brighter the objects.

The literature also suggested to use features like shape and contextual information which can be helpful for detecting buildings. The strategy will be step by step discriminate different urban objects and the use of partial information (index map) distinguishes features (Skackelford & Davis, 2003; Ehlers et al, 2006). In addition their work also discusses about the geometric properties of Road and building which can be easily distinguished by checking asymmetry, length, width, rectangular fit, area as well as their relationship. Fuzzy membership functions can also be used with these variables. Using the above assumption their work developed class membership and their assumed values are presented in the following table.

Class	Membership Function	Limits
Urban Features	Area	200 / 300
	Asymmetry	0 / 0.5
	Border to Impervious	1 / 2
	Similarity to Impervious	
	OR	
	Brightness	1700 / 1800
	Rectangular Fit	0.5 / 1
	Impervious Child Class	
	OR	
	Brightness	1700 / 1800
	Rectangular Fit	0.5 / 1
	Base Soil Child Class	



Chunfang and Kai, 2006 discussed their works about the use of Texture and Correlative Index Measures. By using such measures it's possible to develop correlative indexes by using object length and area parameter. Texture measures can also be implemented which calculates thickness, *smoothness, granulation, randomness, direction, linearity and periodicity*. Objects spatial relationship and its surrounding can be calculated separately the, spatial relationship includes *connection, adjacency, inclusion, and passing.* It is assumed that the spatial relationship will be helpful for determining small targets and distinguishing radiant objects.

Lang, 2003 presented his work for detection of anthropogenic objects and mean value parameter like Length Width ration of objects and spectral difference to the neighbour objects which were used to distinguish buildings and roads. Especially anthropogenic features like roads roof can be modelled by using its fixed width.

2.15.2 Extracting shape Information

Shape information can be extracted by using commercially available software; either Definiens or IDL/ENVI programming. To avoid constrains of writing scripts Definens eCognition software will be used to extract shape information. Available literature shows the following features were mostly used for extracting urban features.

Brightness

Brightness values were measured by the sum of the mean values of the layers containing spectral information divided by their quantity computed for an image object (mean value of the spectral mean values of an image object).

Area: Areas are measured based on size of pixels and consequently the number of pixels forming an object. Therefore in the geo-referenced data system the area of an object is measured by true area covered by one pixel times to the number of pixel forming the object.

Boarder Length: The border length of an image object is defined as the sum of edges of the image object that are shared with other image objects or are situated on the edge of the entire scene. In non georeferenced data the length of a pixel edge is 1

Elliptic Fit: The calculation of the elliptic fit starts form the creation of an ellipse with the same area as the considered object. In the calculation of the ellipse the proportion of the length to the width of the Object is regarded. After this step the area of the object outside the ellipse is compared with the area inside the ellipse that is not filled out with the object. While 0 means no fit, 1 stands for a complete fitting object.

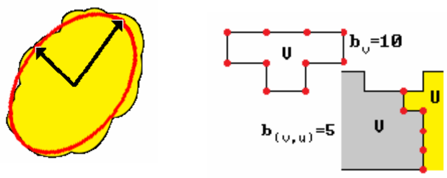


Figure: Measures for elliptic fit and boarder length

2.16 Uncertainties in Segmentation and Classification

Various types of uncertainties associated with the information extraction process from remotely sensed data. Remarkably uncertainty starts from the acquisition of satellite data with noisy sensor measurement and limited accuracy. Afterwards it propagates while processing, compressing as well data filtering stage. While extracting objects form the image as well in the classification process ambiguities may be inherited as well imprecise concept of land cover and land use triggers uncertainties (Benz et al, 2004).

In the science of computer vision *Image Segmentation* is considered as the primary problem. In the object based approach image segmentation is most important operation for delineating object primitives as well facilitates object recognition and delineation (Chang et al, 2007). As there are several methods available for image segmentation, different segmentation yields different kinds of results. (Shi and Malik, 2000;Medioni et al., 2000). The typical problem at here is the classification error at the edge of the objects. Apparently boundaries between two objects are perceptual however the segmentation results less pertinent. The problem of image segmentation is more complicated while there is no definite boundary between objects especially in the in the transitional areas having mixed pixel (Chang et al, 2007). Though it might look continuous however those areas belonging two different objects and segmentation that might ignore those boundaries. Especially in the remotely sensed images discrete boundaries are totally absent (Gahegan and Ehlers, 2000).

While applying contextual classification or par parcel classification using ancillary data layers like parcel boundary, soil type or elevation map with a aim to improve class differentiation then the accuracy relies on the inherent ambiguities of each individual data layers *(Gahegan and Ehlers, 2000)*. Uncertainty also arises with the miss match between data acquisition time and the time of its use. However in temporal sense uncertainty dependent upon the ancillary data type; for example geological maps unlikely became obsolete in the lifetime of a system whereas satellite images became obsoletes even the difference between a day due to atmospheric and environmental condition.

In object oriented approach uncertainty is treated is different way, it relies how well the shape of an objects were preserved compared to its original entity *(Gahegan and Ehlers, 2000)*. As in object based approach individual objects are considered as an independent entity with definite shape, and any pixels included or excluded form entity will cause its shape error. In uncertainty analysis this approach gives a new dimension of spatial uncertainty unlike the shape of pixel which is unique in the entire image. In addition object model may posse's positional uncertainty while the objects were extracted form the images having positional error. Thus the inherited positional error inside image transmitted to the extracted objects *(Gahegan and Ehlers, 2000)*. According to their works uncertainties were illustrated into four models of geographic areas as the following table.

Considering the above situation two different kind of spatial error can be addressed for a given area objects; shape and positional. *As described by Gahegan and Ehlers; 2000) in the following figure* The arrows representation positional error whereas shading shows possible shape of the objects.

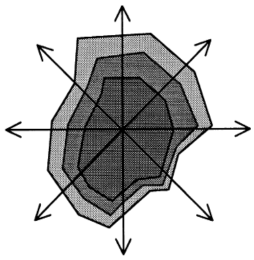
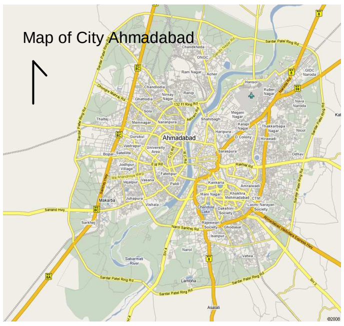


Figure2.16: Two forms of Spatial Uncertainty in an Object inherited from the image from which was formed and due to uncertainty in boundary delineation and position

3 Materials and Method

This chapter presents the methodology of this research; initially there were the discussions about study area and test sites. Later more detailed specification about the available data used in this research. The methodology chapter continues with the discussion about data analysis and modelling which separates the entire methodology into five different sections like geo-rectification, image fusion, image subset selection then image segmentation and finally image classification/rule based feature extraction. Later more detailed descriptions were provided on different part of the methodology. For image Fusion Erdas Imagine Resolution Merge function were used and for Geo-Rectification Advanced Point Matching tool of Erdas Imagine were used. Detailed about image segmentation and image classification were presented in the chapter four and chapter five.

3.1 Study Area



The selected study area was Ahmadabad City located in the western part of India. This is one of the fast growing city in India. The city Ahmadabad is selected to characterize its urban form. Ahmadabad city is the sixth largest city of India located in the western region of India. More than five million people living there. Under the city corporation jurisdiction the extent of the city is 190.84 square kilometer. The river Sabarmati flows inside the city Ahmedabad. The city is renowned for its textile industries. It is observing massive rate of urban sprawl towards all direction around 20 km form its centre(Dalumpines, 2008).

[Figure 3.1: Map of City Ahamabad]

The city is selected for this study is because its one of the highly urbanized city in the developing world and facing rapid pace of development which raises the concern for urban sustainability especially with respect to urban transport and urban environmental aspects. In addition there is ongoing research projects in the city of Ahmadabad related on land urban form and ecological footprint of transport with the application of geo information science. This research was initiated with the concern considered as the primary measure for such projects. Therefore the ongoing project provides a favourable setting for exercise related deriving urban form from high remote sensing techniques and Information related to urban form/urban footprints were treated as the basic input for this project. It is expected that similar kind of research will also be a replicable to the fast growing cities in the developing countries.

3.2 Test Site

The test site characterize by well shaped buildings located on the North Western part of the city. Six different object class were identical in the test site those includes dark roof, white rood, impervious surface, bituminous surface, grass and vegetation. Area extent of the test site was 800X800 meter and 670 numbers of well shaped buildings were digitized over the study area for testing segmented as classified results. There were some informal settlements on the upper left side of the test site, It was realized that segmentation will fail to delineate those buildings therefore single large reference polygon were digitized over those areas. In addition some rooftop having large amount of heterogeneity which might causes over segmentation. Those buildings were also avoided while selecting reference polygon for evaluating segmentation result. One major problem appeared while evaluating segmentation by using different software. It was observed that the ASTRO image segmentation freeware software do not support pixels more than 475 numbers, therefore while doing evolution for segmentation the test site were reduced to 450 number of pixels. 100 numbers of buildings were selected for evaluating segmentation results with a small (450X450) test site area.

3.3 Data Available

Three different satellite image (Cartosat, IRS P6 and Quickbird Mosaic) were used as data input for this research. A DSM was previously generated by using Cattosat Stereo Pair image was also used in this research. All the images has already been procured under the Volvo Research and Education project (VREP). The images having the following attribute.

Table 3.3: Available data for the study area

Satellite	Cartosat	IRS	Google Earth Mosaic
Senor	PAN AFT	IRS P6	Quick Bird
Resolution	2.5 Meter	5.8 Meter	.6 Meter
Date of Observation	January 2007 and April 2007	March 2007	2007
Side Length	31 km	70 km	--
Area Covered	920 sqkm	4900 sqm	--
Accuracy	+/- 25 m / 250 m	450 m	15 Meter
Spectral Band	Panchromatic	Green, Red and NIR	n/a (True color Jpeg Format)

Source: NRSA, 2003; GoogleEarth, 2007

3.4 Data Analysis and Modelling

The overall goal of this research is to derive urban footprint from VHR-S images. Initially Cartosat image will be PanSharpened using IRS P6 to achieve optimum resolution and spectral band. Considering the land use pattern (planned /unplanned) socio economic status (High class residential vs. Slum) the PanSharpened images will be spitted into a subset images. Then segmentation and classification were carried out on the subset. It was realized that the segmentation parameter or classification rule set were only be applicable on the particular subset. The threshold value of segmentation were determined until spitted polygon perfectly matches building outline and reaches acceptable level of heterogeneity (Jacquin et al, 2008; Banz et al, 2004). After segmentation objects were classified using efficient rule sets and finally classification accuracy were measure and presented as percentage. Individual sections of methodology are discussed in the proceeding parts.

Resolution Merge ⇨ **Image Subset** ⇨ **Segmentation** ⇨

Classification / Rule Based Feature Extraction

Figure 3.4: General overview of methodology (After Chen et al, 2007)

3.5 Image Fusion

The image Fusion process allows merging multispectral imagery of relatively low spatial resolution with another co registered panchromatic images of relatively high resolution. This fusion results an increase of spatial resolution to the multispectral low resolution image as well increase the spectral resolution of panchromatic high spatial resolution image. The IRS image used in this research has three spectral bands with spatial resolution of 5.8 meter. Similarly spatial resolution of Cartosat images is 2.5 meter, combining those two image yields 3 band 2.5 m resolution images representing the best characteristics of the both sensors.

Available literature suggests several approaches to perform the image fusion. Commonly used the process known as IHS (Intensity Hue Saturation) HPF (High Pass Filter) Wavelet and Ehler resolution merge process. Under those process a number of model has been suggested to archive the image merge for example Welch and Ehlers (1987) used forward-reverse RGB to HIS transformation which was limited, three spectral bands only. Later Chavez et al, 1991 and others used forward reverse principle component transformation.

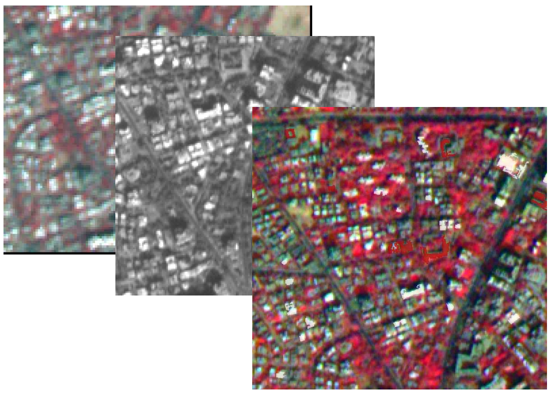


Figure 3.5: Top Left IRS Multispectral images, Middle Cartosat Panchoromatic and bottom Right fused Cartosat image using ITS Multispectral image.

3.6 Geo-Rectification

3.6.1 APM Tool

The Automatic Point Matching tool can Georectify several image layers based on a reference map. CartoSat image were used as a reference map for this project. The reason for considering CartoSat image as reference map is because its been previously geo-rectified using Ground Control Points which was collected using Differential Positioning system. Before applying automatic point matching algorithm all images were re-projected in the same coordinate system. To maintain the consistency in projection system all images were re-projected to the same coordinate system. The both IRS Multispecral and GE Mosaic images were re-projected to WGS 1984 System as well the datum for the projection were also selected as WGS 1984.

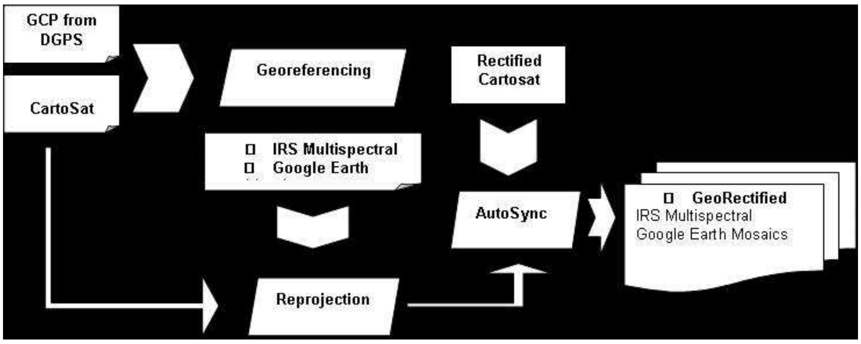


Figure3.6.1: Geo-rectification Process

3.6.2 Data Preparation

Simultaneously Proper use of multiple images requires geometrically corrected map coordinate system. Especially in the application like change detection, resolution merge, mosaic and layer stacking requires highly accurate geometrically corrected image because a single pixel misalignment of features at the same location renders results useless. The current process of geo-rectification process using manual point measurement is prohibitively Labor intensive and difficult to implement for large applications. As well due to limited human visual interpretation its not possible to achieve correction at sub pixel level. There is another way to apply geometric correction which is known as block triangulation which applies imagery together photogrametrically and does not enforce any correlation to the already existing image layers. Therefore to make highly accurate geometrically corrected images IMAGINE AutoSync Automatic Point Matching algorithm were used for this purpose which generates thousands points at a time and produces mathematical model to tie images together. This process significantly reduces time consuming manual point collection and generates better and high accurate results.

3.6.3 Modelling

Several mathematical model are available inside Erdas AutoSync which can be used for geo-rectification. However it's necessary to know mathematical details of those models therefore best suited model can be selected among the alternatives which can produce most accurate results. For this research proposed methodology was Image to image 2D transform which is simplistic and does not require DEM and sensor parameter. However More accurate results can be generated by applying rigorous sensor model and accurate DEM. Inside the APM tool there are options to selects sensors however the required sensors used in this research(IRS, CARTOSAT) was absent inside the tool**.**

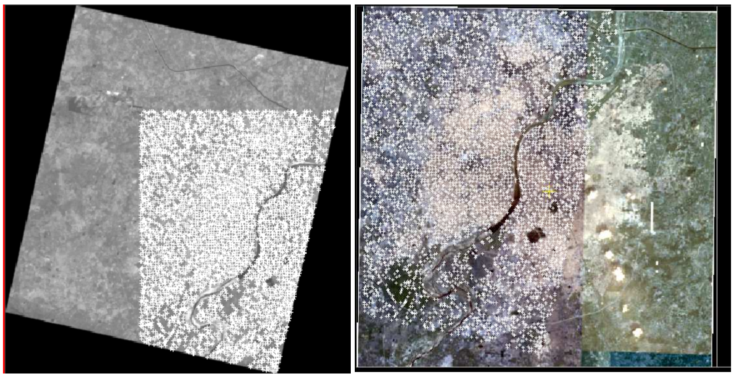


Figure3.6.3 Control points generated using automated point matching technology (Over 5000 points)

3.6.4 Rubber Sheeting

Rubber sheeting is known as two dimensional image to image transformation which is implemented as a piecewise transformation based on the triangles formed from the tie points. This has the property that the transformation is always perfect at the control points and there is always a well behaved transition from triangle to triangle. Using this automated process over 5000 control points were generated and used for geo-rectification. The RMSE error for the APM model were calculated .34, Its possible to reduce the error level by changing the expected error level and to rerun the entire model.

3.6.5 RMSE Analysis

Culminate results of point matching and modeling is expressed in RMSE factor. Initial results appeared large RMSE value and therefore the generated points are inspected to determine whether they are culprits. Initially few points were manually selected Continuous visual inspection alone with RMSE was performed to determine correct judgment of error conditions.

3.6.6 Criteria's for APM

Before applying APM several criteria and conditions are checked which ultimately produce good segmentation results. Basically there are several conditions to be followed to produce good results. The both pros and cons with respect to the required conditions are illustrated here.

- The overlapping area of the used images were more than 50% which is a good indicator for APM results.

- Resolution is another factor that affects point matching results, because it creates a difference in the details of the two images. Avoid mixing input and reference images with a resolution difference larger than a factor of six.

- Spatial resolution of the used images were quite similar (1, 2.5, 5.8) which is a positive in APM operation.

- The images were captured in the same season as well same time of the day but in different year. Similar illumination conditions), and with similar weather situations with good visibility. Radiometric characteristics is highly dependent on the time of capture ad especially seasons.

- Regarding sensor three images were from three different sensors and having different parameter whereas APM produces good results when all the images captured from same sensors.

- Select the same band or a similar band in the images for point matching to ensure similarity of radiometric characteristics.

- An Orthorectified image produces good results and it reduces the impact of vertical displacement and other distortions. The disadvantage at here none of the images were orthorectified.

- The initial misalignment of three of the images were less than 10%, therefore the process did not required initial manual registration.

- Using DSM yields good results especially with mountainous terrain, however the terrain of the study area is flat therefore DSM were not used in this purpose. All the areas having relatively flat terrain.

4. Image segmentation

This chapter provides detailed specification on different segmentation software. Later image segmentation applied using different image segmentation software on GE mosaic image. Image segmentation parameter was determined by applying trial and error approach and finally best segmentation result was drawn by making visual assessment. Quantitative quality assessment was made based on the visual observation in addition descriptive explanation of algorithms used by different segmentation tool was also included. Later quantitative evaluation of segmentation result was done by applying supervised method (stand alone/empirical discripency method). Finally advanced image segmentation was implemented by putting weights on image layers and making selection of spectral band for image segmentation. Final discussion includes advanced image segmentation which explains about the reduction of radiometric resolution to draw optimized segmentation results. The final optimized image segmentation was derived by applying Definiens Developer multi-resolution segmentation.

4.1 Visual quality of image segmentation using Definiens Developer: Definiens Developer Multi-Resolution segmentation was used to test the segmentation result. Scale parameter defied as 50 for image segmentation as well the shape and color properties assigned as .1 and .5 respectively. Image segmentation results were tested using several other segmentation parameters and the scale parameter with 50 most efficiently delineated building rooftops. Visual comparison were made from different segmentation results using different perimeter and finally most optimized segmentation result were chosen for evaluation. Overall segmentation quality in quite good despite there is some over segmentation and very few under segmentation. Over-segmentation appeared because of high level of heterogeneity on building rooftops as well dust cover on the buildings similarly under segmentation appeared due to similar spectral properties of buildings and adjacent ground surface. Obviously there are some irregular or ragged delineated segments occurred over sampled buildings. In addition faulty segmentations appear under the areas of low contrast. Another major reason of mismatch between the reference polygon and segmented result is because the reference polygon was drawn much generalized way represents the outline of buildings ignoring the detailed heterogeneity and variations of building outline. However the segmentation algorithm cannot ignore those variations indeed considers every detailed variation appeared on the building rooftops.

4.1.1 Scientific Description: Multi-Resolution Segmentation

The well known multi-resolution segmentation merge the pixels if an image and generate image objects. The bottom up segmentation algorithm based on the pair wise region merging techniques. The segmentation uses optimization procedure for a given number of image objects and minimizes the average heterogeneity and maximizes their respective homogeneity. The segmentation procedure works according the following rules, representing a Mutual-best-fitting approach.

A. Multi-resolution segmentation starts with single image objects of one pixel and merges them in several loops iteratively in pairs to larger units as long as an upper threshold of homogeneity is not exceeded locally. The combination of the both spectral and spatial properties is the input parameter of homogeneity criteria. In addition there are one more options for modifying the scale perimeter. Higher the values of scale results the large image objects whereas smaller the scale value results smaller objects.

B. Initial stage the seeds are looking for best fitting neighbors for the
potential manage

C. If best-fitting is not mutual, the best candidate image object becomes the new seed
image object and finds its best fitting partner.

D. When best fitting is mutual, image objects are merged.

E. In each loop, every image object in the image object level will be handled once.

F. The loops continue until no further merger is possible.

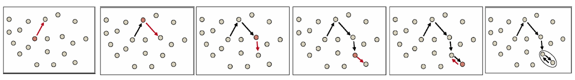


Figure 4.1.1: Scientific description of Multi-Resolution segmentation. (left) Each image object uses the homogeneity criterion to determine the best neighbor to merge with. (Right)If the first image object's best neighbor does not recognize the first image object as best neighbor, the algorithm moves on with the second object finding the best neighbor. This branch-to-branch hopping repeats until mutual best fitting partners are found(3^{rd} 4^{th} and 5^{th} form the left). If the homogeneity of the new image object does not exceed the scale parameter, the two partner image objects are merged together (Right).

The procedure continues with another image object’s best neighbor. The procedure iterates until no further image object mergers can be realized without violating the maximum allowed homogeneity of an image object. With any given average size of image objects multi-resolution segmentation yields the best abstraction and shaping in any application area. The process requires higher memory and slower the performance compared to the some other segmentation techniques.

4.2 Visual quality of ASTRO Image Segmentation: ASTRO was developed by Berkeley Environmental Technology International. ASTRO segmentation results mostly over segmented polygons. Threshold value was increased to ease over segmentation results however in that case it failed to delineate building outline and produces bigger objects which includes buildings and its adjacent impervious surface. The tested threshold value for image segmentation was 10, 15, 20, 25, 30 and the there value of 20 produces the most optimized result. In both cases the shape and compactness values were .5. Compared to Definiens image segmentation visual assessment suggests ASTRO results better regular and smoothed line which is more symmetrical to the reference polygon. Due to license conditions ASTRO online segmentation tool (http://internal.berkenviro.com/bis/) were used for image segmentation instead of the real software. The most optimized ASTRO segmentation offers in total 560 numbers of objects having parameter 89300 meter. Based on visual observation overall assessment of ASTRO considered satisfactory.

4.2.1 Scientific Description: Barkley image segmentation is designed for lightweight image segmentation application. The operation performs segmentation in the first steps of Object Based Image Analysis and in later it include some other analysis on the resulting segments like classification or generation of additional shape and spectral statistics. The tool uses region merging algorithm for the segmentation (Benz et al. 2004). It has good Capabilities to define and extract image objects (polygons).The input parameter required for segmentation is standard format image file with three channels. The size and shape of the objects are controlled by user selected parameters like shape, spectral variation and merging threshold. The tool provides output presenting segmentation of the input images by spatial decomposition into objects. The advantage is the output file format is in Vector geometry (Shapefile) of the object boundaries with spectral and shape attributes. The tool uses Pixel-based region merging algorithm utilizing spectral information, shape metrics (compactness versus smoothness), and a threshold of object size. Objects are seeded and grown based on spectral similarity of adjacent pixels and if the object would meet the shape characteristics. Objects are then iteratively grown and merged based on these same parameters up to the threshold (maximum) given.

4.3 Visual quality of SPRING 4.0 Image Segmentation: Considering visual observation SPRING image segmentation produces best building outlines. The segmentation successfully delineated the desired buildings and has smaller number of unexpected ambiguous polygons. In addition the segmented lines are smooth which is better representation of buildings. SPRING produces a total 630 numbers of objects and having parameter 118538 meter for the entire test site. Like other image segmentation result spring also generated over segmentation on the sampled buildings due to heterogeneity. Homogeneous areas are delineated well but often over-segmented. Visual observation also suggested that the spring segmentation also successfully separated the building outlines and adjacent impervious areas with similar reflectance. However, the ease of operation as well as the data handling of the software is insufficient.

4.3.1 Scientific Description: Spring image segmentation is known as isolated pixel analysis process unlike the statistical classification or conventional classification procedure. Therefore the process uses image segmentation before the classification step. SPRING Image Segmentation divides images into regions which correspond to the application areas of interest (Câmara *et al*. 1996). Region is known as set of connected pixels which are spread bidirectional and that presents uniformity. The process stops when all pixels are segmented into objects. The segmentation algorithm in SPRING uses region growing segmentation method (Câmara *et al*. 1996). It has two parameters, “similarity” and “area”, to configure the segmentation procedure. “Similarity” is a threshold value that determines if two neighbouring pixels (objects) are grouped, while the “area” threshold is used to filter out the objects smaller than this value.

The process followed in spring can also be explained as data grouping techniques. Where only the adjacent regions can spatially be grouped. Initially, the segmentation process labels each pixel as distinct regions. The similarity criteria are computed for each spatially adjacent region. The similarity criteria are based on the statistical hypothesis test, which checks the average among regions. The Similarity measure is based on the Euclidean distance between the average values of gray levels of each region. Therefore, two regions are considered different if the distance between their averages is greater than the Similarity limit chosen. Next, the image is divided into a set of sub images and then an union operation is performed, following an aggregation limit definition. Regions with areas smaller than the minimum chosen are absorbed by adjacent regions more similar to them.

For the union of two neighbor regions A and B, the following criterion is adopted:

1. A and B are similar (average test)
2. The similarity reaches the limit defined
3. A and B are spatially close (among the A neighbors, B is the closest, and among the B neighbors, A is the closest).

If A and B satisfies the above criteria, then, the regions are aggregated, otherwise, the system repeats the aggregation testing procedure.

4.4 Visual quality of PARBAT Image Segmentation: The segmentations generated by the Parbat using split and merge algorithm provide good contour representations, but also there was a lot of very small scattered segments. The drawback of PORABAT is its maximum scene size of 1300 x 1300 pixels. As the test site having 500 X 500 pixels size therefore such limitation couldn't hamper the processing. In addition visual assessment predicts that the segmentation successfully addresses the building outlines especially in the building edge. Over segmentation was also observed in some areas of the test site. For this research the following segmentation threshold values were used tested (10.0, 20, 30, 40 and 50). Visual assessment suggested that the segmentation value around 40 provides the optimized results. The total number of objects generated PARABAT is 1321 which is significantly high compared to the results generated from other image segmentation software.

4.4.1 Scientific Description: PORABAT Image segmentation uses Split-and-merge segmentation as described by Haralick and Shapiro (1985). Split-and-merge segmentation, as applied in this study, consists of a region splitting phase and an agglomerative clustering phase. In the splitting phase the image B is initially considered as a square block of pixel values with mean vector MB and covariance matrix SB. The dimension is determined by the number of bands in the image; in case of IKONOS this equals 4. The later stage this block is splitted into four square sub-blocks (B1, B2, B3 and B4), characterized by vectors of mean pixel values MB1 , MB2 , MB3 and MB4 and covariance matrices SB1 ,SB2, SB3 and SB4 in the sub-blocks. To define homogeneity, a threshold $\in_{ms}$ for the mean and thresholds $\in_{ss}$ for the covariance matrix are considered. These values are chosen in advance and kept constant during segmentation. An image block B is considered homogeneous if

$|MBi - MB| < \in_{ms}$ for i = 1, 2, 3, 4

$|SBi - SB| < \in_{ss}$ for i = 1, 2, 3, 4

and heterogeneous if one of these equations does not apply. Heterogeneous sub blocks are split recursively until homogeneity occurs or a minimum block size of one pixel is reached. The resulting data structure is a regular quad tree. In the clustering phase adjacent block segments are merged if the combined segment is homogeneous. The homogeneity rules are applied in a similar way. Thresholds for mean and covariance matrix are denoted by $\in_{mm}$ and $\in_{sm}$ respectively (Panjwani and Healey, 1995).

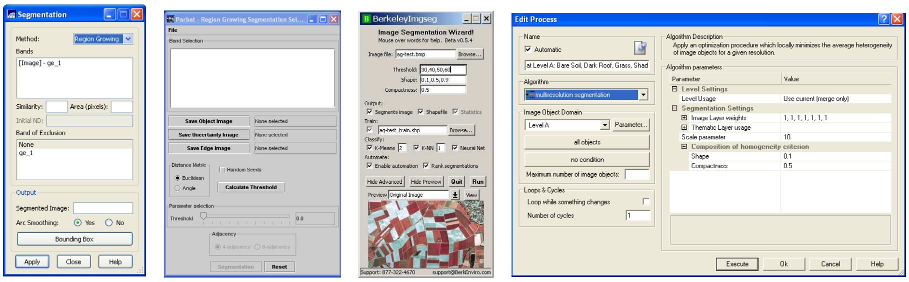


Figure 4.4.2: Graphical Interface of four different Image segmentation software, Left SPRING Image Segmentation window, second from the left PORABAR image segmentation window. Third ASTRO and on the right Definiens Image Segmentation Window.

4.5 Quantitative assessment of Segmentation Result: As like segmentation theory itself there is no established standard procedure available for the quantitative evaluation of segmentation results. However there exist some adhoc approaches which can be applied for segmentation accuracy assessment. Evaluation studies mostly intend to compare various segmentation results to reference polygon (Estrada and Jepson, 2005). The most widely used evaluation of segmentation approaches is known as supervised methods which measures the discrepancy between the reference and the segmented objects. In this research an empirical discrepancy method was used to compare segmentation results on four different mostly used segmentation programs. As different software use different algorithms the segmentation results were varying remarkably. In addition segmentation results also dependent on the parameterisations. Previous works also shows that the appropriateness of each programme is still highly depending on the specific segmentation task.

A total 110 number of different buildings with different areas (varying in location, form, area, texture, contrast, etc.) were selected and each was visually and geometrically compared with the segmented results. Visual comparison to the reference polygon suggests there ware more number of segmented polygon which means over segmentation is more common. Therefore formulas used to calculate over segmentation and under-segmentation was not applicable for this purpose. Rather calculation of area difference or parameter difference between segmented and reference polygons could be more sensible than to calculate over segmentation or under segmentation. For calculating average area difference the Symmetrical difference function of ArcGIS was used which produces error map presenting the symmetrical difference between the reference and classified polygons as well union operation were also implemented to understand the amount of segmented polygon inside the reference polygon or outside the reference polygon.

Symmetrical Difference: The operation calculates the geometric intersection of the input and updated features. Features or portions of features provided in the input and updated features which do not overlap will were assigned to the Output Feature Class. It can also be expressed that the polygon or portions of polygon in the reference Features which are NOT overlapped by segmented features will be written to the Output Feature Class. Therefore the final output will be used to calculate the average difference of areas between the segmented and reference polygon. This application found to be useful for calculating the difference of areas.

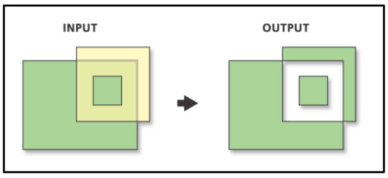


Figure4.5.1: Input and output layers of Symmetrical difference which was used to calculate area difference between segmented and reference polygon

Union between Reference and Segmented Results: Union operation applied to compute the geometric intersection of reference polygon and segmented results. All features were assigned as Output Feature Class which includes the attributes from the Input Features and output features to which it overlaps.

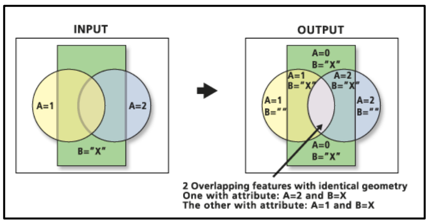


Figure 4.5.2: Overlay analysis using union operator

The geometrical comparison were carried out using the combination of morphological features like avenger difference of area A_i, and average difference of perimeter P_i with reference polygon. For making comparison geographical comparison union and symmetrical difference overlay tools were used. In total there were 110 number of well shaped building considered as reference polygon and the segmented objects underneath the reference polygon were selected by applying selected for making comparison. Obviously such process selected some unexpected bigger objects which was manually deselected and considered as outlier. In most situation the comparison were made with the biggest segmentation polygon inside the reference polygon. Off course some level of biasness is propagated while making selection of segmented results. There was one more measure available which is known as shape index which was not calculated in this research.

Table 4.5.1: Quantitative assessment of different segmentation

Segmentation Program	**Barkley: ASTRO**	**PARBA T**	**SPRING**	**Definiens**
Number of reference areas	110			
Average Difference of areas	131	132	110	48
Average Difference of Perimeters	43	40	34	36
Average Difference of Shape Index	-	-	-	-
Average quality visual evaluations	60%	70%	70%	90%

The calculation made in this sector showing the segmentation result derived from Definiens and Spring producing the most promising result. Considering the area properties Definines objects are very close to the reference polygons. Visual assessment also suggests the best segmentation produced in this process is Definiens segmentation. With this evolution its realized to use Definiens for further analysis.

In addition Definiens provides wide variety of features therefore the feature extraction process will also be helpful while using Definiens. The software having the capability of integrating complex subject matter and the means of semantic network (Jacquin et al, 2008). There are three different reasons which can be address for choosing this tool; first of all its segmentation quality specially segmentation performance on the urban objects. Secondly efficient classification performance using fuzzy based rule sets; and finally its capability to create hierarchical land link of land cover classes by using different level of segmentation(Benz et al, 2004, Jacquin et al, 2008).

4.6 Advanced Image Segmentation

Quality of image segmentation is the most important part of object based image analysis. Feature extraction is totally dependent upon the segmentation results. Therefore it's necessary to put more effort to generate good segmentation results. Conventional way of creating good segmentation result is to run the segmentation using different parameter until it produces good segmentation result. Apart form trial and error there is several other ways to improve segmentation quality; specially data preparation and image layer weighting for segmentation. Following is the brief discussion about optimizing segmentation quality.

4.7 Multi-Image Approach

The use of three different images for the study available from three different sensors therefore it is realized three image layers will be used to derive different information. The GE Mosaic images has good shape properties which is helpful for drawing building outlines but it does not have good spectral properties. This means that the spectral reflectance of vegetation areas and dark shadow areas are quite similar as well the impervious surface at ground level and building roofs appeared in similar spectral reflectance. However the Cartosat Panchromatic image has limitation on spectral properties (panchromatic) and preserves moderately good spatial resolution. Whereas IRS multispectral image has three different spectral bands but resolution is coarse (5.8meter). To get better spectral resolution of Cartosat Image the IRS and Cartosat images were fused together which resulted 2.5 meter multispectral image. Whereas good properties of building outline can be derived using only one spectral band of GE mosaic image. More detail about image layer weighting is presented on the section 3.9.

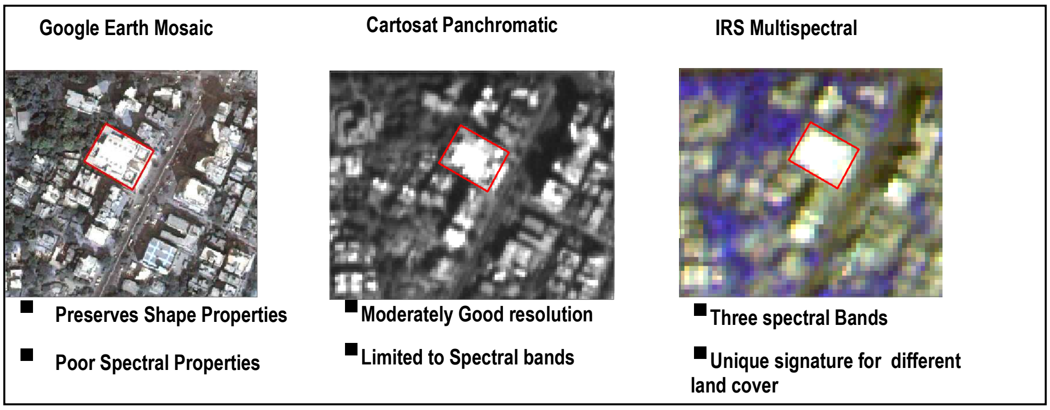


Figure4.7: Three different satellite image used for this research, GE mosaic for building outline and fused Cartosat and IRS image for separation of different land cover.

4.8 Radiometric Resolution

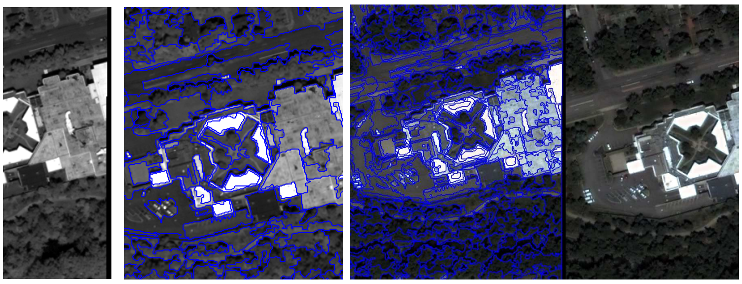


Figure4.8: Optimizing segmentation result by changing data depth, Multi-Resolution Segmentation with same parameter applied on 8 bit panchromatic and 16 bit Multispectral images. Second form the left showing segmentation result on 8 bit panchromatic images; the result is satisfactory and the feature extraction will be easy. Third from the left showing segmentation result on 16 bit multispectral images with same scale parameter, due to high level of heterogeneity (multispectral) and data depth (16 Bit) so many small undesired objects were generated which is difficult to extract.

Spectral similarity between adjacent pixels significantly reduces with the increment of radiometric resolution. This means more likely the segmentation generates two different adjacent image objects in 11 bit data compared to 8 bit data. Therefore applying multi-resolution segmentation using the same scale parameter on images having two different data bits will generate two different results, and off course the 16 bit image generate larger number of unexpected objects which is difficult to extract. Therefore considering the above situation the 8 bit GE image were converted to 4 bit data, this process significantly reduces the high level heterogeneity.

4.9 Image Layer Weighting

Depending on the importance and suitability of segmentation result, image layer will be weighted differently. Image layer having higher weights more of its information will be used in the segmentation process. The purpose of using GE Mosiac image is to draw outline of buildings roads and other urban objects. Whereas pan-sharpened Cartosat image were used for separation of building objects based on the spectral value. For drawing outline of urban object the GE image found most useful as because it has higher spatial resolution therefore during the segmentation process full weight age assigned to GE layer. However GE image has three different bands and the layer having low standard deviation of its brightness value was selected for segmentation. Remarkably low standard deviation of brightness value means objects having low heterogeneity which generates limited number of ambiguous unexpected objects.

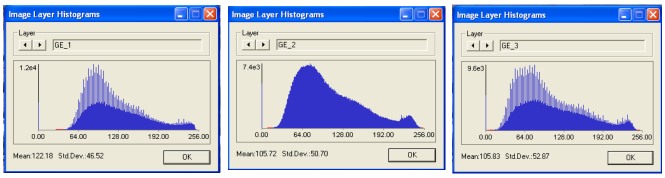


Figure 4.9: Histogram based on the brightness value

4.10 Image Segmentation: Cheeseboard Segmentation

One of the simplest segmentation algorithms is known as cheeseboard segmentation. The algorithm cuts the image into Equal Square of its desired size. The process is known as top down segmentation. This segmentation allows to decide the size of the square and its possible to apply this segmentation at pixel level. Therefore based on the brightness values individual pixels can be selected separately and conditional rule sets can be developed following is an example of cheeseboard segmentation at pixel level. Individual grids representing each pixel which was drawn form cheeseboard segmentation (as presented and discussed in 4.8 section).

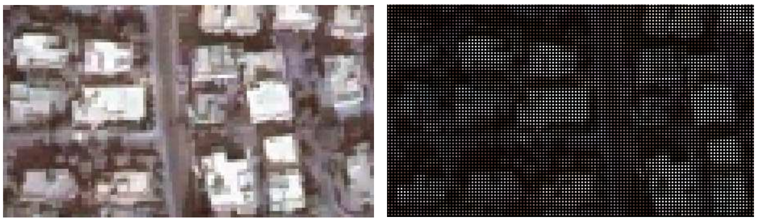


Figure4.10: Left original Image right cheeseboard segmentation applied at the pixel level.

4.11 Image Segmentation: Multi-resolution Segmentation

Multi-resolution segmentation applied on GE image band having lowest standard deviation of its brightness value. It is assumed that the layer having lower standard deviation of its brightness should have objects having lower heterogeneity. The following table presents the multi-resolution segmentation parameter used for segmenting GE mosaic image. The results most objects are over segmented, but at least there is outlines closer to building edge. High heterogeneity of objects causing the over segmentation result. However there is the use of pan sharpened cart sat image which will unique brightness value over building objects. Therefore the buildings can be separated by using the average brightness value of the both Cartosat and GE mosaic image. Following figure marked two over segmented and one perfectly segmented building.

Table 4.11: Image segmentation parameter used in the Definiens developer

<table>
<tr><th>Segmentation and Classification Type</th><th>Object Type</th><th colspan="5">Segmentation Parameters</th></tr>
<tr><td colspan="2" rowspan="3"></td><td rowspan="3">Scale Parameter</td><td colspan="4">Homogeneity Criteria</td></tr>
<tr><td rowspan="2">Colour</td><td rowspan="2">Shape</td><td colspan="2">Shape Setting</td></tr>
<tr><td>Smoothness</td><td>Compactness</td></tr>
<tr><td>Level 1</td><td>Buildings</td><td>50</td><td>.5</td><td>.1</td><td>.5</td><td>.5</td></tr>
</table>

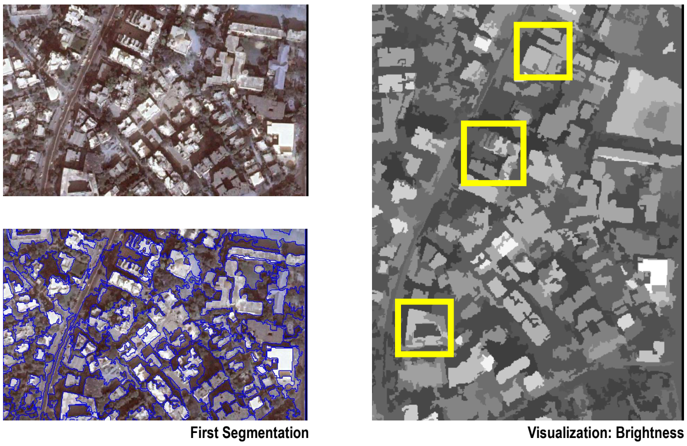


Figure4.11: Optimized Image segmentation result derived by using Definiens Multi-resolution segmentation. Upper left image showing GE Mosaic image, lower left showing segmented outline of objects which is derived from multi-resolution segmentation using the parameter presented in the above table, right images presents average brightness of six different image(pan sharpened Cartosat and GE Mosiac layers)layers. Though there is some over segmentation of objects however average brightness will be helpful for separating objects.

5 Image Classifications

This chapter tries to explore different classification method to optimize the classification results. Initially pixel and object based classification were applied to retrieve building rooftops and the results were visually evaluated. Then Nearest neighbourhood classification (NN) were tested by using several land cover class. Results form NN classification were visually evaluated and observed that the desired building class were not correctly classified. To have better classification of building footprints Feature Space Optimization tool were applied which also failed to retrieve the appropriate building rooftops. Efficient knowledge based classification were applied by using mean brightness and two other features, length and elevation. Threshold value for the three used features was determined by changing their properties and visually checking the results. Finally the classified results were evaluated by applying overlay analysis.

5.1 Pixel vs Object Classification

This section describes the basic difference between the pixel and object based image classification. In object classification image object primitives appearing regular shaped continuous polygons whereas the pixel based classification offers selection of segregated pixels don't have continuity as well missing the contextual information. The result of pixel based classification is known as salt and pepper because it carries noise and missing the contextual information. The following figure 6.8 shows the results of two different classification approaches, object and pixel based. In the both situation threshold values for brightness ranged from 110 to 160 were selected for image object primitives. The threshold level was determined with an objective to select building objects however the both situation selects some undesirable image objects like bare surface or non roof impervious areas having similar reflectance values to roof areas. it is realized that the use of DSM will be able to separate the building rooftops and non roof impervious surface. The advantage of using object based approach is to apply refinement on incorrect building Objects by using the available features like shape properties of objects (length, width area and similar others) to separate buildings rooftops and non roof impervious areas. Details about refinement of building rooftops presented on the following section.

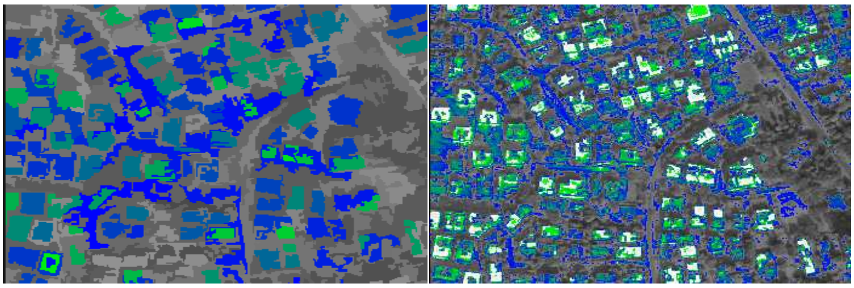


Figure 5.1: Object verses Pixel classification, Brightness value for both case used applied 110-160 range

5.2 NN Classification

Nearest Neighborhood classification is a method of classifying image objects using the class descriptions. The classification process uses a set of samples for different classes. The nearest neighbor classifier utilizes a selection of features and is trained by sample image objects. In comparison to pixel-based training, the object-based approach of the nearest neighbor requires fewer training samples: one sample image object already covers many typical pixel samples and their variations. The procedure consists of two major steps, Sample selection and Image classification. Successful Nearest Neighbor classification usually requires several iterations of sample selection and image classification. The NN classification result is presented in the following figure. Quick visual assessment was made on the classified result which shows many objects were unclassified and ignored. It is realized that selection of more number of samples can eradicate this problem. It was also observed that the NN classification failed to make separation between the dark roof and adjacent impervious surface as well bituminous surface.

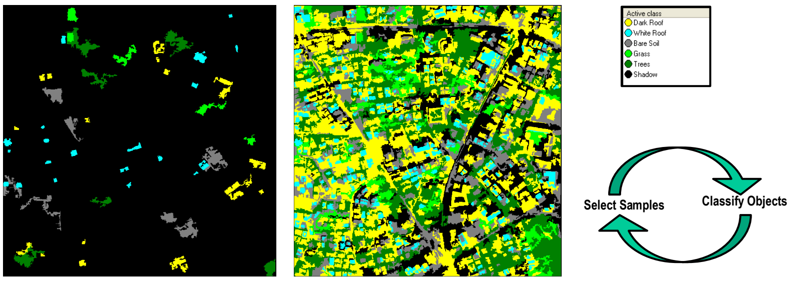
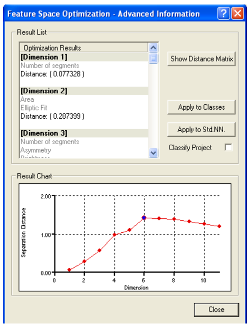


Figure5.2: Standard Nearest Neighborhood Classification result. Samples for NN classification and right classified image using NN classifier (Left). Remarkably the bare soil and non roof impervious surface mixed with the class dark roof (Middle). There requires to develop efficient rule set development to separate those objects. Strategies to improve NN classification result.

5.3 Feature Space Optimization



In the classification process some class can be easily classified by using the spectral values whereas other classes can be best described by using other features like its shape and other geometric properties. By combining several class describing features it is possible Span the feature space inside the neighbourhood classifier. For better separation of building rooftops Defifinens e-cognition offers feature space optimization which was also tested in this research. The feature space optimization uses unlimited number of features as an input instrument in conjunction with NN classification the process tries to find combination of features that is particularly suitable for separating classes. The function allows developing a separate or different NN classifier for each individual class. The process compares the samples of the selected classes with the selected features and ultimately produces largest average minimum distance between samples of different class. To make separation between non roof impervious areas to building rooftops feature space optimization tool were used, initially five numbers of features (area, asymmetry elliptic fit, average branch length and number of segments) were used to test the separation. Before making choice the selected features were tested and applied over the test site and visual observation shows buildings are quite identical compared to the other classes.

Figure 5.3: Separation results drawn form feature space optimization of Definiens Developer

Results derived from feature space optimization shows that the separation distance between different classes is increasing over with the use of number of features. When it was using five different features the separation reaches at the height position. The height separation distance was calculated .733055 between different classes by using six different features. It was realized that the there were still have scopes to use more number of features to have better separation results. The NN classifier again applied and results were visually analyzed, it is observed that feature space optimization based NN classification failed to make better separation between building class to its adjacent impervious surface rather the process results many unclassified objects which ultimately many ignoring buildings. It's difficult to understand how the feature space optimization works inside the tool and how it calculates the separation distance. However the only things its results the classified results which was found unsatisfactory. One main reason can be pointed for ignoring objects or left it unclassified is the use of too many features on the objects which don't comply with the used features. Figure 6.3 shows class separation distance matrix by using a symmetrical table. The values represent here shows class separation distance in the nearest neighborhood classification. For example the distance between dark roof and bare soil is low compared to the distance between tree and white roof.

Class/Class	Dark R...	White ...	Bare Soil	Grass	Trees	Shadow
Dimension: 6						
Dark Roof	0.000000	1.424164	2.907390	1.457330	2.511849	2.241589
White Roof	1.424164	0.000000	4.163710	4.690812	6.763770	6.037806
Bare Soil	2.907390	4.163710	0.000000	4.818344	3.414946	4.328421
Grass	1.457330	4.690812	4.818344	0.000000	1.546748	1.474198
Trees	2.511849	6.763770	3.414946	1.546748	0.000000	1.894897
Shadow	2.241589	6.037806	4.328421	1.474198	1.894897	0.000000

Figure 5.4: Class Separation Distance Matrix produced by using the Selected Features. The matrix displays the distances between samples of the selected classes within the selected feature space. The matrix is symmetric, which is due to the fact that each class is compared to each others.

5.4 Feature Extraction and efficient Rule set Development

It was realized that the neither NN classification nor the use of feature space optimization could produce good classification results. Therefore there requires developing efficient rule set which can efficiently delineate building footprints. It was also realized that stepwise rule sets using different feature would result good classification. The process is known as knowledge base classification, efficient rule set can be deployed to extract building footprint from segmentation result. The knowledge is the rule sets containing if then condition also known as classification rules. Usually buildings having high reflectance value compared to other land cover class. Brightness measures were applied to delineate the building areas to other land covers, it was observed that if the average brightness values for all the used data layers (6 different band) goes beyond 61 then the selected objects were are only buildings, however few other unexpected objects having similar reflectance to buildings were also added in such process which includes bare soil, impervious surface and even the bituminous surface.

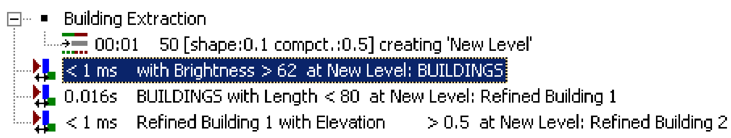


Figure 5.5: Rule set used for refinement of building class

Such situation the shape properties of unexpected objects were reviewed and compared to the building class. It was found that the unexpected objects are longer than all the building rooftops available in the test site. By making visual observation the threshold value for the undesired objects were determined greater than 80 meter. Therefore objects having width less than 80 meter were classified as building objects. The query successfully filtered elongated objects like some segments from road network and few other patches appeared as impervious surface. Unfortunately the process deselects one building which was under-segmented and having width greater than 80 meter. It was realized that there requires manual editing which will reduce length less than 80 meter.

Still there were few other objects misclassified as buildings. Such objects are like the big ground with bare soil, having similar reflectance to building. Separation of bare soil to building areas was difficult; The availability of DSM can help to make better separation. Several literatures shows the use of LIDAR DSM can generate very precise separation. However the DSM used for this research having coarser resolution and it was derived from Cartosat Stereo pair image. In dense urban environment the use of DSM couldn't bring any good result because height of a building interpolated to its adjacent areas. However the DSM was helpful for making separation of objects which is located isolated areas and having big area extent. In the north eastern part of the test site there was one such big bare soil field which was misclassified as buildings. By selecting building class with an elevation higher than .5 meter was quite successfully separated the bare soil to the building class.

Another problem appeared because of using DSM, as it was already mentioned the approach of this research is to use multi image which was captured in different times. One building In the test site was detected in GE mosaic image however it was absent in the Cartosat Image due to temporal variations. The DSM was generated from the Stereo pair image which shows the elevation of that particular is area of the building is less then .5 meter. This is why the process had to compensate one building in the test site while applying query on the image objects having heights greater than .5 meter. The observation from this analysis is that there the user should be vary cautious while applying queries based on elevation or other features on multi image approach. There requires making continuous visual monitoring to such avoid errors. The map produced in the above were converted into GIS ready layers.

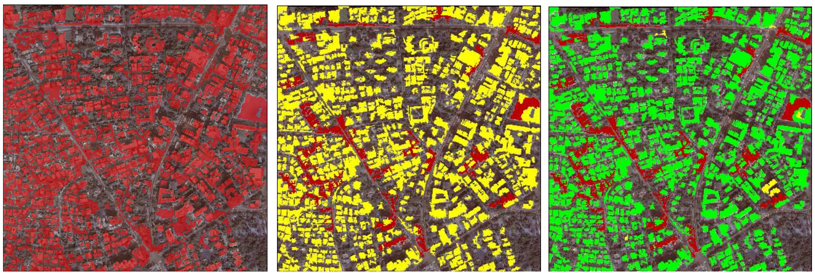


Figure 5.5.1: Three stage refinement of building rooftops, left image showing Image object selected based on brightness threshold, unfortunately many unexpected objects were selected in such process, refinement applied by changing width property of image objects less than 80 which successfully remove many of those unexpected objects (showing red part in the middle image). Second level refinement was applied by applying elevation value greater than .5 meter which deselects few unexpected objects.

5.5 Validation of Classification

Validation of classified building rooftops was implemented by making comparison with the reference polygon. As mentioned in the previous part that the building rooftops was manually digitized form GE mosaic image layers. The digitized polygons were considered as reference polygons and later the digitized buildings were used to validate the classified as building rooftops. Finally the reference polygons were compared to the classified building rooftops. To evaluate the quality of building rooftops 690 numbers of building rooftops were manually digitized. There are several approaches available to evaluate the quality of classified building rooftops. If the classified buildings rooftops completely comply with the drawn reference polygons of Google earth image then high score of classification accuracy were given.

Table5.6: Statistics on classified buildings and reference building class

Type	Number	Area (Sq Meter)
Reference Buildings	690	208449
Classified Buildings	869	228545
Difference	179	20096

Area deviation between reference polygon and classified buildings were calculated by applying subtraction method. The subtracted results were converted into percentage which presents accuracy of the classified building considering only area properties. Evolution made based on area difference shown that the accuracy of classified buildings were 90%. However evolution made based solely on area difference ignores the positional accuracy which failed to explain if a certain classified building is inside the reference polygon or outside the reference polygon. In addition the method also failed to explain how what percentage of classified building areas are correctly classified and what percentage are misclassified. To get answer of such question geographical subtraction operation applied which calculates intersect areas and symmetrical difference between the two datasets.

Overall Accuracy based on total area difference:

Accuracy Percentage [buildings] = $\left(100 - \frac{Area_{difference}}{Area_{reference}} \times 100\right)$

= 90.35 %

The geographical subtraction process generated three different types of objects. The definition of three different kinds of objects is presented above. This objects are helpful to identify percentage of classified buildings which are within beyond or missing part of classified buildings. This helps to calculate accuracy of building in addition percentage of commission and omission *(After Nobrega et al 2007).*

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Accuracy Assessment (Considering Position)

Correctly identified Building: Both reference polygon and classified polygon level a as building which is presented as correct part in the layout.

False Building: Only classified result level as pixel as building which is presented as false building in the map.

Missing Buildings: Only reference polygon level the polygon as buildings, which are presented as missing part in the layout.

Overall Accuracy = Correct / Reference
= 134510/ 208449
= 64.52 %

Omission = (Reference – Correct) / Reference
= (208449 – 134510) / 208449
= 35.4%

Commission = [(Extracted – Correct) / Reference]
= 303447 – 134510 / 208449
= 81.04 %

The overall accuracy was calculated 65% which means the 65% areas of classified buildings are completely within the reference polygon. Considering the complexity of the situation like heterogeneity of building rooftops and poor image quality the percentage considered satisfactory. As there was the use of 1 meter resolution re-sampled GE mosaic image which don’t have good spectral properties causes disadvantage for this approach. It was realized that the use of Quick bird image could bring better result due to its spectral properties and good spatial resolution. As well the absence of LIDAR DSM bought another disadvantage especially for separating building rooftops and impervious areas at ground surface. Secondly the calculated omission error was 35%, which means 35% areas of reference buildings were omitted or ignored in the classified results. Omission error occurred due to the fact about the dirty rooftops, high level of heterogeneity on a single object as well shadow areas. Commission error explained as 80% which was quite unsatisfactory. Unfortunately commission error was too high due to the fact that there were several misclassified impervious surface at ground level appeared building rooftops and showing similar spectral reflectance to buildings. Though the use of DSM and other feature like length was significantly filtered out unexpected objects however there were still few other objects appeared as buildings in the final refined building class.

6 Urban Form Measures

Previous section of this research covered image segmentation and image classification which finally draws building rooftops. This chapter discusses about the use of building rooftops to formulate urban form characteristics which can ultimately feed developing transport indicator. Most characteristics of urban from can only be measured at the city scale, however the building footprint derived in this research covers only the test site. Therefore characterization of urban form was presented in the descriptive manner rather making calculations. Initial discussion covers the issue urban form and its relation to urban travel behaviour as well transports ecological footprints. Later there are the discussions is about deriving urban land use activity form building footprints. The discussion continues about developing transport models form land use activity. The remaining part is about three different transport indicators which are residential population index, proximity index and trip distance estimates. Final discussion covers about the required data to formulate urban form and the prospects of using satellite image to derive urban form characteristics.

Land use relates to the human activity of economic function for a specific piece of land like residential use or industrial use or it can be like natural reserve areas. Human activities shape the urban living environment which ultimately has impacts on urban form. There is a strong interrelationship between urban form and travel characteristics (Stead and Marhsall, 2001). Much of the work originated and tested on developed countries especially in Western Europe and United States. Studies shows that urban form characteristics ranging form regional to local scale have influence on travel pattern as well to the environmental impacts of transport and therefore its related to transport ecological footprints. The elements of urban form closely related to the TEF components, as travel pattern is related to vehicle emissions and land occupied by transport (Barrett *et al*, 2001).

6.1 Building footprint to urban functions

The objet based classified image solely presents building footprints however to characterize urban form there requires second level information like urban function form imagery. Literature suggests RS derived information can also be used for deriving land use information (Batty and Howes, 2001; Batty and Longley, 1994; Hillier and Hanson, 1984; Kruger, 1979a; 1979b; Longley and Harris, 1999; Longley and Mesev, 2000; Mesev et al, 1995). Indeed some researchers are sceptical not just about the concept of deriving urban land use information from satellite image but also scientific basis of such concept (Bibby and Shepherd, 1999). Research work form Barr (2004) tested potential use of Structural Analysis and Mapping System (SAMS) for urban land use. Their process focuses more specifically about urban land cover to land use mapping. Following is the mathematical basis for such process.

6.1.2 Methodology

Research conducted by Barr (2004) presented the use of Delaunay triangulation which calculates the links between buildings objects and the possible shortest distance between them. Zhan et al (2002) described the ways to retrieve structural information of buildings using Delaunay triangulation. Triangulation can be applied to all points of the building objects which presets the relation between buildings. This process will be resulting matrix showing distance between the individual buildings. After calculating the distance matrix assumption can be made to represents building close to each other having similar function therefore shortest distance between buildings will be calculated. A threshold value will be determined to define buildings close to certain distance having similar kinds of land use category. The threshold value will be inferred based on certain assumptions. Finally land use category will be presented within that threshold category.

6.2 Urban Activity Map to Transportation Modeling

The availability of urban land us map can be used for calculating the distribution of various activities in urban areas which ultimately reasonable for making trip by urbanities. Those activities can be generalized into four different types of land use class like residential, commercial, industrial and institutional category. In transport modelling residential areas are considered as trip origins where trips are generated and commercial, industrial and institutional areas are considered trip destinations where trips were distributed. Therefore spatial arrangements of four land use can be associated with the travel pattern. The phenomena can be modelled by interpolating population to the residential building. In addition adding age sex and socioeconomic structures as well vehicle ownership data will bring more precise estimation of travel behaviour. Ultimately all these in terms can be linked to vehicle fuel consumption or emission and consequently remarked as transport ecological footprints.

6.3 Transport Indictor Development

The following discussion is about the use of building footprints land use information to develop transport indicators. Formulation of two indicators *residential population density* and *proximity index*; were described in this section. Both of the indicators used can be used to calculate transport ecological footprint (Dalumpines, 2008).

Residential Population Density

One of the common indicators is known as Residential population density. With high population density in urban area resulting high dependency of public transport conversely with low population density public transport is less efficient resulting in higher automobile dependence. The urban population density can be calculated by dividing population living in urban area to total land occupied by residential buildings.

$$Q_u = P_u / L_u$$

P_U is the population living in the urban area and L_U is the total land occupied by residential buildings. To make such calculations word population is required to distribute the entire residential polygon and then the uniform population density for each of the residential polygon is derived by dividing the assigned population value by the area of the polygon (equivalent in hectares). As the boundary of the test site area doesn't follow the word boundary therefore it's difficult to make such calculations. One more thing is that there is that there are very few

Proximity index

The proximity to transport networks influences travel patterns and consequently transport energy Consumption which is related to the transport ecological footprint (Stead and Marshall 2001). Better access to major transport networks, particularly road and rail networks, increases travel speeds and extends the distance which can be covered in a fixed time. The proximity to major transport networks may lead to travel patterns characterized by long travel distances and high transport energy consumption and therefore a high transport ecological footprint. The use of land use map showing residential buildings will be helpful for determining proximity index. Such information can be used to develop proximity indices map residential buildings within a certain km distance from the public transport network. The index can also be normalized in such a way that buildings closest to the public transport network may receive the highest value.

Trip distance Estimation

Trip distance estimates tries to explore the influence of cities urban form to the average trip or travel distance. The calculation can be made by assigning the Residential building as origin and commercial, institutional, and industrial pixels as destinations. As there is large number of buildings covering for the entire city and making this calculation for so many building will be difficult, therefore samples can be made from several zones of residential buildings as origin and similarly paired numbers of destinations form other land class. Overall mean trip distance can be computed between origin-destination (OD) randomly selected pairs. Considering the above analysis the both network distance and Euclidean distance can measures can be deployed. The close similarity between Euclidean and network distance may be attributed to the fact that the city has a good road network coverage. Travelling around to any point within the city is possible because of a good network of roads. It can be illustrated as other characteristics of urban form.

6.4 Discussions

RS and GIS based Urban form extraction and Transport ecological footprint analysis is data driven approach and completely dependent on the accurate and reliable information. However there are uncertainties in every stage of data processing and the distortion goes higher after summing all the uncertainties. The above discussions abut the use of building footprints for characterizing urban form indicators, The discussion covered the way to develop and calculate indicators rather making calculation and as it is far beyond the extent of this research. In addition the calculations are not possible on to small test site; indeed similar kind of analysis is only possible at the city scale.

6. Discussions and Conclusion

The approach of this research is more application oriented rather than to calculate and estimate the indicators of urban form. More attention was given to the methodological aspects and to improve the segmentation and classification results. The whole idea is to develop efficient methodology for feature extraction process in dense urban environment; if this approach brings success to derive buildings rooftops then the similar methodology can be adopted for the whole city to derive building rooftops and measure urban form indicators.

The both qualitative and quantitative assessment of segmentation suggests SPRING and Definiens can produce good quality of segmentation result. However Definiens has better options for feature extraction quality compared to the other segmentation tool. Better segmentation results can be produced by reducing data depth. The same condition is also applicable by reducing spectral properties of segmentation layer. Therefore In multi-resolution segmentation its important make choice of data layers for image layer weighting. As GE mosaic image were used to draw building outline therefore only single band image in GE image produced optimized segmentation and quite successfully address the building outline. Over segmentation observed due to high level of heterogeneity on building rooftops.

Compared to the results drawn form the pixel classification the object classifier results regular shaped and continuous image primitives. The results drawn form the pixel classification is more likely segregated selection of pixels missing the contextual information. For example few pixels of a building rooftop may classified as buildings and few other parts are misclassified. Such results cannot be useful for developing urban form indicator as there were the requirements of building dimensions remarkably the area of a building where city population will be interpolated. In addition such result is not helpful for counting the number of buildings in a certain neighborhood. But this information is necessary for deriving land use /urban form and transport ecological footprint analysis.

Better separation of misclassified objects were initiated by applying feature space optimization using several geometrical properties of objects like size, length, asymmetry, boarder, index boarder, and few other useful features which failed to make better separation of objects remarkably buildings. Basically feature space optimization tool uses several features to span distance of nearest neighborhood classifier. But the segmentation results image objects in such strange and appeared disordered way that none of the used features can properly address the sampled building objects. Therefore such process results many unclassified objects.

The advantage of using object based approach found to be useful for the refinement of building class by using the available features like shape (length, width area and similar geometrical measures) and spectral properties of individual objects. The both pixel and object classification results misclassified building objects, both cases brightness threshold value were used which results large many undesired ground objects misclassified as buildings remarkably this includes image objects like bare surface or non roof impervious areas having similar reflectance values to roof areas. It is realized that the use of DSM will be able to separate the building rooftops and non roof impervious surface. However the DSM used this research having coarser resolution and the height of a building is interpolated to its adjacent areas. Therefore the use of DSM couldn’t bring any good result for this research. But the utility of DSM observed in the areas like isolated bare soil or ground fields which were misclassified as buildings. In such situation the DSM proved to be very efficient for separating buildings form bare soil. Further refinement of building class form the patches of objects in the ground surface were made by applying the width properties of image objects. By making visual observation of misclassified ground objects a new rule set with width property found to be most useful. The width of the misclassified ground objects or patches of impervious surface were greater than 80 meter which are unlikely for building class. The newly developed rule set with width found to be most useful for building class refinement.

The observation were made during developing the rule set is that the efficiency of ruleset is completely dependent on the properties of image objects this means image object having good geometrical properties or fits to the geometrical measures (eleptic fit, rectilinear fit) are easy to extract. However the heterogeneity of rooftops in the test site was too high to produce any geometrical measures. In addition there were dark roof having dust coverage on some parts causing problems on image segmentation. Some building even don’t have any geometrical properties completely irregular shaped and may be under constriction. Apart from those points poor visibility of image object in the GE image is another constrains for delineating good shape properties. Therefore it is recommended that if the segmentation produces some strange objects which do not have any geometrical properties then there should have the implication of manual editing at some level then rule set might be efficient.

The validation of object based image classification results is still under experimental stage and there is no well established method available for this purpose. Traditional contingency matrix using sample point is not useful for this purpose rather fitness should be measured considering the shape properties of objects. Considering the complexity of the situation like heterogeneity of building rooftops and poor image quality reduced the accuracy results. The use of 1 meter resolution re-sampled GE mosaic image which don't have good spectral properties causes disadvantage for this approach. It was realized that the use of Quick bird image could bring better result due to its spectral properties and good spatial resolution. As well the absence of LIDAR DSM bought another disadvantage especially for separating building rooftops and impervious areas at ground surface, this ultimately increase the amount of commission error which was calculated around 80%. Omission error was low (35%) compared to commission error which is due to the fact about the dirty rooftops, high level of heterogeneity on a single object as well shadow areas.

There were many urban form indicators which have been proposed by nontechnical policy-makers are described and presented only at the conceptual level. The quantification and measure of such indicators is far beyond the extent of this research, because it is not possible to make such estimates with a smaller test site extent and secondly the object based image analysis and calculation is very time consuming and the extraction process required 8 human hour for 1X1 km test site area for an experienced user. Considering available resource like allocated time and complexity this research cannot go in depth calculation of such indicators

Recommendation

The following recommendation was proposed after accomplishing the analysis.

- Object based image analysis at City scale can be deployed to estimate the urban form characteristics at city scale. It is suggested that several subset images covering the whole city should be made for classification and similar methodology can be applied to formulate urban form.
- In line with this research there should have other research works related to the transition from building footprint to urban form should come into consideration. Methodologies like structural composition of land use analysis or landmark based land use forecasting can be followed.
- There should be the use of good quality DSM promising results can be made by using LIDAR data instead of using DSM generated form stereo pair image. It is expected that the use of LIDAR or better quality DSM will successfully separate the building rooftop from impervious ground surface
- While applying MultiMap approach more attention should be given for the improvement of geo rectification process similarly best methodologies should be followed in the image fusion and data merging process. More attention should be given to the temporal variation of acquired data.

- Rather than using GE mosaic image there should have the use of original multispectral Quickbird image which definitely increase the accuracy, The use of Quick Bird not just be helpful for delineating building outlines applying image segmentation but also feature extraction process. There will be the calculation of different index like NDVI or ratio analysis using different spectral bands.

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Annexure

Appendix A: Definiens Segmentation

Appendix B: ASTRO: Berkeley Environmental Technology International

Appendix C: PARBAT Image Segmentation

Appendix D: SPRING: Image Segmentation

Appendix E: Evaluation of DEFINIENS and ASTRO image segmentation result compared with reference polygon

Appendix F: Evaluation of SPRING and PARABAT image segmentation result by comparing with reference polygon

Appendix G: Evaluation of Definiens classification result compared to the reference polygon

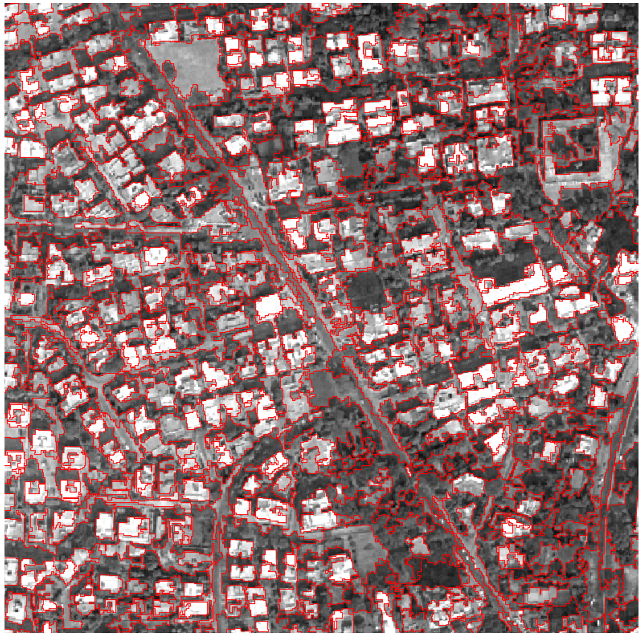
Appendix H: Error map presenting residual polygon

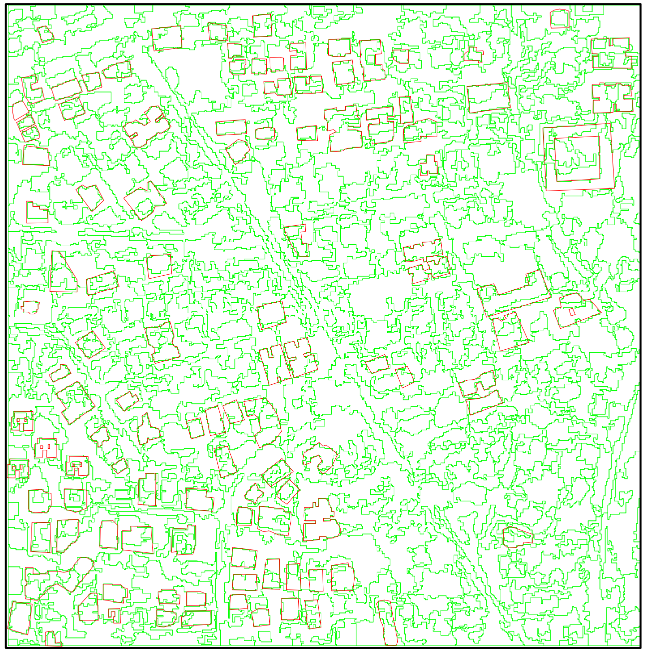
Appendix I: Refined Building Overlayed on the GE Mosaics

Appendix J: Specifications software's used for image segmentation

Appendix K: Detailed Methodology of the work

Appendix A. Definiens Segmentation





Segmentation Results from e-cognition. Multi-resolution segmentation results overlayed on the GE mosaic (left); Right image showing exported results from multi-resolution segmentation and reference polygon. Scale parameter was 50 in addition colour and shape properties were .5 and .

Appendix B. ASTRO: Berkeley Environmental Technology International

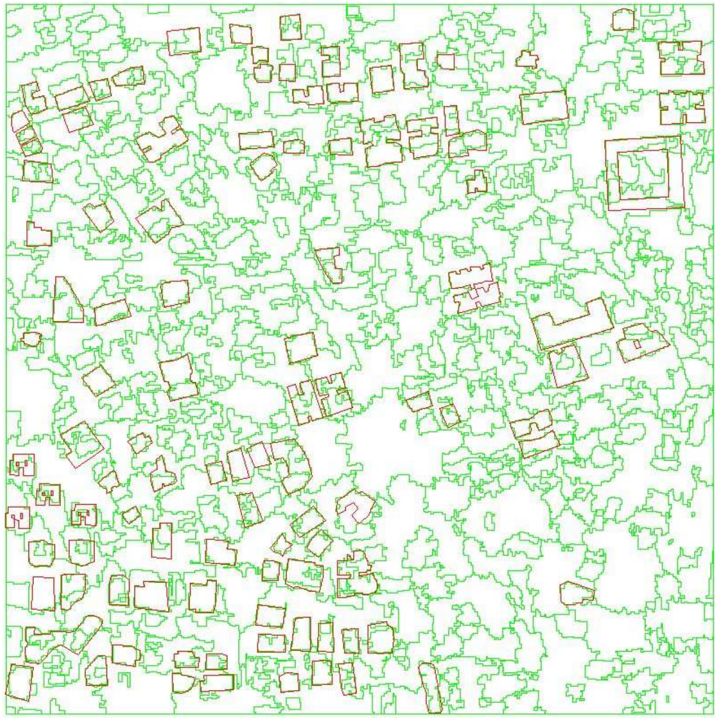


Image Segmentation Results driven form ASTRO developed by Berkeley Environmental Technology International. Region growing segmentation results overlayed on the GE mosaic (left); Right image showing exported results overlayed on reference polygon

Appendix C. PARBAT Image Segmentation

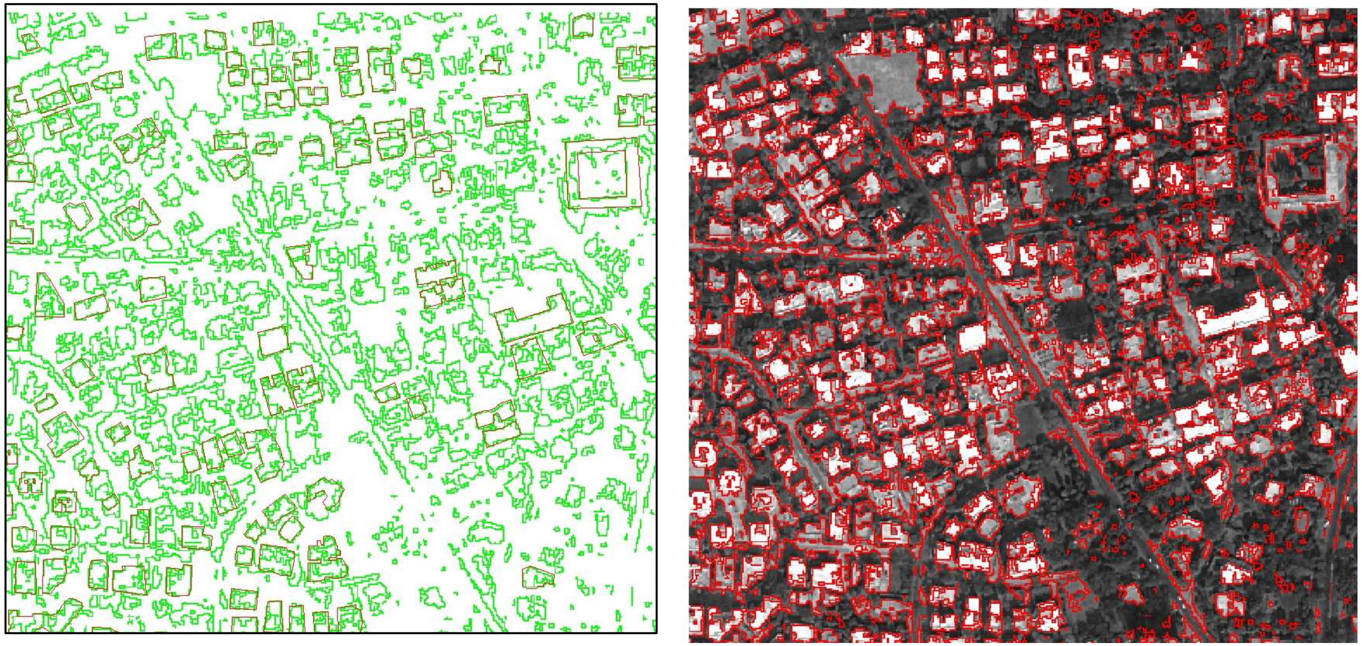


Image Segmentation Results driven form PARBAT. Edge image objects overplayed on the GE mosaic (left); Right image showing exported result overlaid on reference polygon

Appendix D. SPRING: Image Segmentation

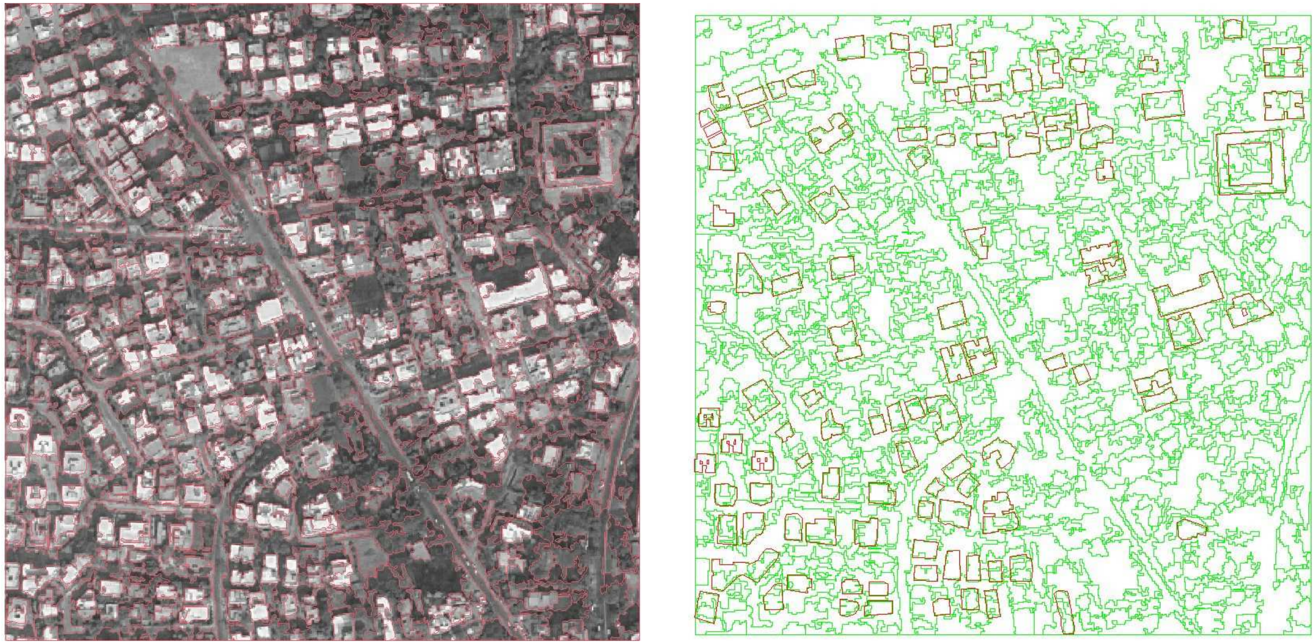
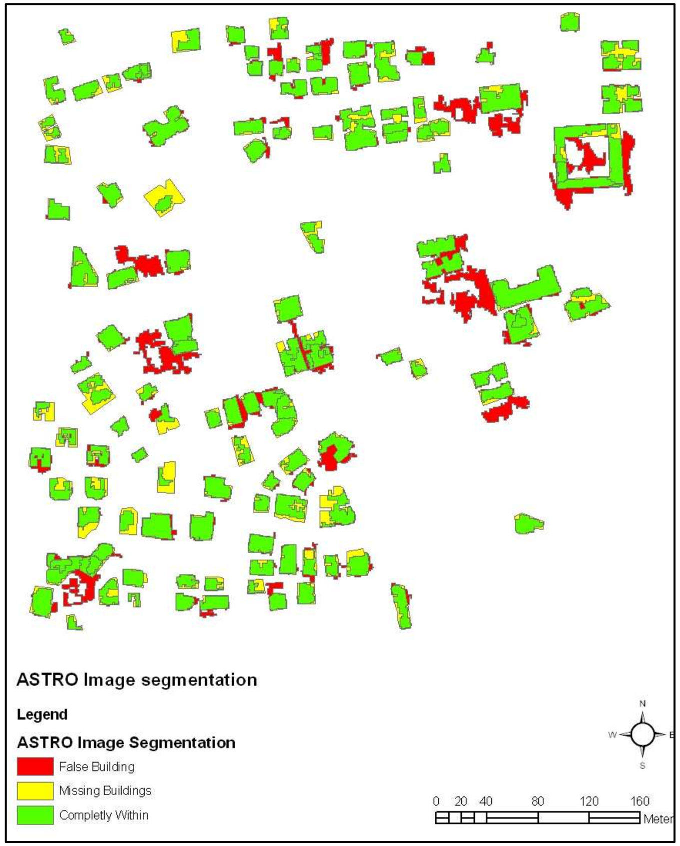
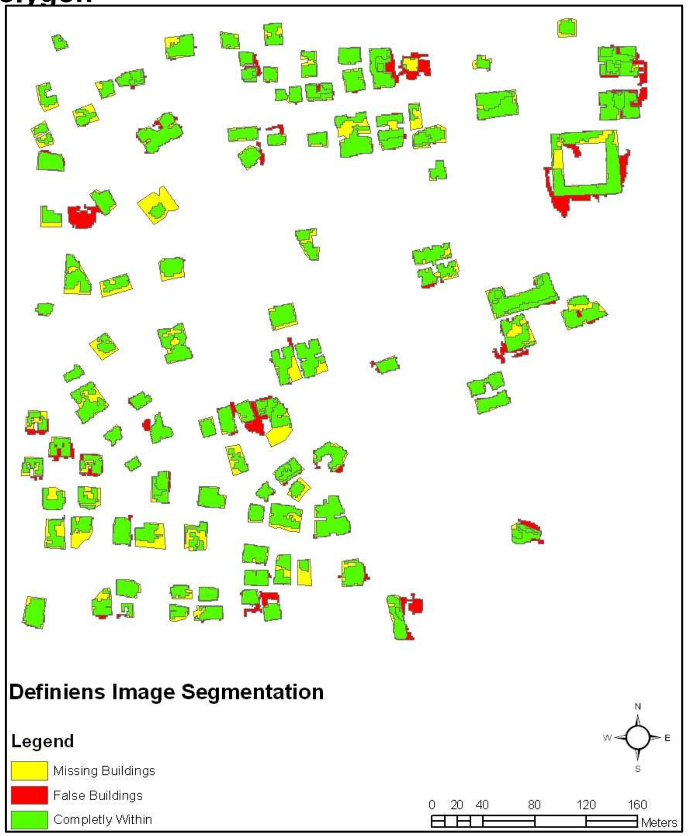
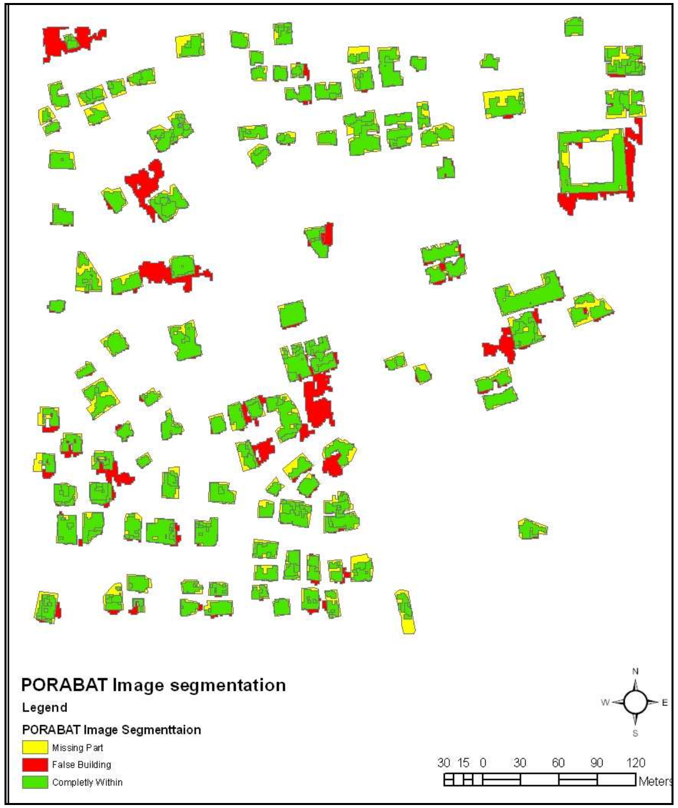


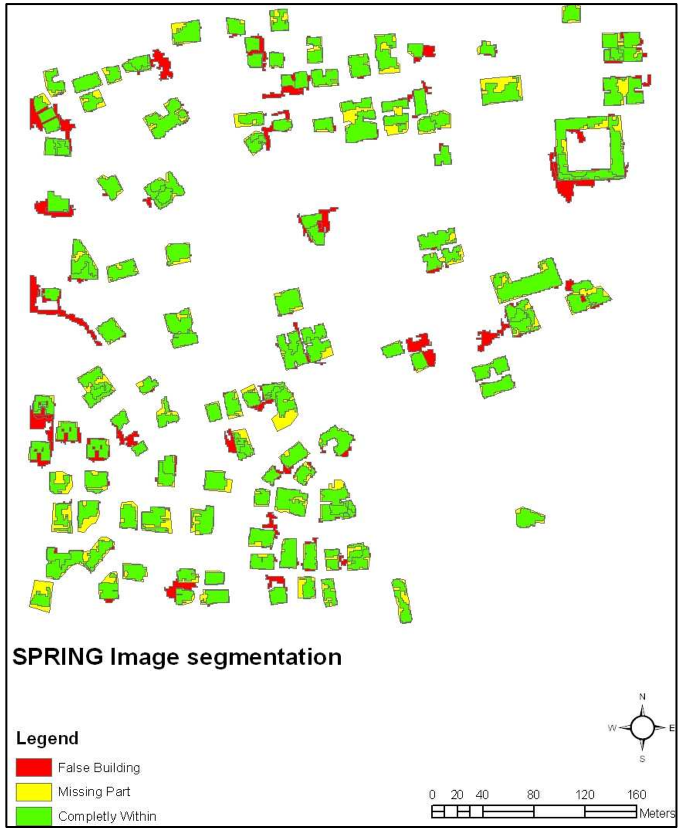
Image Segmentation Results driven form the software SPRING. Segmented object outlines overplayed on GE mosaic (left); Right image showing only object outlines. Parameter for *Similarity* value was 15 and *Area* defined as 100.

Appendix E: Evaluation of DEFINIENS and ASTRO image segmentation result compared with reference polygon



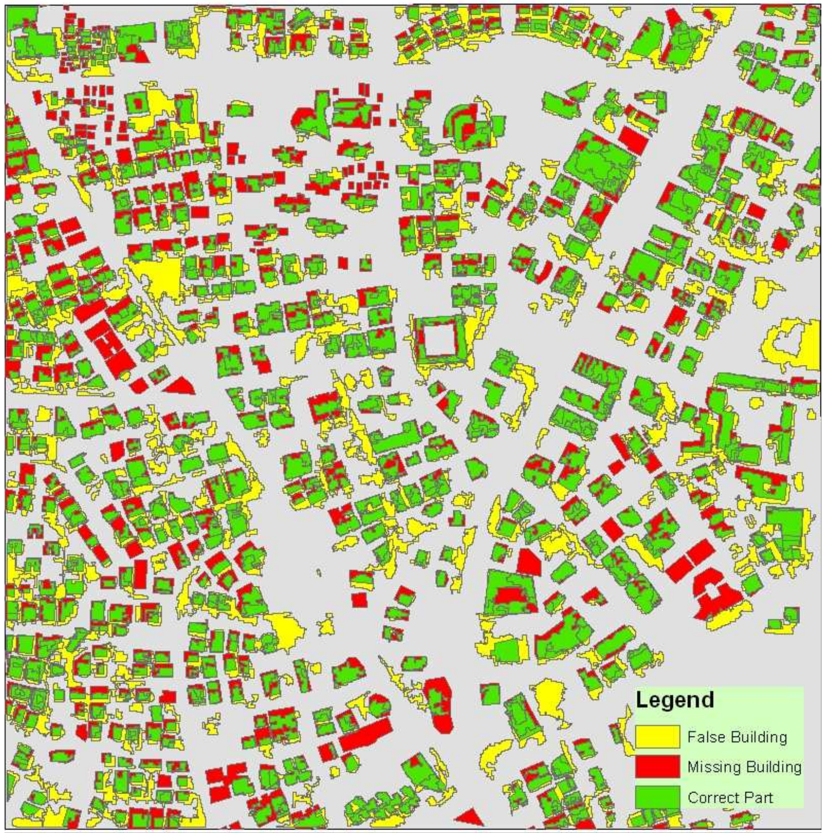






Appendix F: Evaluation of SPRING and PARABAT image segmentation result by comparing with reference polygon

Appendix G: Evaluation of Definiens classification result compared to the reference polygon



Appendix H: Error Map of Definens segmentation presenting residual polygon

Appendix I: Refined Building Overlayed on the GE Mosaics

Annexure J: Specifications software's used for image segmentation

Segmentation Program		Definiens 7	SPRING 5.0.3	Parbat 0.32	ASTRO
Fundamentals	Developer	Definiens Developer, Munchen Germany	National Institute for Space Research (INPE) Sao Jose Dos Campos Brazil	Arko Lucieer ITC, EOS Department Enschede, The Netherlands	Berkeley Environmental Technology International, LLC 3015 Holyrood Oakland, CA USA
	Website	www.definiens.com	www.dpi.inpe.br	www.lucieer.net	http://berkenviro.com/berkeleyimgseg/
	Algorithm	Region Growing Multiresolution Segmentation	Region Growing	Split-and-Merge	Pixel-based region merging utilizing spectral information, shape metrics (compactness versus smoothness), and a threshold object size
	Field of Application	Remote sensing /Medical science /Computer Vison	Remote sensing	Remote sensing	Remote Sensing
	Fundamental References	(Benz,2004) Batz	http://www.dpi.inpe.br/geopro/trabalhos/spring.pdf	Lucieer, 2004	http://berkenviro.com/berkeleyimgseg/BerkeleyImgseg_Metrics_20071105.pdf
	Number of Parameter	3(scale, shape, compactness)	2(Similarity, Area)	3 (2)	3(scale color smoothness)
	Classification Support	yes	yes	Yes	yes
In and Output	Maximum Image size	20 Gigapixel	-	1,300 x 1,300	-
	Maximum Bit Depth	32	-	16 bit	-

	Input Format	Most common RS Imagery	LANDSAT, SPOT, ERS-1 and NOAA/AVHRR Data	Raster (BSQ)	
	Vector Output Format	Arc View Shape file, CSV	RC/INFO (ungenerate), ASCII-SPRING, DXF-R12, ShapeFile and E00	No (external conversion)	ESRI Shapefile, CSV
Availability		License Agreement	Freeware	Freeware	License Agreement

Annexure K: Detailed Methodology of the work