HOMOGENOUS URBAN PATCHES DEFINED BY TEXTURE AND PATTERN FOR THE DETECTION OF SLUMS

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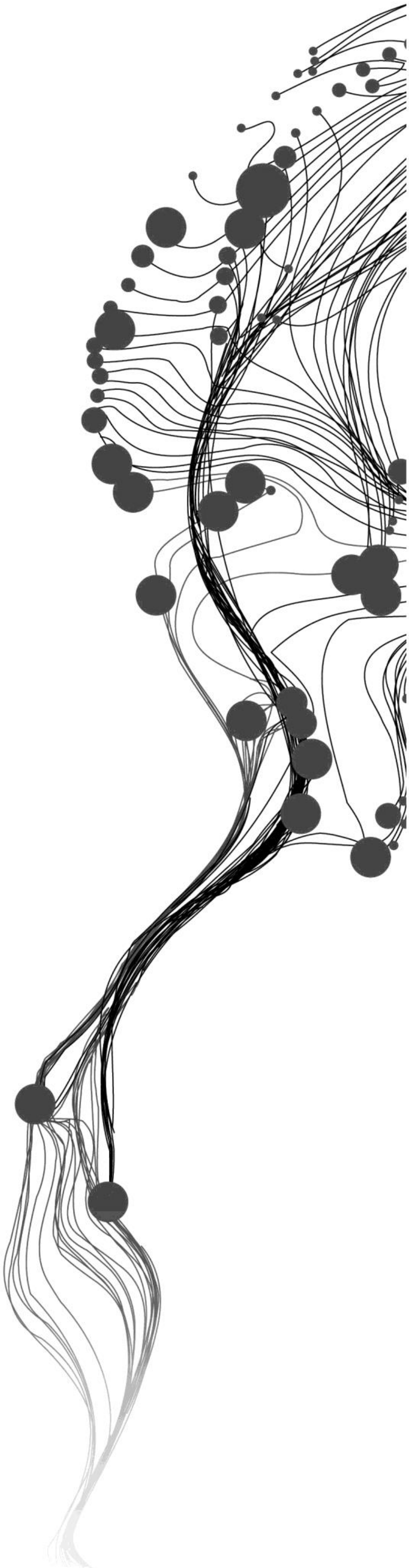

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Enschede, The Netherlands, March, 2012

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Dedicated to:

My parents

ABSTRACT

The growing number of slum population has become a challenge to urban planners and decision makers. Different approaches have been applied to identify and monitor the slum at different stages. Most techniques relay on time taking analysis like through the use of census population data and field based identification methods. The availability of very high resolution images provides a new approach in remote sensing, allowing efficient analysis in the urban environment. The objective of this study is to develop a semi- automatic method using Object Oriented Analysis (OOA) that will enable to identify Homogeneous Urban patches (HUPs) and to characterize them for further texture and pattern based slum detection. In the previous studies HUPs have been delineated manually. Using very high resolution (VHR) pansharpened IKONOS image of New Delhi, the approach of this study is based on (1) delineating HUP boundaries through OOA approach and finding the spatial and spectral characteristics of HUPs through spatial metrics and Gray Level Co-occurrence Matrix (GLCM), (2) analyzing HUPs across different scale images, multi-scale analysis, (3) testing the transferability of the method on another area, and (4) HUP based slum identification. The result shows that HUPs were delineated successfully through a semi-automatic approach. The accuracy of the delineated HUPs is assessed by comparing the manually and automatically delineated HUPs and results an accuracy value of 85% and 71% in the two test areas respectively. Texture and pattern based analysis through spatial metrics and GLCM measures are found to be an important measure in characterizing HUPs. Spatial metrics were providing a higher amount of information for classification of HUPs in to different land use categories. The changes ‘within’ the delineated HUPs and ‘on the boundary’ were clearly recognized from the spatial metrics and GLCM results on different scales. The method can be transferred to another area depending on the nature of the site and the rules that have to be set at the beginning of the analysis. The HUPs show a major advantage in identification and characterization of slums in terms of texture and pattern. The results demonstrate the practicability of the approach in different areas.

Keywords:

Homogeneous Urban Patches, Object Oriented Analysis, Spatial metrics, GLCM, Multi-scale analysis, Slum identification

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Hiwot Abera Yilma
Enschede, March 2012

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LIST OF ACRONYMS

HUP	Homogeneous Urban Patches
OOA	Object Oriented Analysis
VHR	Very High Resolution
ESP	Estimation of Scale Parameter
LV	Local Variance
ROC	Rate Of Change

1. INTRODUCTION

1.1. General introduction

Population growth, rapid urbanization and economic decline make mega-cities deal with insufficient housing problem especially in developing countries. This is the cause that make people to live in the slum environment which is considered as main contributor in increasing the slum population (UN-Habitat, 2003a). The existence of slums could be due to rapid rural to urban migration and increment of poverty (UN-Habitat, 2007b). The formation of these areas could be in two ways; either originated from people settling on unused land or from those settlements which were once in a good condition but loss their desirability after a while. More recently the existence of slums is closely linked to national income distribution and economic development policies (UN-Habitat, 2007a).

There is no universally agreed definition of slums. However, slums often refer a heavily populated run-down area of a city, characterized by substandard lower quality informal housing and squalor with the most unsanitary and poor human living conditions often located in areas that are environmentally deficient or hazard, unstable slopes, river banks, drainage basin and non-vegetated areas. Slums are usually found with high aggregation and with a limited access of: security of tenure and sufficient living area, housing of adequate durability, clean water and sanitation (UN-Habitat, 2003a).

Slums are one of the challenges that governments in most developing and the least developed countries are presently faced with and still unresolved issue (UN-Habitat, 2006). Everyone does not agree with the existence of slum as it has unsafe living environment and as they obviously need improved quality of life. As mentioned by Mathenge (2011), an effective identification and monitoring of slums begins from an understanding of its development stages. In addition, relatively poor knowledge of local and global forces shaping development and producing urban poverty, the complexity of the accompanying phenomena and the uncertainty of urban decision-making processes, call for a better understanding of slum areas (UN-Habitat, 2003b).

Efforts to understand and improve the living conditions of slum dwellers especially within developing countries have been done over the last decade. Although slum detection and mapping has received relatively little attention until recently. Much work is done by examining the general developments of urban remote sensing and limited studies that deal specifically with slums (Sliuzas et al., 2008). Renewed concern about poverty has recently led governments to adopt a specific target on slums which aims to significantly improve the living conditions of most slum dwellers in a better way (UN-Habitat, 2003a). Acquiring precise information about slums that can improve the lives of slum dwellers is actually not an easy task. Getting an information and mapping of slums with a general approach has proven difficulty (Netzband, 2010). This is because slums usually appear with high disorder and various appearances than other types of settlements. Thus, obtaining spatial information about slums which is up to date and integrating it with other phenomena is essential for any action of improvement and to achieve more control about slums development. Comprehensive information on the slums is essential for formulation of effective and coordinated policy for their improvement (Hofmann et al., 2008).

1.2. Role of Remote sensing in analyzing slum

For monitoring the development stages, remote sensing techniques using sophisticated data and methods of image analysis play a very important role in quantitative and qualitative profiling of slums in fast growing cities and megacities (Netzband et al., 2009). The availability of satellite data with a very high resolution has became an essential information source to analyse the highly dynamic nature of informal settlements as it provides spatially consistent and accurate datasets covering wide areas with high detail and frequent time (Herold et al., 2001).

While analysing urban areas on remotely sensed images, one can face confusion between formal-looking informal settlements and informal-looking formal ones. Informal settlements, particularly slums, are mostly recognized on images as more compact areas lacking open spaces and having morphological chaos without geometric features and heterogeneity of spatial structure. Due to difficulties on appearance with variety of tenure arrangements overlapping with other classes, microstructure nature and instable shape of the slum environment, identification and characterization of these areas with in urban environment is substantially more difficult and challenging than other land cover types (Hofmann et al., 2008).

The great value of remote sensing to address these challenges has been proved by different studies. Thomson (2006) is one of those who analyse the potential of remote sensing techniques by using satellite imagery to identify, delineate and assess the variability and associated biophysical characteristics of informal settlements in metropolitan Bangkok through multispectral image processing techniques. The result showed that multispectral image classification has proven to be a valuable addition to distinguish a variety of urban land cover classes. Although analysis of these classes show spectral confusion with different types of urban land cover classes, which resulted in imprecise detection and delineation. This could be the result of low spectral variability. Therefore, it was explained that, the potential for this technique to be of great value for the identification and delineation of very high density housing should not be used only with spectral information; it needs to be supported by other type of analysis utilizing high resolution imagery.

In comparable way it appears that manual interpretation of aerial photograph is more effective means than spectral analysis for identifying such kind of spectrally over lapping land covers. Baud et al. (2010) have applied visual interpretation techniques to analyze the heterogeneity and deprivation of sub-standard residential areas. It is mentioned that visual interpretation is a manual process which involves an intense task and very time consuming especially if large areas or more than one time periods have to be covered and needs well-trained visual interpreters and valuable quality control if reliable output is to be produced. The analysis may require considerable subjectivity and it is difficult to manage the variation that occurs when combining the output of different interpreters. Sliuzas (2004) explained that now days with the use of remote sensing techniques through object-based identification approaches more precise result can be obtained than visual interpretation and pixel based analysis.

High resolution remote sensing images have also been used aiming to interpret distinct levels of poverty from the perspective of urban texture both in regular and irregular patterns (Barros & Sobreira, 2010). Texture was found as a good tool to identify slums through differences of density, land parcelling and probably levels of urban poverty that could be reflected in urban patterns.

It is generally a fact that with very high resolution satellite data, quick detection and characterization of slums is feasible in saving time and cost (Thomson, 2006). However, one should still need to integrate the information extracted from the images with ground truth or local knowledge in order to avoid confusions and to acquire better results (Sliuzas et al., 2008).

1.3. Object Oriented Analysis (OOA) and slum mapping

Object Oriented Analysis (OOA) has become a powerful method for applications of urban remote sensing. In OOA approache an image is initially segmented into a set of regions that are considered to be homogeneous in one or more spatial or spectral properties. Next to segmentation, each object will be classified based on different combinations of the spatial and spectral properties (Thomas et al., 2003). eCognition is one of the advanced image analysis software which allows hierarchal object-based segmentation and classification of different land covers.

OOA approach enables integrations of urban objects to be modelled so that to find an output of more accurate data on urban land cover and land use including slums is possible (Blaschke, 2010).

Different researchers have explained the advantages of classification using object oriented analysis over pixel based classification. Pixel-based classification approaches assign individual pixels to classes of land cover based on their spectral signature and statistical probability of class membership which is mainly the basis of samples of known land cover. Hung & Ridd (2002) have applied pixel based classification and described that the method has some critical issue which is, whether or not pixel based analysis is able to identify and classify impervious surfaces that lay into similar category and there is a probability to have confusion with some classes.

OOA have been used to classify various urban areas in order to detect informal settlements in Delhi, India (Niebergall et al., 2007). Comparing the result with pixel based classification, it is concluded that pixel based analysis is difficult to use in complex urban environment; it uses only spectral values while OOA considers additional information like shape, texture and other relations to the neighbour. Bhaskaran et al. (2010) described that while interpreting an image it is necessary to observe image objects and their mutual relations than single pixel. Small (2003) also concluded OOA remains more accurate than pixel based classification especially in complex urban environment.

1.4. Homogenous urban Patches (HUPs)

Homogeneous Urban patches (HUPs) are image segments with similar properties according to their size, shape, tone/colour, texture and pattern (Peplies, 1974). HUPs could be derived from remote sensing data on the basis of administrative borders. The concept of HUP provides a major advantage to other spatial structure investigations of urban areas from remotely sensed data. It allows the characterization of thematic-defined and irregularly shaped areas, while other approaches merely using a quadratic filtering window and per pixel information as a basis for thematic data analysis (Barr & Barnsley, 1997). For the application of the spatial metric approach these regions can generally be described as areas of homogeneous urban land use structures as entities for the data analysis (Herold et al., 2001).

Liu et al. (2006) developed a general characteristics particularly for HUPs: (i) HUPs have a homogenous texture which is visibly different from that of the neighboring HUPs (ii) HUPs may have several land cover types within it, but has only one land-use. The built-up areas in a residential HUP are usually similar in terms of size, density, and spatial arrangement (iii) where possible, HUP boundaries follow streets and other relevant natural and anthropogenic features such that large built-up patches remain contiguous for their delineation (iv) HUP should be sufficiently large for an adequate landscape metric analysis. Very small homogenous areas are too small for urban land-use characterization. In addition, For multi temporal analysis the most recent available remote sensing data should be utilized for HUP segmentation (Herold et al., 2002).

Considering the above characteristics, HUP boundaries have been delineated by an experienced image analyst through visual interpretation in order to study the correlation between population density and image texture. The result through field checking and peer evaluation showed that the boundaries of the HUPs are highly accurate, which minimizes the propagation of errors in HUP boundaries for further analysis (Liu et al., 2006). In fact, the definition and delineation of HUPs requires an additional processing step (Herold, 2001).

1.5. Spatial metrics

Spatial metrics was developed in landscape ecology to quantify the environmental patterns of a natural landscape. Recently, it has been used to understand urban environment, emphasizing the strong spatial component in between objects of urban structure and related dynamics of change and growth processes (Herold et al., 2003).

Spatial metrics or landscape metrics are quantitative indices to describe structures and patterns of settlements. Spatial metrics can be used to quantify the spatial heterogeneity at a specific scale and resolution of the individual spatial units called patches. According to Herold et al. (2001), spatial metrics are computed based on patch categories in regions of single landuse.

A patch is defined as homogeneous regions for a specific landscape property of interest. The regions are objects made up of pixels which are adjacent to each other and have the same land cover (Liu et al., 2006; Victor, 2007). The spatial metrics consider all patches in the same class, and the landscape as a collection of patches (Herold, 2001). Spatial metrics could be calculated with one of public domain software called FRAGSTATS. While computing, the software considers the areal extent of the patches (McGarigal et al., 2002).

Spatial metrics have the capability to describe the composition and spatial arrangement of the land covers in a landscape. Therefore they can be used to describe urban patterns and structures in a better way (Victor, 2007). Spatial metrics are important measurements contributing to more detailed mapping of urban areas leading towards a more accurate characterization of spatial urban growth pattern (Herold et al., 2002).

The concept of spatial metrics was applicable in most remote sensing analyses. They can also be used to analyze and describe changes in spatial heterogeneity using multi scale data sets. The strength of spatial metrics in representing changes of urban environment has been justified (Herold et al., 2005).

1.6. Texture measures

Texture refers to the spatial distribution of tonal variations in the image (Haralick et al., 1973). Texture measures are among the approaches used to incorporate spatial context information. Textural information has been an important factor in image interpretation. It takes into consideration the distribution and variation of neighbourhood pixel values (Zhang et al., 2001). Texture measures are used to describe the spatial characteristics of land-cover object (Herold et al., 2003). Texture has been found as successful tool to classify images in complex urban environment and characterize informal settlements at different stages of development (Hurskainen & Pellikkam, 2007). It was explained that slums could be approached in a better way by delineating them in terms of texture keeping the concept that the gaps of slum environment are smaller and uniformly distributed than those of non-slum areas (Dubovyk et al., 2011).

1.7. Fuzziness

One of the main requirements of information extraction process in a state of art of image analysis system is consideration and manipulation of uncertain information, that is fuzzy concept (Zadeh, 1965). Whenever thresholds defined they are mostly unsatisfactory idealizations of the real world and subsequently lead to difficulties during classification. If these thresholds are used for ground truth definition, classification results would be compared with idealized reference data and thus performance estimation of the classification might not be optimal (Bezdek & Pal, 1992). With Object Oriented Analysis optimal information can be found by integrating the fuzziness in the boundary of the classes. The classification can be applied for the area of transition where it is difficult to be certain (Benz et al., 2004). Therefore; consideration of fuzzy concept during classification could be important.

1.8. Multi-scale approach

Scale is the spatial and temporal parameterization of our perceptive window on reality. It bounds the ecological phenomena that we can observe (Withers & Meentemeyer, 1999). Geometric precision needs of scale identification. A complete image classification process usually consists of sub processes which have to operate on objects of several scales, multi-scale (Benz et al., 2004). The concept of scale can be viewed as from two perspectives, object segmentation scale (scale parameter) and an image scale.

Object Segmentation scale or scale parameter is the most important parameter that constrain the level of object segmentation. This parameter does not related to numbers of pixels, but rather it determines the maximum allowed heterogeneity in the resulting image objects or segments. The higher the scale parameter, the larger object size. Segmentation scale allows the user to represent different level of image objects where each image object is connected and knows its context, its neighbour, its super object and sub object (Definiens Imaging GmbH, 2002).

Image scale refers to the size of objects that appear in the landscape or in its representation on an image. Every object has its inherent scale; it only appears in a certain range of scales. That is, it determines the occurrence and non-occurrence of a certain object class (Lang et al., 2006). The representation of objects at different image scales corresponds more to the objects of interest rather than only referring to statistical measures in an image (Hay et al., 2005).

In the domain of remote sensing a certain scale is always presumed by pixel resolution, the desired objects of interest often have their own inherent scale. Analyzing an image at different scale is an adequate approach to understand relations within an image and interpret the scene more easily (Kurtz et al., 2010).

1.9. Problem statement

Due to the increasing number of slum dwellers, there is a growing need of effective method to identify and monitor slums and informal settlements (Aminipouri et al., 2008). Lots of efforts have been made for defining and analyzing slums. Jurgens (2008) indicated that there is still a need to have simple and reliable methods for extraction of slums through different scales and to know how they behave in different images and seasons.

HUP has a crucial contribution in extraction of slums, as it provides a major advantage to identify various classes from the images. Therefore, precise information is required on HUP boundaries which is still a challenge for the image interpretation community (Liu et al., 2006). In the previous study HUPs have been delineated manually. Automatic delineation of these regions is not applicable yet.

Liu et al. (2006) pointed that the boundaries of HUPs may be obtained using texture based image segmentation which maximizes between patch textural differences while minimizing within patch differences.

In this regard, this study focuses on semi-automatic Object Oriented Analysis technique to delineate and characterize Homogeneous Urban Patches through spatial metrics and texture measures.

Hurskainen & Pellikkam (2007) described texture and pattern as a tool to classify images and characterize informal settlements at different stages of development. In this study the potential of the method for identification of slums will be analysed.

HUPs will be used as entities to identify slums. The specific HUP rules which have been developed by Liu et al. (2006) will be considered accordingly in the analysis. Based on the findings of Burnett & Blaschke (2003), the effects of object segmentation scale and image scale on identification and characterization of homogeneous urban patches will be assessed through multi-scale approach. This will generally give an insight in the stability of patches and also in uncertainty or error propagation that arise while dealing with various scales. The accuracy of the results could be assessed in combination with different texture/pattern features (Angelo & Haertel, 2003). In addition, to analyze the transferability of the method this study proposes to analyse the HUPs in different areas. Finally the specific characteristics of slums will be identified in terms of texture/ Pattern.

1.10. Research objective

The main objective of this research is to develop a method using Object Oriented Analysis that will enable to identify Homogeneous urban patches and to characterize them for further texture/pattern based slum detection.

1.10.1. Research specific objectives

The following specific objectives have been formulated to address the main objective

1. To delineate and characterize Homogeneous Urban Patches on the images
2. To analyse the effects of image scale on the characteristics of Homogeneous Urban Patches
3. To delineate and characterize Homogeneous Urban Patches on different areas
4. To identify slums from Homogeneous Urban Patches

1.10.2. Research questions

In order to achieve the research objective, some research questions have been formulated and presented in Table 1-1.

Table 1-1: Research objectives and questions

No	Research objectives	Research questions
1	To delineate and characterize Homogeneous Urban Patches on the images	What spatial and spectral characteristics can be used to delineate Homogeneous Urban Patches? How can the definition of Homogeneous Urban Patches be linked in to OOA process? Which spatial metrics can be used to characterize Homogeneous Urban Patches? How can texture help to characterize Homogeneous Urban Patches? How can spatial metrics and texture measures help to classify Homogeneous Urban Patches?
2	To analyze the effects of image scale on the characteristics of Homogeneous Urban Patches	What are the effects of scale on characteristics of Homogeneous Urban Patches?
3	To delineate and characterize Homogeneous Urban Patches on different areas	What spatial and spectral characteristics of HUPs can be recognized in different areas?
4	To identify slums from Homogeneous Urban Patches	Which Homogeneous Urban Patches are slums and what are their specific characteristics in terms of texture and pattern?

2. LITERATURE REVIEW

2.1. Previous slum mapping approaches

Several approaches have been developed for identification and mapping of slums. For instance; Waghmare et al. (2010) have identified slums in Latur, India using high resolution IKONOS satellite image and GIS technique which was supported by ground verification. The slum areas were identified on the basis of visual interpretation and were captured manually using on-screen digitization. Aminipouri et al. (2008) have estimated the slum population in Dar-es-Salaam, Tanzania using VHR orthophotos and based on an accurate object-based inventory of buildings. This approach was found as simple and effective resulting in satisfactory result.

Lemma et al. (2006) have developed a participatory approach that could improve slum monitoring process in Addis Ababa city. It is explained that the participatory approach of data capture at various levels has enabled a deeper understanding of the versatile nature of slums to be acquired.
In the previous studies slums are mostly addressed in terms of poverty and census information (Netzband et al., 2009).

Weeks et al. (2007) have analyzed the slum in Accra, Ghana using census data and remotely sensed imagery. It has been explained that the pattern of slums is not continuous and remote sensing images could be very useful to select slum indicators.

Sliuzas & Kuffer (2008) have analyzed the problem of poverty through VHR remote sensing imagery and using spatial indicators and census data in combination with ground truth and local knowledge. Based on the indicators and census data, they identified poverty in terms of different neighbourhoods of deprivation. However; there has been limitation of having one set of criteria to define poverty. Karanja (2010) have mapped informal settlements in Kisumu, Kenya by involving inhabitants and collecting data per household. Recently, Kohli et al. (2011) develops an ontological framework in order to conceptualize slums in Kisumu, Kenya through generic slum ontology and object oriented analysis.

2.2. Previous work done by OOA

Object-oriented Analysis has been applicable in various studies. For instance, slums of Kisumu, Kenya have been identified and mapped by object oriented analysis and with VHR Geo Eye imagery (Mathenge, 2011).

Informal settlements have been successfully classified and analyzed by using OOA (Niebergall et al., 2008). The final result was compared with pixel based classification and showed its great value on complex urban environment. Another comparison has been made between per pixel classification and object based classification using Quick bird imagery. It is found that OOA results in better classification of homogeneous land covers (Yuan & Bauer, 2006). Moving from being dependent on individual pixel values into a way of incorporating shape, texture, pattern and contextual information through a semi-automatic method has provided a reasonable result by avoiding misguided interpretation. Hofmann et al., (2008) have also detected and mapped informal settlements from QuickBird data by using OOA.

OOA have been also evaluated in identification of motorized vehicle effects in semi-arid to arid ecosystems of the American West. It was described that OOA with the use of high resolution imagery have classified roads, buildings and other urban features in a better way than by pixel based analysis (Mladinich, 2010). Buildings were precisely extracted by OOA in the analysis of urban sprawl (Durieux et al., 2008). Object-oriented method using high resolution imagery has been also applied to classify a large urban area into detailed land-use categories (Herold et al., 2003).

A multi-scale OOA approach have been utilized to assess social vulnerability and to define and estimate variables such as built up areas, road access, and green spaces with associated physical characteristics. An approach was based on the contextual analysis of VHR images and GIS data. Proportion measures have been targeted for calculation of spatial metrics and to characterize neighbourhoods (Ebert et al., 2009).

OOA has been generally applied in a various streams and is still a promising technique to classify objects precisely especially in an urban environment, which is the main interest in this study.

2.3. Previous work on spatial metrics, HUPs and texture/pattern measures

In order to describe the spatial characteristics and changes in an urban environment, the concept of spatial metrics have been applied by different studies. Kohli (2007) analyzed the dynamics of spatial and temporal patterns of land cover changes in urban areas utilizing spatial metrics. The metrics were used in order to quantify built up areas by moving window technique through FRAGSTATS software and gradient analysis. The result showed that spatial metrics combined with gradient modelling were able to quantify the patterns of urban growth successfully. Jain et al. (2011) have applied spatial metrics to quantify and capture changes in an urban environment in Gurgaon, India. It was found that spatial metrics have a potential to quantify the impact of regional factors on urban growth pattern. Spatial metrics have been used also in the field of ecology(Gustafson, 1998).

Su et al. (2008) have applied local spatial statistics and textural measures for object oriented classification of urban areas using high resolution imagery. The result showed that textural and spatial information can be used to improve the object-oriented classification of urban areas using very high resolution imagery.

Liu et al. (2006) have estimated the population using very high spatial resolution imagery through spatial metrics and image texture. Rather than using categorical land use as a surrogate for population density, there has been examined the correlation between census population density and image texture.

HUPs have been delineated by visual interpretation. Spatial metrics have been found the most promising in the study. Karathanassi et al. (2000) has also implemented texture measures to classify built up areas based on different density. Zhang et al.(2001)have identified the spatial pattern of Beijing, China to test the performance of different textual features.

Recently, Van de Voorde et al. (2011) developed an approach based on spatial metrics and continuous impervious surface data in order to map urban areas of Dublin, Ireland. The distribution and spatial configuration of impervious surface cover is quantified at the scale of predefined spatial entities. The result showed that the combination of the selected spatial metrics provided high accuracy.

Now a day there is a great impression on effective and efficient automatic techniques which could be able to analyze and monitor an urban environment. Object Oriented Analysis could be mentioned as one of those techniques.

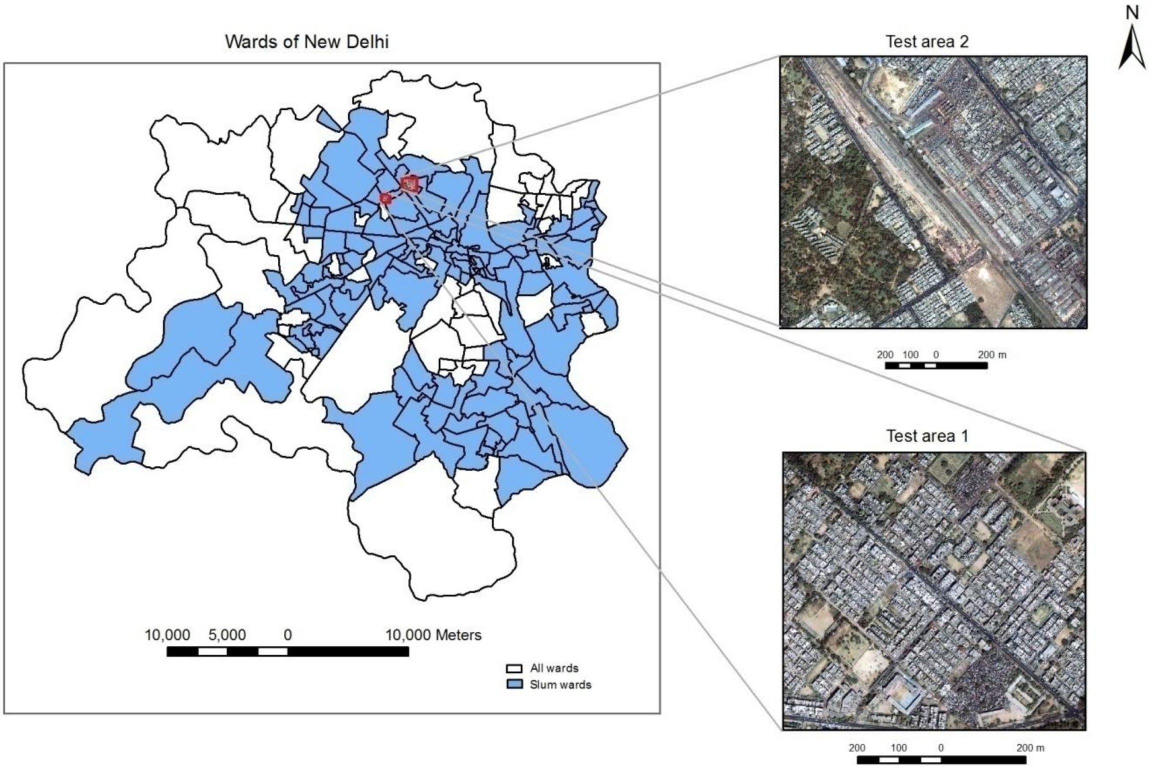
In this study the potential of OOA in delineation of HUPs will be analyzed semi-automatically using eCognition software. The HUPs will be characterized through spatial metrics by FRAGSTATS software. Those HUPs which are slums will be specifically identified and analyzed in the process.

3. MATERIAL AND METHOD

3.1. Material

3.1.1. Data

The data that have been used in this research is very high resolution (1 meter) pansharpened IKONOS image and census data of New Delhi of year 2001. According to the report on 2001 slum population of New Delhi, about 100 wards are identified as wards containing slums (Government of India, 2001). From these wards that contain slums, small test area of 0.3 km^2 which is characterized by different land use/land cover types has been selected/ extracted for the analysis (Figure 3-1).



New Delhi Wards Test area (Pansharpened IKONOS image)

Figure 3-1: Wards of New Delhi and Test areas (Pansharpened IKONOS image)

3.1.2. Software used

Definiens (eCognition 8.64), ArcGIS 10, Public domain software FRAGSTATS, SPSS and Alpha 0.1 which implements through Java Topology Suite (JTS) and Geo tools open source libraries have been used in this research.

3.2. Method

3.2.1. General Methodology

The main objective of this study is developing a method using Object Oriented Analysis (OOA) that will enable to identify Homogeneous urban patches (HUPs) and to characterize them for further texture/pattern based slum detection. In order to detect and characterize HUPs that could be a base for precise slum identification it is important to first consider the definition and characteristics of a HUP. The methodology is described in terms of the flow of research objectives. The first research question focuses on delineation and characterization of HUPs on a single scale image through texture/pattern measures. The second objective focuses on analyzing the effects of image scale (multi-scale approach) on the characteristics of HUPs. The third objective discusses the transferability of the same method on a different area of the same city. The last objective targets slum identification. Figure 3-2 shows the general work flow that has been followed to answer these research questions.

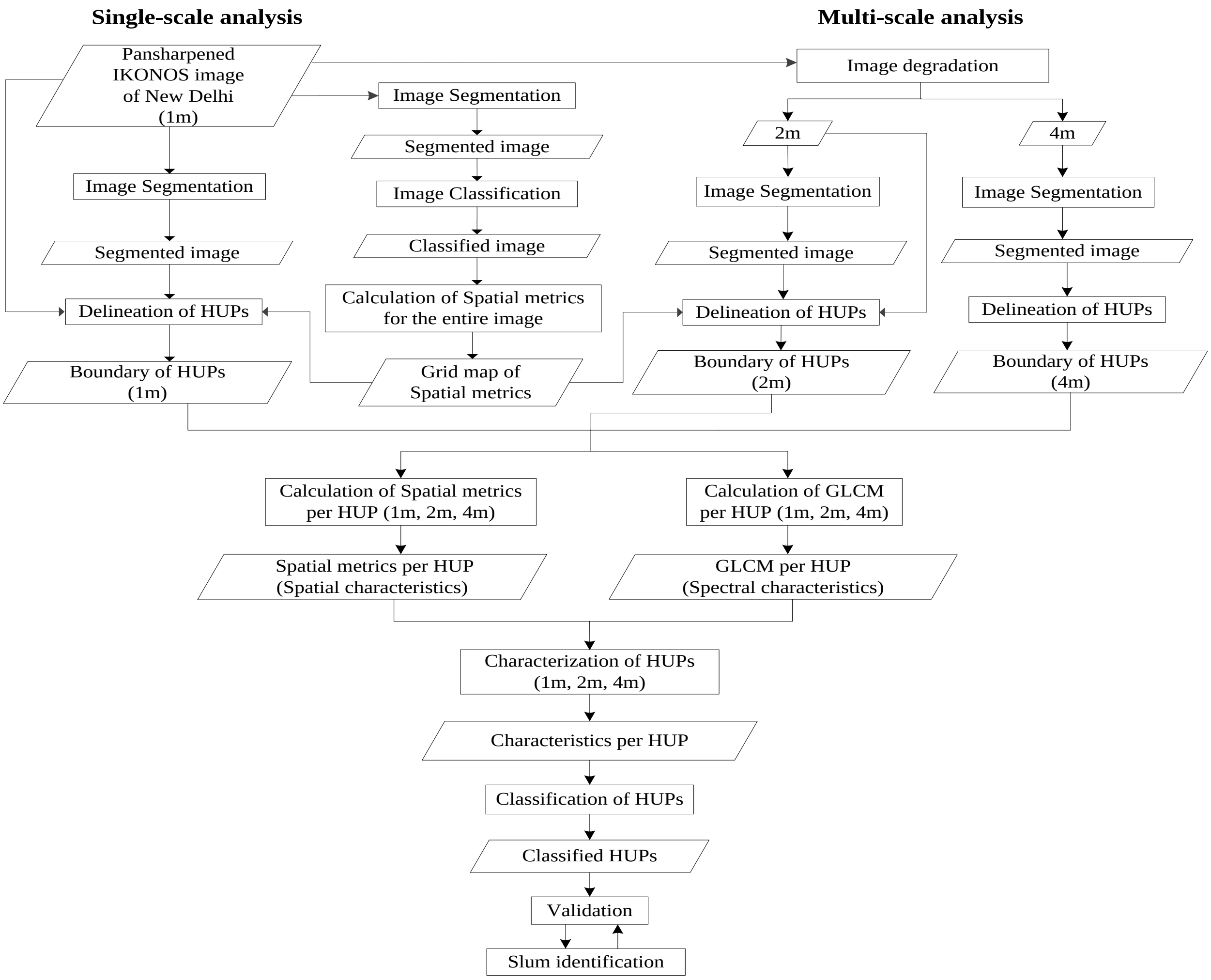


Figure 3-2: Flow chart showing overall methodology

3.2.2. Research objective 1: Delineation and characterization of HUPs

In order to delineate and characterize HUPs through Object Oriented Analysis, this study starts from consideration of the following basic definition and characteristics of a HUP;

Definition

HUPs are image segments with similar properties according to their size, shape, tone/color, texture, pattern and land use (Peplies, 1974).

Characteristics

- HUP has homogenous texture which is visibly different from that of the neighbouring HUP
- HUP may have several land cover types within it, but has only one land use
- The built-up areas in a residential HUP are usually similar in terms of size, density, and spatial arrangement
- Where possible, HUP boundaries follow streets and other relevant natural and anthropogenic features (Liu et al., 2006)

Image Segmentation

The first step of the analysis was segmentation using eCognition software which supports to subdivide the image into different regions that serves as building blocks for further analysis. Multiresolution segmentation has been used as an optimization procedure in order to segment an image. This segmentation algorithm is a bottom up procedure which minimizes the average heterogeneity and maximizes the respective homogeneity within an object. With a given average size of image objects, multiresolution segmentation yields good abstraction and shaping in any application area (Definiens Imaging GmbH, 2002).

Selection of Scale parameter

Different parameters have been used to constrain the image segmentation: Scale parameter, Smoothness and Compactness. The scale parameter relates with the maximum allowed heterogeneity in the resulting segments. The smoothness and compactness allowed the resulting image object to have smooth borders and a compact shape respectively.

The scale parameter was selected by using Estimation of Scale Parameter (ESP) tool. Scale parameters found through ESP tool will only need minor modifications in the segmentation process. The ESP tool builds on the idea of local variance (LV) of object heterogeneity within a scene. The tool iteratively generates image objects at multiple scale levels in a bottom-up approach and calculates the LV for each scale. Variation in heterogeneity is found by evaluating LV plotted against the corresponding scale. The thresholds in Rates Of Change (ROC) of LV (ROC-LV) indicate the scale levels at which the image can be segmented in the most appropriate manner, relative to the data properties at the scene level. The peaks of the ROC curve results on considerable scale parameter. This is because at the peaks, the homogeneity of objects in the scene increases meaning that the highest values of LV just before successive levels along the curve shows scales where objects reached meaningful levels of organization in terms of variation of their homogeneity (Dragut et al., 2010). In addition to this, Benz et al. (2004) expressed the scale parameter in three levels: fine, medium and course. Fine scale parameter for the delineation of trees, buildings and roads, medium for the delineation of groups of trees or groups of buildings and coarse for the delineation of forest or urban area. This study also considers this scale parameter levels accordingly.

In this study, the pansharpened IKONOS image were segmented in to two levels by setting different scale parameters: Level 1 smaller scale parameter targeting detail land cover classification of an image (Section 4.1.1) and level 2 larger scale parameter for the delineation and functional classification of HUPs (Section 4.1.3).

Basically the segmentation is based on colour or spectral information from the bands that we choose to consider in the segmentation. Red, green, blue and near infra-red bands were used in Level 1. More weight were assigned for Near infrared band because near infrared band has been found the most significant single band and accounted for 74.3 percent of the total variances (Liu et al., 2006). In level 2 an extra layer (grid map of spatial metrics) were added to the bands. A larger and equal weight was given for the additional layer and near infra red band. Table 3-1 shows the summary of different levels of image segmentation and the selected parameters in the segmentation process.

Table 3-1: Parameters of image segmentation

Level	Segmentation algorithm	Layer Weights	Scale Parameter	Shape	Compactness	Target object
1	Multiresolution segmentation	Red=1 Green=1 Blue=1 NIR=5	26	0.4	0.2	Built up Vegetation Other
2	Multiresolution segmentation	Red=1 Green=1 Blue=1 NIR=5 Grid map=5	42	0.8	0.2	HUPs

Image Classification

After having the segmented image, object oriented image classification was done. The whole image was classified in to three land cover categories; as built up, vegetation and other types of land cover. Table 3-2 describes the rule set (thresholds) implemented for the classification.

Table 3-2: Classification Rule set (thresholds)

Class	Object feature	Threshold
Built up	Brightness NDVI	<98 <-0.005
Vegetation	NDVI	>0.1
Other	NDVI	<=0.1 >=-0.005

Normalized Vegetation Difference Index (NDVI) was calculated as follows;

$$NDVI = (NIR - Red)/(NIR + Red)$$

Where NIR refers Near Infrared

Calculation of spatial metrics on entire image

By running the classified image through FRAGSTATS software spatial metrics specifically Class Area was calculated for the entire image of class built up, vegetation and other. A standard analysis of round moving window size 10m radius was used. According to McGarigal et al.,(2002). The class Area is calculated as follows;

$$CA = \sum_{j=1}^{n} a_{ij} \, (1/10,000)$$

Where;

a_{ij} = area (m2) of patch ij

Delineation of HUPs

While delineating HUP boundaries, urban patches which are similar in terms of spatial and spectral characteristics have been segmented and grouped together. The output from the selected spatial metrics, which is grid map of class area of built up, vegetation and other land cover types were used as an input layers. More weight was assigned for the grid map layer (Table 3-1). In HUP delineation procedure, the presence of this extra layer added a value that can simplify and facilitate the process.

Merging algorithm has been applied as necessary, keeping in mind that the HUPs should be representing one land use and could comprise more than one land cover.

Calculation of spatial metrics per HUP

Spatial metrics are the basic tools to describe the spatial characteristics of land-cover objects within each HUP (Herold et al., 2003). To determine the spatial arrangement or pattern of the HUP in the test area some appropriate spatial metrics have been selected considering the spatial configuration and composition of patches with in a HUP. Spatial configuration describes the spatial arrangement, position, or orientation of patches within a HUP (Liu et al., 2006). The principal aspects of spatial configuration that has been used in this study are Patch Density (PD), Number of Patches (NP), Edge Density (ED), Total Edge (TE) and isolation/proximity represented by Euclidean Nearest Neighbor Distance (ENN).

Composition describes the variety and abundance of patch types within a HUP without considering their spatial placement. This type of spatial metrics is useful in differentiating types or land use of HUPs (Liu et al., 2006). In this study Percentage of Land (PLAND), Largest Patch Index (LPI) and Class Area (CA) of built up, vegetation and other land cover types with in a HUP are calculated to describe the composition of patches with in a HUP.

After extracting the image per each HUP, the classified image was used as an input for the calculation of spatial metrics through FRAGSTATS software. The general analysis through spatial metrics has been done by two ways: Standard analysis and moving window analysis.

Standard analysis

The standard analysis provides an overall numeric output for the characterization of a HUP. In this study the standard output of about nine spatial metrics were calculated for each HUP.

Moving window analysis

Moving window analysis takes in to consideration those patches which are set to be computed in the analysis. In this study a round moving window of 10 meter has been used for the calculation through FRAGSTATS software. A total of nine spatial metrics were selected to quantify the spatial pattern of patches with in a HUP. The definitions and specific importance of each of these metrics is taken from the documentation of FRAGSTATS software (McGarigal et al., 2002) and presented as follows;

A. Patch Density (PD)

Patch density (PD) measures the number of patches per unit area. It can be used to compare the degree of fragmentation among HUPs. Patch density is a limited, but fundamental aspect of landscape pattern. PD is calculated as follows:

$$PD = \frac{n_i}{A}(10{,}000)(100)$$ ***Equation 3-1***

Where;

n_i = number of patches in the landscape of class 'i'

A = total landscape area (m^2)

B. Number of Patches (NP)

Number of patches has the same basic utility as Patch density as an index, except that patch density expresses number of patches on per unit area basis. NP is calculated as follows:

$$NP = n_i$$ ***Equation 3-2***

Where;

n_i = number of patches in the landscape of class 'i'

NP ≥ 1, without limit

NP = 1 when the landscape holds only 1 patch of the relating patch type; that is, when the class consists of one patch.

Number of patches of a specific patch type is a simple measure of the extent of subdivision or fragmentation of the patch type.

C. Edge Density (ED)

ED shows the density of the edges of the patches that exist in the landscape.

$$ED = \frac{\sum_{k=1}^{m} e_{ik}}{A}(10{,}000)$$ ***Equation 3-3***

Where;

e_{ik} = total length (m) of edge in landscape involving class 'i'

A = total landscape area (m^2)

ED = 0 when there is no edge of class in the landscape; which means, when the entire and boarder of landscape, if present, consists of the relating patch type and it is mentioned that none of the boundary of landscape and edge of background could be treated as edge.

D. Total Edge (TE)

This is the absolute measure of the total edge length of a specific patch type. TE is calculated as follows:

$$TE = \sum_{k=1}^{m} e_{ik} \qquad \textit{\textbf{Equation 3-4}}$$

Where,

e_{ik} =Total length (m) of edge in landscape involving class i; holds landscape boundary and background segments involving patch type i.

TE=0 when there is no edge of class in the landscape; that is when the whole landscape and border of landscape, if present, consists of the relating patch type and it is mentioned that none of the landscape boundary and edge of background could be treated as edge.

E. Isolation/proximity

Isolation/proximity refers to the tendency of patches to be relatively isolated in space from other patches of the same or similar class. In this study Euclidean Nearest Neighbor Distance (ENN) is selected to describe the isolation of patches with in a HUP.

ENN is a simple measure of isolation. For buildings, ENN can help to describe whether the houses are spaced regularly. High density single unit housing display highest orderliness and close to each other. Therefore, its ENN is expected to be small.

$$ENN = h_{kl} \qquad \textit{\textbf{Equation 3-5}}$$

Where;

h_{kl} = distance (m) from patch kl to the closest neighbouring patch of class k, based on patch edge-to-edge distance, computed from cell center to cell center.

ENN is described in two ways: Euclidean Nearest Neighbor Distance Mean (ENN_MN) and Euclidean Nearest Neighbor Distance Standard Deviation (ENN_SD).

Euclidean Nearest Neighbor Distance Mean (ENN_MN)

ENN_MN measures the average distance between two adjacent patches, like built ups or other features.

Euclidean Nearest Neighbor Distance Standard Deviation (ENN_SD)

ENN_SD indicates the regularity of ENN. For instance; in a residential area where houses display a high degree of orderliness, ENN_SD is expected to be low.

F. Percentage of Land (PLAND)

PLAND quantifies the proportional abundance of each patch type in a landscape. For this study, it is used to describe the percentage of built ups, vegetation, and other land-cover types in a HUP. PLAND is calculated as follows:

$$PLAND = P_i = \frac{\sum_{j=1}^{n} a_{ij}}{A} (100) \qquad \textbf{\textit{Equation 3-6}}$$

Where;

P_i = proportion of the landscape occupied by class ‘i’

a_{ij} = area (m2) of patch ‘ij’

A = total landscape area (m^2)

PLAND approaches 0 when the relating patch type (class) becomes increasingly small in the landscape. PLAND = 100 when the whole landscape comprises of a single patch type; which means, when the entire image is comprised of one patch.

G. Largest Patch Index (LPI)

Largest Patch index (LPI) calculates the largest patch index comprised with in total landscape area. It is a simple measure of relative dominance of the patches with in a HUP. LPI is calculated as follows;

$$LPI = \frac{\max_{j=1}^{n} (a_{ij})}{A} (100) \qquad \textbf{\textit{Equation 3-7}}$$

Where,

a_{ij} = area (m^2) of patch ij

A = total landscape area (m^2).

$0 < LPI \leq 100$

LPI approaches 0 when the largest patch of the relating patch type is becoming small and LPI equals 100 when the whole landscape comprises of a single patch of the relating patch type; which means, when the largest patch consists 100% of the landscape.

H. Class Area (CA)

As mentioned above in the calculation of CA for the entire image, CA is calculated asfollows:

$$CA = \sum_{j=1}^{n} a_{ij} \ (1/10,000)$$ ***Equation 3-8***

Where;

a_{ij} = area (m^2) of patch ij

CA will be close to 0 as the patch type becomes rare in the landscape. CA = TA when the whole landscape consists of one patch type; which means, when the whole image consists of a single patch. Class area is a quantifier of spatial composition. It computes the percentage of corresponding patch type.

Like PLAND, CA is a measure of landscape composition but it has an advantage that it considers an different patch sizes (D. Kohli, 2007).

The above calculated spatial metrics resulted in statistical and grid map of built up, vegetation and other land cover types.

Calculation of texture measure (GLCM) per HUP

In order to describe the spectral characteristics of each HUP, one of texture measure element called Gray level Co-occurrence Matrix (GLCM) has been calculated. GLCM tabulates the occurance of gray tone in a particular area in relation with another gray tone (Baraldi & Parmiggiani, 1995). Each element in GLCM is the estimated probability of going from gray-level i to gray-level j given the displacement vector which consists of a direction and distance. GLCM can only be conducted on gray level images (Haralick et al., 1973), so the image was first converted to gray level using near infrared band. Liu et al. (2006) explained that near infrared band was the most significant single band accounted about 74.3 percent of the total variances in the multi-spectral image. In this study, about six GLCM-based texture descriptors have been selected: GLCM entropy, contrast, homogeneity, correlation, mean and standard deviation. The selected GLCMs describe the distribution of gray level values in terms of quantifying the uniformity and disorder in a HUP (GLCM entropy), differences of spatial frequencies (GLCM contrast), linear dependencies (GLCM Correlation), image homogeneity (GLCM homogeneity), average occurrence of gray values (GLCM mean) and dispersion of values around the mean (GLCM standard deviation). These texture descriptors have been previously used to describe the spectral characteristics of a HUP in relation with population density (Liu et al., 2006). For each HUP GLCM was calculated and the spectral characteristics was identified. The definition and explanation of the selected GLCM based measures are taken from eCognition user guide manual (Definiens Imaging GmbH, 2002) and presented as follows;

A. GLCM Entropy

GLCM entropy measures the disorder of an image. Entropy is high when an image is not texturally uniform. The value for entropy is high, if the elements of GLCM are distributed equally. It is low if the elements are close to either 0 or 1. The entropy is expressed as follows:

$$GLCM\ entropy = \sum_{i,j=0}^{Ng-1} g^2(i,j) \ln g(i,j) \qquad \textbf{\textit{Equation 3-8}}$$

Where;
Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix.

B. GLCM Contrast

GLCM Contrast measures the difference between the highest and lowest values of a contiguous set of pixels. A low-contrast image features low spatial frequencies. It shows image variation in the study area. The contrast is expressed as follows:

$$GLCM\ Contrast = \sum_{i,j=0}^{Ng-1} (i-j)^2\, g(i,j) \qquad \textbf{\textit{Equation 3-9}}$$

Where;
Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix. Contrast increases exponentially as i-j increases.

C. GLCM Homogeneity

GLCM Homogeneity ensures image homogeneity. It is the opposite of contrast. If the image is locally homogeneous, the value is high if GLCM concentrates along the diagonal. Homogeneity weights the values by the inverse of the contrast weight, decreasing exponentially according to their distance to the diagonal. The homogeneity is expressed as follows:

$$GLCM\ Homogeneity = \sum_{i,j=0}^{Ng-1} 1/1+(i\_j)^2\ g(i,j)$$ ***Equation 3-10***

Where;

Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix.

D. GLCM Correlation

GLCM Correlation measures the linear dependency of gray levels of neighboring pixels in the image. High correlation values imply a linear relationship between the gray-levels of pixel pairs.

$$GLCM\ Correlation = \sum_{i,j=0}^{Ng-1} (i\_u)(j\_u)g(i,j)/s^2$$ ***Equation 3-11***

Where;

Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix and

$$u = \sum_{i,j=0}^{Ng-1} i.g(i,j) \text{ and } s^2 = \sum_{i,j=0}^{Ng-1} (i-u)^2\ g\ (i,j)$$

E. GLCM Mean

GLCM mean is the average expressed in terms of the GLCM. The pixel value is not weighted by its frequency of occurrence itself, but by the frequency of its occurrence in combination with a certain neighbor pixel value.

$$\text{GLCM Mean} = \sum_{i,j=0}^{Ng-1} gi,j/s^2$$ ***Equation 3-12***

Where;

Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix.

F. GLCM Standard deviation

GLCM standard deviation deals specifically with the combinations of reference and neighbour pixels. Thus, it is not the same as the simple standard deviation of gray levels in the original image. Calculating the standard deviation using i or j gives the same result, since the GLCM is symmetrical. It is a measure of the dispersion of values around the mean. It is similar to contrast or dissimilarity.

$$GLCM\ SD = \sum_{i,j=0}^{N-1} Ng_{i,j}\,(i,j-\mu_{i,j})$$ ***Equation 3-13***

Where;

Ng is the number of gray levels, g(i,j) is the entry (i,j) in the gray-level co-occurrence matrix.

Class separability

In addition to spatial metrics and GLCM, to see how each HUP are separable and to classify them in appropriate category, class separability analysis is done through different band combinations. The band combination which results in lower correlation value is taken as an input to separate the classes. To recognize the class separability Euclidean distance is calculated. Euclidean distance shows between class variation rather than with in class variation (Liwei et al., 2008). It is calculated using the following formula;

$$E(x,y)^2 = (x_1-x_2)^2+(y_1-y_2)^2$$ ***Equation 3-14***

Where; x represents the mean value of band X, and y represents the mean value of band Y.

Classification of HUPs

The characteristics of each HUP which was found from the output of spatial metrics and texture measures (GLCM) were used to functionally classify the delineated HUPs. Spatial metrics and GLCM were used to describe the spatial and spectral characteristics of land-cover objects within each HUP. Functional classification of each HUP through this tools have been found reasonable (Herold et al., 2003).

Spatial metrics have a great contribution in differentiating various types of HUPs since the land cover appearing in a HUP has different level of dominance which support to identify the land use. For instance; an area of built up which is characterized by a higher percentage of vegetation or open spaces could be named as low-density residential area while those areas with a higher built up patches could be of high-density residential (Liu et al., 2006).

To describe the land use of each HUP and to investigate the relationship between spatial metrics and GLCM with land use of a HUP, in this study nine spatial metrics and six GLCM measures were selected. These metrics and GLCM were calculated for each HUP. For the analysis about ten HUPs having different dominance of land cover classes were selected visually from the study area and tested through the spatial metrics and GLCM.

3.2.3. Research objective 2: Multi-scale analysis

To identify weather the boundary of HUPs holds across scale and to analyze within HUP changes among different image scale, the original image was degraded to two different resolution; 2 and 4 meter resolution. The analysis is done in two ways: 'within the HUP' and 'on the boundary of a HUP'. For 'within' analysis the comparison is made between the original (1 meter) and the two degraded images using the selected spatial metrics by standard and moving window analysis. For 'on the boundary' analyses the original 1 meter and 4 meter resolution images are used. From the three classes, here the metrics that has been selected and calculated only for class built up on the three resolution images was sorted to compare the changes across different image scale *(Figure 4-28 to 4-22)*.

3.2.4. Research objective 3: Delineation & Characterization of HUPs on different area

The transferability of the method is tested by selecting different area on the same city. The same rule set that was implemented in Test area 1 is also used here. Like Test area 1, the grid map of Class Area (CA) of Test area 2 is used as an additional layer for the delineation. The calculated spatial metrics and GLCM on Test area 1 are also implement in the same way.

3.2.5. Research objective 4: Slum identification

The identification of slum is based on the already delineated and characterized HUPs. Slums are selected by recognizing the output of the calculated spatial metrics and texture measures integrating with visual interpretation and some pictures found in Google earth.

3.3. Accuracy assessment

In order to assess the accuracy of the delineated HUPs resulted from semi-automatic method; the HUPs were first delineated manually using ArcGIS 10. In parallel, the HUPs that have been delineated semi-automatically through eCognition software were exported as ESRI shape file format. The output of manual and semi-automatic delineation were run in alpha v0.1 software which implements within Java Topology Suite (JTS) and Geo tools open source libraries. As described by Clinton et al. (2010), this software computes the goodness measures for the comparison of manually delineated shape file relative to one or more object based semi-automatic segmentation shape files.

The delineation accuracy is computed by considering over segmentation and under segmentation shifts through the following algorithm which is taken from Clinton et al. (2010):

$$Accuracy = 1 - D_{ij}$$ ***Equation 3-15***

Where ‘D (D-value)’ represents the closeness to semi-automatic segmentation result in relation to a predefined manually delineated objects. ‘i’ & ‘j’ (i=1...n &j=1...m) represents the manual and semi- automatic segmented object respectively.

$$D_{ij} = \frac{\sqrt{\left(Over\ Segmentation_{ij}\right)^2 + \left(Under\ Segmentation_{ij}\right)^2}}{2}$$ ***Equation 3-16***

$$Over\ Segmentation_{ij} = 1 - \frac{area(x_i \cap y_i)}{area\ (x_i)}, y_j \in Y_i^*$$ ***Equation 3-17***

$$Under\ Segmentation_{ij} = 1 - \frac{area\left(x_{i \cap y_j}\right)}{area\ (y_j)}, y_j \in Y_i^*$$ ***Equation 3-18***

Where; x_i (i=1...n) is the set of n manually delineated objects, relative to which the segmentation is to be judged. y_j (j=1...m) the set of all semi-automatic segments in the segmentation of an image having p pixels. xi⋂yi: area of the geographic intersection of manually delineated object x_i and semi-automatic segment y_j. Y_i*: the subset of semi-automatic segments that are relevant to manually delineated object x_i. All the measures evaluated based on the Y_i* set.

4. RESULT AND DISCUSSION

This chapter describes the results of the methodology that has been applied in the preceding chapter. Results are presented in terms of flow of each research question. The analysis of the two test areas are presented in parallel and comparable way. At the end the results are followed by a discussion that interprets the results.

4.1. Delineation of HUPs

4.1.1. Image segmentation and Classification

In order to delineate the HUP on 1 meter pansharpened IKONOS image of New Delhi the analysis has began from creating the hierarchical network of image objects through multiresolution segmentation. Two levels of image segmentation were used; level 1 for the detailed classification of the entire image and level 2 for the delineation of the HUPs. The segmentation and classification result of level 1 is presented in this Section and those related with level 2 will be shown in Section 4.1.3. As described in Section 3.2.2. segmenting boundaries that best fit with an object of interest were found through Estimation of Scale Parameter (ESP) tool. In the analysis of level 1, 50 scale loops were automatically processed (Figure 4-1). The result showed that the peaks of the ROC curve corresponding to scale levels of 17, 20, 26, 35, 38 & 46 indicate the meaningful scale parameters for the segmentation. After testing the finer values of these peaks, a scale parameter of 26 at one of the peaks of the ROC curve with shape and compactness of 0.4 and 0.2 respectively was found the most convenient parameter for the segmentation and detailed classification of the entire image on both test areas.

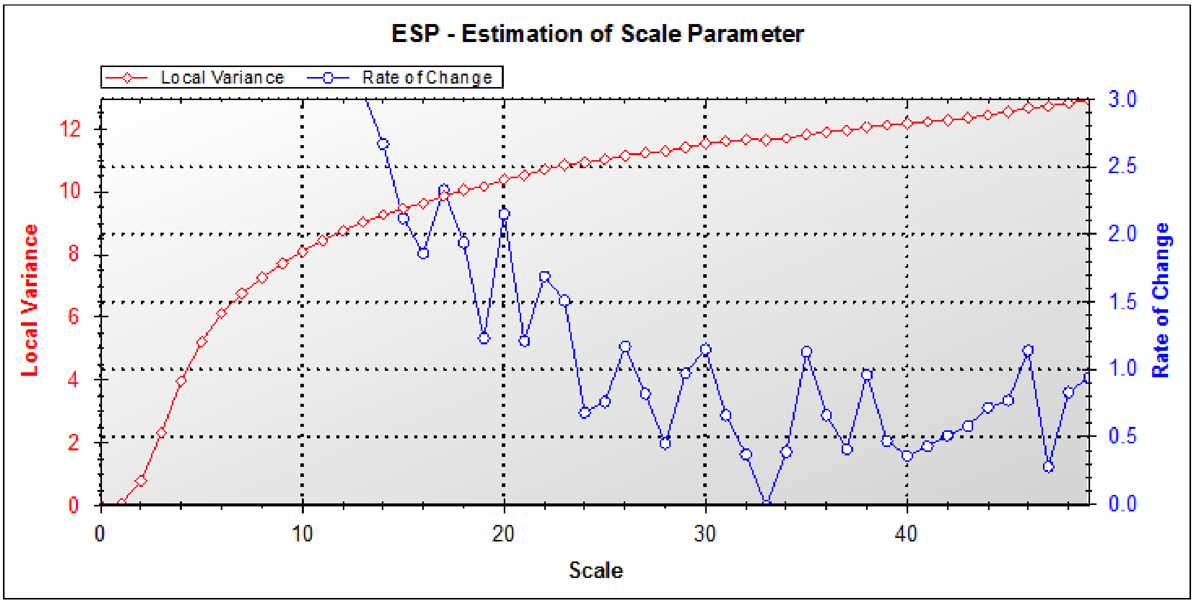
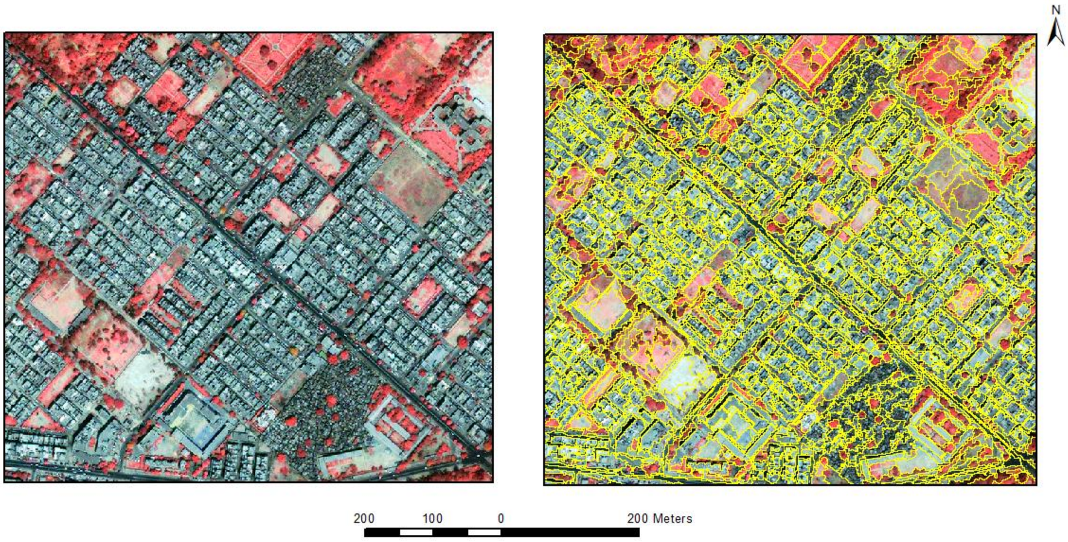


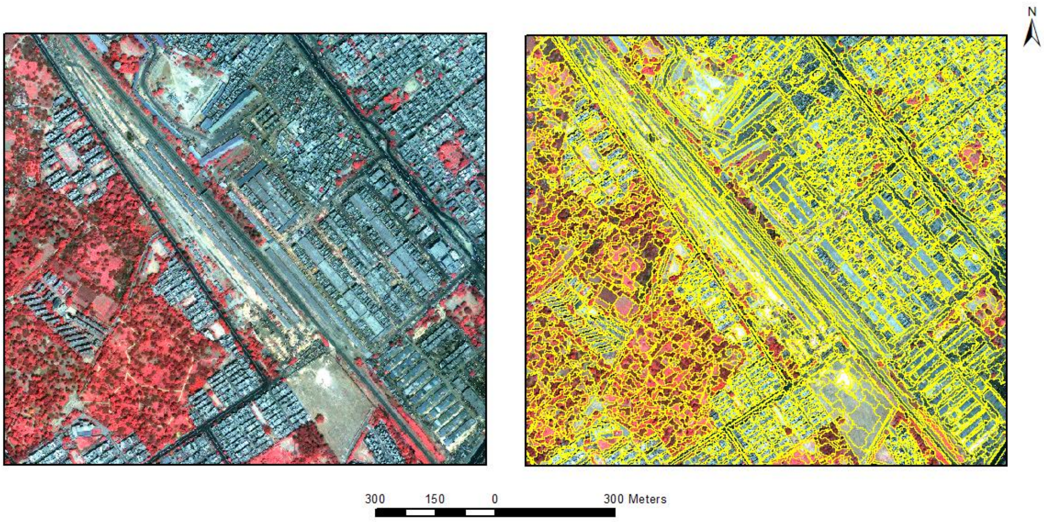
Figure 4-1: An ESP chart for Scale parameter Selection of Level 1 in Test area 1 and Test area 2(Shape: 0.4 and Compactness: 0.2)

The selected scale parameter fits well with different land cover types on the entire image. Figure 4-2 and Figure 4-3 shows level 1 output of multiresolution segmentation using the selected scale parameter in Test area 1 and Test area 2 respectively.



Original view *Segmentation View*

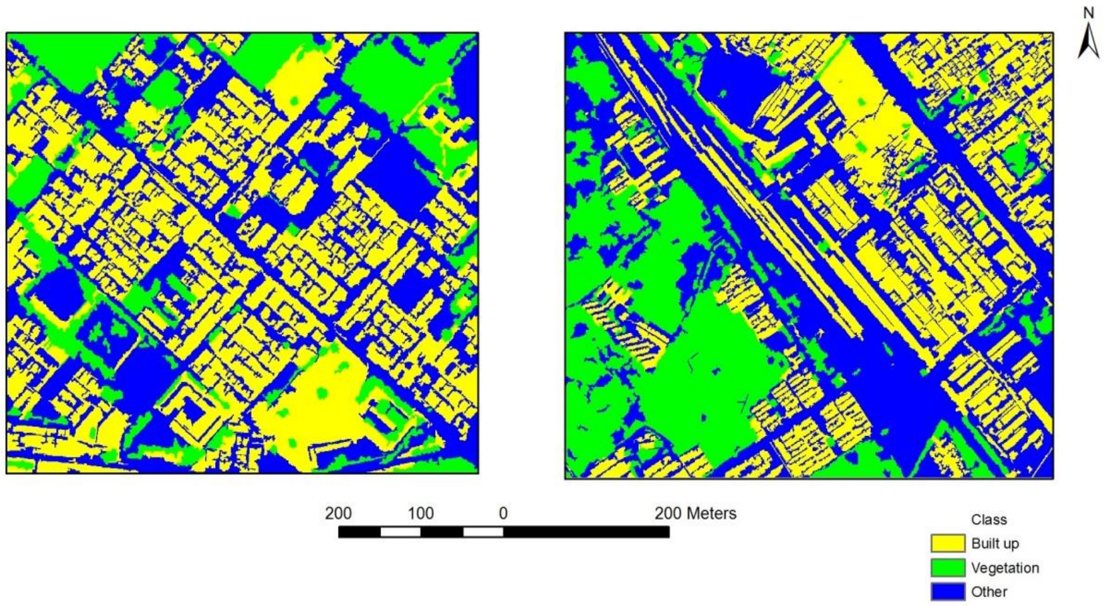
Figure 4-2: Level1 Segmentation of Test area 1
(Scale parameter: 26, Shape: 0.4 and Compactness 0.2)



Original view *Segmentation View*

Figure 4-3: Level1 Segmentation of Test area 2
(Scale parameter: 26, Shape: 0.4 and Compactness 0.2)

The segmented image was classified in to three land cover types; built up, vegetation and other. The result of classification is shown in Figure 4-4.



Test area 1 *Test area 2*

Figure 4-4: Classification of Test area 1 (left) and Test area 2(Right)

4.1.2. Spatial metrics on entire image

Using moving window (10 by 10) analysis the class area of built up, vegetation and other land cover types were calculated in the two test areas resulting in separate grid maps of class areas for each class. Figure 4-5 and Figure 4-6 shows grid map of class area for the three classes in Test area 1 and Test area 2 respectively. The objective of the calculated grid maps was to use them as an additional layer during the delineation of HUP boundaries which is presented in Section 4.1.3.

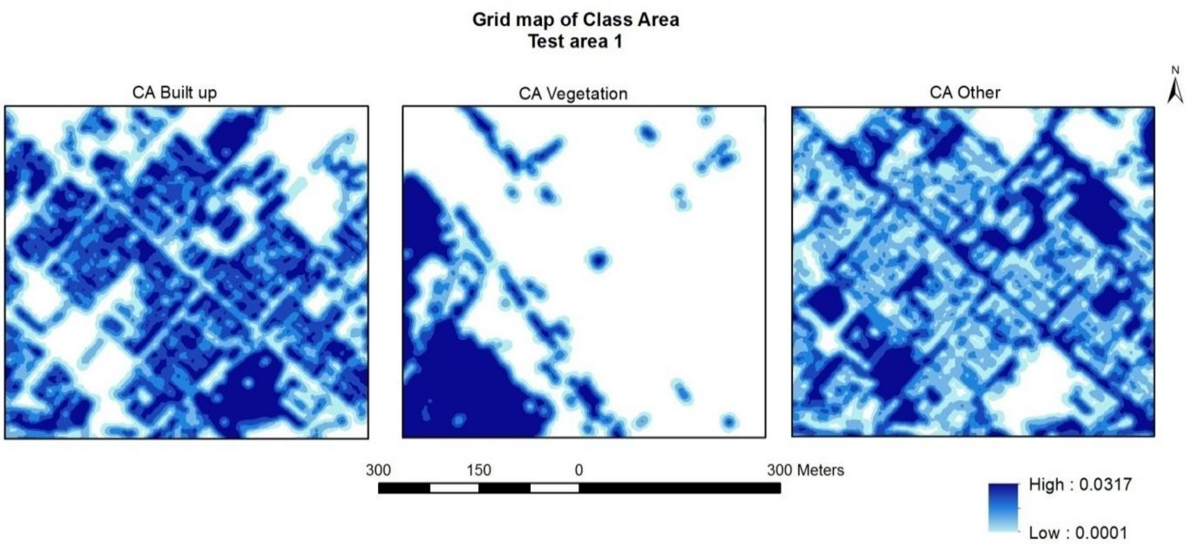


Figure 4-5: Grid map of class area of Built up, Vegetation and other in Test area 1

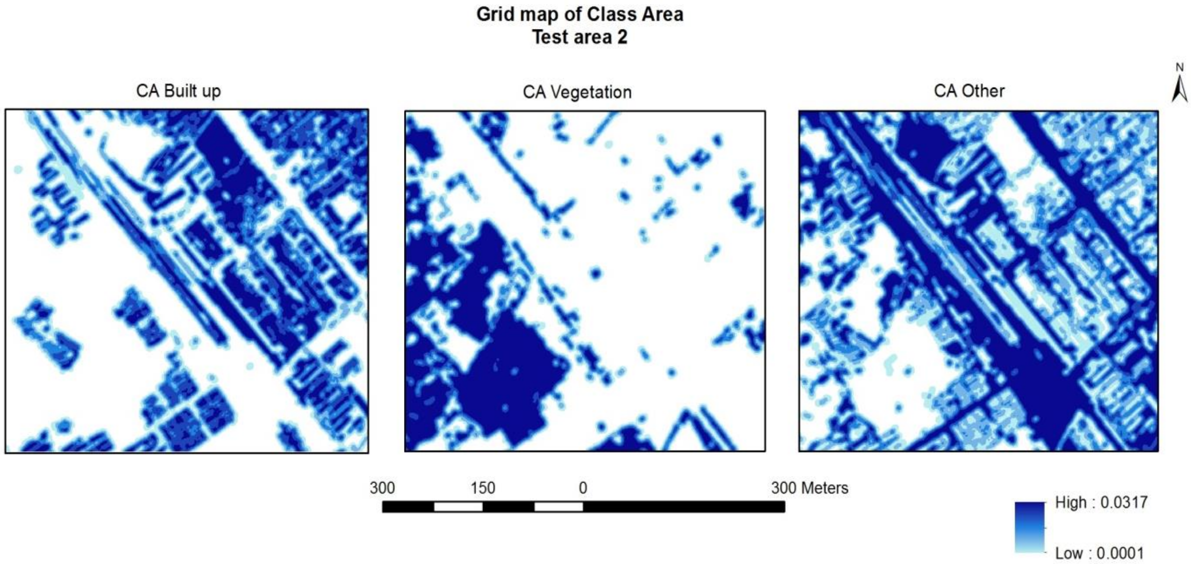


Figure 4-6: Grid map of class area of Built up, Vegetation and other in Test area 2

4.1.3. Boundary of HUPs

While delineating HUP boundaries a higher level of multiresolution segmentation was used; which is level 2. As shown above in Section 4.1.1, the best fit scale parameter was estimated through ESP tool. 100 loops were run in the algorithm. The result showed that the peaks of the ROC curve corresponding to scale levels of 19, 31, 42, 50, 53, 81, 86, 90 indicate the meaningful scale parameters for the delineation of HUPs. Based on this description in Section 4.1.1 the scale parameter around the medium value is testing and a scale parameter of 42 with shape and compactness of 0.8 and 0.2 was found convenient for the delineation of HUPs. ESP graph showing the selected peaks for HUP delineation is illustrated in Figure 4-7.

In addition to the contribution of the best fit scale parameters the boundary of HUPs were delineated using five layers: four from the fused image and one extra layer from the output of spatial metrics, that is grid map of class area. Equal weight of 1 was assigned for the four layers and weight 5 was given for class area layers of built up, vegetation and other. The result showed that the presence of these additional layers especially with the higher weight than the other four layers leads the boundary of the HUPs to fit with an object of interest.

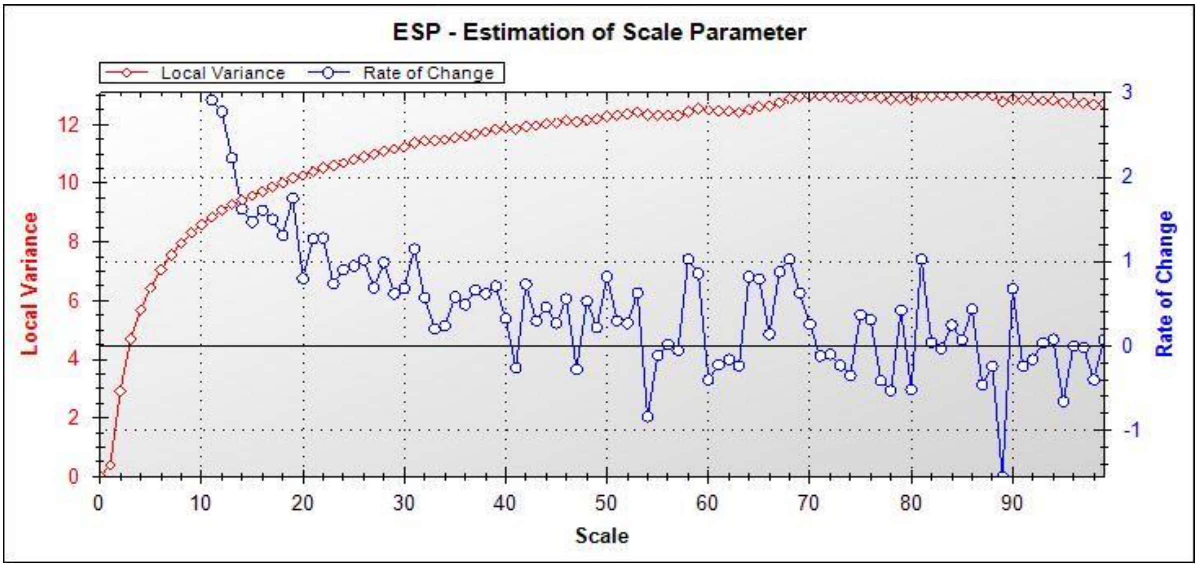
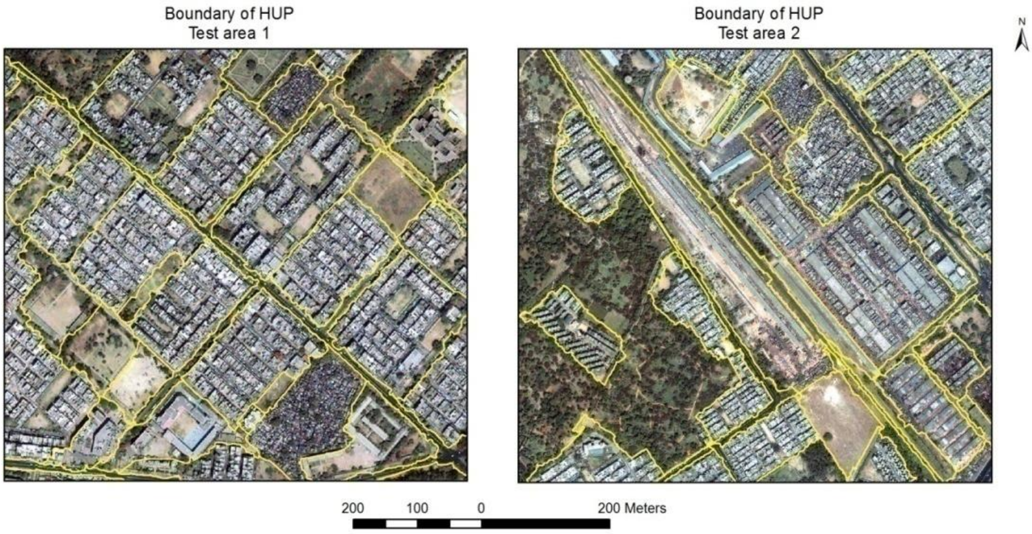


Figure 4-7: An ESP chart for Scale parameter Selection of Level 2 in test area 1 and test area 2
(Shape: 0.4 and Compactness: 0.2)

The result of the delineated HUPs using the above mentioned scale parameter is shown in Figure 4-8.

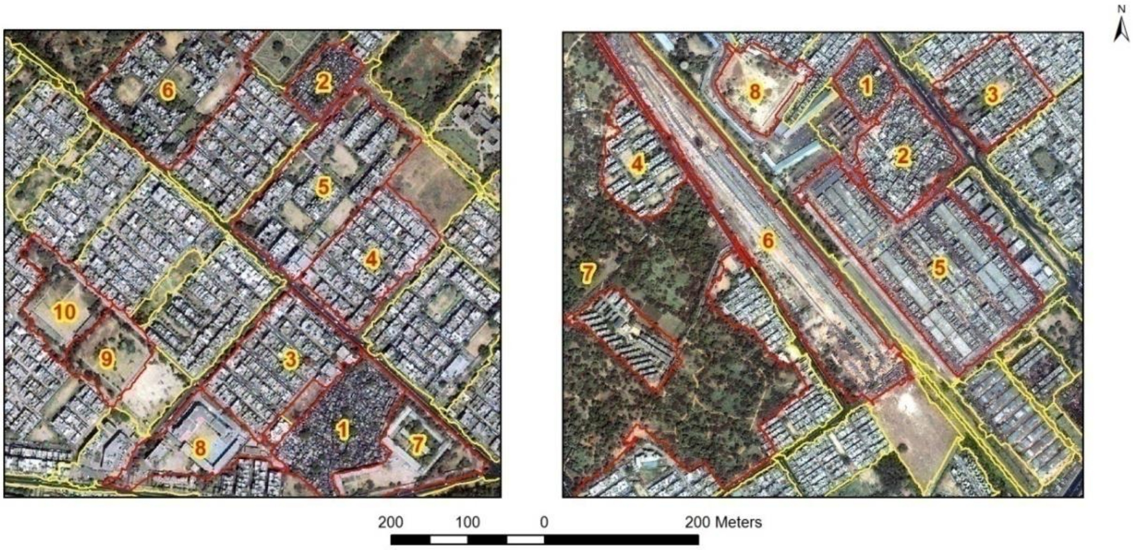


Test area 1 *Test area 2*

Figure 4-8: Delineated HUPs

4.2. Characterization of HUPs

In order to analyze the spatial and spectral characteristics of HUPs, spatial metrics and GLCM measures were calculated for individual HUPs. For the analysis, from the Test area 1 and Test area 2, ten and eight HUPs were selected respectively. The selected samples are presented in the Figure 4-9.



Test area 1with 10 selected HUPs *Test area 2 with8 selected HUPs*

Figure 4-9: Selected sample HUPs in the two Test areas

4.1.4. Spatial metrics per HUP

Nine spatial metrics for each HUP were calculated in the analysis and three of the metrics: Percentage of land, Patch Density and Largest Patch Index showed considerable differences between the selected HUPs, see Table 4-1 and Table 4-2 for Test area 1 and Test area 2 respectively.

Table 4-1: Calculated spatial metrics per HUP in Test area 1(Standard analysis)

HUP_ID	PLAND			PD			LPI		
	Built up	Vegetation	Other	Built up	Vegetation	Other	Built up	Vegetation	Other
1	85.91	7.85	6.24	22.11	0.00	12.74	96.54	1.95	1.51
2	89.68	5.52	4.80	20.00	20.00	60.00	93.65	3.78	2.57
3	70.60	0.84	28.56	9.68	20.97	69.35	76.58	0.60	22.82
4	68.44	0.00	31.56	52.00	0.00	48.00	36.33	0.00	63.67
5	41.55	5.82	52.62	50.00	14.00	36.00	25.61	3.15	71.24
6	29.10	21.71	49.19	46.15	26.92	26.92	18.58	13.62	67.80
7	30.27	32.06	37.66	19.35	16.13	64.52	43.97	18.36	37.66
8	38.44	19.69	41.87	44.12	26.47	29.41	47.85	7.77	44.38
9	3.89	40.69	55.42	32.00	24.00	44.00	4.48	32.42	63.10
10	14.97	38.46	46.57	48.39	22.58	29.03	15.82	26.61	57.57

The result displayed above in Table 4-1 and below in Table 4-2 shows that five HUP sample pairs (1-2, 3-4, 5-6,7-8 & 9-10) have close metrics which seems to have close values of PLAND, PD and LPI depending on the value of the dominating class.

For instance, from Table 1; Percentage of built up in the first three HUP samples is high, so these HUPs have a dominating class of built up and has close values of built up class. The same is true for Test area 2.

Table 4-2: Calculated spatial metrics per HUP in Test area 2 (Standard analysis)

HUP_ID		PLAND			PD			LPI	
	Built up	Vegetation	Other	Built up	Vegetation	Other	Built up	Vegetation	Other
1	95.85	1.75	2.40	5.26	26.32	68.42	97.48	1.50	1.02
2	74.18	4.55	21.27	27.66	14.89	57.45	81.10	1.73	17.17
3	54.05	6.38	39.56	46.94	8.16	44.90	39.45	7.14	53.41
4	36.83	10.62	52.56	32.56	51.16	16.28	19.91	5.38	74.71
5	55.98	0.00	44.02	67.90	0.00	32.10	43.51	0.00	56.49
6	25.80	7.10	67.10	20.00	22.00	58.00	17.43	2.65	79.92
7	0.61	78.74	20.66	18.97	11.21	69.83	0.28	90.90	8.81
8	13.20	2.66	84.14	50.00	10.00	40.00	3.85	2.07	94.08

The graph in Figure 4-10 shows the spatial characteristics of each of the selected sample HUPs through the selected spatial metrics in Test area 1. The characteristic of each sample HUP is shown through Percentage of land, Patch density and Largest patch index. Different colours are used to describe the three classes (Built up, Vegetation and Other) with the three calculated metrics.

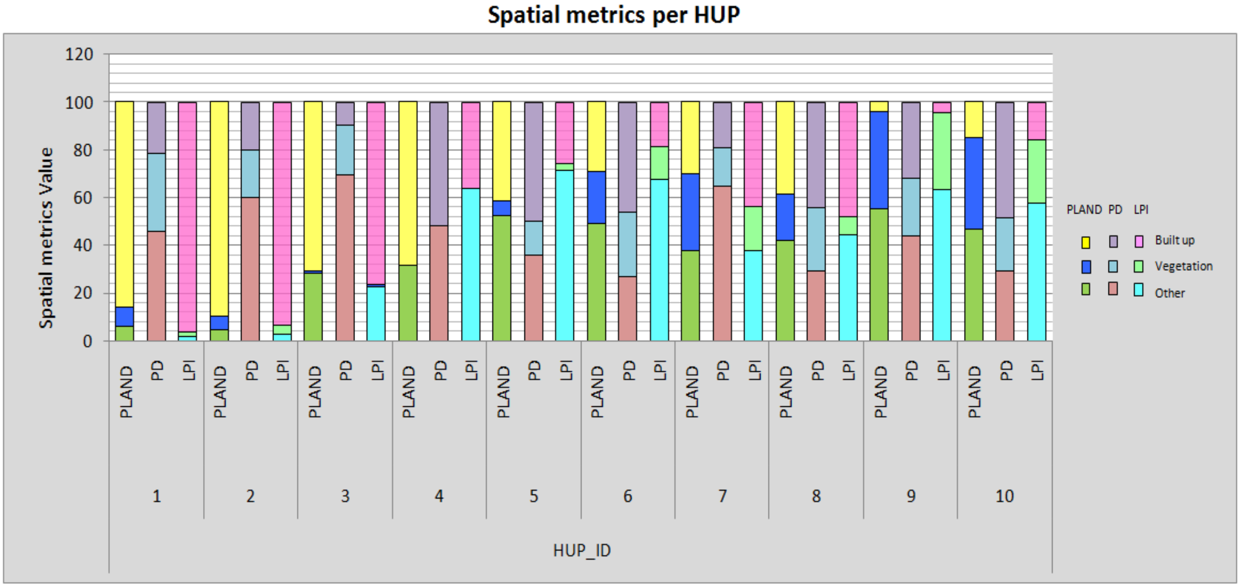


Figure 4-10: Graph of calculated spatial metrics per HUP in Test area 1

The graph in Figure 4-11 shows the spatial characteristics of each of the selected sample HUPs through the selected spatial metrics in Test area 2.

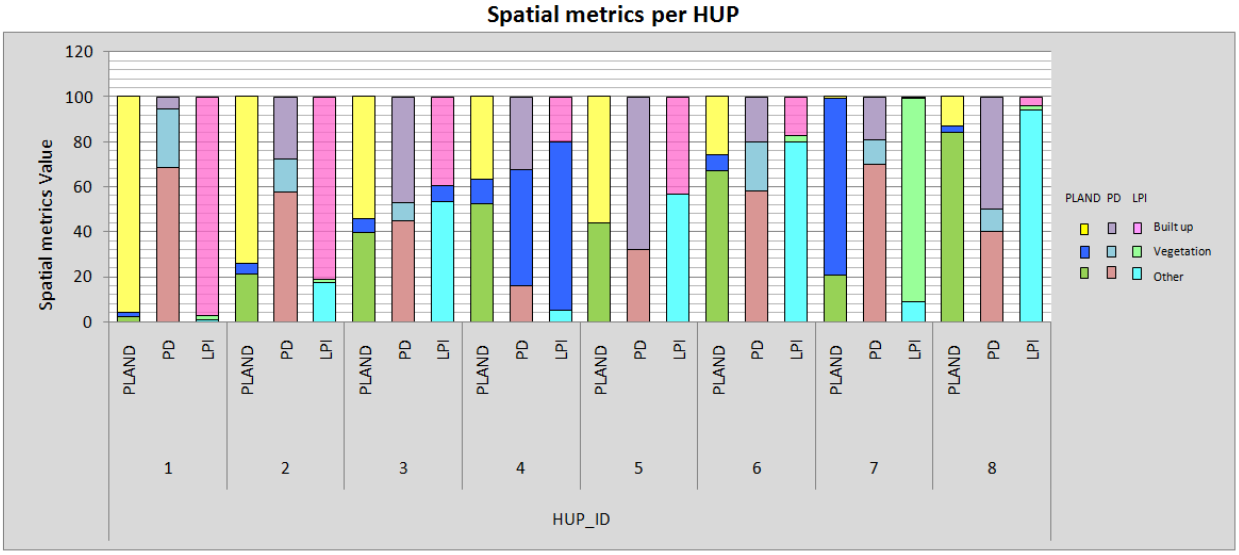


Figure 4-11: Graph of calculated spatial metrics per HUP in Test area 2

4.1.5. GLCM per HUP

The spectral characteristics of each HUP were analysed through the calculation of GLCM. Six GLCM measures were calculated for the analysis, three of the measures, GLCM contrast, GLCM mean and GLCM standard deviation show considerable differences and can be used for the characterization of HUPs. Table 4-3 and 4-4 and the graphs in Figure 4-12 and 4-13 show the result of the calculated GLCM for Test area 1 and Test area 2.

Table 4-3: Calculated GLCM per HUP in Test area 1

HUP_ID	GLCM Contrast	GLCM Mean	GLCM StDeviation
1	166.59	84.56	15.62
2	153.74	84.95	14.64
3	206.36	92.04	18.84
4	219.97	93.26	20.01
5	170.10	101.65	26.09
6	179.29	98.07	24.56
7	134.53	112.81	19.12
8	157.41	101.91	20.28
9	73.86	123.41	22.72
10	80.04	117.58	22.54

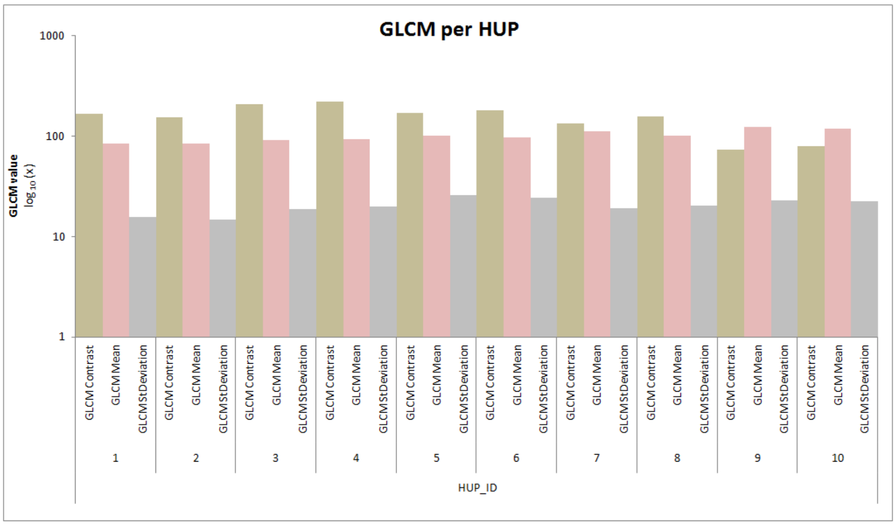


Figure 4-12: Graph of calculated GLCM per HUP in Test area 1

Figure 4-12 and Table 4-3 shows that, In Test area 1, the average gray level value with in a HUP which is expressed by GLCM mean, and a measure of the dispersion of gray values around the mean expressed by GLCM standard deviation have a close value for the class pairs (1-2, 3-4,5-6,7-8 & 9-10). This is one implication that this HUPs could be in the same class.

Table 4-4: Calculated GLCM per HUP in Test area 2

HUP_ID	GLCM Contrast	GLCM Mean	GLCM StDeviation
1	169.88	76.86	15.10
2	164.92	84.06	18.46
3	147.73	85.02	19.33
4	150.50	96.93	23.42
5	127.05	88.62	16.79
6	94.52	103.60	19.20
7	69.21	108.35	20.63
8	65.78	109.68	15.15

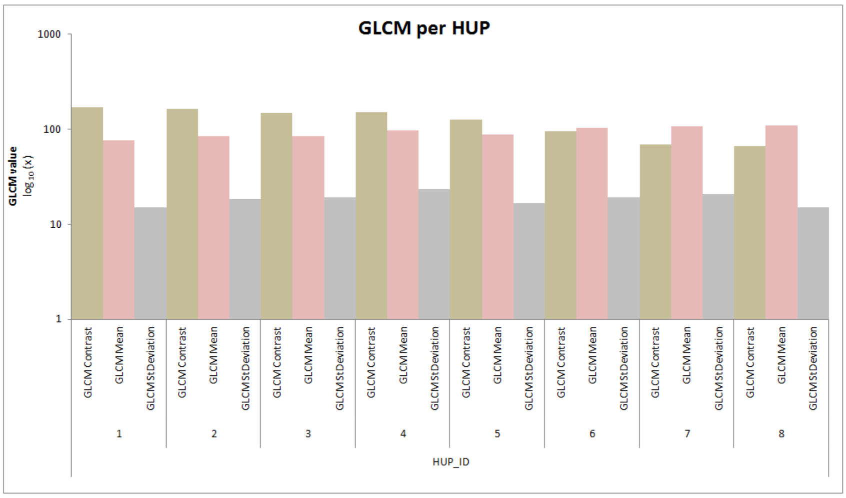


Figure 4-13: Graph of calculated GLCM per HUP in Test area 2

Again here from the graph of Test area 2 in Figure 4-13 and Table 4-4,the measure of gray level variation expressed by GLCM contrast shows close value for HUP 1 and 2. GLCM mean and GLCM standard deviation of HUP 2 and 3 results in close values which contradicts with the spatial metrics output. Thus this relation should be cross checked with the metrics result.

4.3. Classification of HUPs

4.1.6. Class separability

Class separability is the quantitative measure that shows how much the classes are separable from other classes. In order to analyze how each of the HUPs can be separated and to assign appropriate class categories, a knowledge based nearest neighbour algorithm were implemented using the selected samples. Nearest neighbour algorithm works based on user-defined samples. In this study thwe algorithm is trained to differentiate between HUP classes. Ten sample HUPs were selected in the analysis. By using this sample HUPs, 2D feature space is plotted per combination of two bands and the correlation was calculated to identify the least correlated band combination that can be used to separate the classes in the best way. Figure 4-14 and Figure15 shows the result of 2D feature space plot of different band combinations together with calculated correlation value in Test area 1 and Test area 2.

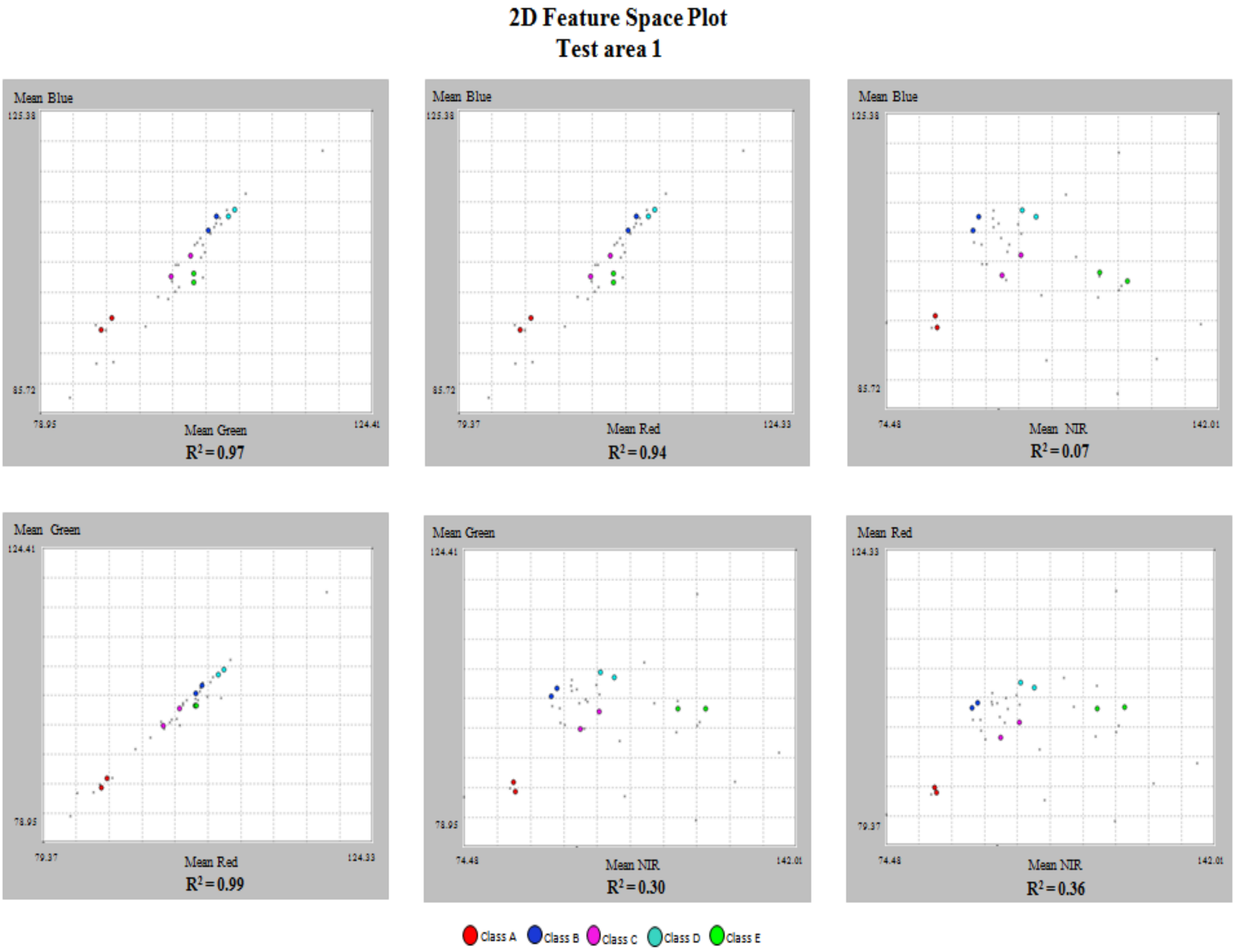


Figure 4-14: 2D feature space plot of Test area1

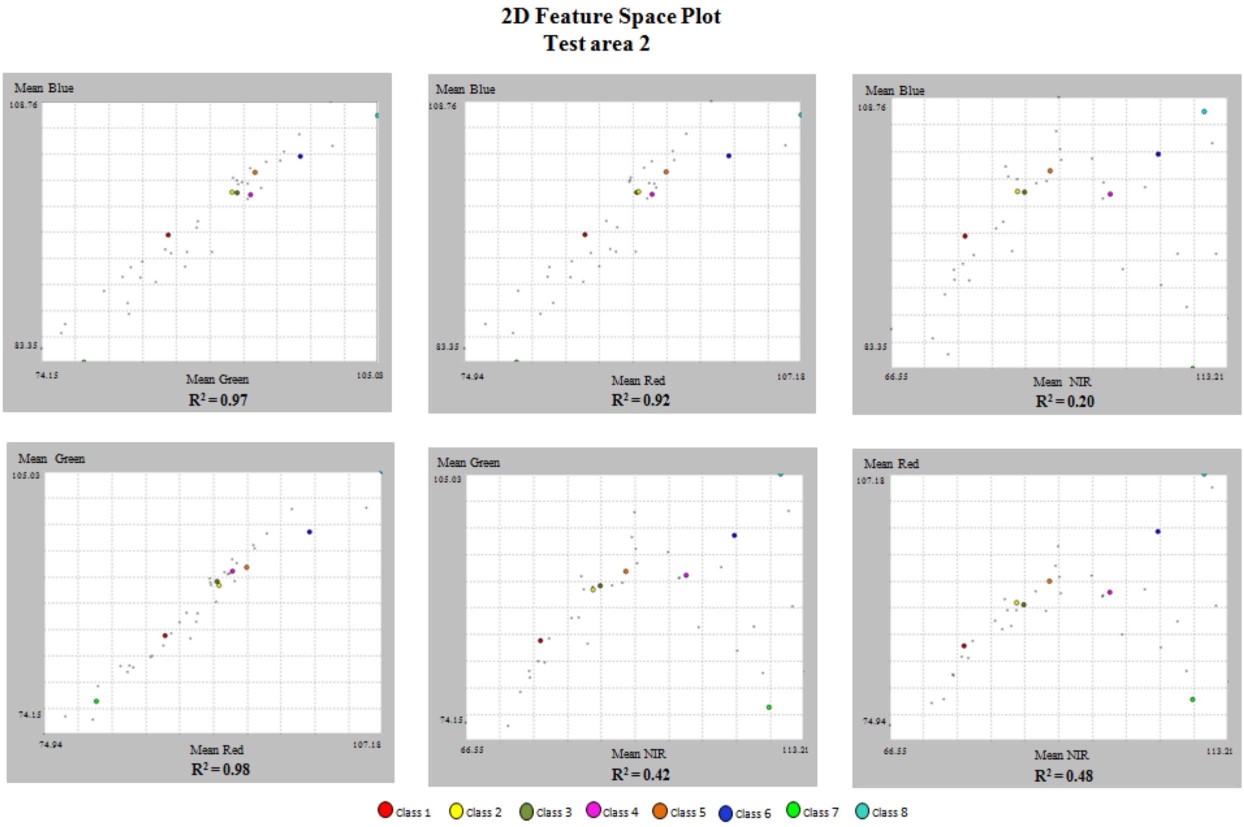


Figure 4-15: 2D feature space plot of Test area 2

The analysis of class separablity relays on the 2D feature space plot with the lowest correlation. In both test areas, a band combination of blue with NIR shows the lowest correlation (R^2) value: 0.07 and 0.20 in Test area 1 and Test area 2 respectively. This result contributes to the appropriate classification of HUPs together with the output of spatial metrics and GLCM result. Figure 4-16 shows the categorized classes based on the output of the feature space plot.

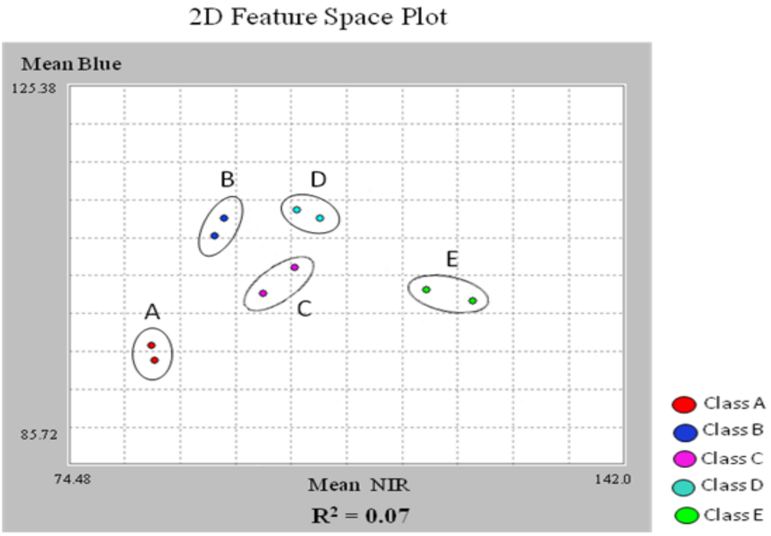


Figure 4-16: 2D feature space plot having lowest correlation of Test area 1

Table 4-5: Classes of HUPs

Sample HUPs	Class Categories
1,2	A
3,4	B
5,6	C
7,8	D
9,10	E

The separability of the classes was analyzed through the computation of Euclidean distance between classes. Computation of Euclidean distance is one way of describing class separability showing the difference or variation between the mean values of two classes. Table 4-6 shows the result of the calculated Euclidean distance between classes based on the high separable band combination output.

Table 4-6: Calculated Euclidean distance between classes

Class combination	Euclidean distance $E(x,y)^2 = (x_1-x_2)^2+(y_1-y_2)^2$
AB	15.42
AC	17.05
AD	23.77
AE	36.55
BC	9.17
BD	10.90
BE	28.94
CD	7.79
CE	20.83
DE	19.20

Based on the integrated result of spatial metrics, GLCM and class separability, HUPs are classified in to specific land use classes and mapped for both test areas. This functional classification is based on mainly on the spatial metrics output and assisted by visual interpretation.

Herold et al., (2003) also utilized the spatial metrics to categorize different land cover classes in to land use regions in combination with ground truth and found the higher advantage of the spatial metrics in land use classification. Each land use category has been described according to their spatial arrangement. In this study, these descriptions or interpretations of land use are adapted to the nature of the two test areas. Table 4-7 shows the land use categories and the description of each class. To some extent, the available panoramio pictures from Google earth were also used to recognize the land use (see Figure 4-18 and 4-19). Some of the descriptions are presented in terms of percentage of the calculated spatial metrics values.

Table 4-7: Land use of HUPs (Test area 1)

Sample HUPs	**Category**	**Functional class**	**Description**
1,2	A	High density residential	High percentage of built up, High Patch density of built up, Low patch index of built up, Low percentage of vegetation, roads or open spaces, Small size residential buildings
3,4	B	Medium density residential	Medium percentage of built up, Medium Patch density of built up, Medium patch index of built up, Medium percentage of vegetation, roads or open spaces. Medium size residential buildings
5,6	C	Low density residential	Low percentage of built up, Low Patch density of built up, Low patch index of built up, Low percentage of vegetation, roads or open spaces. Large size residential buildings
7,8	D	Industrial	High percentage of open spaces, Few vegetation and Large size industrial buildings
9,10	E	Recreational	High percentage of vegetation and open spaces, and recreational elements like playing fields

Table 4-8: Land use of HUPs (Test area 2)

Sample HUPs	Functional class	Description
1	High density residential - 1st level	Same as Test area 1
2	High density residential - 2nd level	Same as Test area 1 and Larger size buildings than 1st level
3	Medium density residential - 1st level	Same as Test area 1
5	Medium density residential - 2nd level	Same as Test area 1 and mixture of large continuous buildings
4	Low density residential	Same as Test area 1
6	Industrial	Same as Test area 1
7	Forest	High percentage of vegetation and small size foot paths
8	Open space	High percentage of open spaces and small scattered trees

All homogeneous urban patches in both test areas are functionally classified and mapped. The combination of spatial and spectral information assists the classification of the HUPs. Figure 4-17 shows the map of HUP according to the land use classes mention in the Tables 4-7 and 4-8 above.

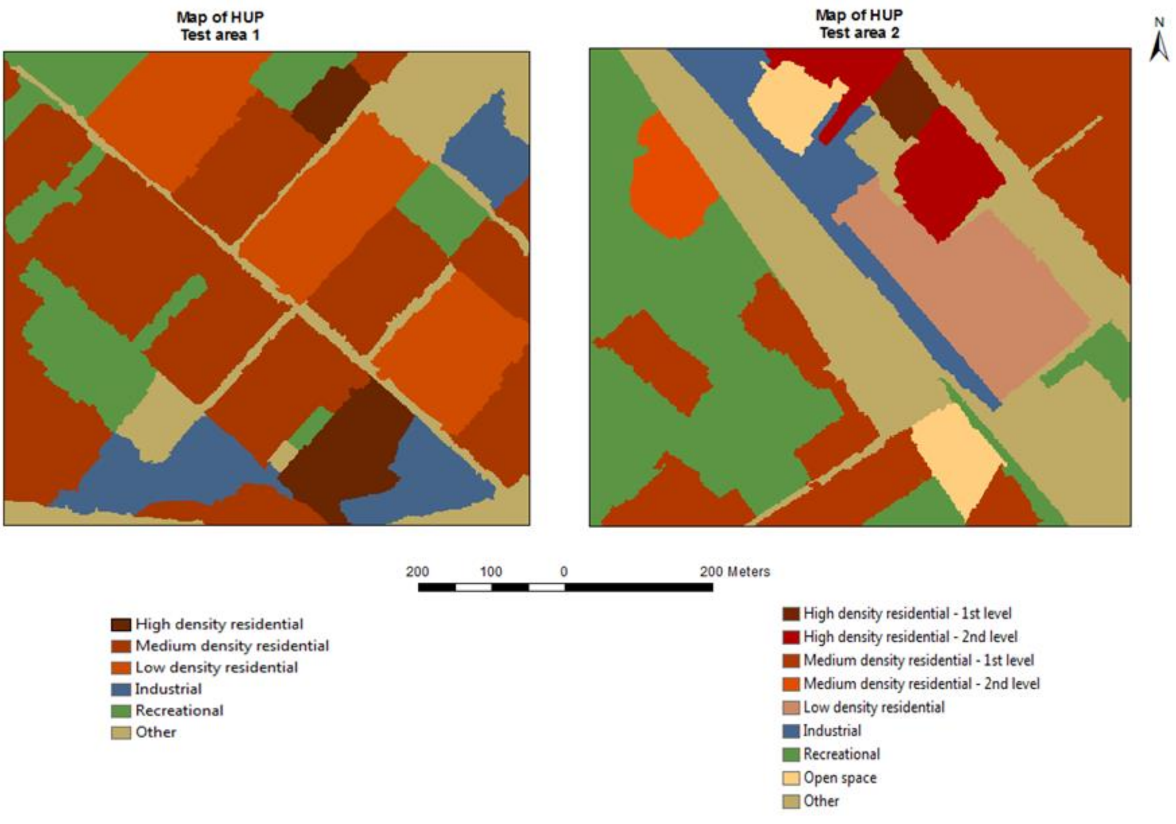


Figure 4-17: Map of HUP in Test area 1 and Test area 2

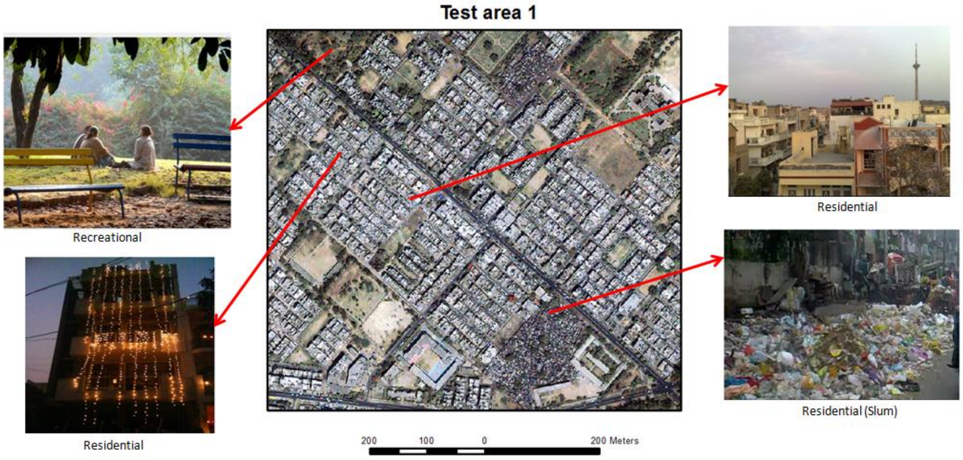


Figure 4-18: Pictures of panoramio in Google earth to support the land use categories - Test area 1

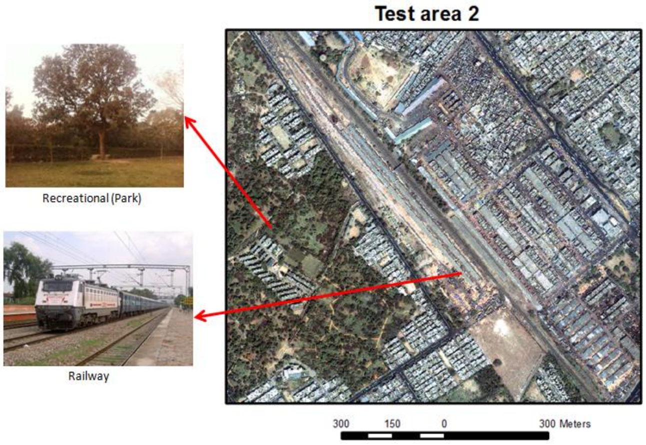


Figure 4-19: Pictures of panoramio in Google earth to support the land use categories - Test area 2

4.4. Multi-Scale Analysis

Multi-scale analysis is done in two ways; one by analyzing changes 'within' a HUP and the other analyzing changes 'on the boundary'.

4.1.7. Analysis within the boundary of HUPs

Analysis within boundary of a HUP is done by comparing HUPs delineated on 1, 2, and 4 meter resolution images of Test area 1(Figure 4-20). Here the boundary of HUPs from 1 m is overlaid on the degraded images of 2 & 4 meter. Three samples were selected for the analysis. The spatial metrics that were used in 1m HUP analysis were calculated through standard and moving window of 10 by 10 size for class built up to analyze changes within each HUP and then the metrics were extracted per HUP sample. Figure 4-21 shows the output of the calculated metrics.

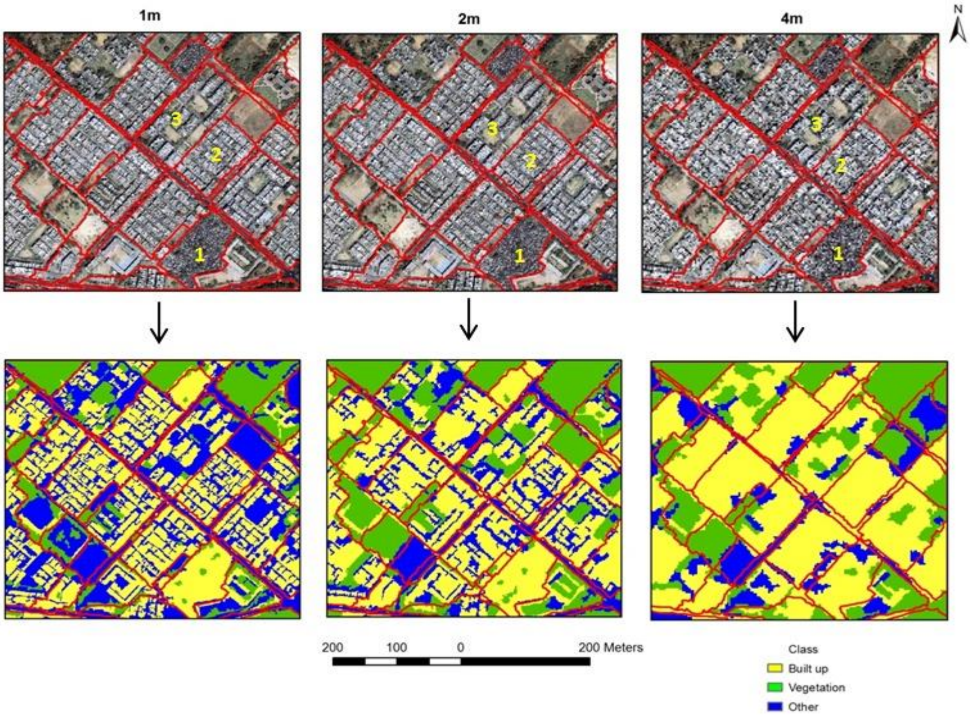


Figure 4-20: HUPs overlaid on the degraded image (above)& on the classified image 1,2 & 4 meters

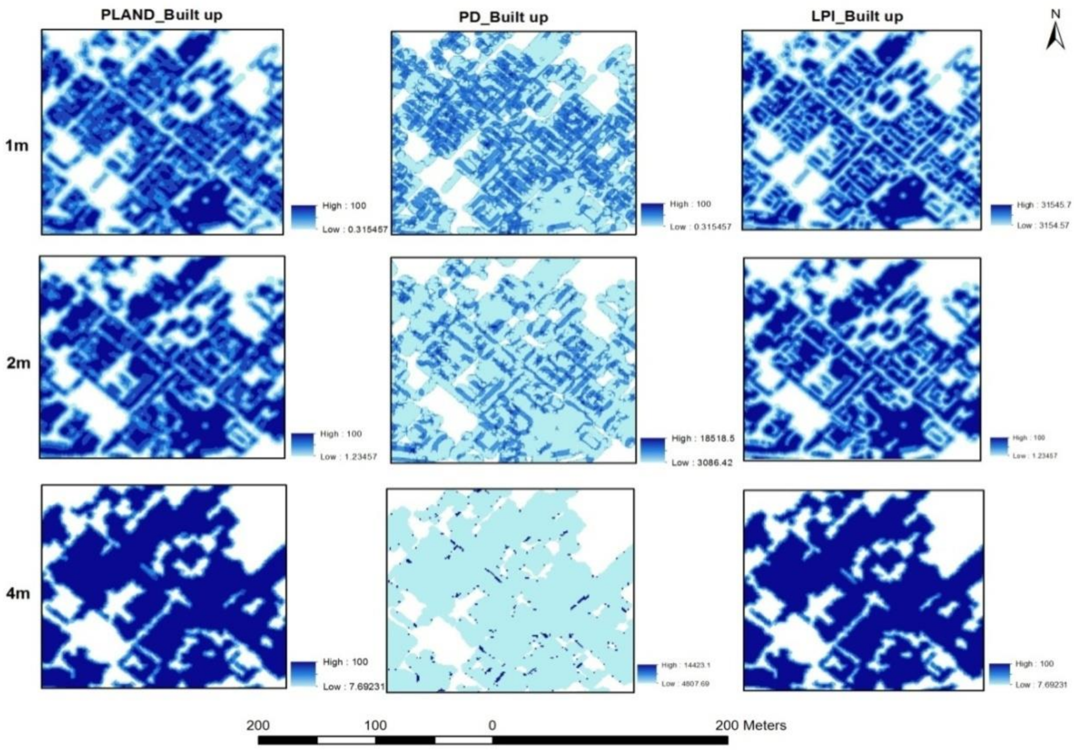


Figure 4-21: Grid map of PLAND, PD and LPI across different scale

Figure 4-22 shows the changes of built up areas across 1, 2, and 4 meter resolution images in the entire image.

From the grid map the entire image and graph in Figure 4-22, it is observed that Class Area of built up which has similar output with Percentage of Land is increasing from 42.9 to 47.64 and then 57.58 in 1, 2 and 4 meter respectively. This implies that the built up areas gets to have higher dominance than other classes. Largest Patch Index is also increasing from 4.51 to 50.97 while going from 1 to 4 meter resolution. This indicates how the isolated small patches of built up become connected and increase to larger built up patch. The Patch Density of built up decreases from 258.99 to 14.90 while going from 1 to 4 meter resolution. This implies the decrement of number of built up patches as a result of the patches combination.

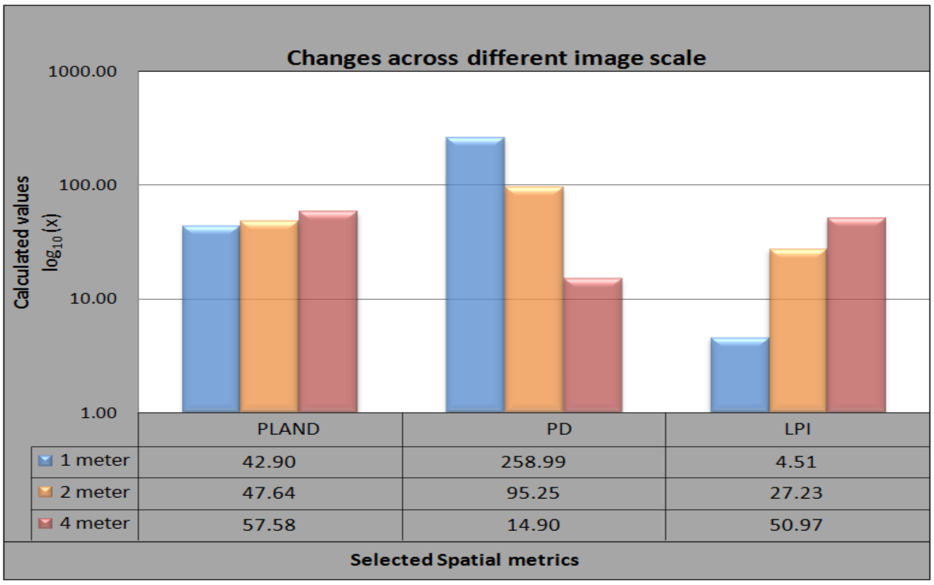


Figure 4-22: Graph of spatial metrics showing changes within a HUP across different scale (Built up)

To analyze the specific changes within individual HUP, the spatial metrics for the three samples are calculated. The result is presented in Table 4-9 followed by a graph in Figure 4-23.

Table 4-9: Spatial metrics calculated for Built up showing changes within a HUP across different scale

	1m			2m			4m		
Sp_metrics	1	2	3	1	2	3	1	2	3
PLAND	85.9121	68.442	41.5549	86.2345	71.8588	43.2203	89.012	75.2635	46.1011
PD	508.9577	656.3005	765.5092	597.2553	653.8771	724.223	587.551	617.2504	701.2901
LPI	85.8255	16.8417	16.2165	97.0302	29.6588	30.2532	116.2257	43.2255	51.2561

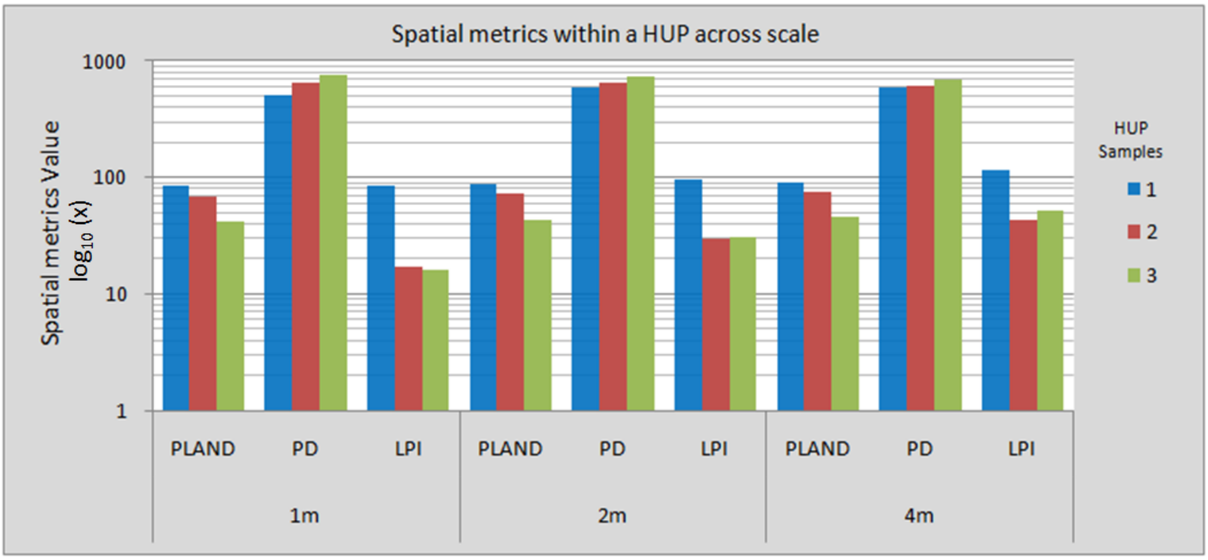


Figure 4-23: Graph of spatial metrics showing changes within a HUP across different scale (Built up)

From the result it is recognized that, in the three samples the percentage of built up patches increases while going from 1 to 4 meter resolution. The same is true for HUPs with other dominating classes. That means the degree of dominance increases within each HUP.

4.1.8. Analysis on the boundary of HUPs

To analyze the boundary of the HUP, 1 and 4 meter resolution images were compared. Like 'within' HUP analysis three samples were taken for the analysis. Figure 4-24 shows the result of delineated HUPs on 4 meter resolution image in comparison with 1 meter resolution image.

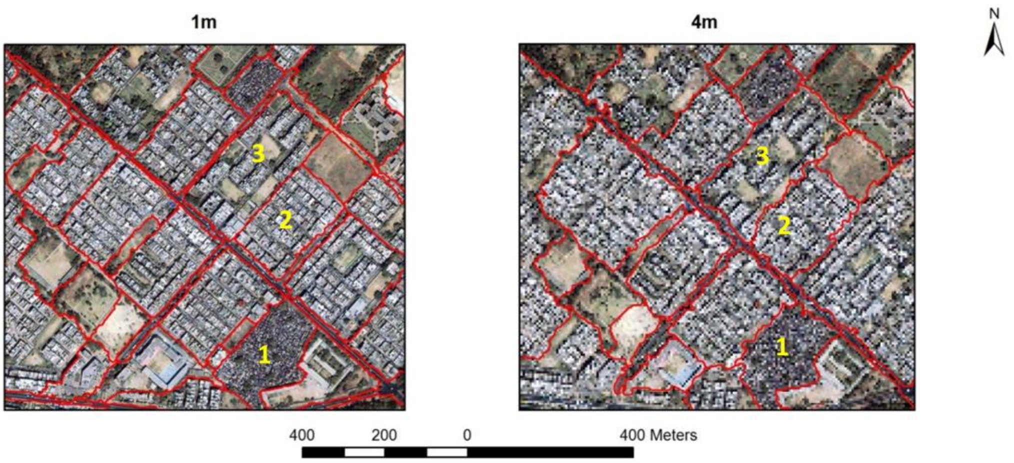


Figure 4-24: HUP boundaries on 1 and 4 meter resolution image

The result of the calculated spatial metrics is described in Table 4-10 followed by illustrating graph in Figure 4-25.

Table 4-10: Spatial metrics within HUP across different scale to analyze change due to the change of boundary

Sp_metrics	1m			4m		
	1	2	3	1	2	3
PLAND	85.9121	68.442	41.5549	99.0582	78.2221	79.255
PD	508.9577	656.3005	765.5092	598.8701	643.665	620.01
LPI	85.8255	16.8417	16.2165	119.5708	22.25	38.209

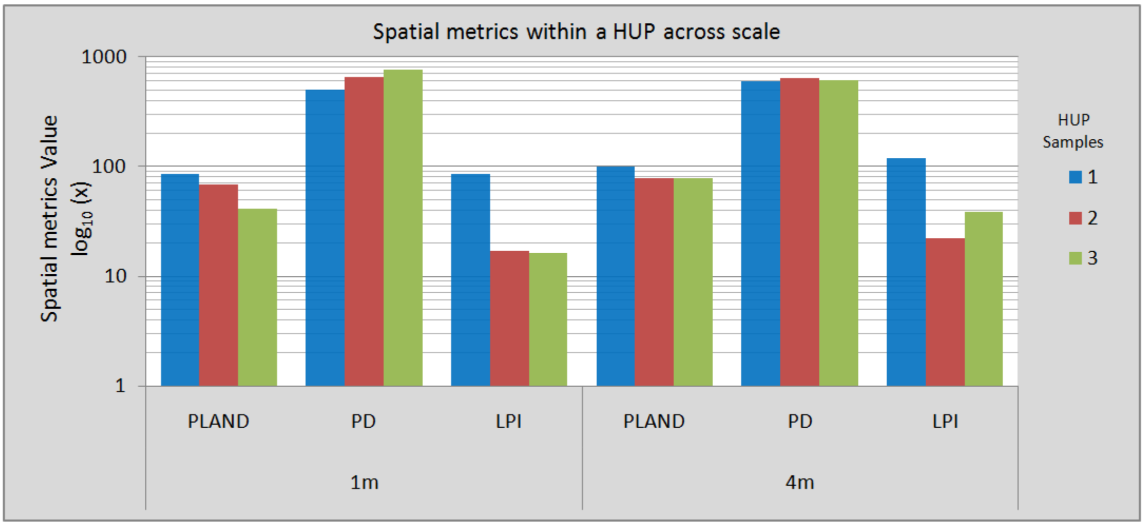


Figure 4-25: Graph of spatial metrics showing changes within a HUP across different scale to analyze changes on the boundary of HUPs (for class Built up)

The result of the calculated GLCM is described in Table 4-11 followed by illustrating graph in Figure 4-26.

Table 4-11: Calculated GLCM within a HUP across different scale in comparison with changes in area of a HUP to analyze change due to the change of boundary

GLCM	1m			4m		
	1	2	3	1	2	3
GLCM Contrast	166.5943	219.9723	170.1007	480.908997	684.4852	605.3367
GLCM Mean	84.56196	93.25792	101.6484	85.820681	93.4615	101.5974
GLCM SD	18.61823	20.01371	26.09278	19.147384	20.26144	25.90443
Area_pixel	19662	19820	30894	1217	1379	2004

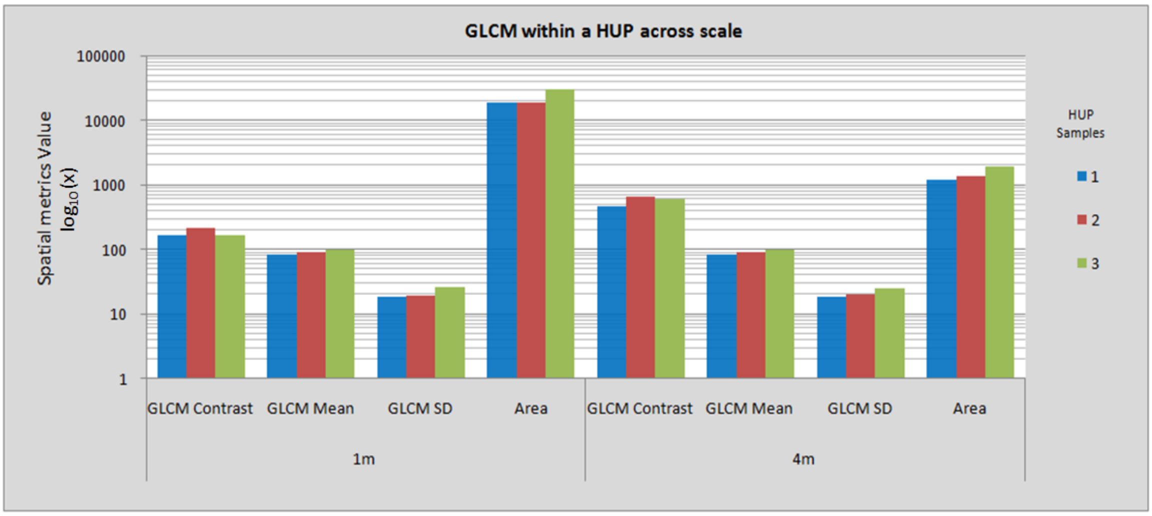


Figure 4-26: Graph of GLCM showing changes within a HUP across different scale to analyze changes on the boundary of HUPs (for class Built up)

The result shows that the extent or area pixel of each sample HUP decreases in 4 meter than 1 meter leading to have different boundary for the specific HUP. This is because the pixels get to be merged reflecting the dominating class. Small patches start to be eliminated while large features like major roads still remains. Like 'within' the boundary analysis, the spatial metrics and the calculated GLCM also show variations across scale. This generally implies that delineating the boundary of the HUP is scale dependent. Thus, the type of the image resolution has a great contribution in the delineation of homogenous urban patches.

4.5. Accuracy assessment

The accuracy of the delineated HUPs was assessed by comparing the manual and semi-automatic delineation. The delineation is done only by one person, so the homogeneity criterion is viewed in one way. If multiple test persons perform the delineation, multiple outputs could be found depending on the perception they have, which results in different accuracy. Figures 4-27 and 4-29 show the automatic and manually delineated HUPs in both test areas followed by the graph that compares the result (Figure 4-28 and 4-30). The accuracy result of Test area 1 and Test area 2 is presented in Table 4-12 and Table 4-13 respectively.

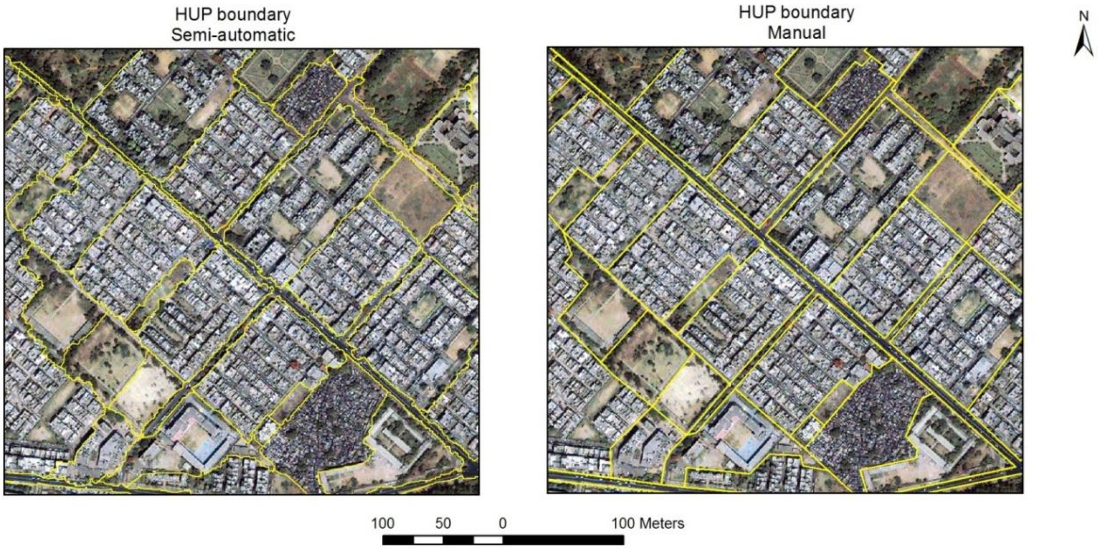


Figure 4-27: Automatically and manually delineated HUPs on Test area 1

Table 4-12: Calculated accuracy of Test area 1

Segmentation	Value	D- value	Accuracy
Over Segmentation	0.13	0.15	0.85
Under Segmentation	0.11		

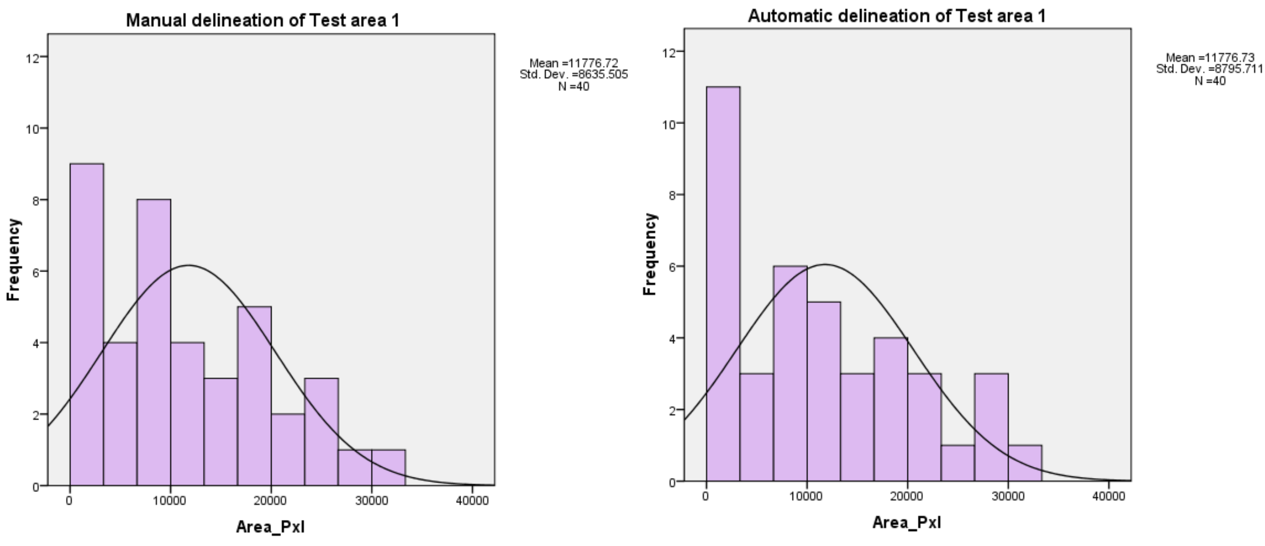


Figure 4-28: A graph showing the accuracy of the delineated HUPs in Test area 1

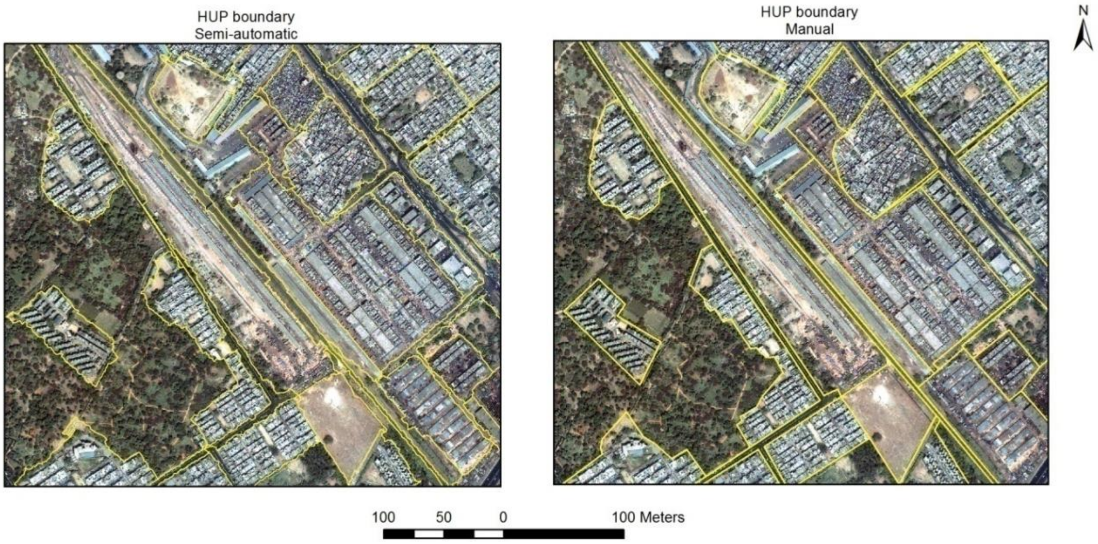


Figure 4-29: automatically and manually delineated HUPs on Test area 2

Table 4-13: Calculated accuracy of Test area 2

Segmentation	Value	D- value	Accuracy
Over Segmentation	0.27	0.29	0.71
Under Segmentation	0.17		

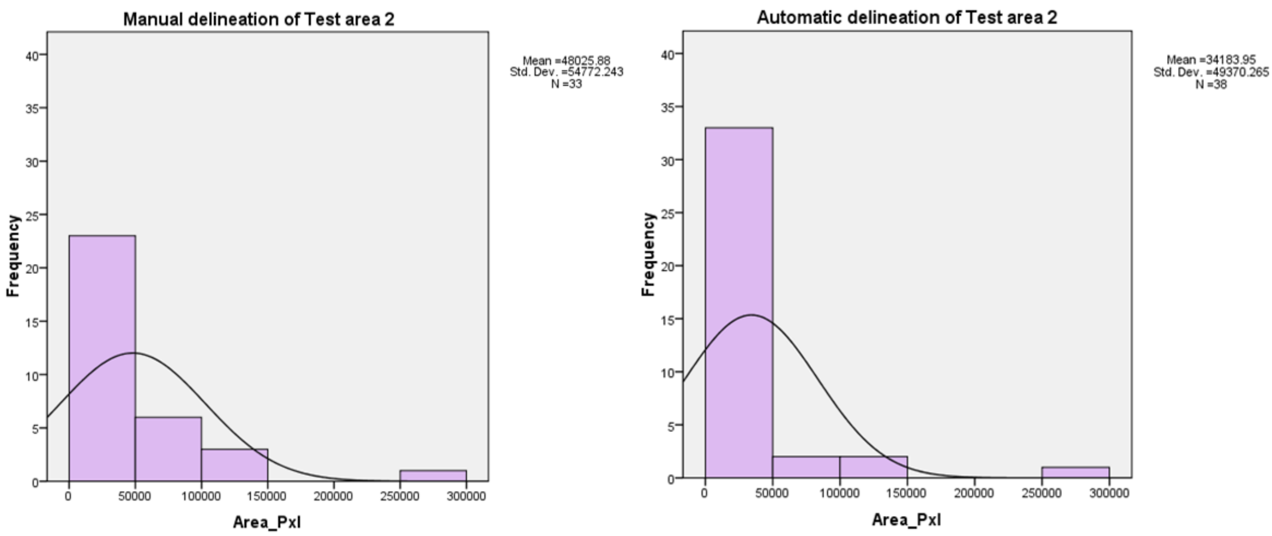
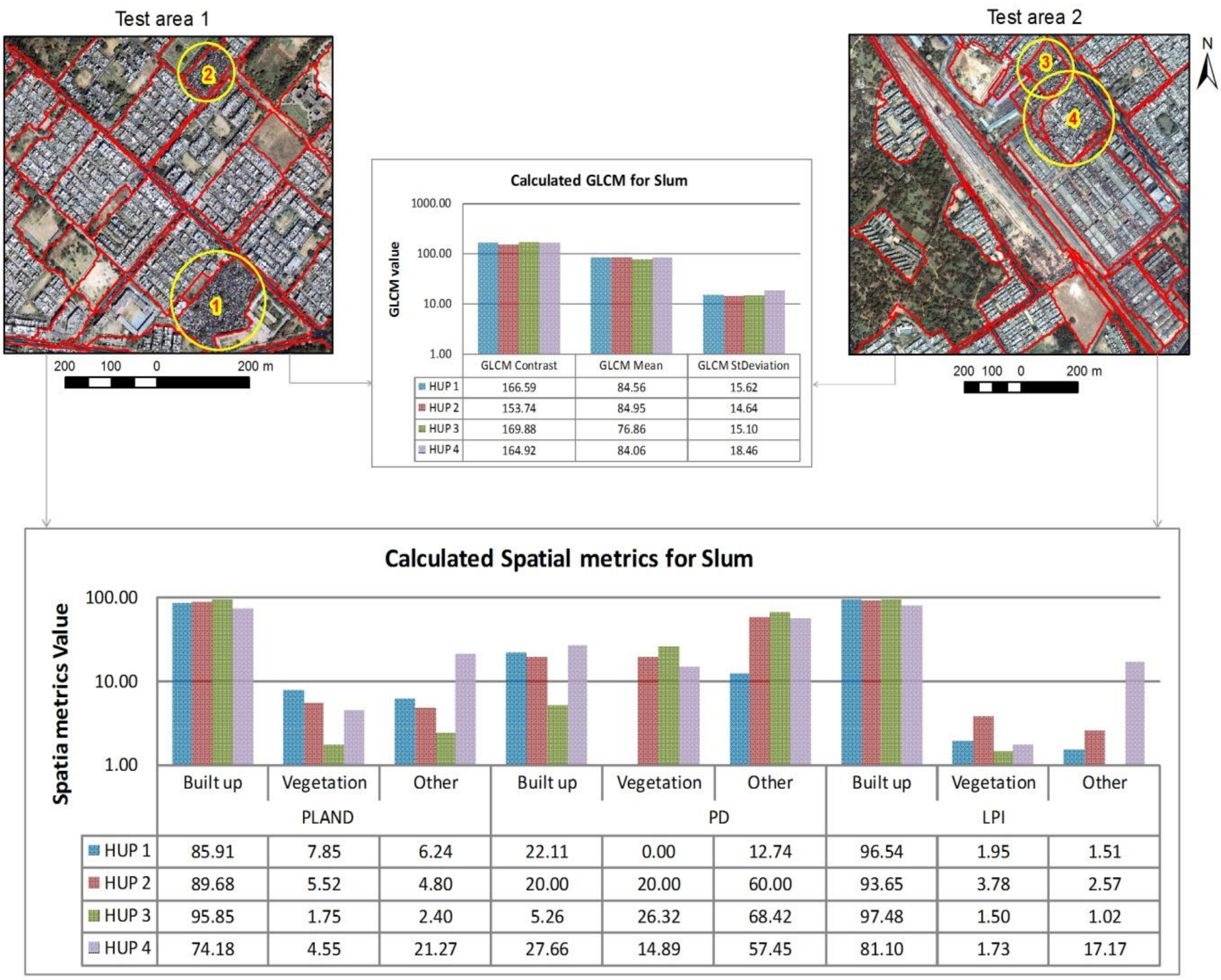


Figure 4-30: A graph showing the accuracy of the delineated HUPs in Test area 2

4.6. Slum identification

The final outcome of the study is identified slums through the already characterized homogeneous urban patches. Figure 4-31 shows the result of the identified slums with their specific spatial and spectral characteristics in both test areas. The delineated HUPs with yellow colour indicate those of HUPs which are slums. Each of them is numbered in order to relate them with the calculated result of GLCM and spatial metrics. The graph clarifies the specific characteristics of the slums in terms of texture/pattern. These HUPs result in a higher percentage of built up in comparison with other HUPs, implying that the built up patches remain continuous with a very few open spaces. Sample 4 seems to group in a different category of slum than the three samples since it contains relatively bigger size buildings, different pattern and more open spaces which is shown by lower patch density and patch index of built up. The calculated texture values show the spectral characteristics of the sample HUPs (see the graphs in Figure 4-31 which are presented in combination with the image).



	GLCM Contrast	GLCM Mean	GLCM StDeviation
HUP 1	166.59	84.56	15.62
HUP 2	153.74	84.95	14.64
HUP 3	169.88	76.86	15.10
HUP 4	164.92	84.06	18.46

	PLAND			PD			LPI		
	Built up	Vegetation	Other	Built up	Vegetation	Other	Built up	Vegetation	Other
HUP 1	85.91	7.85	6.24	22.11	0.00	12.74	96.54	1.95	1.51
HUP 2	89.68	5.52	4.80	20.00	20.00	60.00	93.65	3.78	2.57
HUP 3	95.85	1.75	2.40	5.26	26.32	68.42	97.48	1.50	1.02
HUP 4	74.18	4.55	21.27	27.66	14.89	57.45	81.10	1.73	17.17

Figure 4-31: Identified slums in Test area 1 and Test area 2

4.7. Discussion

This section discusses about the obtained results which are reported in the above section. The discussion is presented according to the flow of the reported result.

4.7.1. Delineation and characterization of HUPs

The boundaries of the HUPs in pansharpened IKONOS 1m resolution image of New Delhi, were delineated based on the general definition and characteristics of a HUP as mentioned in Section 3.2.2. OOA approach supports the image to be first segmented in to different regions that are taken to be homogenous in terms of spatial and spectral characteristics. In addition to this, the grid map of spatial metrics particularly Class Area (CA) of built up, vegetation and other land cover types, that are found through the moving window analysis, assists as an extra layer while delineating the boundary of the HUP in both test areas (illustrated in Section 1.1.2). The scale parameter 42 provides a good delineation of the HUP boundaries.

The accuracy of the delineated HUPs was assessed by comparing the manually and automatically delineated HUPs. According to the explanation of Zhan et al. (2005) the found accuracy of 85% and 71% with a goodness of fit (D-value) of 0.15 and 0.29 in Test area 1 and Test area 2 respectively, is acceptable and lays in the good range of accuracy. That is, it is explained that, when objects from manual delineation are overlapped with an automatic delineation by at least 50%, objects are said to be matching, which means that objects share position, size and shape and can be taken as correct and complete. Actually the required accuracy depends on the objective of the analysis. The outcome of the accuracy could vary depending on the homogeneity concept that the person has while delineation, the rules which have to be set for the automatic delineation of the HUPs and the person who implement the manual delineation. Even if 71% of segmentation accuracy in Test area 2 is in the range of matching, it shows lower value in comparison with Test area 1. The difficult nature of Test area 2, like gradual change of some HUPs which is limiting the precise delineation of the boundaries could have an effect in the accuracy of HUP boundaries (See Figure 4-8, Test area 2). Whatever the case the interference of ground truth information could play a crucial role for better accuracy results.

The spatial metrics and Gray Level co-occurrence Matrix (GLCM) proved to be a crucial measure in characterizing the spatial and spectral nature of the delineated HUPs. The output of the selected spatial metrics is integrated with the selected GLCM measures so as to contribute for the best identification of HUP classes. These combined measures provide information in distinguishing between each HUP. In both test areas GLCM contrast, GLCM mean and GLCM standard deviation showed close values with in classes of the same category. However; as found before by Herold et al. (2003), comparatively, the spatial metrics were giving the major differences between HUP classes. From the calculated metrics, Percentage of land (PLAND) is found to be a good descriptor in both test areas by showing the abundance of patches with in a HUP that could help to differentiate the type of land use of each HUP. Liu et al. (2006) also found PLAND as one of a good indicator to separate the functional classes of a HUP. The number of patches and the degree of fragmentation of each class in a HUP is shown by Patch density (PD). PD of built up is found to be high where the percentage of built up is high. LPI shows the relative dominance of the land cover classes with in each HUP.

As illustrated in Table 4-1, the result of the five pairs of samples (1-2, 3-4, 5-6, 7-8 and 9-10) in Test area 1 shows close values of PLAND, PD and LPI; implying that they could fall in the same category of classes. The percentage of built up and Patch density of built up in the first two sample pairs of HUPs is comparatively higher than other samples. This is one indicator that these HUPs are having dominating class of built up which leads to identification of the land use of a HUP. For example, in both test areas the highest percentage of built up and lower vegetation and open spaces reflects the land use of the HUP to be high density residential. With the same metrics application Test area 2 resulted in eight different land use class categories depending on the level of dominance classes (Table 4-2).

For the characterization of HUPs in Test area 2 the GLCM mean was not fully successful. For example, from eight classes the GLCM mean value is almost similar for class 2 and 3 which is also reflected in class separabilty result, 2D feature space plot (Figure 4-15). This is because the reflectance of the two HUPs appears to be similar which is not allowing separation between the two HUPs. At the same time, while checking the spatial metrics output the pattern of the two HUPs appears to be different, meaning that, they cannot be in the same class, as it contradicts the characteristics of homogeneity (Table 4-4). It can be generally observed that the GLCM mean that was successfully identifying different HUP classes in Test area 1 became limited while trying to implement it in Test area 2. This implies that integrated analysis through spatial metrics and GLCM has a great value in characterization of homogeneous urban patches.

4.7.2. Multi-scale analysis

As the HUPs were delineated and characterized in 1 meter resolution image, the changes of these characteristics were also identified on different resolution images: 2 and 4 meter resolution (Figure 4-18). The result shows that the Percentage of built up and Largest Patch Index of built up within each sample of HUPs increases with decreasing resolution, while the patch density decreases (Figure 4-19 to 4-21). That is the number of built up patches within individual HUP decreases while going from 1 meter towards 4 meter resolution (Figure 4-19). The neighbouring buildings appear to be merged showing that small roads, scattered trees and other minor features gets to be eliminated and major roads remains with the decrement of the resolution. There is no big difference in the characteristics of HUPs between 1 & 2 meter like that exists between 1 & 4 meter resolution (see Table 4-9). As illustrated in Figure 4-22, the boundary of the HUPs delineated in 4 meter resolution image, so as to see the spatial and spectral changes due to boundary shifts.

The entire result shows that number of HUPs decreases from 40 to 26 while going from 1 meter to 4 meter resolution and PLAND, PD & LPI increases. The same is true for GLCM contrast and GLCM mean (Table 4-10). Due to small features appears to be merged with the dominating land cover class, the area (Area pixel) of the sample HUPs is also decreasing while going from 1 to 4 meter resolution (see Figure 4-24 and Table 4-10). It is recognized that the boundary of HUPs is scale dependent. Thus, it is important to use a high resolution images to characterize homogeneous urban patches without losing spectral and spatial information of small land cover features that exist within a HUP. This leads to better accuracy that approaches the reality. In parallel, other classes could have also a probability of reflecting exaggerated level of dominance in low resolution images.

4.7.3. Slum identification

The calculated spatial metrics and GLCM proved to be a crucial measure in identifying slums through characterization of all HUPs in both test areas. The spatial metric results showed differences in spatial arrangement or pattern of built up areas that can be observed between slum and non-slum HUPs. The GLCM shows the texture differences. These differences indicate the location of the slum and non-slum HUPs. Actually, there is no separate analysis that is done to characterize HUPs which are slums but the calculated spatial metrics and GLCM for slums is sorted from the whole result of the HUPs (Figure 4-28). This approach is found to be feasible in addressing different types of homogeneous urban patches in comparable way.

The selected three metrics for HUPs which are slums show a close pattern in both test areas. Percentage of Land (PLAND) of built up appears to have higher value in the slum HUPs than other types of HUPs. HUPs which comprise slums are identified by high percentage of land and those without slum by low values. PLAND (which has equivalent to output of CA) of built up remains continuous in slum HUPs (See grid map of spatial metrics in Figure 4-5 and 4-6).This is because open spaces in Slum HUPs are very low in comparison with other formal residential types, the buildings appear to be dense.

Largest Patch Index (LPI) index was found to be another metrics that shows the largest patch of built up within a HUP described by the density. The strength of LPI in identification of slums was also proved by Mathenge (2011). Sample 4 slum HUP results in lowest LPI and PLAND of built up than the other three slum HUP samples. As can be seen visually from the Figure 4-28 and from the metrics result the spatial arrangement and size of the built ups in Sample 4 is different from the other. Patch density (PD) in the two test areas shows the built ups density with in a HUP. High density is observed in high density residential HUPs. The texture measure, particularly GLCM found to be a good describer in spectral characteristics of HUPs. Generally the combination of the six parameters from spatial metrics and GLCM proved to identify and characterize the slum HUPs in terms of their spatial arrangement and texture. However further analysis in testing more spatial metrics and texture measures for characterization of HUPs leads to the better detection of slums.

5. CONCLUSION AND RECOMMENDATION

This section presents a general summary of the research according to the objectives proposed at the beginning of the analysis. Recommendations are also provided based on the findings of previous sections.

5.1. Conclusion

In this study, delineation and characterization of HUPs through an object oriented analysis is performed procedurally. The HUPs were delineated based on the basic definition and characteristics of homogeneous urban patches. In addition to the set of rules in object oriented analysis, spatial metrics particularly Class Area, were providing an additional support for the delineation HUP boundaries. The spatial and spectral characteristics of each HUP were described in terms of pattern and texture utilizing spatial metrics and GLCM measures respectively. Each HUP is categorized depending on the class separabilty analysis. The functional classification of the categorized HUPs is done through the calculated spatial metrics and GLCM results and with an integration of visual interpretation. The spatial metrics is found providing a higher amount of information in functional classification of HUPs.

The changes in the characteristics of the HUPs that can be seen in different resolution images are addressed by multi-scale analysis. The effect of scale in the characteristics of HUPs was recognized by first degrading an image to two different resolution images: 2 & 4 meter. 'Within' and 'On the boundary' HUP changes were analyzed while moving from one scale to the other. The spectral and spatial changes across scale were seen clearly from the spatial metrics and GLCM values.

The transferability of the method is analyzed by selecting another test area in the same city. The selected and applied spatial metrics and GLCM is proved to be almost successful in the characterization and classification of HUPs in Test area 2. The accuracy of the HUPs in both test areas is assessed by comparing manually and automatically delineated HUPs and a value of 85% and 71% is found in the two test areas respectively, which lays in acceptable range of value.

The slums were identified depending on the already characterized HUPs in both test areas. The particular spatial and spectral characteristics of the slum HUPs were selected and analyzed separately. The integrated output of the selected metrics and texture measure leads to the better identification of slum areas.

In conclusion, this study found that the detection of slum through delineation of Homogeneous Urban Patches and characterizing them in terms of pattern and texture to be promising and efficient approach while addressing other categories of land use at the same time. It can be said that this approach can be transferred to another area depending on the nature of the site, the type of the image to be used and the extent of the homogeneity criteria which has to be set in the beginning of the analysis.

5.2. Recommendation

In relation with this study some directions for future studies are proposed and listed accordingly.

- Since this study make the analysis of delineation and characterization of HUPs on image of the same year , further research is recommended on delineation and characterization of HUPs over time (Temporal analysis)

- The HUPs are analyzed using images of the same sensor on the same city. It is recommended to test the method on images of different sensors of the same city. This could help to check whether the method can be transferred to images of another spatial and/or spectral resolution.

- In this study the HUPs are delineated and their accuracy is assessed through comparison of manual and automatic delineation. In order to analyze it in a better way, it is recommended to integrate multiple test persons or visual expertise, who delineate HUP boundaries by using the common rule of homogeneity. This could provide a wide range of perception about homogeneity concept.

- During the analysis nine spatial metrics and six texture measures were tested. Further test of more spatial metrics and texture measures on characterization of HUPs is recommended. Especially the location of slum is not usually identified through the limited metrics or texture measures. It is important to investigate and asses different indicators.

- This study does not include ground truth information in the analysis. It is recommended to analyse the HUPs integrated with ground data. This ensures the preciseness of the research in a better way.

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