DETECTING INFORMAL BUILDINGS FROM HIGH RESOLUTION QUICKBIRD SATELLITE IMAGE, AN APPLICATION FOR INSITU UPGRADING OF INFORMAL SETELLEMENT FOR MANZESE AREA - DAR ES SALAAM, TANZANIA

By

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Thesis submitted to the University of KwaZulu-Natal for the
Partial fulfillment of the requirements for the degree of Masters of Environment and Development in the Centre for Environment, Agriculture and Development,
School of Environmental Science

Pietermaritzburg

2005

DEDICATION

I dedicate this work to my Parents, Brothers and Sisters who always offered me support throughout my academic life

ACKNOWLEDGMENT

First and fore most, I would like to acknowledge and express my sincere thanks to IT2 – Project, for offering me a fellowship that enabled me to pursue my Masters Studies at the University of KwaZulu-Natal.

My sincere gratitude and appreciation are to my supervisor Dr. Onisimo Mutanga, Senior lecturer in the School of Environmental Science Department of Geography, University of KwaZulu-Natal Pietermaritzburg for his guidance, valuable and constructive discussions, relevant materials and encouragement through the process of accomplishing this research. I also extend my special appreciation to Dr. Dennis Rugege, Senior Lecturer and Director of Land Information Management Programme, Centre for Environment, Agriculture and Development (CEAD- UKZN) for his contribution and academic support during the entire course.

I am also greatly indebted to The Tanzanian Ministry of Lands and Human Settlement Development (MLHSD) for providing me with Quickbird Satellite image and Vector Data used in this Research. In particular I am sincerely thankful to Mr. Eric Mwaikambo a staff working with (MLHSD) for his mutual cooperation in facilitating the process of data acquisition.

Ms. Faith Nzimande, of CEAD deserves my personal gratitude and respect as well for her tireless administrative support throughout my study period at the University. I am also very grateful to my fellow students in CEAD for valuable discussions and experience we shared.

As I cannot mention all individuals who participated to facilitate the compilation of this report in one way or another, I would like to extend my general gratitude to every one who supported me.

Lastly but not the least I wish to thank the Centre of Environment, Agriculture and Development for providing me with resources and technical assistance in accomplishing this research.

ABSTRACT

Documentation and formalization of informal settlements ("insitu" i.e. while people continue to live in the settlement) needs appropriate mapping and registration system of real property that can finally lead into integrating an informal city to the formal city. For many years extraction of geospatial data for informal settlement upgrading have been through the use of conventional mapping, which included manual plotting from aerial photographs and the use of classical surveying methods that has proved to be slow because of manual operation, very expensive, and requires well-trained personnel.

The use of high-resolution satellite image like QuickBird and GIS tools has recently been gaining popularity to various aspects of urban mapping and planning, thereby opening-up new opportunities for efficient management of rapidly changing environment of informal settlements.

This study was based on Manzese informal area in the city of Dar es salaam, Tanzania for which the Ministry of Lands and Human Settlement Development is committed at developing strategic information and decision making tools for upgrading informal areas using digital database, Orthophotos and Quickbird satellite image.

A simple prototype approach developed in this study, that is, 'automatic detection and extraction of informal buildings and other urban features', is envisaged to simplify and speedup the process of land cover mapping that can be used by various governmental and private segments in our society. The proposed method, first tests the utility of high resolution QuickBird satellite image to classify the detailed 11 classes of informal buildings and other urban features using different image classification methods like the Box, maximum likelihood and minimum distance classifier, followed by segmentation and finally editing of feature outlines.

The overall mapping accuracy achieved for detailed classification of urban land cover was 83%. The output demonstrates the potential application of the proposed approach for urban feature extraction and updating. The study constrains and recommendations for future work are also discussed.

DISCLAIMER

The research described in this Mini-dissertation was carried out at the Centre for Environment, Agriculture and Development under Land Information Management Programme, University of KwaZulu-Natal. All the views and opinions expressed therein remain the Sole responsibility of the author, where the use has been made of the work of others it is dully acknowledged in the text.

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LIST OF ACRONYM

CEAD....................Centre for Environment, Agriculture and Development
DEM.....................Digital Elevation Model
DSM.....................Digital Surface Model
DXF.....................Data Exchangeable Format
GIS......................Geographical Information System
GPS.....................Global Positioning System
MDC....................Minimum Distance Classifier
ML.......................Maximum Likelihood
MLHSD................Ministry of Land and Human Settlement Development
UNCHS................United Nations Centre for Human Settlement (Habitat)
UTM....................Universal Transverse Mercator
UNCED..............United Nations Conference on Environment and Development
UKZN.................University of KwaZulu-Natal
ViSP...................Visual Settlement Planning
WGS...................World Geodetic Coordinate System

COMPONENT (A)

CHAPTER ONE

1 Introduction

1.1 Problem statement

The rapid growth of urban informal settlements has become the most complex and pressing challenges to land managers in developing countries. This is as a result of slow pace in planning and surveying, which underpins the registration process of land rights that can allow proper planning for various developments as well as possible use of such land rights to access credits for investment. The majority of poor people lack long-term security of tenure to the land upon which they have settled in rapidly expanding urban areas (Christensen, 2005).

Informal settlement is characterized by dense settlements comprising communities housed in self-constructed shelters under conditions of informal or traditional land tenure. A UNCHS global report on human settlement of 1986 pointed out that between 30 to 60 percent of residents of most large cities in developing countries live in informal settlements (Baltsavias & Mason, 1997). In Tanzania, informal housing settlements provide shelter to the majority of the urban poor. According to the World Bank report (2002), 'approximately 70 percent of the total population of Dar es Salaam lives in such areas while other major towns figures around 60 percent'.

The increasing level of poverty, population and lack of sustainable housing polices in Tanzania resulted into rapid urban growth coupled with poor housing, health and environmental conditions. In the 1960's, the approach used to deal with growing informal settlements particularly in Dar es salaam was that of slum clearance with the intention of developing high quality houses on those sites. However, the approach was later abandoned due to economic and social costs. There have been other intermediate national strategic approaches for upgrading informal houses before 1992 when UN Habitat introduced an environmental planning and management strategy, which among other things was to support various settlement upgrading programs (World Bank report, 2002). The strategy came about through agenda 21[1] which laid out principles of sustainable development with the overall objective to improve social, economic and environmental quality of human settlements (UNCED, 1992 cited in Abbot and Douglas, 2001)

Upgrading of informal settlement differs quite fundamentally from development of a vacant land for housing. This is due to dynamic environment, which is constantly adjusting to changing pressure and processes (political, economical and social) that cause, shape and either maintain or threaten the existence of these areas. In this regard, documentation and formalization of informal housing settlements ("insitu" i.e. while people continue to live in the settlements) needs appropriate mapping and registration system of real property to allow proper planning for other development to take place. It is principally aimed at fast and simple process of integrating the informal city to the formal city in order to stimulate economic growth and upgrading of social life setup of the urban poor as advocated by 'De soto's program (Silayo, 2005). In this program, owners get licenses to recognize the ownership of their properties that can later be used as collaterals to acquire loans from various financial institutions. Alternatively, this may be applicable for compensation purposes in effect to the change of land use by the government or any other organization.

Apparently, parcels in informal settlements are created through the process of adjudication by identification of boundaries, delineation and finally registration. Most parcel ownerships in such areas cover the size of individual buildings due to the closeness of neigbouring houses, and hence become useful basic spatial units that can govern the entire planning process.

Various mapping methods have been applied in conducting informal settlement regularization process. For example, conventional land surveying methods have

[1] Embodied recommendations from 1992 United Nations Conference on Environment and Development (UNCED)

previously been extensively used for many of these project types. However, higher cost of equipments, expertise and time remain a hindrance to the wider application of such methods.

The use of existing medium or large scale Aerial Photographs and topographical base maps could be an alternative solution in this regard, because large spatial scale simplifies onsite feature identifications. However, their relevance are still limited to outdated maps and aerial photographs, and the key problem remains on how to cost effectively update such datasets to meet the demands of the rapid changing environment given the limited budgets, equipment and personnel in the local administration.

The use of high-resolution satellite image and GIS tools to document and formalize informal settlements has been gaining popularity in recent years. High-resolution satellite images like Quickbird have drawn attention in various aspects of application and this has been due its high temporal resolution, which makes it possible for image scenes to be constantly up-dated hence becoming more potential for covering new developments occurring in a particular locality. In addition, the high level of detail, variance of spectral and spatial information contents contributes towards their potential application for rural and urban mapping.

The current settlement upgrading approach used in Tanzania is analogous to the recent work in Cape Town, South Africa, presented by Abbot and Douglas (2001), their report highlights the implementation of the methodology termed as Visual Settlement Planning (ViSP) that uses spatial information and GIS approach for 'insitu' settlements upgrading. It is a cost-effective approach adopted in one of the programmes developed in Belo Horizonte, Brazil and tested in Kenya after realizing that the implementation of full scale settlement upgrading was not a feasible one. The process is done within a modular GIS environment, which involves digitization of shacks from Aerial photographs and integrates settlements physical aspects and social processes to analyze issues and potential planning response, together forming an information backbone of the entire project.

So far, many of these projects that use high-resolution satellite images have not yet considered automation techniques for feature extraction. Instead, images are used as backdrop information on a computer screen to assist visual feature identification to facilitate manual on-screen digitization. As a consequence of conducting manual work, these methods have proved to be less economical in terms of time, labour intensiveness and erroneous data inputs. In this regard, the development of a technique that automatically detects and extracts information from high-resolution satellite images is an important step towards efficient planning and management of informal settlement.

Research problem tree

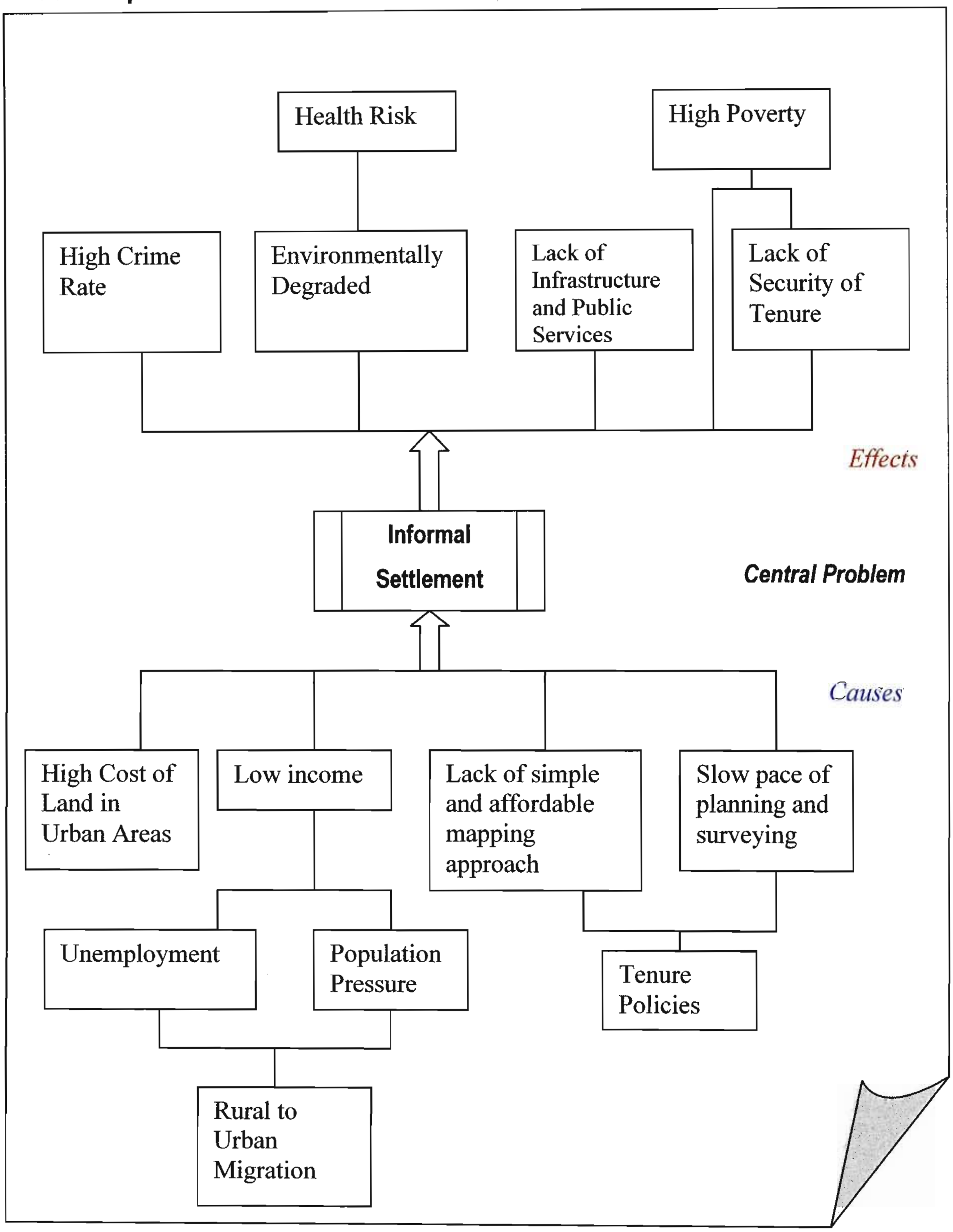


Figure 1:1 Research problem tree

1.2 Aim of the study

This research intends to develop a technique for automatic building detection and extraction to address inefficiencies of convention mapping and digitization approach. The new approach is envisaged to produce a smart vector map product that can contain a wider variety of data for physical, environmental and social processes in order to simplify and speed-up the process of parcel mapping, infrastructure planning, building inventorying, areas assessment, and various impacts monitoring mechanism to accommodate the rapidly changing environment in informal areas.

1.3 Research questions

This study was guided by the following research questions;

- Can the spatial information contained in QuickBird satellite image be used to detect and classify informal settlements with high accuracy?
- How accurate is the new approach of digital image classification and segmentation compared with the conventional methods of digitization?
- Can classification algorithms used for image processing improve the accuracy of the product vector map?
- How useful are the image classification methods in classifying urban land cover from QuickBird high-resolution image at various scales?

1.4 Research hypothesis

The following hypothesis were generated from the above stated research questions;

- Most of building boundaries in informal settlement are representation of informal parcel boundaries.
- There is diverse spectral information between neighboring building rooftops. Such diversity can be used as basis for individual building classification.
- Image processing algorithms have different classification performances that entirely depend on the existing phenomenon on the ground and spatial content of the image.

1.5 Research objectives

1.5.1 Main objective

The main objective of this research is to develop a feature extraction technique that can be applied to detect informal buildings from QuickBird satellite image. The materialization of such a technique will pave the way for land managers to use as a tool for effective upgrading and management of informal settlement especially in planning for infrastructure, building inventorying and have control of various monitoring mechanisms.

1.5.2 Specific objectives

The specific objectives of the study are;

- To develop a technique using Quickbird satellite image that can discriminate informal settlement and ultimately identify and classify individual buildings.
- To assess the accuracy and performance of the image analysis process based on ground truthing information.
- To evaluate the efficiency of the method by comparing the result with the manual systems of data extraction that are currently used.
- To convert classified raster image data into vector feature polygons to be used for database development.

1.6 Conceptual framework

Feature detection technique for this research will be based on a classification function

$C_f = f\,(t, g, c)$

Where C_f represents a classification function

t ⇨ object texture (Different features have different texture)

g ⇨ object geometry (spatial Characteristics)

c ⇨ the context in which the classification is conducted (feature spectral characters)

The successful implementation of this function depends on a clear understanding of fundamental concepts of image processing algorithms and band relationships of a particular image scene.

1.7 Thesis structure

The current Chapter, **Chapter 1**, covers the general introduction, purpose and scope of the research; it includes problem statement, research hypothesis, aim and objectives, conceptual framework and research questions.

The remaining chapters and appendices are summarized below as follows:

Chapter two: Literature Review

This chapter covers mainly an introduction to some basic related knowledge of data especially on space sensors observation, spectral, radiometric and spatial image characteristics, High-resolution Quickbird image and Image processing. It also highlights the feature detection technique suggested by previous studies and evaluation of approach efficiency.

Chapter three: Materials and Methodology

The chapter explains the location of the case study area and reasons for its selection. It also explains how various steps were sequentially organized and conducted in order to achieve the stated objectives.

Chapter four: Data Analysis and Result Discussion.

This chapter gives details on data analysis approach, present results, and general interpretation and assessment of the output.

Chapter five: This chapter concludes the study, highlights constraints and recommendations for future work.

Appendices: This covers all output maps, processed images and tables

CHAPTER TWO

2 Literature Review

This chapter covers mainly the principles behind remote sensing observations and various approaches for data processing and interpretations.

2.1 Space sensors observations

Remote sensing is a science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device without being in contact with the object, area, or phenomenon under investigation (Lillesand & Kiefer, 2000).

In general remote-sensing observations rely on the measurement of electromagnetic (EM) energy. EM energy takes several different forms in which the sun is the most important source of EM energy on the earth's surface. Earth's resources satellite sensors are mainly divided into two categories. The first category is that of passive sensors that are characterized by the ability to detect energy of reflected sunlight, or detect energy emitted by the earth itself. While second category comprises that of active sensors like the Radar, that emits their own energy and then measures the amount of energy reflected back from the target. The figure 2:1 below represents the phenomenon on how passive and active sensors operate.

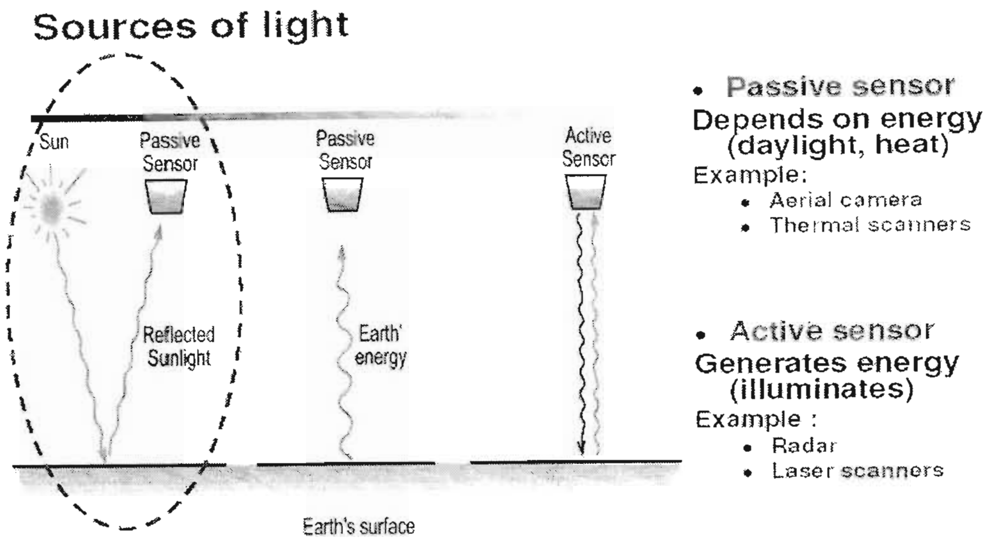


Figure 2:1 Types of space observation sensors: Source, Janssen *et al*, (2004)

2.2 Digital image characteristics

2.2.1 Radiometric and spectral image characteristics

Radiometric and spectral image characteristics actually refer to the part of the Electromagnetic Spectrum measured and the differences in the energy that can be observed (Janssen *et al*, 2001). The spectral signature characteristics play a major role in classifying different land covers. We should recognize that the broad features types are normally spectrally separable. On the other hand the degree of separation between feature types is a function of where exactly we look at, spectrally.

2.2.2 Spatial image characteristics

This refers to the smallest unit-area measured and indicates the minimum size of objects that can be detected for the selection of appropriate data types; thus it is important to understand the information requirements for specific application. In recent years, several higher spatial resolution satellite images have been introduced and applied in various aspects. Space systems like Quickbird and other several new satellite sensors being developed are capable of generating imagery with spatial resolutions as fine as 0.6m in Panchromatic mode and 2.8m in Multi-spectral mode (Dutta & Kamrujjaman, 2004). Toutin and Cheng (2002 cited in Mayunga *et al,* 2005) investigated the potential of QuickBird for spatial data acquisition and showed that QuickBird sensors have narrowed the gap between satellite images and aerial photographs, which have resolution ranging from 0.2 to 0.3. Thus becoming more recommendable for various mapping applications because many details and other elements of phenomena can clearly be identified, thus opening up a new window for urban land use information studies.

2.2.3 Visual image interpretation

Images generated by remote sensors are subject to interpretation before the remote sensing data can become useful information. While this research aimed at developing a suitable automation process for information extraction, currently most of the practical interpretations are based on the human eye-brain system, which is a science and an art of observing images with the objective of identifying different objects and judging their significance by relating their colours and patterns (Hurskainen & Pellika, 2004; Konecny, 2003). The human eye-brain system remains a method at hand when all other methods fail or are not available for some reason.

There is an extensive application of visual image interpretation approach as a result of satellite image spatial resolution improvement. Some areas of application include; assessments of damages caused by natural calamities like the Tsunami, which occurred in South Asia in December 2004 (ITC, 2005). It has also been used to assess damages of the so-called operation 'Murambatsvina' as a result of demolition of shanty settlements in Zimbabwe in May 2005 (Winter, 2005). This type of assessment is done by means of image temporal analysis, where by two or more successive passes of satellite images are taken at particular intervals over the same area and compared.

2.2.4 *Image processing*

The concept of using satellite images for the purpose of developing databases needs further integration of image processing approach beyond human eye-brain system interpretation. There is a need to consider various techniques for land cover mapping from multi-spectral data for which a database can be established.

Image processing refers to various schemes applied to manage data for purpose of extracting useful information to the user. The idea of image processing is wide and objectively complex in many aspects of applications.

2.2.5 *Digital image classification*

The objective of this operation is to replace visual analysis of the image data with qualitative techniques for automatic identification of features on the scene. It normally involves the analysis of multi-spectral image data and the application of statistically based decision rules for determining the land cover identity of each pixel in an image. Janssen *et al,* (2001) highlights that; the prime interest on images is not only about brightness values, but rather more about thematic characteristics, thus the focus should be more on translation of continuous variability of image data into map patterns that provide meaning to the user and obtain insight in the data with respect to ground cover and surface characteristics. The principle behind image classification is that pixels are assigned to a class based on its feature vector by comparing it to predefined clusters in the feature space. By doing that, all image pixels result into a classified image that can be represented by the function;

$f(x) = \Delta\lambda_1 + \Delta\lambda_2 + \Delta\lambda_3 + \ldots\ldots\ldots\ldots\ldots\ldots + \Delta\lambda_n$

$\Delta\lambda_I$ = Spectral classes.

n=is the number of attributes which describes each image feature or training class.

Common classification procedures can be broken down into two broad subdivisions based on the method used: unsupervised classification and supervised classification

2.2.5.1 Unsupervised classification

In this method all pixels (feature vectors) on the image are plotted in a feature space, and the feature space is analyzed to group feature vectors into clusters. The classifier does not utilize training data as the basis for classification. Instead, it involves a model that examines the unknown pixel in an image and aggregates them into a number of classes based on natural clusters present in the image values (Lillesand & Kiefer, 2000).

2.2.5.2 Supervised classification

This is a much more widely used classification technique that requires knowledge of the area at hand that helps the operator to define spectral characteristics of the classes by defining sample areas called training areas. The process is divided into two phases; a training phase, where a user trains the computer by assigning a limited number of pixels to what class they belong in the particular image followed by decision making phase, where the computer assigns a class label to all other image pixels by looking for each pixel to which of the trained classes this pixel is more similar (ILWIS User Guide, 2001).

2.2.5.2.1 Sample training areas

So far there are two approaches used to develop training areas from an image. Lillesand and Kiefer (2000), presents the methods as either by delineating small polygons that are used as a viewing window or using a manual seed approach where by a single seed pixel is chosen from prospective training areas. Based on application aspects between the two methods, in this study delineation of polygon approach was adopted because the process seems to be complete and more representative of all spectral values of an image.

Irrespective of how training areas are delineated when using any statistically based algorithm such as the maximum likelihood method (sect. 2.4.1.3), the theoretical lower limits of the number of pixels that must be contained in a training set is n + 1, where n is the number of spectral bands (Lillesand & Keifer, 2000). Theoretically, in our three bands Quickbird imagery example, a minimum of only four pixel observations would be adequate. Obviously the use of fewer than four observations would make it impossible to appropriately evaluate the variance and covariance of the spectral response values.

In practice, a minimum of 10n to 100n pixels can be used since the estimates of the mean vectors and covariance matrices improve as the number of the pixel in the training set increases within reason and the more pixel that can be used in training, the better the statistical representation of each spectral class will be.
The figure 2:2 below shows convention of image data into thematic data using supervised classification.

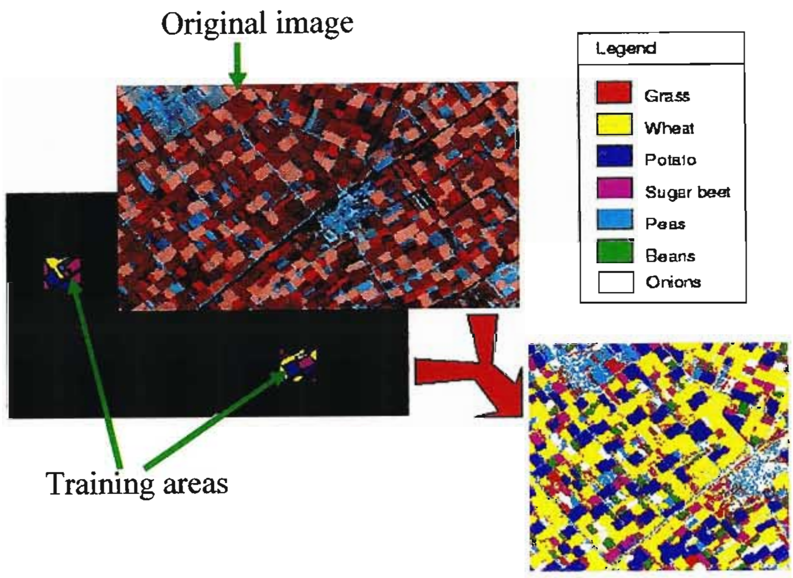


Figure 2:2 Sample-training areas and the output-classified image: Source, Janssen *et al*, (2004)

2.2.5.2.2 Test statistics areas
The test statistics areas are regions of representative of uniform land cover that are considerably different and more extensive than training areas. They are often located during the training stage of supervised classification by intentionally designing more candidate training areas than are actually needed to develop the classification statistics. A subset of these may then be withheld for the post-classification accuracy assessment. The accuracies obtained in these areas

represent at least a first approximation to classification performance throughout the scene. However, being homogeneous, test areas might not provide a valid indication of the classification accuracy at the individual pixel level of land cover variability.

2.2.5.3 Classification algorithms

2.2.5.3.1 Parallelepiped

This classifier is the simplest classification method that can easily be visualized; it is based on defining the upper and lower limits for each class. The limits depend on minimum and maximum values, or the mean and standard deviation per class. When the lower and upper limits for each class are defined, a multi-dimensional box is drawn around the class means and that is why it is sometimes called a Box Classifier.

For each class, the size of the box can be calculated as:

(Class mean ± standard deviation per band) x multiplication factor

The number of boxes depends on the number of classes, In the process, an unknown pixel is checked to see if it falls in any of the boxes then the corresponding class name is assigned, and if a feature vector falls within two boxes, the class name of the box with the smallest product of standard deviations is assigned, i.e. the class name of the smallest box. Pixels that do not fall inside any of the boxes will be assigned the unknown class[2]. Although this method seems to computational efficient in attempting to capture boundaries of each class, there are limitations associated with overlapping of boxes that divulge failures for the algorithm to adopt clusters shape (Zachary, 1999).

2.2.5.3.2 Minimum Distance

The basis for the Minimum distance classifier (MDC) is the emphasis on location of cluster centers. During classification the Euclidean distance from an unknown pixel to various cluster centers are calculated. The unknown pixel is assigned to that

[2] Adopted from ILWIS 3.2 Program help

class to which the distance is least. The MDC classifier seems to be mathematically simple and computationally efficient but it has certain limitations; it is insensitive to different degrees of variance in spectral response data, besides the shape and size of the cluster is not considered (Lillesand & Keifer, 2000).

2.2.5.3.3 Maximum Likelihood

This classifier is by far the most popular classification algorithm for multispectral data for it quantitatively evaluates both the variance and covariance of the category spectral response patterns when classifying an unknown pixel. It is done with an assumption that the distribution of the group of points is normally distributed. The normality theory is generally reasonable for common spectral response distributions. Under this assumption, the distribution of a category response pattern is completely described by the mean vector and the covariance matrix.

The formula used in Maximum likelihood reads:

$d_i(x) = \ln|V_i| + y^T V_i^{-1} y$, [3]

Where:

d_i =distance between feature vector (x) and a class mean (m_i) based on probabilities

V_i=the *n* x *n* variance-covariance matrix of class *i*, where *n* is the number of input bands

$|V_i|$=determinant of V_i

V_i^{-1}=the inverse of V_i

$y = x - m_i$; is the difference vector between feature vector x and class mean vector m_i

y^T =the transposed of y

For each feature vector, x the shortest distance, d_i to a class mean, m_i is found;

If this shortest distance to a class mean is smaller than the user-defined threshold, then this class name is assigned to the output pixel.

[3] Adopted from ILWIS 3.2 Program help

The probability density functions are useful to classify an unidentified pixel by computing the probability of the pixel value belonging to each category. The computer would calculate the probability of pixel value occurrence in the distribution as of class 'like informal neighborhood then followed by the likelihood of its occurring in class 'like urban agriculture' and so on. After evaluating the probability in each category, the pixel would be assigned the most likely class (highest probability value) or labeled "unknown" if the probability values are all below a threshold set by the analyst during selection of sample areas (Lillesand & Kiefer, 2000).

2.2.6 Multi-resolution image segmentation

Image segmentation and classification have closely related objectives; both approaches are forms of component labeling that can result into various ground features representation. With image segmentation approach, the image scene is first segmented into statistically homogeneous regions that become basic objects of all following operations, and then both spectral characteristics and a series of shape parameters can be considered into classification (Gigandet, 2004; Konecny, 2003; Frauman & Wolff, 2005).

Image segmentation process can be implemented by either edge detection technique that traces all those pixels that belong to the borders of the objects, or by region growing which considers association among regional pixels. The classification algorithm may then apply on region-by-region basis rather than on pixels (Konecny, 2003).

2.3 Related works on feature detection and extraction from high resolution digital image

The idea of automatic detection and extraction of man made structures from digital images have been a focal point of photogrammetry and satellite image processing research for the past 20 years. There is a wider variation of feature extraction approaches as a result of non-homogeneity of urban structures, which also leads into variation of degree of automation and detection rate. Many of these approaches are feasible only for small image sets or on restricted urban structures, which results into a variation of degree of automation and detection rate, (Barry & Ruther, 2001).

Ruther,Martine and Mtalo (2001, cited in Barry & Ruther, 2001) presented a building extraction technique from digital image; this approach generates a 2D building blobs derived from a normalized Digital Surface Model (DSM). A Digital Elevation Model (DEM) is then developed considering ground surface points available between buildings, and later the DEM is subtracted from DSM using a raised structure hypothesis utility. Shadows and Contours representing building outlines are the outcome of this technique.

The recent approach for feature extraction in remote sensing is based on the concept of object-oriented classification. It involves feature segmentation using multi-resolution image based on threshold value that combine both spectral and shape heterogeneity of objects characteristics and later classified by means of fuzzy logic and the traditional nearest neighbour algorithm, (Dutta & Sekker, 2004; Hurskainen & Pellikka, 2004; and Gigandet, 2004).

Pixel-based analysis algorithms are at a halt far from being discouraged as most of algorithms developed so far, still rely on image texture and energy-intensity information to perform image processing for feature detection and extraction. The solution for this is to consider approaches that can combine more than one algorithm towards image processing and analysis.

Most models developed for automatic feature detection and extraction proved to be successful to some extent especially when applied on well-structured settlements sheltered by homogeneous roof materials (Hurskainen & Pellikka, 2004). This means that the detection approach for informal housing settlements needs to consider a range of factors like colour, shape, texture, and context of the entire image scene as a result of the complexity of unstructured heterogeneous roofing materials that surfaces such areas. The model developed in this research involves traditional classification and post-processing image segmentation technique or an iterative detection technique that can cover variation of information on image data.

Feature extraction techniques are based on image classification routine, which normally involve quantitative techniques of analyzing multi-spectral image data and the application of statistically based algorithms on an image. The decision rule is based on the geometry and pattern characteristics present in an image (Lillesand & Kiefer, 2000).

2.4 Efficiency analysis review

The expected products from GIS and Remote sensing images are maps or a summary of map information (Skidmore, 1999 cited in Stein *et al*, 2002). Possibly, any approach adopted for data processing, efficiency is the most important aspect to be considered. This section will qualitatively highlight efficiency with respect to accuracy, time, labour intensiveness and expertise as variables that can contribute towards cost effectiveness or ineffectiveness of any adopted approach.

2.4.1 Accuracy

Conventionally accuracy is the common measure for data quality used in GIS and remote sensing. It is the closeness of an estimate to an actual value. The type of accuracy dealt with in this study include; positional and attribute accuracy.

2.4.1.1 Positional accuracy

This is a measure of variance of the position of a map feature from the true position of the entity. It is said to be relative if the locations of features on a map are compared with those of the same feature on another map. And when locations of features on the map are compared with their true position on the ground it is termed as absolute accuracy.

Testing of position accuracy for GIS and Remote sensing output data can be either by means of deductive estimate or by comparing directly to the source or to the source of higher accuracy. *Deductive estimates* is the assessment of potential errors that may occur in each production stage and their propagation. Accuracy is computed from knowledge of errors introduced by different sources. Example of error propagation;

Total error $\sigma = \sqrt{(\sigma_1^2 + \sigma_2^2 + \sigma_3^2. \ldots\ldots + \sigma_n^2)}$

where σ represent an error

and n represent different sources of error.

Comparison to the source involves comparison of the output to the source by the use of check plot overlaid on, and registered to the source documents. Sometimes this can be done by comparing the output to the source of higher accuracy that involves well-defined points to set accuracy standards such as large scale map, high resolution image, use of global position system (GPS), survey raw data etc.

2.4.1.2 Attribute accuracy

This is a measure of closeness of attribute value to the actual ones. The analysis of attributes accuracy differs from that of position accuracy and even within attribute aspect itself the analysis is subjected to the nature of data. A better test for attribute accuracy is by preparing a confusion matrix (see sect.3.6 for a detailed discussion).

2.4.2 Cost benefits between manual and automatic approach

The development of various computer programs for data interpretation and automation has been a significant breakthrough towards the resultant maps and their respective databases on computers. It allows data to be integrated, processed, viewed and understood more quickly than in conventional approach. Cost benefit analysis between automation and digitization approaches in this study is more qualitative than quantitative, since a number of variables that could guide quantitative performance analysis were not considered during digitization process.

2.4.2.1 Cost in terms of time and labour intensiveness

Adopting automation approach helps to considerably minimize the associated labour costs and office work, as a result saving both cost and time. Above all, data sets can also be reprocessed and integrated with other technology like GPS to suit other applications without additional cost.

2.4.2.2 Expertise

The cost for initial investment for GIS and remote sensing automatic data management systems are relatively high. However, the long-term benefits as a result of application diversity are far than obvious.

3 Materials and Methodology

3.1 Introduction

This chapter describes the study area, overview of data type and methods for data analysis used to achieve the objectives set out in chapter one.

3.2 Case study area

The proposed technique for this study was tested in Manzese Area, a suburb of Kinondoni municipality that forms part of the City of Dar es salaam (figure 3:1 below). Other district municipalities include Temeke and Ilala. The suburb is approximately 4 Km from the city center. Like many other unplanned areas in the city, Manzese settlement, which is about 1Km^2 stem from the past rapid rural to urban migration since the country's independence in 1961. It is currently highly populated and unemployment rate is about 75%. The major source of income of this group is through informal activities and micro-enterprises (World Bank report, 2002). Buildings are predominantly informal with various complex forms, sizes and roofs of diverse compositions. Lack of infrastructure services and public facilities are some of the major characteristics of the area.

Manzese area is suited for this particular study for two main reasons; first is because of its informal characteristics, and Secondly, the presence of the pilot project for informal settlement formalization conducted by the Tanzanian Ministry of Land and Human Settlement Development also aggravated the undertaking of this study, since the project uses the same datasets (i.e. satellite images and GIS tools). The scope of the study is limited to Manzese informal settlement although the satellite image scene used covers beyond this area of interest and this brings about a more diversified analysis significance of broad land cover types such as urban agriculture and some areas that depicts semi and/or formal settlement characteristics.

The maps in the figure 3:1 below show the location description of the test site.

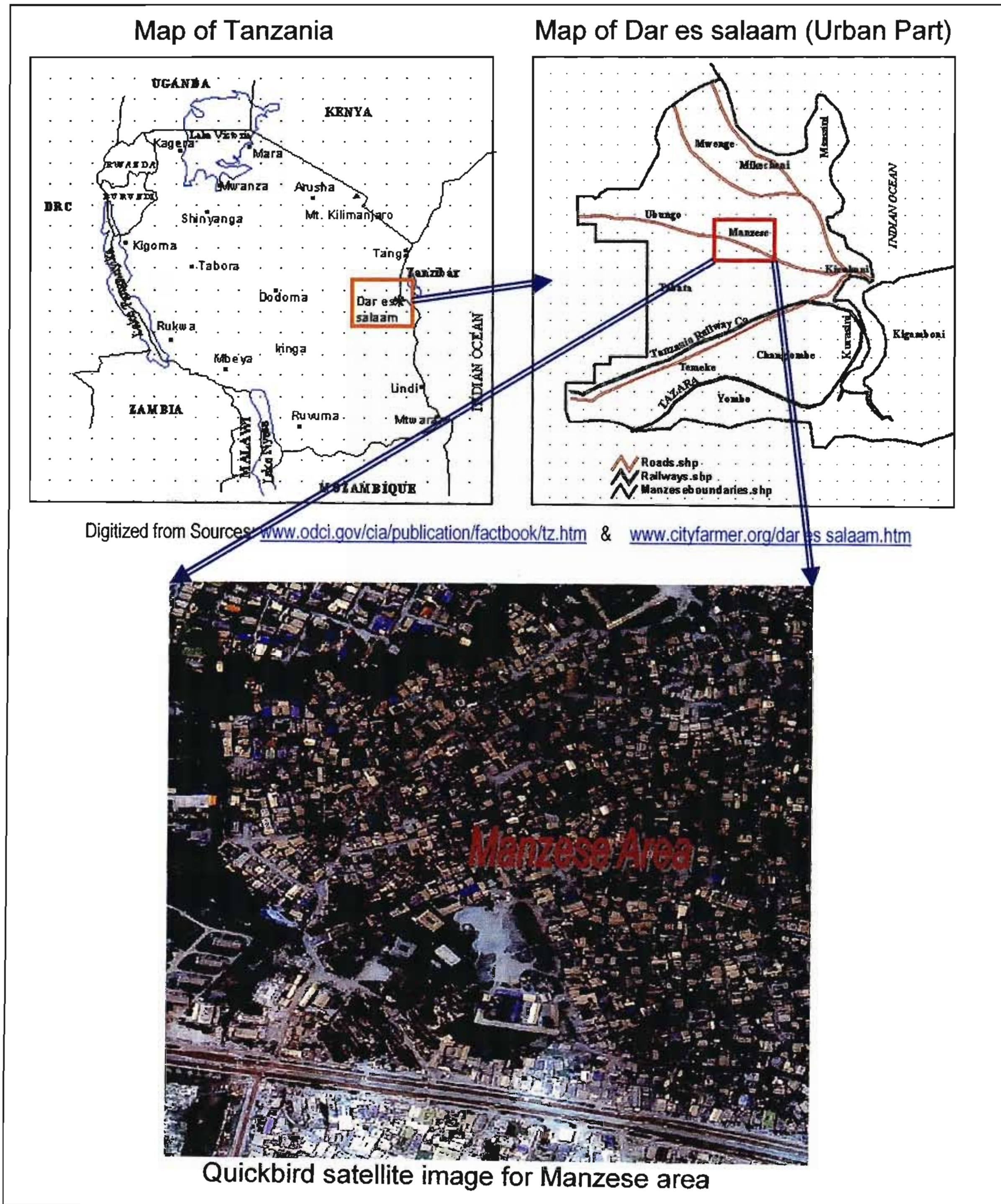


Figure 3:1 Location of the study area.

3.3 Image processing approach

The main procedure for image processing in this study included image pre-processing, sample training, classification, output accuracy assessment and classified feature segmentation (i.e vectorization of classified image).

The framework in Figure 3:2 was adopted as a suitable approach for this study to detect and extract informal buildings and other urban features.

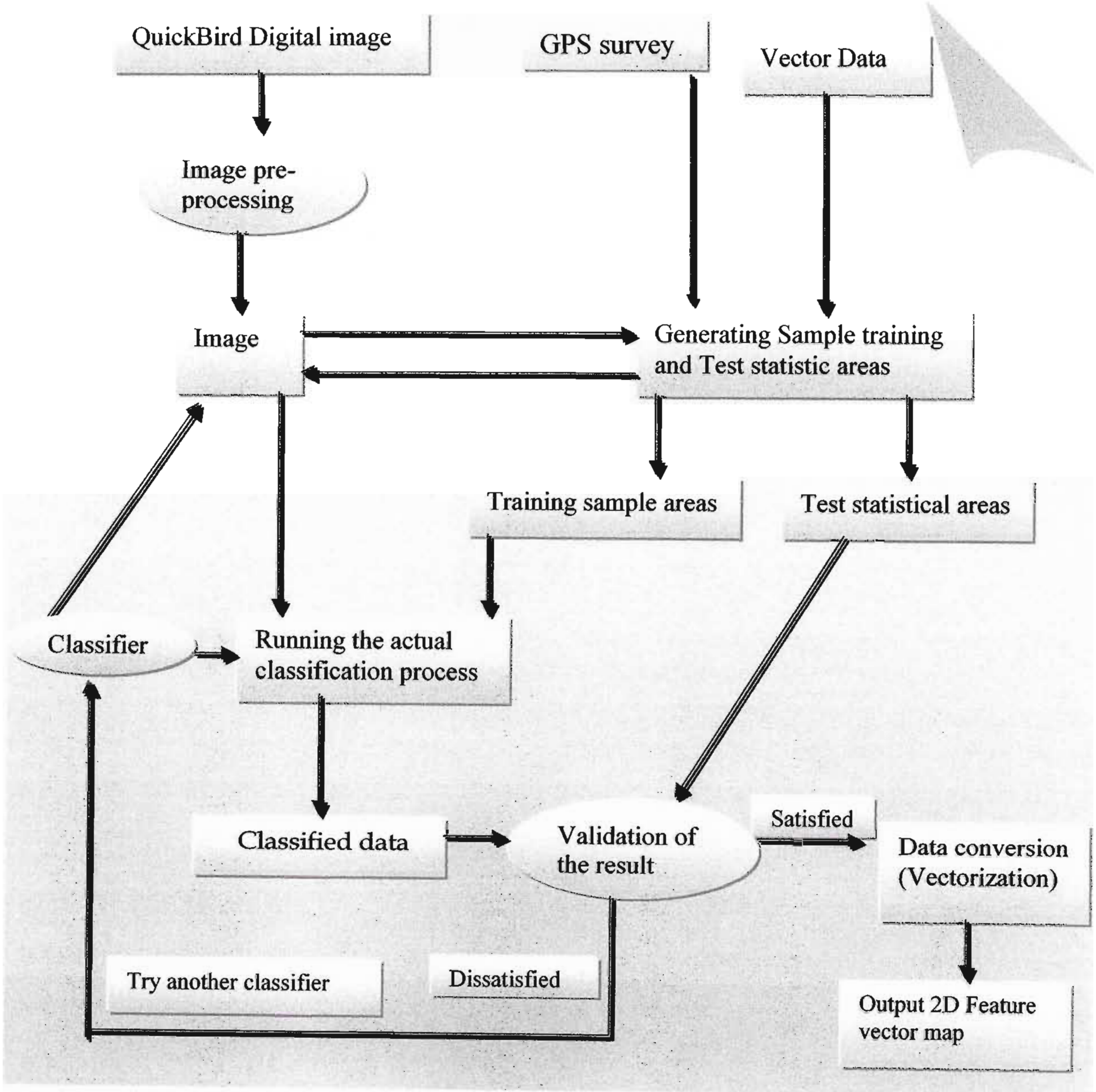


Figure 3:2 Image processing framework for informal building detection

3.3.1 Data

This study used high-resolution Quickbird satellite image and digitized vector shape file in Table 3-1 and Figure 3:3 respectively, were acquired from the Tanzanian Ministry of Land and Human Settlement Development. Both datasets were in UTM coordinate system, thus no further geometrical transformation and georeferencing was required due to precise matching between the datasets.

3.3.1.1 Quickbird images data

The metadata for Quickbird satellite image used in this study has the following specific information in table 3-1 below.

Table 3-1 QuickBird information

Acquisition Date	2004
Orbit Altitude	450 Km
Map Projection	UTM Zone 37, WGS 84
View Angle	Nadir
Revisit Time	1-3.5 days depending on Latitude (30° off-nadir)
Swath Width	4.9 Km x 4.9 Km for one scene (1km x1km for area of interest)
Metric Accuracy	23-meter horizontal (CE90%) without ground control
Resolution	Pan: 61 cm (nadir) to 72 cm (25° off-nadir) MS: 2.44 m (nadir) to 2.88 m (25° off-nadir)
Image Bands	Pan: 450 - 900 nm Blue: 450 - 520 nm Green: 520 - 600 nm Red: 630 - 690 nm

3.3.1.2 Vector data

Vector data used in this study was prepared through manual sketching of informal building parcels from printed QuickBird satellite image and later digitized in GIS environment to develop vector shape files and database containing socio-economic information (represented in figure 3:3 below). The output vector data is in UTM zone 37, WGS 84 reference coordinate system. This particular data source was used to capture attribute codes corresponding to various building's roof information.

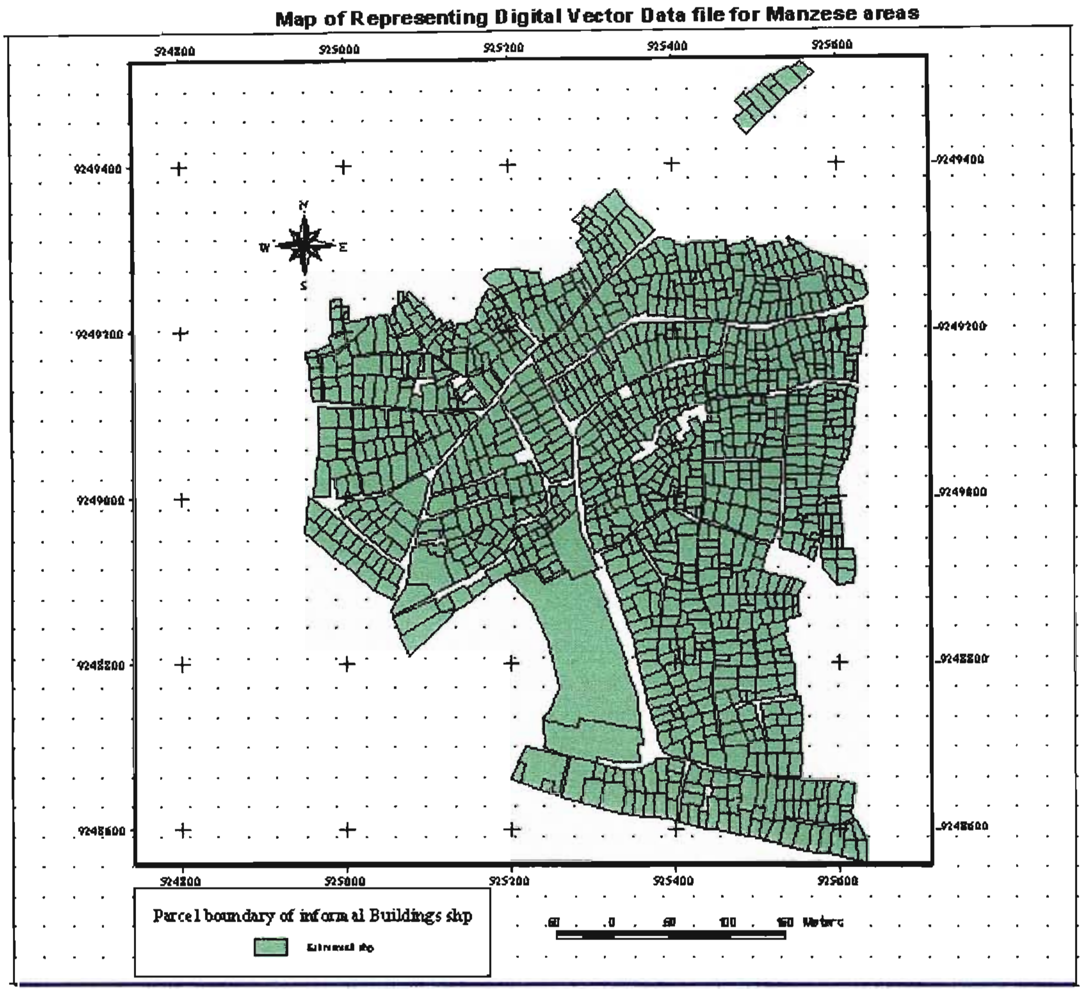


Figure 3:3 Map representation of digital vector data file

Additionally, feature verifications was conducted by field observation using handheld GPS, for which corner points of some areas of interest identified as suitable training areas were measured by determining coordinates of corner points and later in the process these points were joined by straight lines to define sample polygons to represent the actual situation on the ground (appendix c).

3.3.2 Data processing

Data processing involved downloading and importing of images and vector data as well as analyzing the data using ILWIS, Arc View GIS and Microsoft-Excel software. For this particular case the strategy for image processing was accomplished in two phases; The first involved classification of major land cover types, while the second phase dealt with minor classes aimed at discriminating individual buildings using roofing material homogeneity and other land cover characteristics as the basis for undertaking the classification process.

3.4 Generation of training and test sample areas

Development of training and test statistic sample areas was done by on screen digitization of sample polygons from QuickBird image, used as a backdrop on computer screen. Vector data which constituted building's roof descriptions and set of coordinates from GPS observations were overlaid on QuickBird satellite image to facilitate the process of assembling pixels to their respective categories.

3.4.1 Sampling design consideration

The description of training and test statistical sample areas is also another extremely important component in order to achieve higher classification performance of the output image. A combination of simple, stratified and cluster random sampling approaches were adopted to develop polygons representing sample areas. It should be noted that delineation of polygons is a necessary and considerable approach for random assembling of pixels in their respective classes; meanwhile, the analyst task was to concentrate in picking up features of the same category. Yet, efforts were made to make sure that training sites were chosen from almost all data segments distributed throughout the image scene.

Separation between training and test statistic areas was done by random selection of areas. This was done by numbering all polygons representing sample areas and later generated random numbers using Microsoft-excel software within the required range to ascertain the compilation of training and test statistical sample areas.

3.5 Image classification

Digital image classification uses the spectral information represented by digital numbers in one or more spectral bands and attempt to classify each individual pixel based on this information. The basic principle of classification is to assign a label to each instance, where each label corresponds to a class of its own properties that are represented as a region or pixels in the image data (e.g. tiled roofs, rust or white iron sheet, main road, vegetation, etc). The final themes were produced using supervised classification by employing statistical algorithms such as; Maximum likelihood, Box classifier and Minimum distance classifier. Based on visual and statistical interpretation of the output image, confused land cover types were removed or merged with other classes and reclassified iteratively in order to enhance the classification results.

3.6 Classification accuracy assessment

Several characteristics about classification performance are expressed by error matrix, which is intended to estimate the mapping accuracy of an image or map. The matrix is constructed from areas sampled from map or image then compares the relationship between the sampled reference (ground truthing) data and the corresponding results of an automated classification.

As reported in appendix A (error matrix Table 0-1, 0-2 and 0-3); pixels of training sample set classified into proper land cover categories are located along the major diagonal of the error matrix. The diagonal line helps to determine the *overall mapping accuracy*, which is the ratio of the total number of classified pixels to the total number of pixel checked in each class. Likewise, the accuracies of individual categories is calculated by dividing the number of correctly classified pixels in each category by either the total number of correctly classified pixel in the corresponding row or column. *Producer accuracies* result from dividing the number of correctly classified pixel in each category by the number of training set pixel used for that category, the producer accuracy number indicates how well training set pixels of the given cover type are classified. *User accuracies* are computed by dividing the number of correctly classified pixel in each category by the total number of pixels that were classified in those categories. It indicates the probability that a pixel classified into a given category actually represents that category on the ground (Lillesand & Kiefer, 2000).

Additionally, Kappa index (K) statistics is calculated for each error matrix of the respective classification algorithm. K is a measure of the difference of the actual agreement between the reference data and an automated classifier and the chance of agreement between the ground truth data and random classifier (Skidmore, 1999). Conceptually, K is computed by;

$$K = \frac{\text{Observed accuracy} - \text{Chance of Agreement}}{1 - \text{Chance of Agreement}}$$

$$K = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum(X_{i+} * X_{+i})}$$

Where X_{ii}=Total number of observation in row i and column i on the major diagonal

X_{i+} =Total of observations in row i

X_{+i} =Total of observation in column i

N =the total number of observation included in the matrix.

Note: The processing algorithms for ILWIS software are based on pixel classification analysis using the distribution mean, median and standard deviation (See in appendix A). This implies that interpretation relied on pixel information and not on polygon statistics, as they were only useful in the preliminary stage of assembling pixel to their respective classes.

3.7 Image segmentation (Vectorization)

After conducting image classification and post classification, segmentation was employed to divide the output image into manageable class regions. The image was vectorized into line segments of feature polygons using ILWIS software then exported into Arc view GIS as DXF file for further editing. Editing process followed after overlaying the segmented vector file on the original QuickBird image to facilitate manual editing of feature outlines and removal of unwanted polygons, since noise information could easily be visualized on the original image. It should be noted that in 2D mapping, most buildings are considered to represent rectangular shapes. Nevertheless, one needs to be aware of the complex phenomenon of informal areas and its shape diversity so that the final output represents the actual situation on the ground.

4 Results and Discussions

High spatial resolution satellite images offer new opportunities for many applications. In theory, a better classification is possible as high-resolution image offer more information, while in practice, many new problems appear. Due to high spatial resolution, objects that are too small to locate in low-resolution images are visible in high-resolution image and as a result the number of different classes that can be detected increases and discrimination between classes becomes more difficult (Skidmore, 1999 cited in Stein *et al*, 2002).

4.1 Image classification and assessment

4.1.1 Phase One

In this phase, three major feature categories were defined to classify major land cover types that included; built up areas, urban agriculture, and roads for which maximum likelihood algorithm was used to conduct the coarse classification process.

A total of 116 polygons (i.e. 57508 pixels) with an average of 88 (45848 pixels) training areas and 28 (11660 pixels) accuracy assessment sites (Table 4-1, 4-2 and 4-3) were developed using three methods.

1. Using coordinates obtained from field visit for which areas of interest for feature categories were surveyed using Garmin hand held GPS[4].
2. Using vector data consisting of building description and
3. Direct on-screen digitization from Quickbird image as the spatial scale allows ground feature identification of all phenomenons depicted on the image scene.

The use of these three methods facilitated a fulfillment for developing sufficient number of training and test statistic areas (see section 2.4.1.2). The number of

[4] A device used to measure locations by describing point coordinates to their respective positions

polygons developed for each class was proportional to the area of that class in the total ground data.

Table 4-1Training and test statistical areas for major land cover types

Feature Class	Number of sample training areas used		
	Ground survey	Vector data	Image
Agriculture	4	0	20 + 8*
Built up area	1	13 + 2*	12 + 7*
Roads	1	0	38 + 10*
Total	116 Areas (i.e.= 57508 pixels)		

Table 4-2 shows the statistical distribution of digital values for broad classification from sample training area polygons of each class

Table 4-2 Statistical distribution of digital values for broad classification

Agriculture					
Band	Mean	StDev	Nr	Pred	Total
1:	124.2	37.9	171	135	13185
2:	133.8	31.2	211	144	13185
3:	90.5	31.7	226	94	13185
Built up area					
Band	Mean	StDev	Nr	Pred	Total
1:	126.9	44	315	90	26173
2:	128.4	39.1	322	98	26173
3:	117.3	37.5	381	94	26173
Roads					
Band	Mean	StDev	Nr	Pred	Total
1:	138.5	47.3	133	200	6490
2:	140.4	39.1	130	195	6490
3:	126.4	30.3	118	166	6490
Sum of sample training pixels					**45848**

* Test statistic sample areas

Figure 4:1 below shows the broad classification output image for major land cover types obtained by using maximum likelihood classifier.

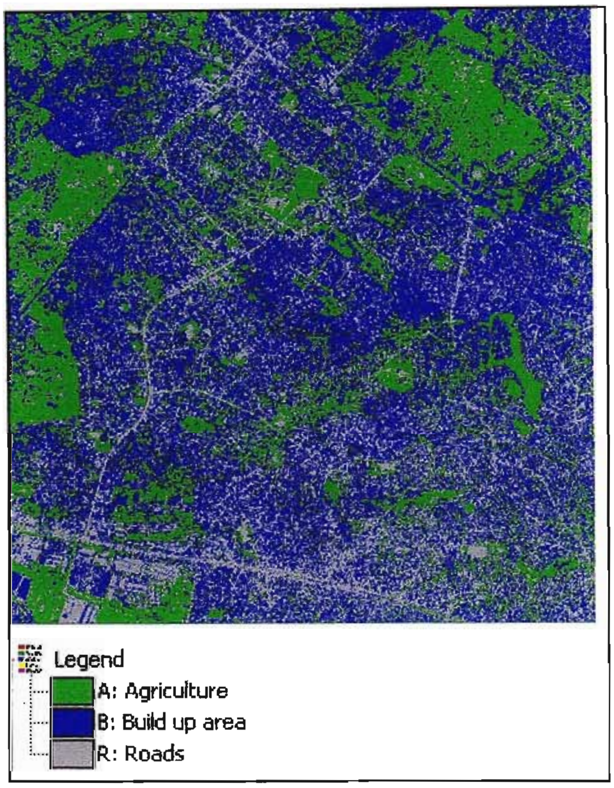


Figure 4:1 Classified image of the case study area depicting major land cover types

Error matrix computations (in Table 4-3) used pixel values and not polygons. Polygons were only useful in the preliminary stage to facilitate pixels assembling in the respective categories.

Table 4-3 Error matrix for major land covers classification process.

	Agriculture	**Build up area**	**Roads**	**Total**	**User Accuracy**
Agriculture	**4007**	851	1511	**6369**	0.63
Build up area	13	**2605**	1737	**4355**	0.60
Roads	38	195	**703**	**936**	0.75
Total	**4058**	**3651**	**3951**	**11660**	
P. Accuracy	0.99	0.71	0.18		**7315**

Note: records in the table 4-3 represents the number of pixels

Total number of observation N=11660

Sum of the Diagonal ΣX_{ii} = (4007 + 2605 + 705) = 7315

Average User Accuracy = (63 + 60 + 75)/3 = 66 %

Average Producer Accuracy= (99 + 71 + 18)/3 = 63 %

Overall Accuracy = $100^*\Sigma X_{ii}/N$ = 100*(7315/11660) = 63%

Computations for Kappa coefficient;

X i+	*X+i*	*(x i+ *X+i)*
4058	6369	25845402
3651	4355	15900105
3951	936	3698136
	Sum	**45443643**

$\Sigma (X_{i+*} X_{+i})$ = (4058 x 6369) + (3651 x 4355) + (3951 x 936) = 45443643

$$Kappa = \frac{N\sum_{i=1}^{r} X_{ii} - \sum_{i=1}^{r}(X_{i+} * X_{+i})}{N^2 - \sum(X_{i+} * X_{+i})}$$

Where: X_{ii}=Total number of observation in row i and column i on the major diagonal, X_{i+} =Total of observations in row i, X_{+i} =Total of observation in column i and N =the total number of observation included in the matrix.

There fore Kappa = $\frac{11660^*7315 - 45443643}{11660^2 - 45443643}$ = 0.44

4.1.1.1 Interpretation

After conducting a coarse image classification, visual interpretation showed that all the three themes were well represented with the exception of some patches that resulted from misclassification as a result of sharing representation of pixel values among land cover types. However, after analysis using error matrix, the achieved overall classification accuracy for maximum likelihood classifier was 63% with kappa coefficient of 0.44. This unsatisfactory result is consequently associated with high spatial resolution images, since objects that are too small to locate in low-resolution images become visible in high spatial resolution image. For this reason the number of different classes that can be detected increases and discrimination between classes becomes more difficult (Skidmore, 1999). This implies that, when carrying out broad classification from high spatial resolution the validation of classified results using algorithm is likely to produce poor accuracy than one can expect from visual interpretation since classification algorithms uses some aspects that cannot be considered visually.

Resemblance of pixel values between road category and that of buildings as well as big trees in built-up areas contributed towards affecting the process success at this level. This is because developed training and test statistic polygons covered wider areas providing possibility for pixel values of one category to be implicated into another cover type and finally affecting the entire results.

4.1.2 Phase Two

Procedures employed in a previous phase were also adopted at this classification stage, except that the number of classes and spatial training areas were relatively higher to cover the image information variability in order to facilitate the task of discriminating individual buildings and other urban features for which 11 Information classes were categorized. At this level, three classifiers were employed in the classification process that included; The Box, Minimum distance and Maximum likelihood classifier. Later classifiers were compared for their classification performance using their respective confusion matrices (appendix A).

A total of 189 polygons (86374 pixels) with an average of 112 polygons (46238 pixels) for training and 77 polygons (40036 pixels) for test statistic sample areas were generated using polygons from vector data and image layer resulting into an average of 17 samples polygons for each class.

The process of separating training and test statistic areas was conducted on the basis of individual classes for the purpose of having manageable number of polygons. These class polygons were first assigned unique numbers before being selected to their respective groups by matching to random numbers generated from tables in Microsoft-excel software.

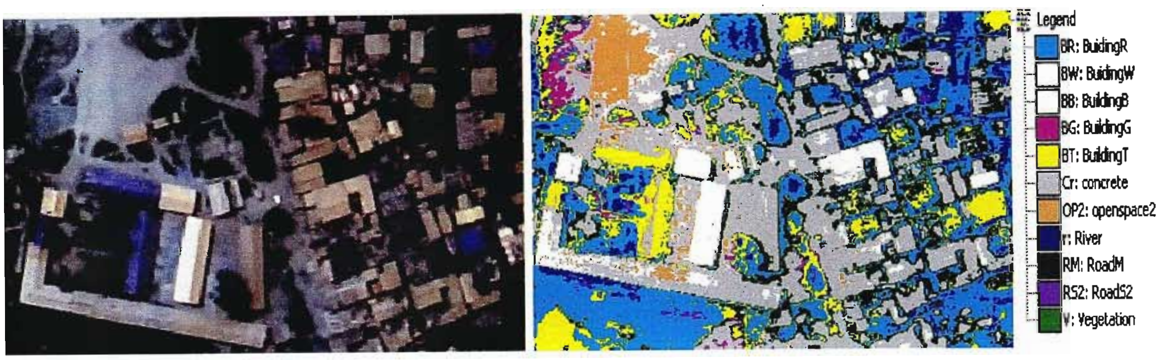
Feature categorization was developed using roofing material homogeneity and other urban structures as the basis for conducting training and classification process. Sample classes developed at this level included; white iron sheet, green sheets, blunt sheets, rusty sheets, tiles, concrete, street road, river bank, major road, open space and vegetation (Table 4-4). Attribute information from the vector data file were used to extract feature categories, and other additional samples were directly developed from the raster image given that on higher resolution image features can easily be identified, related or discriminated by their colours, shapes, and texture.

The developed land cover types and their respective training and test statistics are represented in Table 4-4 below.

Table 4-4 Land cover classes used for training and test sample sets

Code	**Theme**	**Land Cover Characteristics**	**No. Training areas**	**Test statistic**
V	Vegetation	Green vegetation	7	5
OP	Open space2	Open space	8	5
BW	Building W	White iron sheet	11	8
BG	Building G	Green Iron sheet	10	6
BR	Building R	Rusty iron sheet	13	9
BB	Building B	Blunt/Tarnish iron sheet	15	10
BT	Building T	Tiles or asbestos material	8	4
RS2	Roads1	Street roads	15	13
RM	Road M	Main roads (Tar road)	8	5
Cr	Concrete	Concrete roofs	8	4
r.	River bank	River/ Stream	6	4
		Total	**112 + 77= 189**	

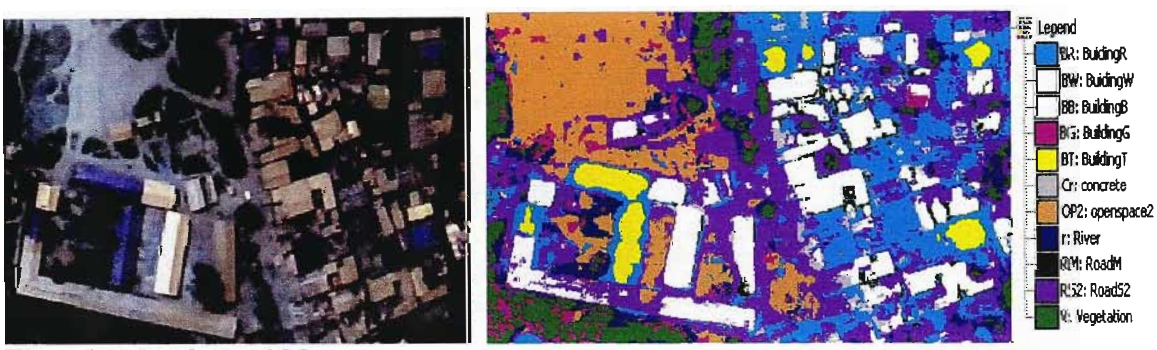
Images below (Figure 4:2, 4:3 and 4:4) represent classification results from The Box, Minimum distance and Maximum likelihood classifier.



Multiplicative factor 1.73

Overall classification accuracy = 40.78 %

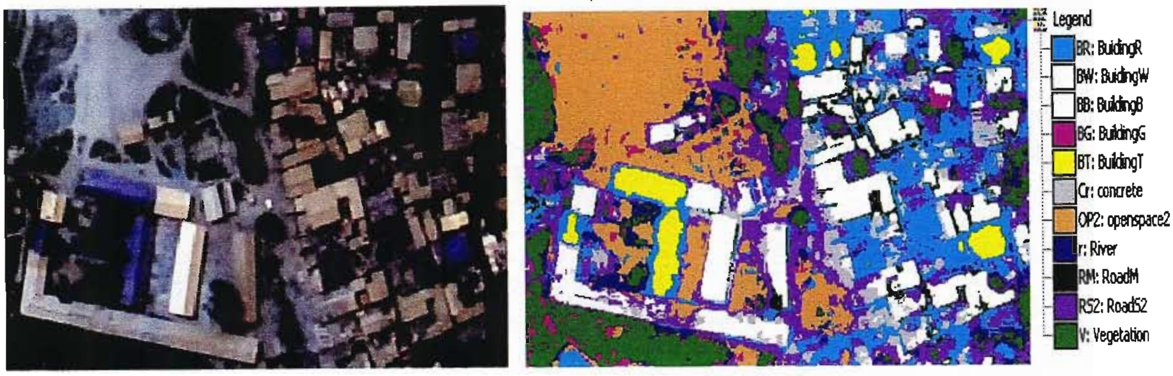
Figure 4:2 Image classified by box classifier



Threshold value =100

Overall classification accuracy = 79.81 %

Figure 4:3 Image classified by minimum distance classifier



Threshold value =100

Overall classification accuracy = 83.21 %

Figure 4:4 Image classified by maximum likelihood classifier

4.1.3 Accuracy assessment of classified maps

Measurement of classified mapping accuracy and agreement between image and ground truth data were accomplished using confusion matrices to compute their respective the overall accuracy and kappa coefficient. The total percentages of correctly classified pixels were computed using 77 test sample areas (i.e. 40036 pixels) for all spatial models (Table 4-5).

Table 4-5 Confusion matrix for maximum likelihood classifier

	BR	**BW**	**BB**	**BG**	**BT**	**Cr**	**OP2**	**r.**	**RM**	**RS2**	**V**	**Total**	**User accuracy**
BR	**1447**	1	2	0	44	8	10	145	71	85	0	**1813**	0.79
BW	0	**1143**	172	0	0	0	0	0	0	0	0	**1315**	0.87
BB	10	363	**3922**	0	0	44	0	0	157	0	0	**4496**	0.87
BG	0	0	0	**561**	0	0	483	10	1	0	213	**1268**	0.44
BT	0	0	0	0	**3064**	0	0	0	0	0	0	**3064**	1.00
Cr	218	16	48	0	0	**303**	0	0	130	366	0	**1081**	0.23
OP2	5	1	0	0	0	0	**14687**	615	2	90	1	**15401**	0.94
r.	12	0	0	0	0	0	515	**2963**	0	0	105	**3595**	0.82
RM	19	5	78	0	0	116	0	0	**2128**	40	0	**2386**	0.89
RS2	461	215	14	3	2	18	571	51	112	**379**	94	**1920**	0.15
V	3	0	0	0	0	0	649	330	0	0	**2715**	**3697**	0.73
Total	**2175**	**1744**	**4236**	**564**	**3110**	**489**	**16915**	**4114**	**2601**	**960**	**3128**	**40036**	
Producer Accuracy	0.67	0.66	0.93	0.99	0.99	0.62	0.87	0.72	0.82	0.39	0.87		**33312**

Note: V= Green vegetation, OP2= Open space, BW= White iron sheet, BG= Green Iron sheet, BR= Rusty iron sheet, BB= Blunt/Tarnish iron sheet, BT= Tiles or asbestos, RS2= Street roads, RM =Main roads (Tar road), Cr = Concrete roofs and r = River/ Stream

x_{i+}	X_{+i}	$\Sigma x_{i+*} X_{+i}$
2175	1813	3943275
1744	1315	2293360
4236	4496	19045056
564	1268	715152
3110	3064	9529040
489	1081	528609
16915	15401	260507915
4114	3595	14789830
2601	2386	6205986
960	1920	1843200
3128	3697	11564216
$\Sigma(x_{i+*} X_{+i})$	**Sum**	**330965639**

Below are computation of overall mapping accuracy and kappa coefficient based on results of the error matrix (Table 4-5)

Total number of observation N = 40036

Sum of diagonal

$$\sum_{i=1}^{r} x_{ii} = 1447+1143+3922+3064+303+14687+2963+2128+379+2715=33312$$

$$\text{Overall Accuracy} = \frac{1}{N}\sum_{i=1}^{r} x_{ii} = 33312/40036= 83.21\ \%$$

Where; X_{ii}=Total number of observation in row i and column i on the major diagonal

$$\sum_{i=1}^{r}(x_{i+} * x_{+i}) = 330965639$$

X_{i+} =Total of observations in row i, X_{+i} =Total of observation in column I

$$K = \frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} = \frac{\theta_1 - \theta_2}{1 - \theta_2}$$

Where: X_{ii}=Total number of observation in row i and column i on the major diagonal, X_{i+} =Total of observations in row i, X_{+i} =Total of observation in column i and N =the total number of observation included in the matrix.

$$\theta_1 = \sum_{i=1}^{r} \frac{x_{ii}}{N} = 0.8320 \quad \text{and} \quad \theta_2 = \sum_{i=1}^{r} \frac{x_{i+}x_{+i}}{N^2} = 0.20648$$

Therefore Kappa Coefficient (k) = $\frac{40036*33312 - 330965639}{40036^2 - 330965639} = 0.788$

The asymptotic variance of k, σ^2(k) can be computed by the equation below for which its output was later used to evaluate the normal curve deviate (z-statistic).

$$\sigma^2(k) = \frac{1}{n}\left(\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2 - \theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4}\right)$$

Where: $\theta_3 = \sum_{i=1}^{r} \frac{x_{ii}(x_{i+} + x_{+i})}{N^2} = 0.36911$ and $\theta_4 = \sum_{i,j=1}^{r} \frac{x_{ij}(x_{i+} + x_{+i})^2}{N^3} = 0.26573$

σ^2(k)=5.284*10^{-6}

σ = 0.00259

The overall classification mapping accuracy achieved was 83.21% while its Kappa coefficient (K) was 0.788 and the asymptotic variance (σ^2(k)) was 5.284*10^{-6}. Classification accuracy assessment for the Box and Minimum distance are presented in Table 4-6 below.

Table 4-6, summarizes the overall mapping accuracy, kappa coefficients and the asymptotic variance for the 3 classification models. Computations of Error matrices for Minimum distance and Box classifier are on the appendix A (Table 0-1, 0-2 and 0-3).

Table 4-6 Summary for mapping accuracy, kappa coefficient and asymptotic variance

Classifier	**Map accuracy**	**Kappa coefficient**	**Asymptotic variance**
Maximum Likelihood	83.21 %	0.788	$5.284*10^6$
Minimum Distance	79.81 %	0.749	$5.893*10^6$
Box (Parallelepiped)	40.78 %	0.333	$6.518*10^6$

Results on mapping accuracy in Table 4-6 showed that maximum likelihood classifier performed better than minimum and the Box classifier, the Box classifier yielded the lowest classification accuracy.

4.1.3.1 Interpretation

Visual and statistical analysis showed that the output image for individual building classification clearly depicted all 11 land cover types to the highest classification degree especially where Maximum likelihood and Minimum distance algorithm were employed. However there were general intricacies with some classes, for example big trees and shadows in built up areas contributed toward misclassification between these categories.

Maximum likelihood algorithm provided better accuracy of classified results than the Box and Minimum distance classifier. This is because maximum likelihood classifier uses a probability density function for each spectral class, which looks upon the probability of a pixel value belonging to a particular category and the likelihood of its occurrence in another category (Lillesand & Kiefer, 2000). Themes like 'street road against rusty and blunt buildings, and concrete surface against major road ' was affected as most of street roads pixels resembled rust and blunt building pixels category that interfered with the representation of these particular themes. This also contributed towards difficulties encountered by Minimum distance classification because some pixel classes were very close to one another in the measurement space while others had high variance consequently being affected by Euclidean distance of pixels belonging to class centers. However, the situation was dealt with by defining a convenience threshold value (100) to limit the search distance leading into minimum effect as most clusters were privileged resulting into enhanced performance accuracy of model.

Classification accuracy for the Box classifier was relatively lower due to the fact that the classifier only considers the range of values in each category which is defined by highest and the lowest spectral values (Skidmore, 1999). This difficulty was encountered in the classification process as a result of high variance of some spectral classes that lead into mixing-up of pixels because of overlapping of category intervals therefore affecting the entire classification result.

4.2 Classifier performance evaluation

This section aimed at comparing the performance of classifiers. Producer accuracy results of individual land cover types for each classifier (see Table 4-7) were used for this analysis. Producer accuracies information indicates how well training set pixels of the given cover type were classified.

Table 4-7 Showing performance of each classifier

	Producer accuracy of individual themes for each Classifier										
Classified Themes	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V
Classifier											
Box/Parallelepiped	0.27	0.78	0.17	0.32	0.69	0.70	0.34	0.76	0.82	0.00	0.00
Minimum Distance	0.67	0.69	0.90	0.99	0.98	0.45	0.82	0.73	0.73	0.66	0.72
Maximum Likelihood	0.67	0.66	0.93	0.99	0.99	0.62	0.87	0.72	0.82	0.39	0.87

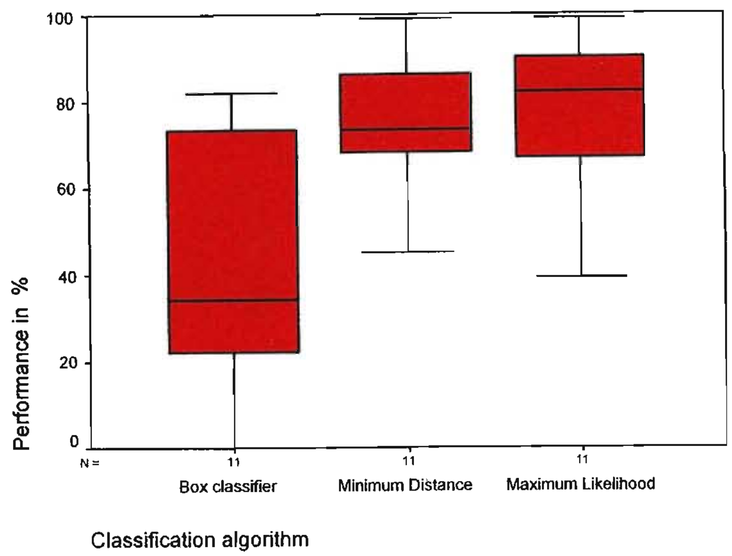


Figure 4:5 Assessment of classifier performance using the Box plot interpretation

The Box plot presented in Figure 4:5 was developed using SPSS for windows software and the producer accuracies in Table 4-7 above were used as data input, the results showed that the median for Maximum likelihood classifier is relatively higher compared to the Box and Minimum distance classifiers.

4.2.1 Testing for significant difference between the maps accuracy

Testing for statistically significant difference between classified maps from different models is important when analyzing and comparing the significance of using one classifier over another. Skidmore and Congalton (1999 and 1983 respectively, cited in Stein *et al,* 2002) suggest a technique for testing whether the two error matrices are significantly different by applying a discrete multi-variate analysis. This is done by varying the type of classifiers while other factors such as the date of image collection and training areas are kept constant for which the better analysis can be achieved by using k-values to test for statistically significant difference between images (i.e. k_1, k_2 and k_3 as representing image 1, 2 and 3 respectively) and their associated variance by evaluating the normal curve deviate (z). Therefore, the null hypothesis can be formulated as: there is no significant difference in the k-values between error matrices. Alternatively, the difference between k-values of error matrices is significant.

Formally formulated as;

$H_O \Rightarrow k_1 = k_2 \text{ or } k_3$

$H_1 \Rightarrow k_1 \neq k_2 \text{ or } k_3$

Where; k_1 refers to Kappa value for maximum likelihood classifier, k_2 refers to Kappa value for minimum distance classifier and k_3 refers Kappa value for the box classifier

At α = 0.05 significance level, the null hypothesis is rejected using the normal curve deviate statistics (z) if Z_t >1.96 (hence $Z_{\alpha \text{ at } 0.05}$ = 1.96).

An example below shows how the significance testing for maximum likelihood and minimum distance was computed; the results for other significance tests are presented in Table 4-8 below.

Maximum likelihood against Minimum distance

k_1 =0.788 (kappa value for maximum likelihood error matrix)

k_2 = 0.749 (kappa value for Minimum distance classifier)

σk_1=0.00204

σk_2 =0.00210

$$Z_1 = \frac{k_1 - k_2}{\sqrt{\sigma(k_1) + \sigma(k_2)}} = 0.606$$

Where: Z_1 Represent the Z-test statistics for maximum likelihood and minimum distance classifier, k_1 and k_2 = Kappa coefficients of likelihood and minimum distance classifier respectively, σk_1 = product of kappa coefficient of maximum likelihood classifier and its associated standard error, and σk_2 = is the product of kappa coefficient of minimum distance classifier and its associated standard error.

Computations for Z_2 and Z_3 statistics for results presented in the table 4-8 below are presented in Appendix D

Table 4-8 Comparison of test for significant differences between the output maps (z statistic)

Method	Box Classifier	Minimum Distance	Maximum Likelihood
Box Classifier			
Minimum Distance	6.96		
Maximum Likelihood	7.68	**0.606**	

Bold: Not significant at 0.05

4.2.1.1 Interpretation

From the results presented in the table 4-8 above, it can be concluded that at 95% confidence level, the output of Maximum likelihood is not significantly different from that of Minimum distance classifiers. Also it revealed that there is a reason to reject the null hypothesis for the Box classifier and conclude that the output of the Box classifier is significantly different from that of Maximum likelihood and minimum distance classifier.

4.3 Post processing stage

At this stage the output image from maximum likelihood classification was converted into vector format using segmentation function in ILWIS software, then exported to Arc view GIS for editing of feature outlines. This process was aimed at simplification and generalization of ground details as manifested on classified images. It included removal of unwanted segments and misclassified features while maintaining most of prominent features like buildings. Most of the unwanted segments came up as a consequence of "salt and pepper" effect of classified image output as a result of inherent of spectral variability encountered by the classifier when applied on pixel-by-pixel basis in the classification process.

The vector image below (Figure 6:6) represents the results after image segmentation and post processing, while Figure 6:7 shows the output vector image superimposed on the original Quickbird image.

Figure 4:6 Results of image segmentation and post processing

Figure 4:7 Output vector map overlaid on the base QuickBird image

4.3.1 Interpretation

Although image classification accuracy for this particular case was reasonably high, the segmented results showed that, the need of human intervention for further manual editing is inevitable so that mapping accuracy results can be enhanced and the actual phenomenon existing on the ground is truly represented.

The image below (Figure 4:8) is an overlay of maximum likelihood classified image and the database vector map that were superimposed to see whether the classified informal building borders match to parcel boundaries of the digitized map.

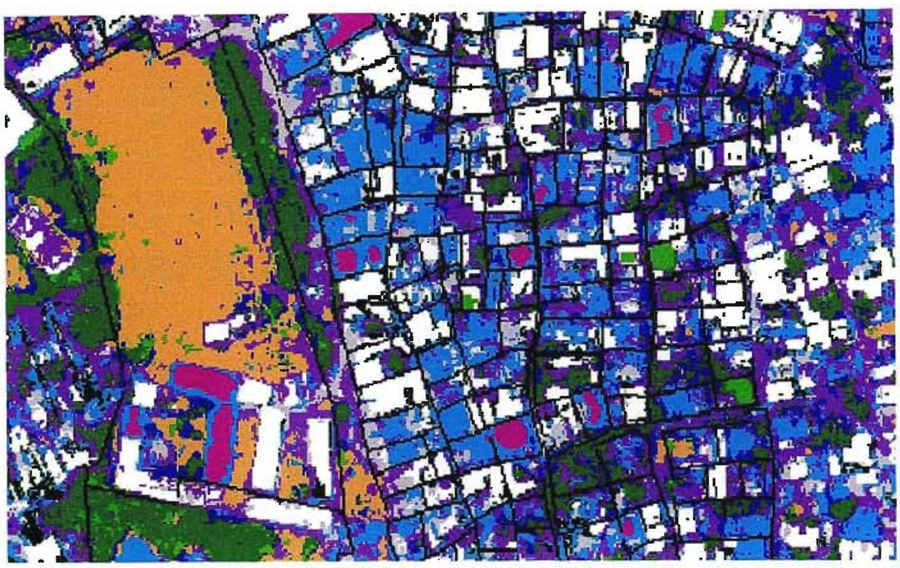


Figure 4: 8 *Digitized vector map overlaid on the classified image*

As previously discussed in section 2.4 regarding efficiency comparisons between automation technique against convention method of digitization in terms of the accuracy of the output, labour intensiveness and cost effectiveness for the whole process. This study reveals that; automation technique offers more flexibility and saves time when dealing with whatever form of data processing. However, there are errors associated with the implementation of this automation approach, for example developed boundaries are not exactly defining building borders as they can appear on the original dataset as a result of variability of spectral information within any particular category and confusion along building borders. Nevertheless this problem was dealt by applying majority filter kernel to the classified image.

5 Conclusion and Recommendation

5.1 Conclusion

A simple prototype approach for urban feature detection and extraction particularly on informal buildings has been presented, and tested the utility of high-resolution Quickbird image using different digital classification algorithms and segmentation of classified results. The approach is appropriate for processing any high-resolution digital image.

Broad image classification process resulted into an unsatisfactory 63% overall accuracy as a result of the effect caused by high inter-pixel variation associated with most high-resolution images, the scenario which is equally valid for QuickBird satellite image. This decreases the likelihood of neighbouring pixels from being similar, hence objects that are too small to locate in low-resolution images become visible in high-resolution image and as a result the number of different classes that can be detected also increases and the discrimination between classes becomes more difficult (Skidmore, 1999). Thus means, broad classification can only be more appropriate for images with a relatively low spatial resolution.

The maximum of 83% overall accuracy for individual buildings and other urban feature classification was achieved by employing Maximum Likelihood algorithm. Although the reported results sounds satisfactory for this purpose, the output vector map is yet to be reliable for database development and this was due to noise results as a consequence of over-detection and over extraction caused by texture and shape instability of many informal buildings leading to non-gray level uniformity even within same category. However the approach revealed potentials for future mapping application of informal settlement and other urban features.

The results also revealed that, the proposed approach could achieve far better accuracy if employed in well-structured areas. This was justified by the fact that all big buildings on the scene with characteristics resembling those of formal and semi formal areas were well detected and delineated.

Maximum likelihood classifier showed higher performance of 83% than Minimum distance (80%) and the Box classifier (41%). However, at α = 0.05 significance level the results revealed that mapping accuracy for Maximum likelihood and Minimum distance were not significantly different whilst it was vice versa for Box classifier which showed significance difference to both Maximum likelihood and Minimum distance.

5.2 Recommendations for future work

From the above conclusion, recommendations on future work to improve the applicability of the proposed approach can be considered along the following aspects.

Although image texture and energy intensity information is the base for digital image processing, the aspect of feature shapes plays a significant role when working within the urban context. Consideration to incorporate algorithms that are capable of dealing with aspects of feature shapes can contribute towards suppressing the noise level as a result of misclassification and over detection.

Most of the image Post-classification smoothing algorithms that are used so far, like the majority filter have not completely addressed inefficiencies resulting from salt and pepper effect. A solution for this problem can bring new advancement for digital image processing for urban applications.

Consideration of developing an automatic roof shape-fitting algorithm capable of detecting various shape dominant lines can be a step towards full automation of this proposed approach.

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COMPONENT B

6 ARTICLE

This article has been submitted for publication in the South African Geographical Journal

Detecting Informal Buildings from High Resolution Quickbird Satellite Image in Dar es salaam, Tanzania

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6.1 Abstract:

Documentation and formalization of informal settlements needs appropriate mapping and registration system of real property in order to integrate informal settlements into the formal city. For many years extraction of geospatial data for informal settlement upgrading have been through the use of conventional mapping, which included manual plotting from aerial photographs and the use of classical surveying methods that has proved to be slow, expensive and requires well-trained personnel.

The advent of high spatial resolution satellite images such as QuickBird has opened-up new opportunities for automatic detection and extraction of informal buildings and other urban features which could otherwise be masked by course resolution images. This study tests the utility of high resolution QuickBird image to detect and accurately map informal buildings in Manzese area, Dar es salaam. The overall mapping accuracy achieved for detailed classification of urban land cover was 83%. The output demonstrates the potential for further application of the proposed approach for urban feature extraction and updating. Besides, study constrains and recommendations for future work have also been discussed.

6.2 Introduction

The rapid growth of informal settlements has become the most complex and pressing challenges to land managers in developing countries. This has been as a result of slow pace in planning and surveying, which underpins the registration process of land rights of rapid growing informal settlements (Christensen, 2005).

In Tanzania, informal settlements that provide shelter to the majority of urban poor people stems from the past rural to urban migration since the country's independence in 1961.Currently about 70% of the total population in Dar es salaam lives in such areas, while other major towns figures around 60% (World Bank report, 2002; Baltsavias & Mason, 1997). The rapid growth of informal areas is also a result of an increasing level of poverty, population and lack of sustainable housing policies. In the 1960's the approach used to deal with growing informal settlements particularly in Dar es salaam was that of slum clearance with the intention of developing high quality housing in these areas. This approach was later abandoned due to economic and social costs. There have been other intermediate national strategies for upgrading informal houses before 1992 when UN Habitat adopted agenda 21[5] which laid out principles of sustainable development with the overall objective of improving social, economic and environmental quality of human settlements and finally be incorporated into the formal city (UNCED, 1992 cited in Abbot and Douglas, 2001).

For many years, mapping approaches for informal settlement upgrading have been through the use of conventional mapping that included manual plotting from aerial photographs and classical surveying methods that has proved to be expensive, slow and requires highly skilled personnel. As a result, they failed to harmonize with pace of rapidly growing informal areas (Ruther, Martine and Mtalo, 2002).

[5] Embodied recommendations from 1992 United Nations Conference on Environment and Development (UNCED)

The use of high-resolution satellite image and GIS tools to document and formalize informal settlements has been gaining popularity in recent years. High-resolution satellite images like Quickbird have drawn attention in various applications, and this has been due to its high temporal resolution that makes it possible for image scenes to be constantly up-dated, thus becoming more potential for covering new developments occurring in a particular locality. In addition, the high level of detail, variance of spectral and spatial information contents contributes towards the prospective application for rural and urban mapping.

The current settlement upgrading approach used in Tanzania is analogous to the recent work in Cape Town, South Africa, presented by Abbot and Douglas, (2001). Their reports highlights the implementation of the methodology termed as Visual Settlement Planning (ViSP) that uses spatial information and GIS approach for 'insitu' settlements upgrading. ViSP is a cost effective approach adopted in one of the programmes developed in Belo Horizonte, Brazil and tested in Kenya after realizing that the implementation of full scale settlement upgrading was not a feasible one. The process is done within a modular GIS environment, which involves digitization of shacks from Aerial photographs and integrates settlement physical aspects and social processes to analyze issues and potential planning response, together forming an information backbone of the entire project.

So far, many of these projects that uses high-resolution satellite images have not yet considered automation techniques for feature extraction. Instead, images are used as backdrop information on a computer screen to assist visual feature identification in order to facilitate manual on-screen digitization. As a consequence of conducting manual work, these methods seems to be less economical in terms of time, labour intensiveness and erroneous data inputs. In this regard, the development of a technique that automatically detects and extracts information from high-resolution satellite images is an important step towards efficient planning and management of informal settlement.

The objective of this study was to test the utility of high reslution QuickBird satellite image for automatic building detection and extraction to address inefficiencies of convention mapping and digitization approach. Different image classification methods like the Box, maximum likelihood and minimum distance classifier were tested and compared followed by segmentation and finally editing of feature outlines in order to produce a smart vector map.

6.3 The study area

The proposed technique for this study was tested in Manzese Area, a suburb of Kinondoni municipality that forms part of the City of Dar es salaam. Other district municipalities include Temeke and Ilala. The suburb is approximately 4 Km from the city center. It is currently highly populated and unemployment rate is estimated to be 75%. The major source of income of this group is through informal activities and micro-enterprises (World Bank report, 2002). Buildings are predominantly informal with various complex forms, sizes and roofs of diverse composition. Lack of infrastructure services and public facilities are some of the major characteristics of the area.

6.4 Spatial data collection

This study used high-resolution Quickbird satellite image and the digitized vector shape file that were acquired from the Tanzanian Ministry of Land and Human Settlement Development. Both datasets were in UTM coordinate system, for that reason no further geometrical transformation and georeferencing was needed due to precise matching between the two datasets. QuickBird image used in this study was acquired in the year 2004 and had the following specific information.

Table 6-1 QuickBird information

Map Projection	UTM Zone 37, WGS 84
View Angle	Nadir
Revisit Time	1-3.5 days depending on Latitude (30° off-nadir)
Swath Width	4.9 Km x 4.9 Km for one scene (1km x1km for area of interest)
Metric Accuracy	23-meter horizontal (CE90%) without ground control
Resolution	Pan: 61 cm (nadir) to 72 cm (25° off-nadir) MS: 2.44 m (nadir) to 2.88 m (25° off-nadir)
Image Bands	R, G, B and Near Infra-red

The vector data used was prepared through manual sketching of informal building parcels from printed QuickBird satellite image and later digitized in GIS environment to develop vector shape files and database containing socio-economic information. This particular data source was used to capture attribute codes representing various building's roof information.

Feature verifications was conducted by field observations using handheld GPS, for which corner points of some areas of interest identified as suitable training areas were measured by determining their coordinates and later in the process these points were joined by straight lines to define sample polygons to represent the actual situation on the ground.

6.5 Methodology

The strategy for image processing was done in two phases, which included coarse aimed at classifying major land cover types like build-up areas, urban agriculture and roads. Meanwhile minor land cover classification which is the focus of this article intended at discrimination of individual buildings on the basis of their roofing material homogeneity and other urban land cover characteristics.

The main procedures for image processing included; image pre-processing, sample training, classification, output accuracy assessment and classified feature segmentation (i.e vectorization of classified image). The framework in Figure 6:1 below was adopted as a suitable approach for this study to detect and extract informal buildings and other urban features.

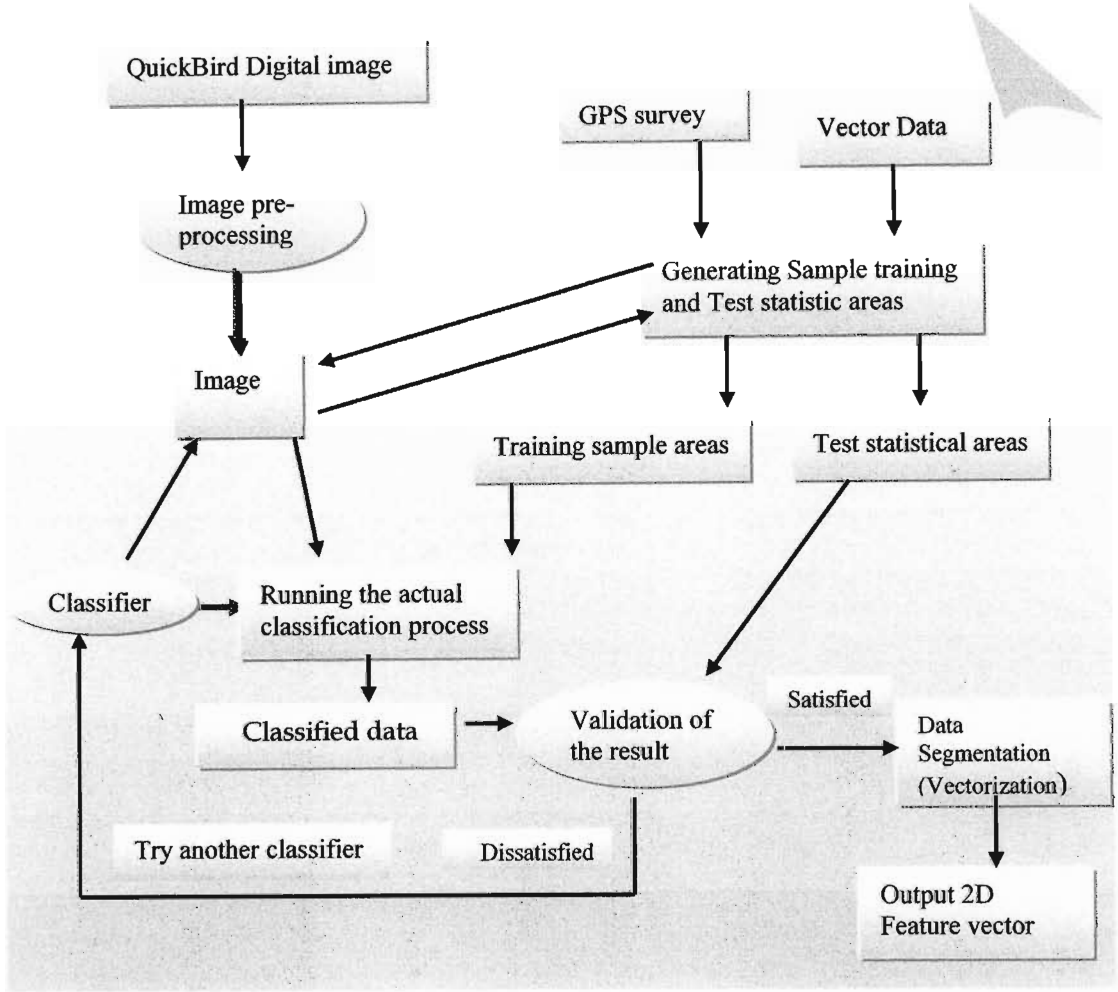

Figure 6:1: Image processing framework for informal building detection

6.5.1 Sampling design consideration for data collection

Description of training and test data sets was done by on-screen digitization of sample polygons from QuickBird image which was used as a backdrop on a computer screen. Vector data that constituted building's roof descriptions and set polygons developed from coordinates of GPS field observations were overlaid on the image to facilitate the process of assembling pixels to their respective categories. A total of 189 polygons (86374 pixels) with an average of 112 polygons

(46238 pixels) for training and 77 polygons (40036 pixels) for test statistic sample areas were generated using polygons from vector data and image layer resulting into an average of 17 samples polygons for each class. Separation between training and test statistic areas was conducted on the basis of individual classes. These class polygons were first assigned with unique numbers before been selected into their respective group by matching to random numbers generated using Microsoft-Excel software.

Feature categorization was developed using roofing material homogeneity and other urban structures as the basis for conducting training and classification process for which 11 sample categories were developed, these included; white iron sheet, green sheets, blunt sheets, rusty sheets, tiles, concrete, street road, river bank, major road, open space and vegetation (Figure 6:2 and Table 6-2). Attributes from the vector data file were used as reference information for sampling, however other additional samples were directly developed from the raster image given that on higher spatial resolution images features can easily be identified, related or discriminated by their colours, shapes, and texture.

6.6 Results

6.6.1 Image classification and assessment

The principle behind classification is to assign a label to each category. Each label must correspond to a class of its own property represented as a region or pixel in the image data. The final themes were produced using maximum likelihood, Box/parallelepiped and minimum distance classifiers. Based on visual and statistical interpretation of the output results, misclassified categories were removed and reclassified; by assembling relevant pixel categories and finally cross-examined using error matrix to check for result improvement. Figure 6:2 below represent output map image for maximum likelihood classifier, which yielded the highest classification accuracy.

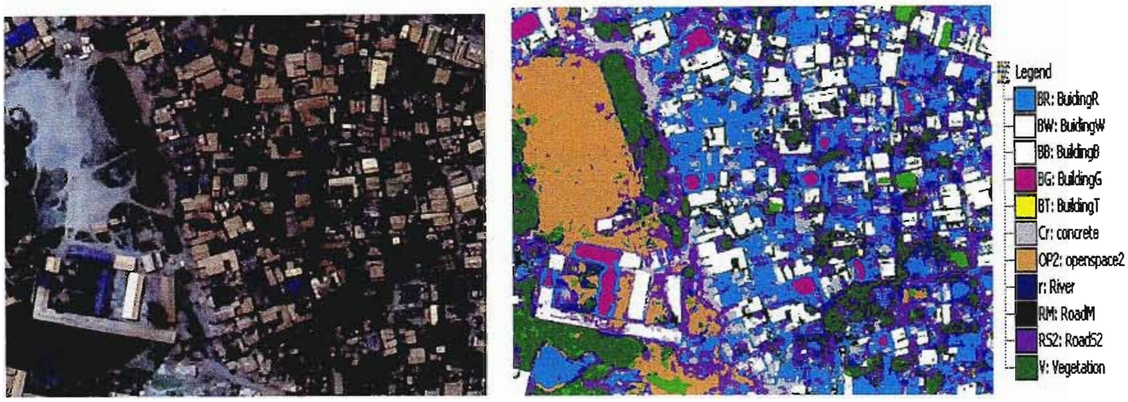

Figure 6:2: Image classified by maximum likelihood classifier

6.6.2 Image segmentation

This stage basically aimed at dividing the output image into manageable class regions. The classified image was vectorized into line segments of feature polygons using ILWIS software. The product image was then exported to ArcView GIS for further editing by overlaying the segmented vector file to the original QuickBird image for better visualization of unwanted line segments. Figure 6-3 below represents the final output image for this process.

Figure 6:3: Results of image segmentation and post processing

6.6.3 Accuracy assessment of classified maps

Measurement of classified mapping accuracy and agreement between image and ground truth data were accomplished using error/confusion matrices to compute their respective overall accuracies and kappa coefficients which was needed for testing the significance difference between output maps. The total percentages of correctly classified pixels were calculated using 40036 test sample pixels for all spatial models. Table 6-2 below represent the confusion matrix for maximum likelihood classifier, used to compute overall accuracy and kappa coefficient of the output image data.

Table 6-2:Confusion matrix for maximum likelihood classifier

Codes	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V	Total	User accuracy
BR	**1447**	1	2	0	44	8	10	145	71	85	0	**1813**	0.79
BW	0	**1143**	172	0	0	0	0	0	0	0	0	**1315**	0.87
BB	10	363	**3922**	0	0	44	0	0	157	0	0	**4496**	0.87
BG	0	0	0	**561**	0	0	483	10	1	0	213	**1268**	0.44
BT	0	0	0	0	**3064**	0	0	0	0	0	0	**3064**	1.00
Cr	218	16	48	0	0	**303**	0	0	130	366	0	**1081**	0.23
OP2	5	1	0	0	0	0	**14687**	615	2	90	1	**15401**	0.94
r.	12	0	0	0	0	0	515	**2963**	0	0	105	**3595**	0.82
RM	19	5	78	0	0	116	0	0	**2128**	40	0	**2386**	0.89
RS2	461	215	14	3	2	18	571	51	112	**379**	94	**1920**	0.15
V	3	0	0	0	0	0	649	330	0	0	**2715**	**3697**	0.73
Total	**2175**	**1744**	**4236**	**564**	**3110**	**489**	**16915**	**4114**	**2601**	**960**	**3128**	**40036**	
Producer Accuracy	0.67	0.66	0.93	0.99	0.99	0.62	0.87	0.72	0.82	0.39	0.87		**33312**

Note: V= Green vegetation, OP2= Open space, BW= White iron sheet, BG= Green Iron sheet, BR= Rusty iron sheet, BB= Blunt/Tarnish iron sheet, BT= Tiles or asbestos, RS2= Street roads, RM =Main roads (Tar road), Cr = Concrete roofs and r = River/ Stream

Below are computations based on information from the error matrix in Table 6-2 above;

Sum of the diagonal $\sum_{i=1}^{r} x_{ii}$ =33312

Overall mapping accuracy $= \frac{1}{N}\sum_{i=1}^{r} x_{ii}$ = 33312/40036= 83.21 %

$\sum_{i=1}^{r}(x_{i+} * x_{+i})$ = 330965639

x_{i+} =Total of observations in row i, x_{+i} =Total of observation in column i

Kappa coefficient (k) = $\frac{N\sum_{i=1}^{r} x_{ii} - \sum_{i=1}^{r}(x_i * x_{+i})}{N^2 - \sum_{i=1}^{r}(x_{i+} * x_{+i})} = \frac{\theta_1 - \theta_2}{1-\theta_2}$

Where; x_{ii}=Total number of observation in row i and column i on the major diagonal
x_{i+} =Total of observations in row i, x_{+i} =Total of observation in column i and
N =the total number of observation included in the matrix.

$\theta_1 = \sum_{i=1}^{r}\frac{x_{ii}}{N}$ = 0.8320 and $\theta_2 = \sum_{i=1}^{r}\frac{x_{i+}x_{+i}}{N^2}$ = 0.20648

Therefore Kappa coefficient (k)= $\frac{40036*33312 - 330965639}{40036^2 - 330965639}$ = 0.788

The asymptotic variance, σ^2(k) and kappa coefficient k was computed using equation 3 below; its output was later used to evaluate the normal curve deviate (z-statistics).

$$\sigma^2(k) = \frac{1}{n}\left(\frac{\theta_1(1-\theta_1)}{(1-\theta_2)^2} + \frac{2(1-\theta_1)(2\theta_1\theta_2-\theta_3)}{(1-\theta_2)^3} + \frac{(1-\theta_1)^2(\theta_4 - 4\theta_2^2)}{(1-\theta_2)^4}\right)$$

Where: $\theta_3 = \sum_{i=1}^{r}\frac{x_{ii}(x_{i+}+x_{+i})}{N^2}$ = 0.36911 and $\theta_4 = \sum_{i,j=1}^{r}\frac{x_{ij}(x_{i+}+x_{+i})^2}{N^3}$ =0.26573

x_{ij} = Is the value in the error matrix at the intersection of ith row and jth column.

Therefore; σ^2(k)=5.284*10^{-6}

The overall classification mapping accuracy achieved for maximum likelihood was 83.21% while its Kappa coefficient (k) was 0.788 and the asymptotic variance was 5.284*10^{-6}. Classification accuracy assessment results for the Box and minimum distance are also presented in Table 6-3 below.

Table 6-3, summarizes the overall mapping accuracy, kappa coefficients and the asymptotic variance for the 3 classification models.

Table 6-3: Summary for mapping accuracy, kappa coefficient and asymptotic variance

Classifier	Map accuracy	Kappa coefficient	Asymptotic variance
Maximum Likelihood	83.21 %	0.788	5.284*10^6
Minimum Distance	79.81 %	0.749	5.893*10^6
Box (Parallelepiped)	40.78 %	0.333	6.518*10^6

Results on the mapping accuracy in Table 6-3 showed that maximum likelihood classifier performed better than minimum distance and the Box classifier. The Box classifier yielded the lowest classification accuracy as compared to the two models.

6.6.4 Classifier performance evaluation

This section aimed at comparing the performance of classifiers. Producer accuracy results for individual land cover types for each classifier (Table 6-4) were used for this particular analysis. Producer accuracies information indicates how well training set pixels of the given cover type were classified.

Table 6-4: Showing performance of each classifier

	Producer accuracy of individual themes for each Classifier										
Classified Themes	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V
Classifier											
Box/Parallelepiped	0.27	0.78	0.17	0.32	0.69	0.70	0.34	0.76	0.82	0.00	0.00
Minimum Distance	0.67	0.69	0.90	0.99	0.98	0.45	0.82	0.73	0.73	0.66	0.72
Maximum Likelihood	0.67	0.66	0.93	0.99	0.99	0.62	0.87	0.72	0.82	0.39	0.87

Note: V= Green vegetation, OP2= Open space, BW= White iron sheet, BG= Green Iron sheet, BR= Rusty iron sheet, BB= Blunt/Tarnish iron sheet, BT= Tiles or asbestos, RS2= Street roads, RM =Main roads (Tar road), Cr = Concrete roofs and r = River/ Stream

The Box plot presented in Figure 6:4 below was developed using SPSS for windows software and producer accuracies in Table 6-4 above were used as data input, and the results showed that the median for maximum likelihood classifier is relatively higher compared to the Box and minimum distance classifiers.

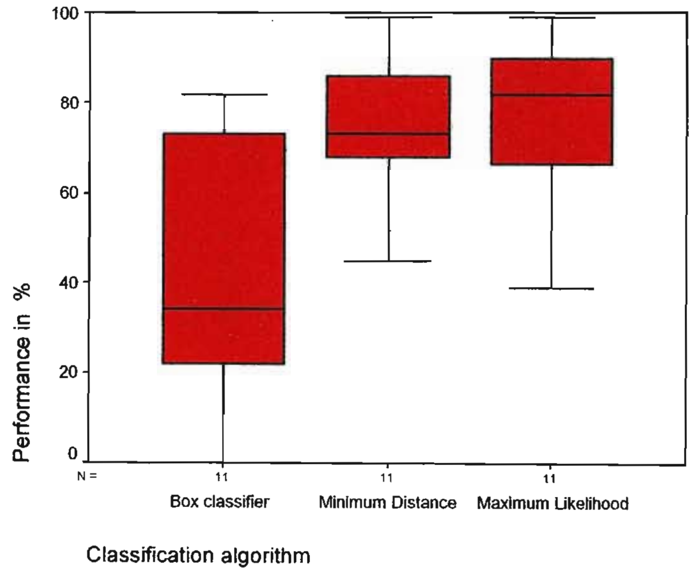

Figure 6:4 Assessment of classifier performance using the Box plot interpretation

6.6.5 Testing for significant difference between the maps accuracy

Testing for statistically significant difference between classified maps from different models is important when analyzing and comparing the significance of using one classifier over another. Skidmore (1999) and Congalton (1983) suggest that, a technique for testing whether the two error matrices are significantly different by applying a discrete multi-variate analysis. The technique is done by varying the type of classifiers while other factors such as the date of image collection and training areas are kept constant. This analysis can be achieved by using k-values to test for statistically significant difference between images (i.e. k_1, k_2 and k_3 as representing image 1, 2 and 3 respectively) and their associated variance by evaluating the normal curve deviate (z). Therefore, the null hypothesis can be formulated as: there is no significant difference in the k-values between error matrices of the different classifiers. Alternatively, the difference between k-values of error matrices is significant.

Formally stated as:

$H_O \Rightarrow k_1 = k_2 \text{ or } k_3$

$H_1 \Rightarrow k_1 \neq k_2 \text{ or } k_3$

Where: k_1 refers to Kappa value for maximum likelihood classifier, $k_2 \Rightarrow$ Kappa-value for minimum distance classifier and $k_3 \Rightarrow$Kappa value for the box classifier

At α = 0.05 significance level, the null hypothesis is rejected using the normal curve deviate statistics (z) if Z_t >1.96 (hence $Z_{\alpha \text{ at } 0.05}$ = 1.96).

An example below shows how the significance testing for maximum likelihood and minimum distance was computed, the results for other significance tests are presented in Table 6-5.

Maximum likelihood against Minimum distance

k_1 =0.788 (kappa value for maximum likelihood error matrix)

k_2 = 0.749 (kappa value for Minimum distance classifier)

σk_1=0.00204

σk_2 =0.00210

$$Z_1 = \frac{k_1 - k_2}{\sqrt{\sigma(k_1) + \sigma(k_2)}} = 0.606$$

Where; Z_1 Represent the Z-test statistics for maximum likelihood and minimum distance classifier, k_1 and k_2 = Kappa coefficients of likelihood and minimum distance classifier respectively, σk_1 = product of kappa coefficient of maximum likelihood classifier and its associated standard error, and σk_2 = is the product of kappa coefficient of minimum distance classifier and its associated standard error.

Result for computations of Z_2 and Z_3 statistics are presented in the table 6-5 below

Table 6-5: Comparison of test for significance differences between the output maps (z statistic)

Method	Box Classifier	Minimum Distance	Maximum Likelihood
Box Classifier			
Minimum Distance	6.96		
Maximum Likelihood	7.68	**0.606**	

Bold: Not significant at 0.05

From the results presented in Table 6-5 above, it can be concluded that at 95% confidence level, the output of Maximum likelihood is not significantly different from that of Minimum distance classifier. It also revealed that, the Box classifier significantly differs from that of Maximum likelihood and minimum distance classifier.

6.7 Discussion

This study has reflected the prospect in using high spatial and temporal resolution QuickBird image for detecting and mapping informal settlements. Based on visual and statistical analysis, the results showed that, the output image for individual building classification clearly managed to depict all 11 described land cover types to the highest classification degree especially where maximum likelihood and Minimum distance algorithm were employed.

Maximum likelihood algorithm provided better accuracy of classified results of 83% than minimum distance (80%) the Box classifier (41%). This is because the maximum likelihood classifier uses a probability density function for each spectral class, which looks upon the probability of a pixel value belonging to a particular category and the likelihood of its occurrence in another category (Lillesand & Kiefer, 2000).

Minimum distance classification accuracy was affected because some of pixel classes were very close to one another in the measurement space while others had high variance, consequently being affected by Euclidean distance of pixels belonging to class centers. However, the situation was dealt with by defining a convenience threshold value of 100 to limit the search distance leading into minimum effect as most of clusters were privileged, and thus enhancing the performance accuracy of the model.

Classification accuracy for the Box classifier was relatively lower due to the fact that the classifier only considers the range of values in each category which is defined by highest and the lowest spectral values (Skidmore, 1999). This complexity was encountered in the classification process as a result of high variance of some spectral classes that lead into mixing-up of pixels because of the overlapping of category intervals therefore affecting the entire classification result.

6.8 Conclusion and Recommendation for future work

A simple prototype approach for urban feature detection and extraction particularly on informal buildings has been presented and tested the utility of high spatial and temporal resolution Quickbird image using different digital classification algorithms and segmentation of classified results. The approach is appropriate for processing any high-resolution digital image.

Maximum likelihood classifier showed higher performance of 83% than minimum distance (80%) and the Box classifier (41%). However, at α = 0.05 significance level the results revealed that mapping accuracy for maximum likelihood and minimum distance were not significantly different, whereas it was vice versa for

Box classifier, which showed significance difference to both maximum likelihood and minimum distance.

The results also revealed that, the proposed approach could achieve far better accuracy if employed in well-structured areas. This was justified by the fact that all big buildings on the scene with characteristics resembling those of formal or semi formal areas were well detected and delineated.

Although the maximum of 83% overall accuracy for individual buildings and other urban feature classification achieved sounds satisfactory for this purpose, the output vector map is yet to be reliable for database development and this is due to noise results as a consequence of over-detection and over extraction caused by texture and shape instability of many informal buildings that leads into non-gray level uniformity even within same classified category, while on the other hand the approach have shown some potential for mapping applications of informal areas and other urban features.

From the above conclusion the authors recommends that;
Although image texture and intensity information is the basis for digital image processing, the aspect of shape plays a significant role when working within the urban context. Consideration to incorporate algorithms that are capable of dealing with aspects of feature shapes can contribute towards suppressing the noise level as a result of misclassification and over detection.

Most of the image Post-classification smoothing algorithms that are used so far, like the majority filter have not completely addressed inefficiencies resulting from salt and pepper effect. A solution for this problem can bring new advancement for digital image processing for urban applications.

6.9 Acknowledgement

The authors are grateful to the IT2- Fellowship Project for funding this research. We also extend our gratitude to the Land Information Management Programme of the University of KwaZulu-Natal, South Africa, and the Tanzanian Ministry of Lands and Human Settlements for providing data, facilities and technical support that made this study successful.

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APPENDICES

Appendix A

Image accuracy assessment using error matrices

Error matrices for maximum likelihood classifier

Table 0-1 Error matrix for detailed classification of land cover types for the maximum likelihood classifier.

	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V	Total	User accuracy
BR	**1447**	1	2	0	44	8	10	145	71	85	0	**1813**	**0.79**
BW	0	**1143**	172	0	0	0	0	0	0	0	0	**1315**	**0.87**
BB	10	363	**3922**	0	0	44	0	0	157	0	0	**4496**	**0.87**
BG	0	0	0	**561**	0	0	483	10	1	0	213	**1268**	**0.44**
BT	0	0	0	0	**3064**	0	0	0	0	0	0	**3064**	**1.00**
Cr	218	16	48	0	0	**303**	0	0	130	366	0	**1081**	**0.23**
OP2	5	1	0	0	0	0	**14687**	615	2	90	1	**15401**	**0.94**
r.	12	0	0	0	0	0	515	**2963**	0	0	105	**3595**	**0.82**
RM	19	5	78	0	0	116	0	0	**2128**	40	0	**2386**	**0.89**
RS2	461	215	14	3	2	18	571	51	112	**379**	94	**1920**	**0.15**
V	3	0	0	0	0	0	649	330	0	0	**2715**	**3697**	**0.73**
Total	**2175**	**1744**	**4236**	**564**	**3110**	**489**	**16915**	**4114**	**2601**	**960**	**3128**	**40036**	
P. Accuracy	**0.67**	**0.66**	**0.93**	**0.99**	**0.99**	**0.62**	**0.87**	**0.72**	**0.82**	**0.39**	**0.87**		***33312***

Average Accuracy = 70.21 %

Average Reliablity = 77.55 %

Overall Accuracy = 83.21%

Σx_{i+}	ΣX_{+i}	$\Sigma x_{i+} X_{+i}$
2175	1813	3943275
1744	1315	2293360
4236	4496	19045056
564	1268	715152
3110	3064	9529040
489	1081	528609
16915	15401	260507915
4114	3595	14789830
2601	2386	6205986
960	1920	1843200
3128	3697	11564216
	Sum	**330965639**

Kappa=0.788

Error matrices for Minimum distance classifier

Table 0-2 Error matrix for detailed classification of land cover types for the minimum distance classifier.

	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V	Total	User accuracy
BR	**1459**	1	1	0	58	33	20	229	173	120	0	**2094**	**0.69**
BW	1	**1212**	299	0	0	0	0	0	0	0	0	**1512**	**0.80**
BB	8	286	**3813**	0	0	35	0	0	208	0	0	**4350**	**0.87**
BG	0	0	0	**561**	0	0	659	20	1	0	488	**1729**	**0.32**
BT	0	0	0	0	**3050**	0	0	0	0	0	0	**3050**	**1.00**
Cr	73	2	12	0	0	**219**	0	0	62	150	0	**518**	**0.34**
OP2	0	0	0	0	0	0	**13860**	607	0	43	0	**14510**	**0.95**
r.	6	0	0	0	0	0	754	**3002**	0	0	264	**4026**	**0.75**
RM	10	4	37	0	0	92	0	0	**1888**	12	0	**2043**	**0.92**
RS2	618	239	74	3	2	110	1322	108	269	**635**	123	**3503**	**0.15**
V	0	0	0	0	0	0	300	148	0	0	**2253**	**2701**	**0.83**
Total	**2175**	**1744**	**4236**	**564**	**3110**	**489**	**16915**	**4114**	**2601**	**960**	**3128**	**40036**	
P.Accuracy	**0.67**	**0.69**	**0.90**	**0.99**	**0.98**	**0.45**	**0.82**	**0.73**	**0.73**	**0.66**	**0.72**		**31952**

Average Accuracy = 69.27 %
Average Producer accuracy = 75.82 %
Overall Accuracy = 79.81 %

Σx_{i+}	ΣX_{+i}	$\Sigma x_{i+} X_{+i}$
2175	2094	4554450
1744	1512	2636928
4236	4350	18426600
564	1729	975156
3110	3050	9485500
489	518	253302
16915	14510	245436650
4114	4026	16562964
2601	2043	5313843
960	3503	3362880
3128	2701	8448728
	Sum	**315457001**

Kappa =0.749

Error matrices for Box classifier

Table 0-3 Error matrix for detailed classification of land cover types for the Box classifier.

	BR	BW	BB	BG	BT	Cr	OP2	r.	RM	RS2	V	Total	User accuracy
BR	**587**	0	3	191	103	14	1648	348	199	31	1917	**5041**	**0.12**
BW	0	**1249**	57	0	0	1	5	0	0	0	0	**1312**	**0.95**
BB	2	193	**716**	43	8	10	1020	20	0	0	0	**2012**	**0.33**
BG	0	0	1	**183**	0	0	1155	3	0	10	0	**1352**	**0.14**
BT	533	0	0	0	**2106**	0	1376	60	0	5	46	**4126**	**0.51**
Cr	316	104	3289	114	69	**341**	4638	144	265	521	3	**9804**	**0.03**
OP2	0	61	0	0	46	0	**5824**	373	0	0	0	**6304**	**0.92**
r.	23	0	0	0	14	0	165	**3106**	0	0	961	**4269**	**0.73**
RM	698	2	170	33	9	123	1083	54	**2135**	393	41	**4741**	**0.45**
RS2	16	0	0	0	697	0	1	0	2	**0**	160	**876**	**0**
V	0	0	0	0	0	0	0	0	0	0	**0**	**0**	**0**
Total	**2175**	**1609**	**4236**	**564**	**3052**	**489**	**16915**	**4108**	**2601**	**960**	**3128**	**39837**	
P.Accuracy	**0.27**	**0.78**	**0.17**	**0.32**	**0.69**	**0.70**	**0.34**	**0.76**	**0.82**	**0**	**0**		**16247**

Average Accuracy = 38.00 %

Average Producer accuracy = 44.91 %

Overall Accuracy = 40.78 %

Σx_{i+}	ΣX_{+i}	$\Sigma x_{i+} X_{+i}$
2175	5041	10964175
1609	1312	2111008
4236	2012	8522832
564	1352	762528
3052	4126	12592552
489	9804	4794156
16915	6304	106632160
4108	4269	17537052
2601	4741	12331341
960	876	840960
3128	0	0
SUM		**177088764**

Kappa=0.33

Statistical distribution

Statistical distribution of reflectance data for fine classification from sample area polygons of each class

Table 0-4 Statistical distribution of reflectance data for broad classification

Band 1

	Mean	StDev	Nr	Pred	Total
RoadM	97.2	11.2	114	92	2338
BuildingR	96.4	16.8	254	93	7698
Building W	171.7	20.5	60	180	2376
BuildingB	132.5	17.6	202	120	6198
Building G	107.1	19.4	75	121	2498
BuildingT	120.7	15.6	94	121	2530
Concrete	129.6	17.3	103	132	2443
Open Space	148.5	22.9	353	169	10488
River	50.7	18.2	163	45	4325
RoadS2	114.2	36.7	102	150	3892
Vegetation	61.6	7.6	100	64	1452

Band 2

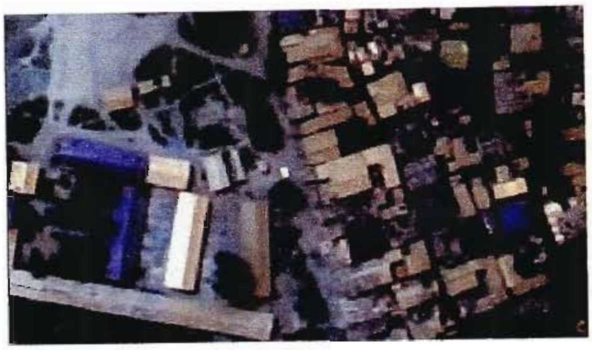
	Mean	StDev	Nr	Pred	Total
RoadM	107.3	8.3	140	104	2338
BuildingR	95.9	12.3	240	98	7698
Building W	180.5	19.2	88	181	2376
BuildingB	144.7	14.7	212	137	6198
Building G	133.8	15.2	81	138	2498
BuildingT	93.8	11.4	116	89	2530
Concrete	131	14.4	98	133	2443
Open Space	144	18.6	404	161	10488
River	65.7	13.6	166	62	4325
RoadS2	117.5	29.8	91	144	3892
Vegetation	80.4	7.1	96	83	1452

Band 3

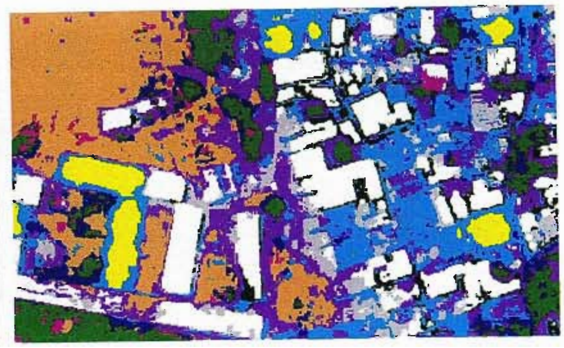
	Mean	StDev	Nr	Pred	Total
RoadM	106	9.8	115	109	2338
BuildingR	85.9	14	221	86	7698
Building W	178.1	23.3	68	163	2376
BuildingB	139.9	14.8	222	137	6198
Building G	107	15.2	83	112	2498
BuildingT	84.8	11.1	100	85	2530
Concrete	124.2	14.2	104	127	2443
Open Space	121.2	20	462	139	10488
River	46.2	14.8	205	35	4325
RoadS2	106.2	29.3	74	133	3892
Vegetation	58.3	5.7	143	57	1452

Appendix B

Output maps



Original satellite image



classified image

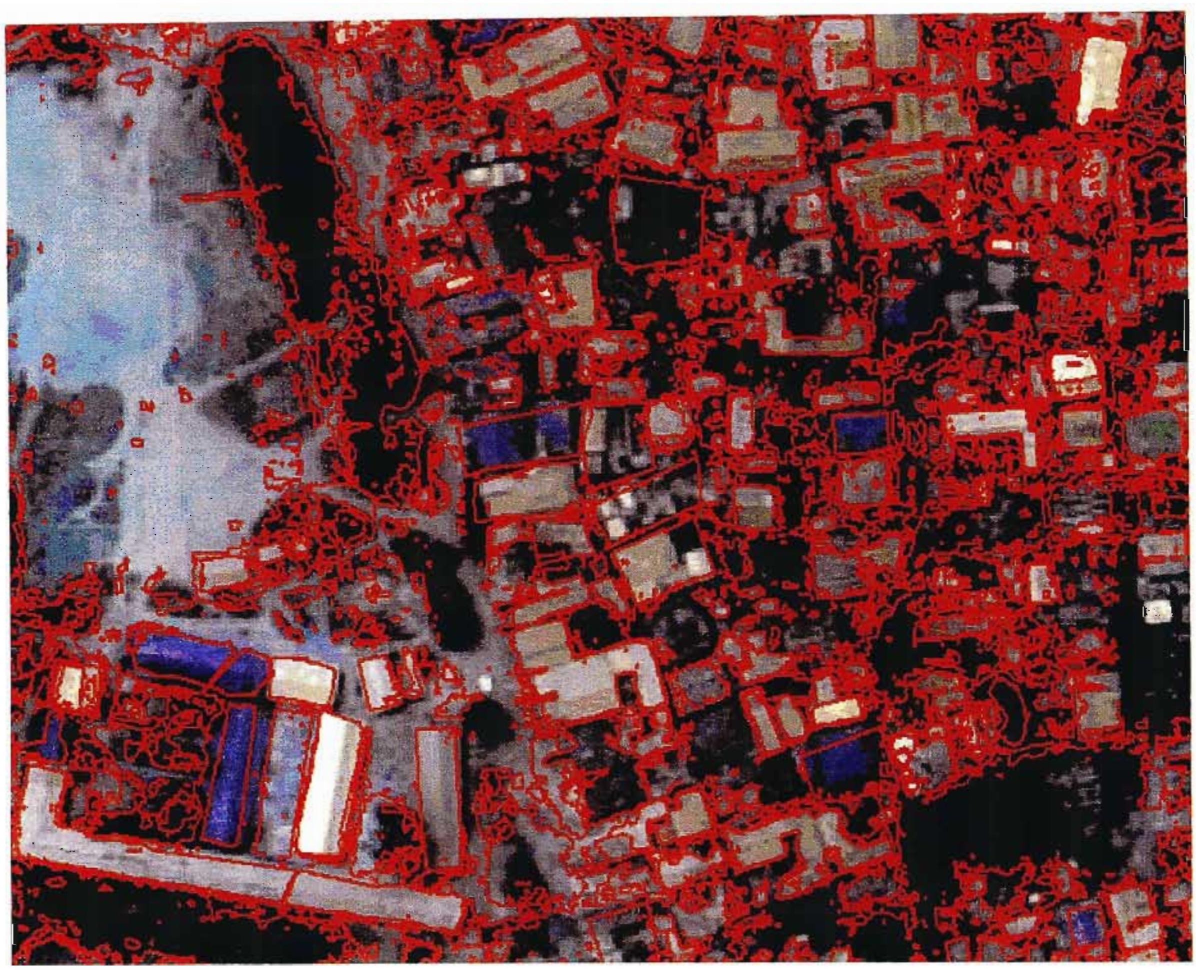


Figure 0:1 Extracted informal building polygons by means of classification superimposed to the original quickBird image

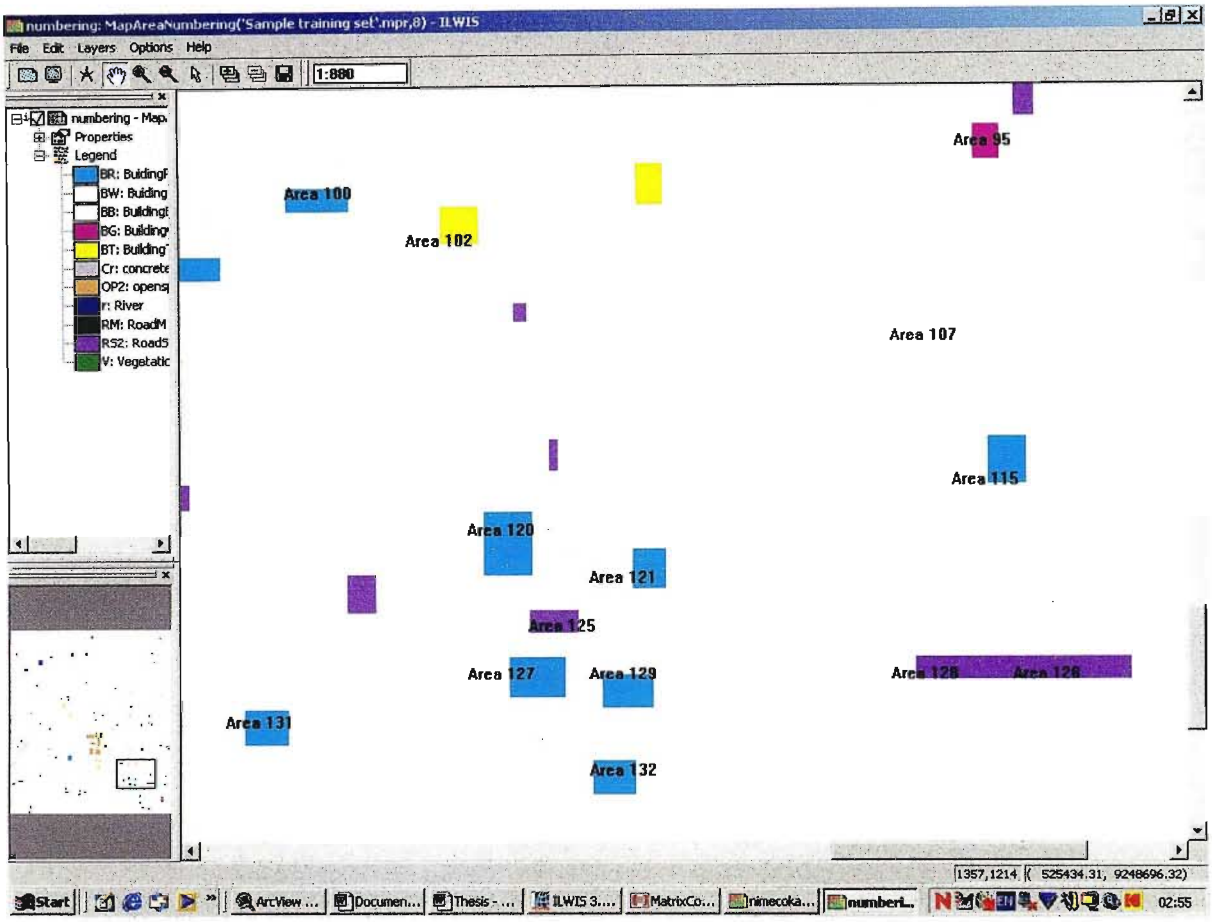


Figure 0:2 Numbering of polygons for training and test statistics sample areas

The labeled numbers on polygons were used for random grouping of sample areas in their respective training or test statistical categories during sampling stage.

Appendix C

Training areas from waypoints observed by GPS

```
Ground Truthing Areas
------------------------------------------------------------
     Informal areas    Open  525880.83   9248493.52
               525882.40   9248586.98
               525835.28   9248675.73
               525926.39   9248703.22
               525968.80   9248673.38
               526022.20   9248631.75
               525988.43   9248548.50
          Closerect   525956.23   9248473.10
-----------------------------------------------------

     Urban Agriculture Open  524149.80   9249975.58
               524137.23   9249863.27
               523996.64   9249914.32
          Closerect   524003.71   9250026.63

          Open  524471.03   9251353.19
               524369.71   9251203.96
          Closerect   524240.12   9251346.12
-----------------------------------------------------

     Formal areas      Open  524341.63   9251079.47
               524475.40   9250988.66
               524361.27   9250831.58
          End   524221.37   9250934.66
-----------------------------------------------------

     Wetland      Open  524880.37   9249231.31
               524891.42   9249113.50
               524623.89   9249057.05
          Closerect   524726.97   9249313.53
```

Appendix D

Test statistics computations

At α = 0.05 significant level, the null hypothesis is rejected using the normal curve deviate statistics (z) if Z_t >1.96 (hence $Z_{\alpha \text{ at } 0.05}$ = 1.96).

Maximum likelihood against Minimum distance

K_1 =0.788 (kappa value for maximum likelihood error matrix)

K_2 = 0.749 (kappa value for Minimum distance classifier)

σK_1=0.00204

σK_2 =0.00210

$$Z_1 = \frac{k_1 - k_2}{\sqrt{\sigma(k_1) + \sigma(k_2)}} = 0.606$$

Maximum Likelihood against Box Classifier

K_1 =0.788 (kappa value for maximum likelihood error matrix)

K_3 = 0.333 (kappa value for the Box classifier)

σK_1=0.00204

σK_3 =0.00147

Z_2= 7.68

Minimum Distance against Box classifier

K_2 = 0.749 (kappa value for Minimum distance classifier)

K_3 = 0.333 (kappa value for the Box classifier)

σK_2=0.00210

σK_3 =0.00147

Z_3= 6.96