

Spatiotemporal analysis of urban growth of five global cities using remote sensing, population estimates and GDP growth

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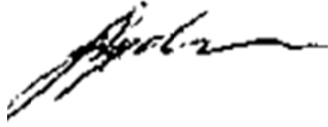
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MSC (Masters by Course Work & Research Report)

A Research Report submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg, in partial fulfilment of the requirements for the degree of Master of Science

DECLARATION

I declare that this Research Report is my own, unaided work. It is being submitted for the Masters of Science in GIS and Remote Sensing at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.

A handwritten signature in black ink, appearing to be 'A. L. M.', written in a cursive style.

(Signature of candidate)

Signed on this 23rd day of August 2017

Abstract

This study used an object orientated image nearest neighbour classification method to quantify the urban area extent of five global cities over a period of 25 years. The cities analysed were Cairo (Egypt), Delhi (India), Dhaka (Bangladesh), Lagos (Nigeria) and Shanghai (China). The observations were made every 5 years from 1990 to 2015, six observations for each city using Landsat 5, 7 and 8 imagery.

The accuracy assessment process resulted in a minimum average overall accuracy of 78.29% and a kappa coefficient of 72.88% and a maximum average overall accuracy of 83.4% and a maximum kappa coefficient of 80.46%.

The classification results were used to quantify the size of the urban footprint of each of the cities. These results were used to analyse the relationship between UN population estimates and physical urban growth. A Pearson's correlation and a regression analysis, for each city and its population estimates, were used to further analyse the relationship. All the regression models resulted in a correlation coefficient of above 0.95 except for Dhaka with 0.868. All the regression analysis models had an R^2 above 0.90, except Dhaka at 0.77. The results showed that the population estimates do not follow the urban area growth trends and a weak relationship was identified.

The quantified size of the urban footprint was also used to analyse the relationship between GDP growth, as estimated by the World Bank and physical urban growth. A Pearson's correlation and a regression analysis was performed for each city and its population estimates, to further analyse the relationship. All the regression models resulted in a correlation coefficient of above 0.90. Regression analysis models all had an R^2 greater than 0.90, except Cairo at 0.81 and India at 0.89. The analysis pointed to a weak positive relationship. The results also indicated a complex relationship between economic growth and urban growth for all five cities and their countries. A potential lag effect between economic growth and urban area growth was identified. These results showed that there is indeed the relationship between urban growth and economic growth, though in all five cases the relationship is weak. The fact that these results differ between the countries also indicate that the relationship is highly complex.

Dedication

I dedicate this dissertation to my wonderful loving wife, without her support and advice I would not have been able to complete this study. I would also like to thank my parents for their continued support. Furthermore, I would like to thank the rest of my wonderful family for their support during this time.

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Firstly I would like to acknowledge my supervisor, Dr Merlo for her guidance and advice. Her support and advice drove me to complete this study. I have always been driven by the need to learn and study more. Dr Merlo has guided me during my Masters and today I can proudly say I have learned more than I could ever have imagined and have completed one of the biggest challenges of my life, with her help Dr Adam, has taught me and guided me on the processes of remote sensing. His years of experience and expert knowledge have been guided me during this study.

I would like to thank Mrs Krommenhoek, who has sparked an interest in statistics that I did not know I had.

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CHAPTER ONE - INTRODUCTION

1.1. Introduction

In 2014 it was estimated that 54% of the world's population (3.9 billion) resided in urban areas. This is expected to increase to 66% by 2050 (UN, 2014). Due to various reasons the growth is uneven across the world, for example, an estimated 90% of all urbanization from 2014 to 2050, is expected to occur in Africa and Asia (UN, 2014).

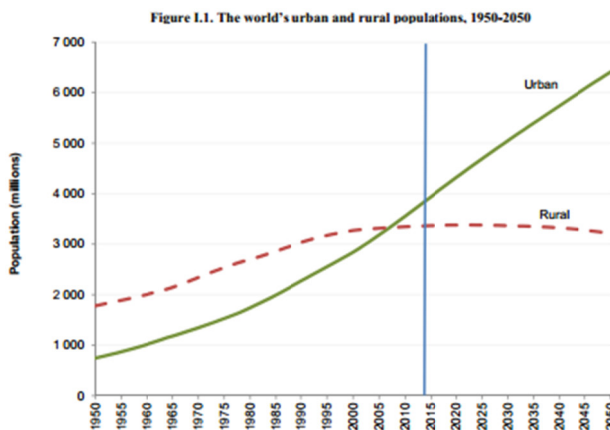


Figure 1: A graph illustrating that the world's total urban population (in green) has overtaken the rural population (in red) in 2010 (Source UN, World Urbanization Prospects, the 2014 Revision, Figure 2, p7)

Studies have indicated that due to the agglomeration of economies, cities are major contributors to national economies. Cities are important drivers of development and poverty reduction not only in urban areas but also in rural areas. This is due to the fact that cities are the centre points for economic activities, government institutions, educational and cultural institutions (Wheeler *et al.*, 1998).

Despite the advantages that urban areas provide if there is no or little economic growth that accompanies the growth of the urban population and urban areas, social and economic problems can emerge in these areas (Quigley, 2007). It has been hypothesized that the extent to which a city capitalizes on agglomeration would depend on political and economic structures which cannot always be controlled by government (Pacione, 2009).

Some countries and cities are unable to provide services for an ever expanding population (this is due to migration and/or natural growth) and as a result, informal dwellings and slum areas might contribute to worsening health, social, and economic problems (Shabu, 2010). For example, the lack of clean drinking water and good sewage removal systems in informal settlements contributes to various diseases, such as typhoid and diarrhoea (Pacione, 2009).

Environmental problems caused by urbanisation are extensive, and depletion of natural resources to sustain urban areas is a major problem in many countries around the world. These problems are usually caused by the lack of services, inability to enforce land use policies and low economic growth (Middleton, 2003).

Due to these problems experienced by cities, it is imperative that we develop an understanding of urban growth. A better understanding of urban growth can help shape policies to limit the negative effects of urbanisation.

Statistically, there is a strong relationship between urbanization and higher levels of GDP for most developed countries, especially when looking at an extended period (Chen *et al.*, 2014, Chenery *et al.*, 1968, Henderson, 2003). But research has highlighted the importance of re-examining the traditional view on the relationship between urbanization and economic growth and a need to rethink the relationship, especially for developing countries. Furthermore, the actual size of a city does not reflect the economic prosperity of a country or city (Turok & McGranahan, 2013).

Despite these issues, cities are still highly productive centres, with manufacturing, economic and educational facilities concentrated within large metropolitan areas (Duranton, 2014). An analysis of the productivity for the 750 biggest cities in the world, showed that they account for 57% of the world's GDP (Duranton, 2014). A big issue with large cities is that they sometimes “fail to relocate the production of mature products to secondary cities” (Duranton, 2014). This is especially true in developing countries, where large cities receive more investment, better services and a greater concentration of economic and industrial activities. The results in smaller urban areas to get less economic investment, a lack of labour and as a result

they tend to produce lower quality goods that results in less investment (Duranton, 2014)..

Remote sensing with the use of satellite sensors began in the 1960's as a method of investigating alterations of the Earth's surface and monitoring and modelling these changes (Howarth & Boasson, 1983). Satellite images can successfully be used to map changes over time by using historical archived data (Jensen & Cowen, 1999). Remote sensing therefore provides an ideal means for quantifying the growth of urban areas.

The study aimed to use an object based image classification method to quantify the size of the growing urban footprint and compare the rate of growth in urban footprint expansion between 5 global cities. Landsat 5, Landsat 7 and Landsat 8 images were used in this study, over a period of 25 years.

The rate at which urban population grows has a major impact on a city's physical urban footprint growth. As a result, the study measured how strong the relationship is between physical urban growth and the rate at which the population has grown, as estimated by the UN.

The rate at which countries GDP grow might have an impact on the rate of physical urban growth, as the economy grows more employment opportunities are created and more people move to urban areas. Therefore, future planning policies would need to take future economic growth into consideration. As a result, the relationship between GDP growth, estimated by the World Bank, and the measured size of the expanding urban footprint was explored.

1.2.Research problem, aims and objectives

1.2.1. Research problem

Most of the countries around the world have experienced a shift from a predominantly rural population to a more urbanised population. It has been predicted that this trend is set to continue. It is expected that Asia and Africa will experience

the majority of the foreseeable urbanisation (UN, World Urbanization Prospects, 2014).

This shift to a more urbanised population has brought a number of benefits, for example the agglomeration of labour, job opportunities, and better living conditions. However urban agglomeration is subject to a number of problems such as poverty, high unemployment rates, and rapid changes in the social composition of communities and neighbourhoods (Blanchard & Volchenkov, 2009). The urban areas have on the environment is varied, depending on a large number of reasons (Middleton, 2003). A lack of proper service delivery, e.g. sewage removal of garbage removal, can have a major impact on the environment. The large concentration of population in urban areas can have a major impact on air quality, as more people rely on motorised transport which burns fossil fuels. Industrial activities can contribute to water pollution, above and below ground (Middleton, 2003). The environmental impact of urban environments differs for almost all cities, this is due to different socio-economic conditions, neither the less the above mentioned environmental issues are only a brief overview of the impact urban areas have on the environment. It can be argued that in theory, as a country's economy grows and expands over time the urban population would also grow along with to supply labour (Wheeler *et al*, 1998).

The relationship between urban growth and economic growth is highly complex. For in less developed countries the urban population continues to grow but with little economic prospects and as a result, limited employment opportunities are available (Pacione, 2009).

To make provision for future urban growth a scientific understanding of cities is needed, especially on the relationship between economic growth and urbanisation.

1.2.2. Research question

The research was guided by the following questions:

- What is the rate of change of the urban footprint over five different global metropolitan areas, each in a different country, from 1990 to 2015, in 5-year increments?

- Is there a relationship between the rate of urban population growth and the growth of their urban footprint and can a comparison be made between the five metropolitan areas?
- Is there a relationship between GDP growth of the countries sampled and the growth of their urban footprint?

1.2.3. The aim of the study

The main aim of this study is to compare the rate of urban footprint growth for five global metropolitan areas, which have experienced the greatest increase in population from 1990 to 2015 as estimated by the UN. The reason for selecting the fastest growing city, by population, is that these urban areas might react more to GDP growth than other cities. This is because theoretically an increase in economic growth is accompanied by an increase in job opportunities, due to the agglomeration of manufacturing and services. This increase in job opportunities might attract more people to the urban areas in search of job opportunities and better living standards.

In this study, urban areas are defined as all manmade surfaces covering the physical environment. These include residential buildings, commercial buildings, industrial buildings and road surfaces. Due to agglomeration of economic activity, all of the above mentioned manmade structures should theoretically expand together as a country's economy grows over time. These manmade surfaces are identifiable on remotely sensed images through the unique spectral signatures of these surfaces, compared to natural vegetation, soil or water.

The relationship between the physical expansion of urban areas, UN population estimates, and World Bank GDP growth estimates was analysed. This was done by identifying urban areas for the five metropolitan areas using a nearest neighbour object-oriented classification method for Landsat imagery of the years 1990, 1995, 2000, 2005, 2010 and 2015.

1.2.4. The objectives of the study

The objectives of the study were:

1. A neighbour object-oriented classification approach was used to classify Landsat images for five global metropolitan areas, with the scope of identifying their urban footprint variation for the period 1990 to 2015.
2. To assess the absolute growth of the urban footprint for 5 metropolitan areas including its surrounding nodes, for the period 1990 to 2015.
3. To investigate the relationship between UN population estimates and urban footprint expansion estimates derived from the image classification process.
4. To investigate the relationship between World Bank GDP estimates and urban footprint expansion estimates derived from the image classification process.

1.3. Justification of this study

With a large concentration of people in urban areas, the pressure on the environment, services, food and aid are increasing in these regions.

The study will give an estimation of the rate at which urban areas grow in different regions around the world.

This study will try to establish the relationship between urban growth and GDP growth. If a trend is identified, this study might be helpful to guide future studies on the relationship between land use change and GDP growth. Also, environmental protection, aid allocation, economic, political and disaster management policies can be altered or adapted to allow for a more sustainable urban growth strategy as the economy or/and population continues to increase or decreases.

1.4. Limitations

It needs to be noted that, the cities selected for this study were not meant to be representative of the urbanization experienced by the five countries as a whole.

Environmental and geographical factors play an important role on urban expansion. For example physical barriers like rivers and mountains can limit the expansion of urban growth, environmental factors can also influence urban growth, and for

example frosts and even desert areas can further limit horizontal growth of urban areas. This study did not take these factors into consideration due to time constraints.

This study does not distinguish between different built-up land use types, e.g. industrial, formal residential or informal residential. This is despite of the fact that the relationship between land cover change and land use change is interconnected. The main reason for this is due to the scope of the study and time constraints. A more detailed study for each city would yield more information to assist in the analysis of the impact of urbanization on the environment, economy, and society but is beyond the scope of the present research project.

Land use policies adopted by some countries try to limit the horizontal expansion of urban areas and emphasize vertical expansion. Information on land use policies and how these policies are enforced would have been time consuming and difficult to acquire. As a result, this study did not include land use policies in its analysis.

Political factors might also influence the structure and growth of urban areas. This study did not include these factors in the analysis due to time constraints. A larger sample of cities would yield more detailed and accurate information for each of the countries. Such a sample will give a more information on how economic growth affects different sized urban areas.

A limitation to remote sensing with satellite images is the fact that remote sensing can't directly measure social well-being or health issues, but only allow for an indirect measure, e.g. pollution. A study that's able to incorporate social and health data measured by qualified psychologists/social workers and health workers would be able to study the exact impact of urbanization.

Only six time based measurements of urban area sizes was made for each of the cities, this was due to time constraints. A small sample like this might influence the results of some statistical tests.

The relatively low resolution of Landsat images (30m) is a drawback due to a fact that a single pixel might contain a mixture of land cover types. This might result in an inaccurate classification of land use types.

1.5.Outline of the Chapters

This concludes chapter one, which set out the research question, aims and objectives. Chapter two reviews and discusses the literature relevant to this study. Chapter three describes the methodology followed in this study. It starts off by describing how the five cities were selected and goes on to discuss the image acquisition process, classification method followed and finally how the data was analysed. Chapter four puts forth the results of the image segmentation process, the classification process accuracy assessment, the urban area sizes derived from the classification process and finally the results of the analysis on the relationship between urban growth and population estimates and GDP estimates. Chapter five discusses in detail the results put forward in chapter four. Chapter six concludes this report by highlighting the findings in the conclusion and finally the recommendations identified during this study.

CHAPTER TWO - LITERATURE REVIEW

In this chapter the literature consulted and reviewed during this study is covered. Firstly, the definition of urban is explored. There are a number of definitions as what a city is and where urban areas are located in a landscape. Once the definition of urban areas has been defined we explore the regional and global variation of urbanisation. The relationship between economic growth and urbanisation is explored, before looking at the influence of population estimates and urban growth. Then the question of how urban growth can be measured using remote sensing techniques is explored.

2.1 Defining Urban areas

The literature reviewed highlights the challenges of defining the concept of 'urban' and, as a consequence, identifying the extent of urban areas. The main identifying characteristics of an area that can be seen as urban were identified by Rashed and Jurgens (2010) as follows:

1. Population size of the urban area.
2. The use of land within a specific area.
3. The population density.
4. Economic and social organization within the area.

The difficulty of defining urban space is further highlighted by the UN Demographic Yearbook 2005. This contains a number of definitions for urban areas, which varies between world regions and countries. For example in Botswana, urban areas are defined as any area where an agglomeration of 5000 or more people and 75% non-agricultural economic activities take place. In India, urban is defined as all places having 5000 or more people and a population density of no less than 400 persons per square kilometre (UN, 2005).

All these definitions do not include an important aspect of urban areas, namely the interaction between neighbouring urban cores.

Schneider and Woodcock (2007) combined a number of definitions from various authors to define urban space. These definitions are set out as:

- a) “the movement of people and goods within and across the city” (Castells, 1996)
- b) “[Urban space] is made up of multiple nuclei, as clusters develop at different distances from the original urban core” (Harris & Ullman, 1945)
- c) “the city is an economic unit, includes small towns dependent upon a symbiotic relationship with or is dependent on the urban core” (Duranton & Puga, 2005).

Conceptualizing the metropolitan area in this way puts focus on the idea that large cities do not function independently and need to be analysed along with smaller villages, towns and cities surrounding the main urban core (Schneider & Woodcock, 2008).

For this study the definition of urban will not only take into account the largest concentration of built-up land-cover areas, the metropolitan areas, but also the smaller nodes surrounding the metropolitan areas. The reason for this is that a city does not function independently from the surrounding towns/cities, especially in regards to its economic activities. Theoretically growth in GDP will not only have an effect on large cities but also the nodes surrounding large cities. For this reason, it is important to study not only the metropolitan area but also smaller economic nodes.

2.2 Regional perspective on urbanization

Is the rate of urbanization the same for all countries or regions and if not can this variation in growth be explained?

The literature reviewed indicated that the growth of cities differs from country to country and region to region due to different social, demographic and economic factors. According to the UN World Urbanization Prospects report (2014), Europe, Northern America, Latin America and the Caribbean along with Oceania experience a rapid period of urbanization from the 1950's. The rate started to decrease over time. Africa and Asia however did not experience the same rate of urban growth as

the other world regions. Urbanization for these two regions has shown a steady increase over time as shown in Figure 2.

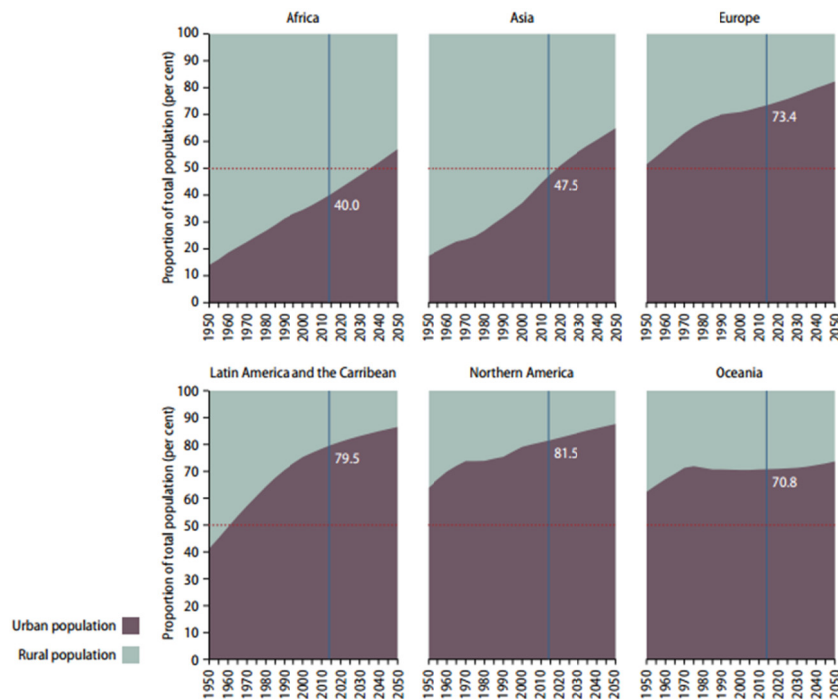


Figure 2: A graph illustrating the different rates of urban growth for different areas around the world (Source UN, World Urbanization Prospects, The 2014 Revision, Highlights, p.8)

In the USA the percentage of the population urbanized increased from 61% to 77% between 1950 and 1990, this shift can be explained by a rapid economic growth phase from the 1950's. Latin America and the Caribbean have seen a rapid increase of urbanization from the 1960's to 1990's, with 71.4 % of the population being urbanized by 1990 (UN, 2014).

Despite a slower economic growth compared to the USA for the same time period, the Latin American and the Caribbean region still experienced a rapid urbanization phase from the 1960's (UN, 2014). Europe, however, experienced an uneven urbanization pattern, with a rapid slowdown in the rate of urbanization for some countries due to demographic changes. Some regions in Asia have also experienced rapid urbanization due to the adoption of economic policies, e.g. China, India and Myanmar (UN, 2014).

2.3. Urbanization and economic growth

Urban studies have been, for the most part, reluctant in pursuing an international comparison between urban cities and the drivers of urban growth (Robinson, 2013). Studies have concluded that there is some evidence that urbanization can increase the level of GDP (Fujita *et al.*, 2014). Therefore, it might be said that an increase in GDP can encourage urbanization and in return the increase agglomeration of people and economies can increase GDP.

Literature showed that urbanization is a sign of prosperity (Chang & Brada, 2006). However, the complexity of cities and the relationship between cities and prosperity have been highlighted with new scientific disciplines and theories like self-organization theory (Portugali, 2006). These new approaches changed the way in which cities are studied and they are now being seen as biological systems, with a strong sense self-organization and pattern, even in cities that seem to be chaotic (Batty, 2012). With this new perspective on urban areas, showed that the relationship between urban area growth and economic growth is highly complex. Furthermore, that concentration of urban areas does promote economic growth. On the other hand, urban primacy, the formation of a main urban core that has obtained a great level of dominance over smaller areas, impacts negatively on economic growth (Bloom *et al.*, 2008).

In less developed countries, the rural population continues to grow but with little economic prospects resulting in people migrating to urban areas in search of employment opportunities (International Organization for Migration, 2014). This can occur despite the fact that some cities experienced little economic growth and as a result, limited employment opportunities are available (Pacione, 2009). Research has shown that the link between economic growth and urbanization in some developing countries studied are not clear (Shabu, 2010).

Today less developed countries are integrated into a globalized system and the global change in government, labour and consumerism might influence the levels of urbanisation despite low levels of GDP growth. Petrakos and Brada (1989) showed that under authoritarian governments rule, urban areas see disproportionately more

development in services than rural areas. Also, some of these authoritarian governments favour an urban cantered population which allow for more control over people than rural people (Petrakos & Brada, 1989).

A study on the relationship between GDP growth and urbanization for China, from 1975 to 2002, showed that there is an urban lag with the urban areas under-urbanized as the economy grows. Reasons for this include migration policies. The result of the lag had a negative effect on the economic growth as the demand for labour could not be met with a slow growing urban population (Chang & Brada, 2006).

In this study the relationship between GDP growth and the physical urban expansion will be explored. However, the GDP measurement has come under critique as it is sometimes used to infer a level of living standard. But GDP measurement was never designed for this purpose and does not reflect the real social and economic wellbeing of people or the cost of economic growth on the environment (Kenny, 2005). Due to a lack of good historical data and a not widely accepted “quality of life” index, this study used GDP as a measure of economic growth only and not an estimate of standard living.

GDP is an indicator of a country's economic growth, as stated by the World Bank:

$$GDP = Pc + GrI + GoI + GoS + (Ex - Im)$$

where: *Pc*: private consumption

GrI: gross investment

GoI: government investment

GoS: government spending

Ex: exports

Im: Imports

2.4. Population estimates and urbanization

An intersection observation made by Angel *et al.*, (2005), in which they analysed policy development and urbanization, found that as an urban population doubles the urban area triples. This has significant implications for service delivery and sustainability. If their observation is true, it means that governments need to be

prepared to supply services over an urban area which triples in size as the population grows, thus placing stress on resources.

A weak positive relationship between urban expansion (identified with remote sensing techniques) and population growth (indicated by the LandScan population density data) was identified by Hou *et al.*, (2016). Hou *et al.*, (2016) used a grid-cell-based analyses method to integrate the LandScan data with landcover data derived from remotely sensed data in the aim of quantifying the population density.

2.5. The influence of geographical and environmental factors on urban growth

Physical geography can have a major influence on the location of settlements and the way they grow over time. For example Pacione (2009) highlights the fact that Egypt's villages and urban areas traditionally formed next to the Nile river and continued to expand along the river system. Another example is settlements that formed along the Yellow river in China, these expanded and grow over time along the river system. This was due to the agricultural potential of the river banks.

Today these factors are just as important, rivers are sources of fresh water for urban areas. Areas considered for residential and commercial development are heavily influenced by the access to water (rivers), aesthetics of the environment and soil type to name a few (Wheeler *et al.*, 1998).

2.6. Measuring urban growth with the help of Remote Sensing

How can urban growth be measured, to allow for a comparison over time and between different cities? Due to the fact that urban areas cover large areas, it is a daunting task to physically measure the area covered by urban areas.

Using aerial and satellite images in the process of identifying and measuring urban area size have become invaluable. Images can be stored and archived and used at a later date, for identifying, classifying and quantifying urban areas. The process of using remotely sensed images or data to identify, classify or quantify phenomena is called remote sensing.

Taubenböck *et al.*, (2011) used an object oriented classification method on Landsat image and a pixel based classification method on Synthetic aperture radar data in the aim of identifying, quantifying and monitoring urban area growth of 12 Mega cities. The authors achieved an overall classification accuracy greater than 80% for all cities studied, allowing the classification results to be successfully applied to the monitoring of the 12 megacities. The study concluded results showed that satellite images allow for a spatial temporal measurement of urban areas.

A novel way to identify and measure population density over urban areas was developed by Hou *et al.*, (2016). Their method relied on the integration of LandScan population density data with land cover data, classified from Landsat 7 and Landsat 8 images, by using a Grid-cell-based method. The study managed to show how urban growth can be quantified and be used to identify particular patterns of growth. For the city of Cairo, the rate of urban growth was estimated at 2.79% and the urban expansion follows transportation corridors Hou *et al.*, (2016).

A critical aspect of urban growth is its population, without a population labour, a city might not be able to grow. Various remote sensing methods have been proposed in the aim of estimating population size. These methods do however rely on the integration of national census data with remote sensing data (Jorge *et al.*, 2012). Using Landsat TM data Yuan *et al.*, (1997) found that high correlations can be observed between classified land cover and population counts from census data. Harvey (2002) used Landsat TM data to classify residential and non-residential areas and integrate the results with census data. This allowed the author to calculate a population estimate per classified pixel.

In theory, urban growth is related to economic growth and hence people's living standards. Various methods of measuring and monitoring urban growth have been used, for example Landsat 7 TM images were used to measure the growth of Bangkok in Thailand (Madhavan *et al.*, 2001). While other studies use night-time satellite images to identify urban areas illuminated by lights (Sutton, 2003). This method will however not be applicable to areas where people live in informal settlements with little electrical access. Remote sensing has been shown to be a

valuable tool in the policy assessment relating to urban growth, population growth and environmental issues within cities (Bhatta *et al.*, 2010a; Miller & Small, 2003).

2.7. Using Remote Sensing to analyse Gross Domestic Product

Faisal and Shaker, (2014) analysed the relationship between nine Canadian cities and GDP growth. They managed to show that it is indeed possible to use remotely sensed urban area growth estimates to predict GDP growth. The study by Faisal and Shaker (2014) identified urban areas using a Normalized Difference Built-up Index (NDBI) and Normalized Difference Vegetation Index, derived from Landsat images. The study showed that there is indeed a strong relationship between urbanisation and GDP.

Despite the results shown in the study, as previously mentioned the relationship is not as clear for less developed countries (Quigley, 2007).

2.8. Change detection analysis

A change detection analysis quantifies the differences between different images from different time periods. With the increase in availability of satellite images, change detection has become a more popular and affordable method to analyse changes that have occurred over time (Campbell, 2011).

A change detection method used by Manonmani *et al.*, (2010) illustrates how change detection can highlight changes, over time, to a study area containing multiple land-cover classes.

A challenge to analysing temporal change detection is that if a large number of pixels are misclassified in year 1 but is correctly classified in year 2, the change detection method identifies areas where major changes have occurred (Campbell, 2011).

2.9. Image classification methods

Multiple image classification methods have been developed with the aim of identifying various materials, including vegetation, soil, built-up areas, minerals and atmospheric particles. Each classification method has its advantages and disadvantages.

Object oriented approach to image classification tries to delineate groups of pixels into objects on the bases of the object's texture, size and shape (Djenaliev & Hellwich, 2014). Research has also shown that the accuracy of object oriented classification is in general, better than that of pixel based classification (Djenaliev & Hellwich, 2014). Some of the studies achieved an accuracy of 88% to 94% for high-resolution images (Djenaliev & Hellwich, 2014).

The literature reviewed indicated that traditional pixel classification methods, such as maximum-likelihood classification, cannot effectively handle complex urban landscapes. As a result, object oriented classification methods have been shown to be more accurate for the classification of urban areas from satellite images. However, the accuracy of object oriented classification has been shown to increase as the resolution of images increase. This is especially noticeable when comparing object oriented classification results from Spot 5 images and Landsat ETM+ images (Wenli *et al.*, 2013). As a result, the use of Landsat images in this study was a disadvantage.

Frohn *et al.*, (2008) compared a multi-resolution segmentation object oriented classification process to a maximum likelihood classification process on pan sharpened single season and multi season Landsat 7 ETM+ data (15m resolution). The results indicated that the object oriented classification process had an accuracy of 90.2% for the single season dataset compared to a 78.4% accuracy using a maximum likelihood classification process. The multi-season dataset had similar results with accuracy of 90.8% for the object oriented classification process and 79.0% for the maximum likelihood classification process (Frohn *et al.*, 2008).

2.10. Image indices and band combinations to be used in the classification of land-cover classes

Indices and band combinations are both forms of spectral enhancement methods, by combining different image bands in various ways to enhance unique spectral signatures from various materials. Some indices can assist in highlighting and identify vegetation while others water, soil or built-up features, to name a few. In this study a number of different indices were used in the classification process.

2.9.1. Normalized Difference Vegetation Index (NDVI) to identify vegetation features

NDVI is an indicator that uses the red and near-infrared portion of the electromagnetic spectrum to assess the health of vegetation. Healthy vegetation absorbs the red portion of the electromagnetic spectrum, but scatters the near-infrared portion. This is because strong absorption would cause damage to cell tissue. Unhealthy or sparse vegetation cover reflects more of the red portion and less of the near-infrared portion (Holme *et al.*, 1987). NDVI is measured in a range from 1 to -1, where 1 represents healthy vegetation, -1 representing mostly soil with no vegetation cover. NDVI is calculated as (Holme *et al.*, 1987).

$$NDVI = (Near\ Infrared - red) / (Near\ Infrared + red)$$

These properties of NDVI allow it to be widely applicable in vegetative studies, for example crop yield estimation and carrying capacities to mention only a two.

2.9.2 The Band Ratio for built-up Areas (BRBA) to identify built-up features

BRBA is a ratio between the red band and Short-wave infrared 1 band, as discussed by Waqar *et al.*, (2012). The paper by Waqar *et al.*, (2012) compared the classification results from the BRBA index to other built-up area indices. The results showed that the BRBA is helpful to separate between non built-up areas and built-up areas. With 85.086% accuracy in classifying built-up areas compared to 73.75% for the NDBI index and 76.115% accuracy for the NBI index. The BRBA index is described by Waqar *et al.*, (2012) as:

$$BRBA = Red / Short-wave\ Infrared\ 1$$

2.9.3. Enhanced Built-Up and Bareness Index (EBBI) to identify built-up features

EBBI can be used to identify built-up areas and bare land areas using an index that applies near infrared (NIR), shortwave infrared (SWIR), and thermal infrared (TIR) bands (As-syakur *et al.*, 2012). EBBI is calculated as:

$$EBBI = (Short-wave\ Infrared - Near\ Infrared) / \sqrt{(Short-wave\ Infrared - Thermal\ Infrared)}$$

As-syakur et al (2012) studied and compared the results for several indices, IBI, NDBI, UI, NDBal and NDVI to the EBBI index on an IKONOS satellite image. The results from identifying urban areas produced an accuracy of 66.24% for the EBBI index, which was significantly higher than that of the other indices, with ranged from 51.87% to 54.25%.

2.9.4 .Normalized Difference Built-up Index (NDBI) to identify built-up features

NDBI is based on the high reflectance of built-up areas in the mid infrared portion of the electromagnetic spectrum, compared to the lower reflectance in the near infrared portion (Cibula *et al.*, 1992). NDBI is calculated as (Cibula *et al.*, 1992):

$$NDBI = (Short\text{-}wave\ Infrared - Near\ Infrared) / (Short\text{-}wave\ Infrared + Near\ Infrared)$$

However, some studies have shown that for some vegetation types the reflectance of MIR wavelength increased as leaf water content decreased. This might cause some falsely identified built-up areas (Cibula *et al.*, 1992).

A study to measure the accuracy of the NDBI index, by Wu *et al.*, (2005), produced an accuracy of 78.7%. Additional research showed that the accuracy of NDBI, to identify built-up areas, was relatively high at 78.7% (Xu, 2007).

2.9.5. The shortwave infrared 1 band to identify water features

The shortwave infrared 1 (SWIR 1) band is a specific band in a satellite image not and index. This portion of the electromagnetic spectrum is absorbed by water. This allows the utilization of the SWIR band from Landsat images to be used to identify water bodies (Frazier *et al.*, 2000). The importance of the SWIR band and its relationship with water need to be highlighted as it was used in this study to identify water features.

2.9.6. Normalized Difference Water Index (NDWI) to identify water features

NDWI is an index that can be used to identify water features within an image. NDWI is calculated as:

$$NDWI = (Green + Near\ Infrared) / (Green + Near\ Infrared)$$

This index can be used to identify water, due to the high absorption of the NIR portion of the electromagnetic spectrum and the high reflectance of the green portion McFeeters (1996). The result of this index produces an image that enhances water features with a positive value and zero or negative value for vegetation and soil (Xu, 2007).

CHAPTER THREE - RESEARCH METHODOLOGY

This chapter will explain the methodology followed, for this case study, to meet the aims and objectives of the research. Firstly the criteria for selecting the five cities that were used in this study are discussed. Then the process of selecting and pre-processing Landsat images is covered. This is followed by an explanation on what object orientated classification is and the steps followed to create image objects and how these objects were classified to represent different land-cover types. To ensure that the classification process was successful classification accuracy was performed, the details of this test is also explained. The process of analysing the relationship between the population estimates and the urban area growth is presented. And finally, the analysis done to study the relationship between physical urban growth and World Bank GDP estimates is explained.

A list of datasets used along with their sources is provided in Appendix B. A list of software packages used during this study is provided in appendix B.

Figure 3 is an illustration of the methodology workflow followed during this study.

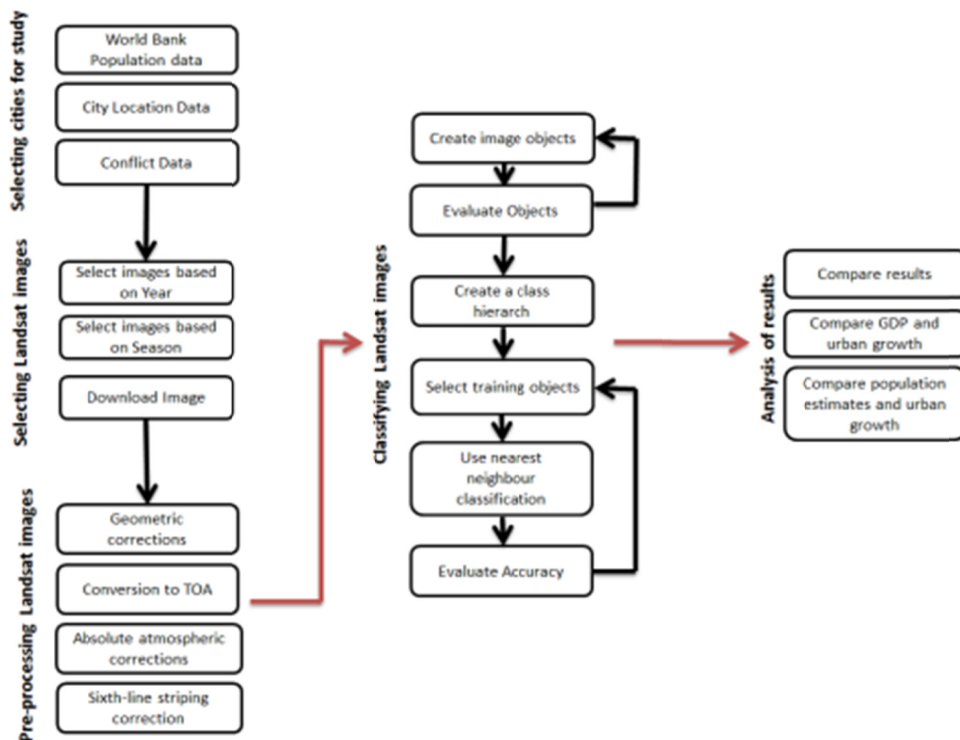


Figure 3: Methodology workflow diagram

3.1. Selecting the five metropolitan areas for this study

The cities selected for this study were the five cities that have experienced the largest absolute population growth from 1990 to 2015, as estimated by the UN population estimates. The reason for using an absolute measure of population growth rather than relative growth was because the urban footprint size, of each city, was measured in absolute terms and not using the amount of change that has occurred between observations. This ensured that a comparison could be made.

The reason for using population estimates rather than population density estimates is due to the lack of reliable data on population density figures per urban area. The UN Data Query webpage only contains population estimates per urban agglomeration area and not population density. Other unofficial data on population density was not used due to a lack of sources and little explanation on the methodologies used to derive urban population density figures. Furthermore, by using absolute population numbers the study can pick the fastest growing cities independent of the type of the spatial pattern of growth. For example, by using density the study might have selected cities with low population numbers but is highly concentrated resulting from the spatial pattern of growth.

Five of the ten cities that have experienced the largest population growth from 1990 to 2015 are located in China (3) and India (2). Only one city was selected per country, to diversify the pool of cities chosen

City location data was acquired from the United Nations Code for Trade and Transport Locations website (available at https://www.unece.org/cefact/codesfortrade/codes_index.html). The downloaded CSV file contained two fields with the Latitude and Longitude location of each city. These two coordinate fields were used to create an ESRI point shapefile.

To limit variables that might skew the results, countries that have experienced war or major civil conflicts, for multiple years, from 1990 to 2015 were excluded from the study. Data on conflict was acquired from the Department of Peace and Conflict Research at Uppsala University in Sweden. This dataset classifies conflict into three groups, namely: war, minor, NA (Erik *et al.* 2016, Gleditsch *et al.*, 2002).

The cities located in countries affected by conflicts classified as war were excluded from this study, due to the impact major conflicts might have on the population numbers of urban areas, either due to in or out migration.

To analyse the data and select the samples to be used in the study, all the data have been consolidated into a single MS Access database. This allowed the data from different sources to be joined using the ISO codes. In the Access database, a new table was created that combined all the data, to allow for accurate analysis and sampling.

A calculation was done to determine how much the population has grown from 1990 to 2015 for each city. This was done by subtracting the estimated population for 2015 from the estimated population for 1990 of each of the cities in the dataset.

After compensating for the influence of conflict the list of cities to be included in the study is shown in table 1 and the geographical location of each city is shown in fig 4.

Table 1: The 5 cities that were selected for this study

<i>City</i>	<i>Country</i>	<u>UN Population Estimates (1000)</u>		
		<u>1990</u>	<u>2015</u>	<u>2015 - 1990</u>
Al-Qahirah (Cairo)	EGY	9892	18772	8880
Delhi	IND	9726	25703	15977
Dhaka	BGD	6621	17598	10978
Lagos	NGA	4764	13123	8359
Shanghai	CHN	7823	23741	15918



Figure 4: A map indicating the location of the 5 cities sampled for this study

A list of the 10 cities that have seen the greatest estimated population growth is shown in Appendix A. The only city that was excluded from the analysis was Karachi in Pakistan, due to major conflicts in 1990 and 2004.

3.2. Satellite image acquisition and image pre-processing

Due to the availability of free of charge archived Landsat data, dating back to the 1980s, Landsat images were used for the classification and identification of urban areas. A big drawback of Landsat images is its moderate spatial resolution of 30m, which can cause some issues regarding classification accuracy (Waqar *et al.*, 2012).

The Landsat images were downloaded from the USGS Earth Explorer website (<https://earthexplorer.usgs.gov/>). Landsat 5, Landsat 7 or Landsat 8 images, for 1990, 1995, 2000, 2005, 2010 and 2015 were acquired for each of the five cities included in the sample. Only images with a cloud cover smaller than 10% or images with less than 30% cloud cover not covering the urban area were used in this study to reduce the pre-processing time. A leeway of one year before and one year after the target date was allowed in cases where no images were available or the images did not meet the criteria for cloud cover, as set out above. The properties of each of the three Landsat satellites are shown in table 2.

Table 2: Attributes of the Landsat 5 TM, Landsat 7 ETM+ and Landsat 8 OLI sensors (Source: U.S. Department of the Interior and U.S. Geological Survey, 2016)

<i>Landsat satellites:</i>	<i>Landsat 5 satellite</i>	<i>Landsat 7 satellite</i>	<i>Landsat 8 satellite</i>
Mission Launch	Mar 1984	Apr 1999	11 Feb 2013
Mission Ended	Jan 2013		
Coastal/Aerosol			(0.452 - 0.0512) 30m
Blue	(0.45 - 0.52 μm) 30 m	(0.45 - 0.52 μm) 30 m	(0.33 - 0.59) 30m
Green	(0.52 - 0.60 μm) 30 m	(0.52 - 0.60 μm) 30 m	(0.636 - 0.673) 30m
Red	(0.63 - 0.69 μm) 30 m	(0.63 - 0.69 μm) 30 m	(0.851 - 0.879) 30m
NIR	(0.76 - 0.90 μm) 30 m	(0.76 - 0.90 μm) 30 m	(1.566 - 1.651) 30m
SWIR-1	(1.55 - 1.75 μm) 30 m	(1.55 - 1.75 μm) 30 m	(10.6 - 11.19) 100m
TIR	(10.40 - 12.50 μm) 120 m	(10.40 - 12.50 μm) 120 m	(11.5 - 12.51) 100m
SWIR-2	(2.08 - 2.35 μm) 30 m	(2.08 - 2.35 μm) 30 m	(2.107 - 2.294) 30m
Pan		Pan (0.52 - 0.90 μm) 15 m	(0.503 - 0.676) 15m
Band 9			(1.363 - 1.384) 30m

3.2.1. Selection of Landsat images based on seasonal criteria

The Landsat images were selected not only based on year but also on the season the images were acquired. The reason for this is to use images with more predominant vegetation cover, from seasons with higher rainfall. This is to limit the misclassification of bare soil as built-up areas, as bare soil might be covered by vegetation during the rainy season. An example where the misclassification of bare soil and urban areas might be predominant is in areas with a dry climate, for example, Delhi in India and Cairo in Egypt.

For this study seasons with high rainfall were identified and the corresponding Landsat images were acquired. If no images were available for the identified period or if the images had a high cloud cover percentage that is more than 10%, an alternative image or images were selected. These images could be within the two months following the optimal rainfall season. The reason for this is that vegetation growth will still be active after the rainy seasons. However the period of vegetation growth after rainfall seasons would differ for each of the regions in this study, this study only concentrated on the basic criteria set out above. It needs to be noted that during high vegetation growth seasons, buildings and roads might be covered by vegetation canopies thus influencing classification results.

The climate data for each city were acquired by using the rWBclimate R package. The data provided in this package are sourced from the World Bank climate knowledge portal (available at <http://sdwebx.worldbank.org/climateportal/index.cfm>). This package can obtain historical weather data, from the World Bank that can be used in climate analysis (Hart, 2014).

The climate data provided by the World Bank is structured to provide average climate conditions across distinct climate zones. The climate zones for each of the five cities were established by using the online World Bank climate knowledge portal.

The results from the analysis of the climate conditions showed the possible optimum dates varied for each of the five regions. Table 3 shows the average rainfall in millimetres for each month by city, it also indicates the months that are optimum for

image acquisition. Figure 5 is a visual representation of table 3, in which the rainfall for each month by city is shown along with the optimum image dates.

Table 3: This table indicates the average rainfall for the 5 areas of interest. The highest rainfall months and optimal image download date are also indicated.

<u>Month</u>	<u>Cairo</u>		<u>Delhi</u>		<u>Dhaka</u>		<u>Lagos</u>		<u>Shanghai</u>	
	<u>Avg. Rainfall (mm)</u>	<u>Optimum image date</u>	<u>Avg. Rainfall (mm)</u>	<u>Optimum image date</u>	<u>Avg. Rainfall (mm)</u>	<u>Optimum image date</u>	<u>Avg. Rainfall (mm)</u>	<u>Optimum image date</u>	<u>Avg. Rainfall (mm)</u>	<u>Optimum image date</u>
Jan	1.48		20.53		4.04		8.52		15.58	
Feb	1.39		29.75		12.91		21.25		20.86	
Mar	1.99		37.45		29.94		68.43		29.62	
April	2.35		27.28		101.65	Yes	129.29	Yes	49.02	
May	2.73		21.55		222.97	Yes	168.97	Yes	58.23	
June	2.82		26.97		361.28	Yes	205.45	Yes	102.45	Yes
July	12.77	Yes	83.76	Yes	396.20	Yes	212.04	Yes	213.46	Yes
Aug	19.24	Yes	78.95	Yes	299.34	Yes	175.48	Yes	170.55	Yes
Sep	5.12		30.30		289.34	Yes	221.49	Yes	85.05	
Oct	1.94		8.37		158.11	Yes	157.93	Yes	38.59	
Nov	1.50		8.79		15.44		31.33		22.36	
Dec	1.43		13.56		4.78		11.89		12.25	

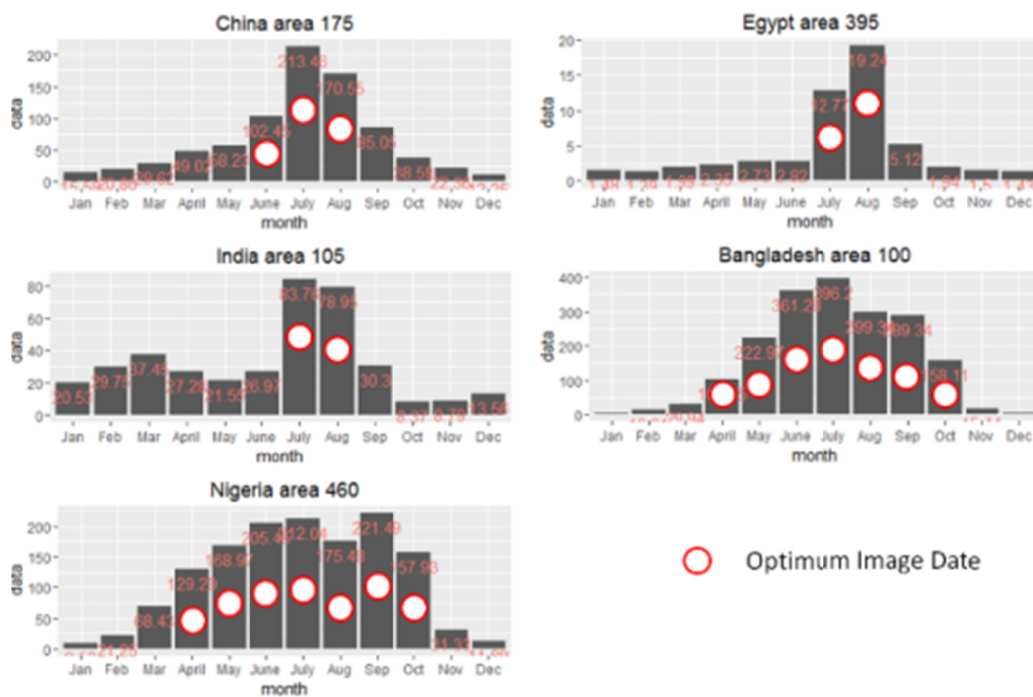


Figure 5: Histogram plots of rainfall for the 5 areas of interest. The highest rainfall months and optimal image download date are also indicated

Images were acquired for the majority of the cities that cover the dates under investigation. The only exception is Lagos in Nigeria, where there were no Landsat images, with low cloud cover, available from 1987 to 2000. Therefore no classification was done for the year 1995. The Landsat satellite paths and rows used for each of the study areas is shown in table 4.

Table 4: The five cities selected for this study

<u>City</u>	<u>Country</u>	<u>Path</u>	<u>Row</u>
Cairo	Egypt	176	039
Dhaka	Bangladesh	137	043 & 044
Delhi	India	146	040
Lagos	Nigeria	191	055
Shanghai	China	188	038 & 039

The R code used to elaborate the data shown in table 3 and Figure 5 is shown in Appendix C. In total 54 images were used in this study (see Appendix D).

3.2.2. Pre-processing of Landsat images

Before any scientific measurements can be made from Landsat images, some image pre-processing steps are required.

3.2.2.1. Geometric corrections

During this study, all downloaded images were checked to ensure they are geometrically correct and overlaying consistently. For this study, no geometric corrections were needed; this is because all the images have been corrected before the download.

3.2.2.2. Atmospheric corrections

Electromagnetic energy (sun light) passes through the atmosphere twice before it is detected by a sensor. The atmosphere has a number of different effects on the

electromagnetic energy, some wave lengths get absorbed others scattered and reflected. Atmospheric correction can correct these effects, to a large degree, resulting in images that are much clearer and usable for a classification process.

Atmospheric corrections were done to account for atmospheric degradation. A modified Dark Object Subtraction (DOS) correction method, proposed by Chavez *et al.*, (1988) was used due to the advantage in that it estimates the scattering effects across all the spectral bands (Campbell, 2011). All atmospheric corrections were done using ERDAS 2014.

3.2.2.3. Top of atmosphere correction

The angle at which light from the sun enters the atmosphere influences the amount of reflected light being measured by a sensor. If the angle is great (steep) the light needs to pass through a larger part of the atmosphere, this increases the atmospheric effect on the light. This effect is dependent on the time of day and day of the year the image is acquired (Campbell, 2011).

To compensate for this effect, a Top of Atmosphere Reflectance (TOA) was calculated using ERDAS 2014.

The equation for the TOA process set out by Campbell (2011) is shown below:

$$\rho_{\lambda} = (\pi \times L_{\lambda} \times d^2) / (ESUN_{\lambda} \times \cos(\Theta))$$

Where:

ρ_{λ} : spectral reflectance for wavelength λ (TOA)

λ : Wavelength

L : spectral radiance

d : Earth-Sun distance

$ESUN$: mean solar exoatmospheric irradiance

Θ : solar zenith angle

3.2.2.4. Radiometric correction

Remote sensing sensors like Landsat store the values for each pixel as a digital number, which ranges from 0 to 255. These numbers are not the percentage of light reflected from an object. 0 represent the darkest object in the image and 255 the

brightest objects. As a result it becomes virtually impossible to compare two images because the brightest object in one image might not be the brightest in the next.

Radiometric corrections were made to convert the digital numbers to radiance values (expressed as a percentage light reflected). This can be used to study the spectral properties of different materials.

This process uses variables recorded by the sensor when the image was acquired and is used to convert the digital numbers to reflectance values. The equation to calculate the reflectance values are shown below (Campbell, 2011).

$$L_{\lambda} = ((L_{\max} - L_{\min}) / (Q_{\text{calmax}} - Q_{\text{calmin}})) \times ((Q_{\text{cal}} - Q_{\text{calmin}}) + L_{\min})$$

Where:

L_{λ} = Cell radiance value

Q_{CAL} = digital number

L_{MIN} = spectral radiance scales to QCALMIN

L_{MAX} = spectral radiance scales to QCALMAX

Q_{CALMIN} = the minimum quantized calibrated pixel value

Q_{CALMAX} = the maximum quantized calibrated pixel value

3.2.2.5. Pan-sharpening

Pan-sharpening is the process of combining a higher resolution panchromatic Landsat band (15m), only available for Landsat 7 and 8 not Landsat 5, with moderate resolution Landsat bands (30m) to produce a higher resolution image (15 m). No pan-sharpening images were used for image classification; this was to ensure that the resolution for all the classification results had a similar resolution of 30m. Pan-sharpened images, created for Landsat 7 and Landsat 8 images, were however used in the accuracy assessment step. This process was done using ERDAS 2014.

3.2.2.6. Scan line striping error (SLC-Off) correction on Landsat 7 images

In 2003 the Landsat 7 ETM+ sensor malfunctioned causing gaps in the images, this are called scan line stripping error (SLC-Off) (Campbell, 2011). The Scan Line Corrector (SLC) is a device designed to compensate for the forward motion of the Landsat 7 satellite during image scanning. Due to the malfunction of the SLC strip lines can be observed on all Landsat 7 ETM+ images acquired after May 2003.

Figure 5, is an illustration of the function the SLC device served and how the malfunction of this device influenced images after May 2003.

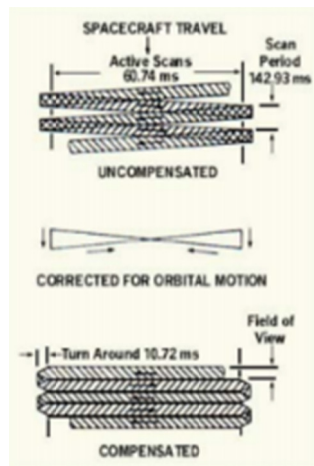


Figure 6: Illustration of the functionality of the SLC device. (Source: U.S. Geological Survey, 2003, Figure A, p5)

The effect is less noticeable at the centre of an image but is most predominant on the edges of images. Despite the SLC malfunction, it is estimated that more than 75% of an effected image should still be radiometrically and geometrically correct (U.S. Geological Survey, 2003).

The SLC-Off problem had to be corrected to make any accurate classification and analysis possible. One process set out in literature involves filling the gaps using interpolation methods (Zhang *et al.*, 2006). It is my feeling that these methods might cause a significant inaccuracy classification of urban areas as urban areas are dynamic and constantly changes. Furthermore, image objects to be created within eCognition would not be representative of real-world features. Another method is to use an older SLC-On image to fill the gaps, for example localized linear histogram match (LLHM) (Desai & Ganatra, 2012). However, these images were acquired before the SLC-Off error occurred and will not reflect urban growth in 2005 or 2010, for example. Another method, which was used in this study, is to utilise the random nature of the overlapping strip lines of SLC-Off images. The location of scan line striping errors is not always located at the same position on every image (Mohammad *et al.*, 2014). As a result areas affected by scan line strips on one image might not be affected in another.

To accomplish this, a primary image (image1) was selected based firstly on year, secondly on season and lastly cloud cover. A secondary image (image2) was selected based firstly on the year (corresponding with image1), secondly on the season (close to image1) thirdly cloud cover and finally, does image2 fill in the strip lines observed in image1. If image2 only partially fill the strip lines in image1 a tertiary image (image3) was selected based on the same criteria as that of image2, but covering the rest of the gaps not covered by image2.

A model was created in ERDAS Imagine 2014 which replaces all the values = 0 in image1 with values from image2 and/or image3, if the values in image2 and/or image3 > 0. Figure 9 shows an example from Cairo where two landsat images were combined with the above mentioned process to produce an image that is free of scan line errors.

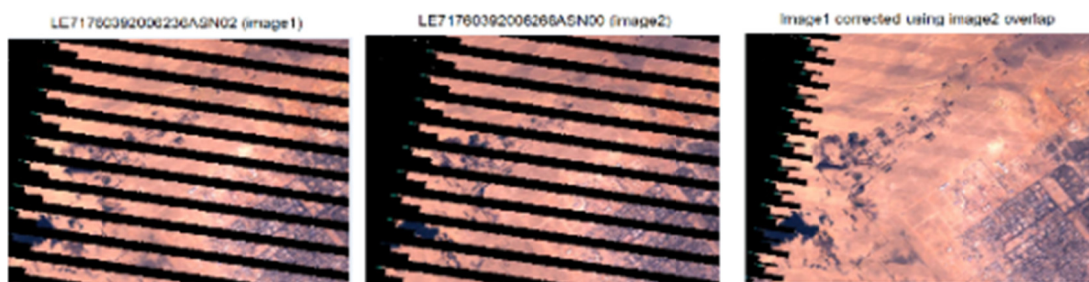


Figure 7: An example of overlapping Landsat 7 (SLC-Off) acquired images over different time periods. The NULL values in the main image (image 1) are replaced by the values from the secondary image (image 2) where the values are not NULL in image 2.

3.3. Image segmentation and object classification

Traditionally digital images were analysed and classified on a pixel level (Arturo *et al.*, 2004). This means that each pixel is classified independently from neighbouring pixels. The problem with this approach is that some pixels should be classified together as a group, as they might form a physical object on the earth's surface. Object orientated image analysis is designed to overcome this limitation by identifying image objects, a group of pixels that share similar properties and is identified as an object with a specific colour, texture and shape (Burnett and Blaschke, 2003). This process of image object creation is called image segmentation. In addition to creating objects based on pixel properties, object orientated image analysis can also take into consideration the properties of

neighbouring objects. An example will be if an object is classified to belong to the water land-cover class, objects bordering that object and have a low shortwave infrared reflectance, is more likely to be water than an object surrounded by vegetation. During the classification process, each object is classified and not the pixels.

The object creation (segmentation) and object classification process consisted of the following steps within the eCognition software:

1. Using a multiresolution segmentation algorithm to create image objects.
2. Evaluate results of the image objects and refine weights if needed
3. Create a class hierarchy that contains all the land-cover types to be classified.
4. Select training objects to be used in the classification.
5. Use feature space optimization to identify the features (bands and indices) that best separate each of the sampled classes within a feature space.
6. Classify the image objects using a nearest neighbour classification method, by using the results from the feature space optimization function.
7. Evaluate results and calculate accuracy.

Each of the above mentioned steps is covered in detail below.

3.3.1. Image segmentation

eCognition can segment a multispectral image into objects based on pixel values for each band and visual borders (Arturo *et al.*, 2004).

Segmentation algorithms can, in general, be grouped into two main categories namely global behaviour-based algorithms and local behaviour-based algorithms (Kartikeyan *et al.*, 1998).

Global based algorithms are based on the analysis of pixels within a feature space, which is clustered within a histogram of the data in which image segmentations can be created (Kartikeyan *et al.*, 1998).

Local based algorithms are more focused on the variations of pixel values in a small neighbourhood (Kartikeyan *et al.*, 1998). Local based algorithms can be grouped into two different approaches, namely edge-based methods and region growth methods (Frohn *et al.*, 2008).

Local edge-based methods firstly identify edges within the image; pixels that are located within an identifiable edge become a segment. A disadvantage of edge-based methods is that small objects are obscured by boundary pixels (Geneletti & Gorte, 2003).

In a local region growing method, a small neighbourhood of pixels is analysed to identify pixels that are homogeneous. If a group of pixels is similar regarding pixel values, they are grouped into objects (Kartikeyan *et al.*, 1998). A disadvantage is that results might be affected by the order in which the image is processed (Geneletti and Gorte, 2003).

Due to the relatively low resolution of Landsat images (30m) objects cannot be created for individual buildings but rather large concentrations of buildings or built up areas. For this reason, image objects need to be large enough to include groups of pixels that represent objects that correspond mostly to what can be perceived as an object. A multiresolution image segmentation algorithm (bottom-up segmentation) was used to achieve this goal.

A multiresolution segmentation algorithm creates objects with an iterative algorithm by grouping objects until a threshold of variance, in each object, is reached. (Breetz *et al.*, 2004). Multi-resolution segmentation has the advantage of creating elongated objects to represent features like roads, but only if the weights of heterogeneity is set correctly.

Before the object creation process is initialized, the weight value for heterogeneity needs to be set by the user. Within eCognition, heterogeneity is defined as primary object features with similar colour and shape (Benz *et al.*, 2004). The heterogeneity weight value is a limit to the level of heterogeneity between objects to be clustered.

To find the optimum weights to be used, a range of weight values were tested for each of the cities. This was to ensure the weight values selected for this study would ensure that the image objects created will contain a minimum mixture of land-cover types. For this, a test area was selected for each of the cities on which the weights for the multiresolution segmentation algorithm were tested. The test areas were then segmented multiple times with each of the different weight settings. The objects were then exported to an ESRI shapefile format, from eCognition. The shapefiles were opened in QGIS where 30 image objects were randomly selected (referred to as test objects). The land-cover class within each of the test object were verified on the Landsat images.

Land-cover refers to the material covering an area of the earth's surface, such as water, vegetation, soil and manmade materials (e.g. roads and buildings). If a test object contained 90% or more of a single observed land-cover class, a value of 1 was assigned to these objects, indicating that it is correctly created. However, if an object contains less than 90% of a single observed land-cover type, a value of 0 was assigned to the object; this indicated that the object was not correctly created.

The percentage of objects correctly created was calculated by dividing the number of correct objects, with a value of 1, by the total number of test objects. This allowed for the calculation of an object accuracy percentage. The results were evaluated and the weight value that produced the best results was applied to the segmentation process.

3.3.2. Defining a class hierarchy for all the land-cover types to be classified

The type of land-cover classes differs for each of the five different cities. This is due to the variation in vegetation, soil, sand, rocks and other environmental factors as well as different manmade structure. However for the majority of images classified, the main classes were urban (Built-up area), high dense vegetation, low dense vegetation, bare soil and water. These classes were expanded upon where the variation between classes differed significantly across Landsat images.

Figure 8 shows an example of the Class Hierarchy window in eCognition. In the window the land-cover classes, to be identified and classified, were created.

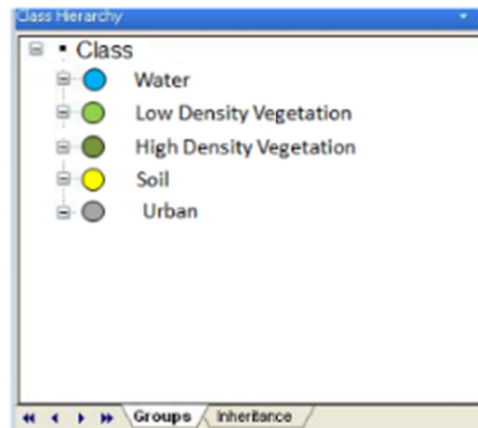


Figure 9: An example of the class hierarchy created in eCognition

3.3.3. Select training objects to be used in the classification process

Training objects, to be used in the nearest neighbour classification, were selected randomly for each of the land-cover classes. Objects that could not be correctly identified during this process were not selected as training areas.

The number of training areas was determined by evaluating the variation in reflectance from similar land-cover types. Because factors like physical geography, environmental or climate factors and vegetation types might differ over the geographical areas covered by each Landsat scene (170 km North - South X 183 km East - West), the reflectance values for each type of land-cover type might differ. As a result, the training objects for each land-cover type had to include most of the variation in reflectance that is observed for each land-cover type. This was done to limit incorrect classification of land-cover types with almost similar reflectance properties.

To ensure that samples for each land-cover class selected were unique in terms of its spectral histogram and is normally distributed, the Sample Editor window was used to constantly compare how unique the samples were.

The Sample Editor window allows for a comparison between spectral histograms of sampled land-cover classes (Britz *et al.*, 2004). Figure 9 shows an example for the Sample Editor window. The window shows the spectral histograms, for all features,

for the sampled Urban and Vegetation land-covers classes. The window allowed for samples selected to be unique and not overlap with samples for a different class.

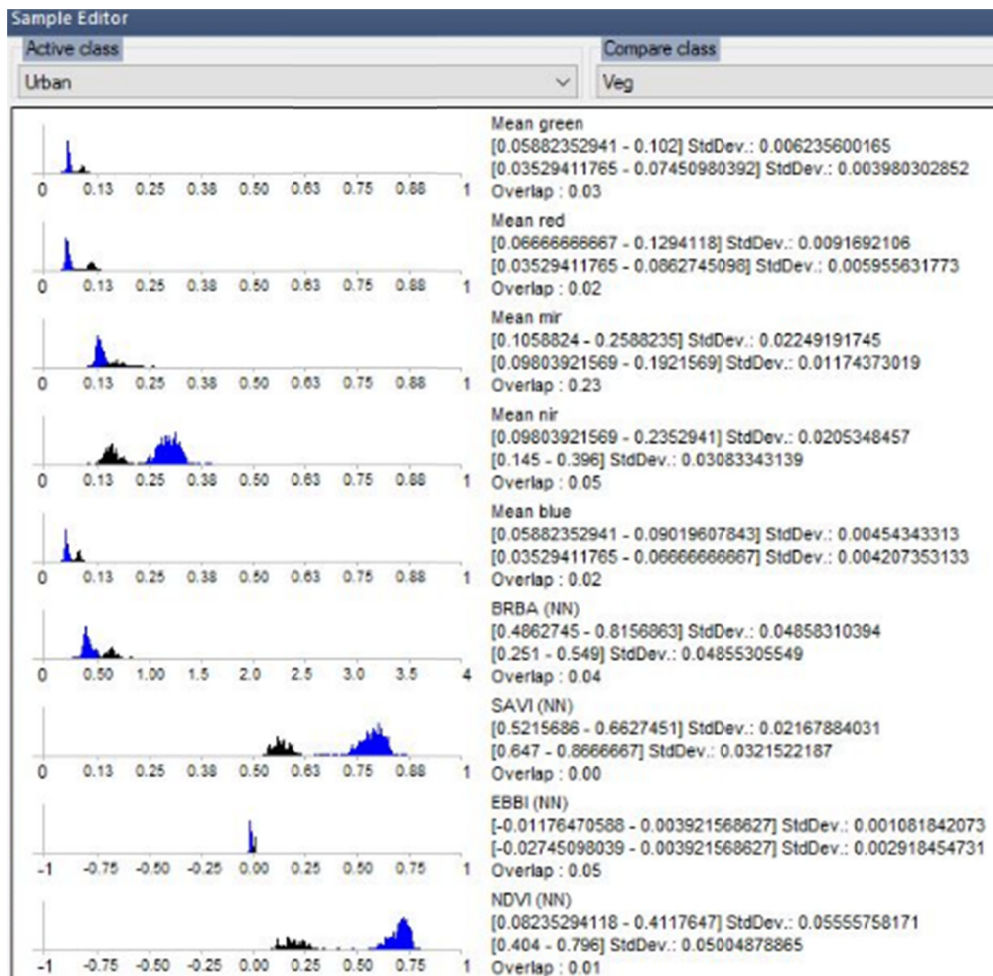


Figure 10: An example of the Sample Editor window that was used to assist in ensuring samples selected for one class did not overlap samples of other classes. The window shows the urban land-cover class sampled versus the vegetation land-cover class samples. The results show the spectral reflectance of the two classes for various band and feature.

3.3.4. Feature space optimization to select best features (bands and indices) for image classification

Feature space optimization (FSO) allows for an automatic evaluation of the distance between sampled objects within a feature space and selects the feature or combination of features that result in the largest average minimum distance between sampled objects. As a result, it is important to select samples carefully so that the feature space for each class can be defined accurately within the feature space (Andrea *et al.*, 1997).

Figure 10 shows an example of the Feature Space Optimization function window. The results from a test are also shown in Figure 11, where the greatest distance between classes is at 0.245 with five dimensions, meaning five features were identified that will allow for the greatest distance between classes within a feature space.

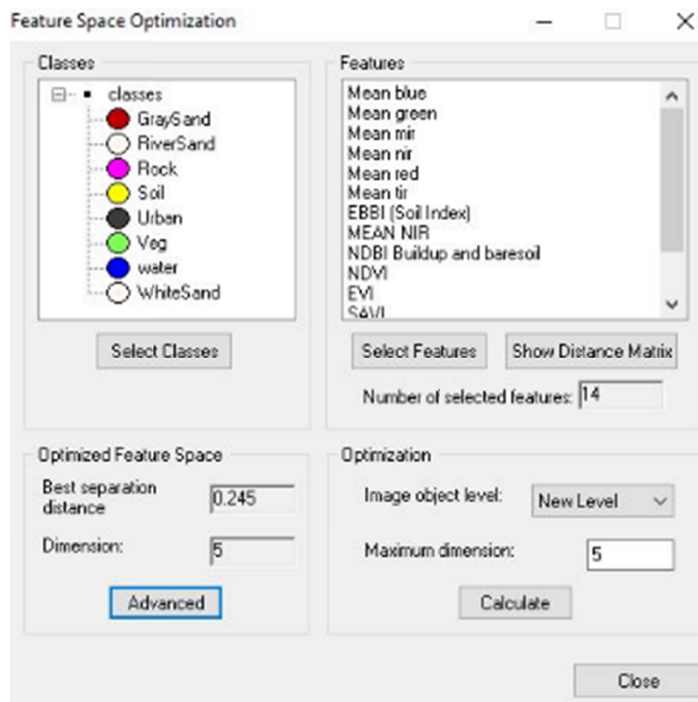


Figure 11: An example of the Feature Space Optimization tool and the results achieved when the classes to be classified are provided along with the Features that were used in the classification.

For the FSO analysis, the classes to be classified are selected along with the features (bands and indices) that were analysed and tested which allowed for the largest distance between classes for accurate classification.

Figure 11 is a visual illustration of a FSO test result, in the image five features were identified that allowed for the greatest distance between classes.

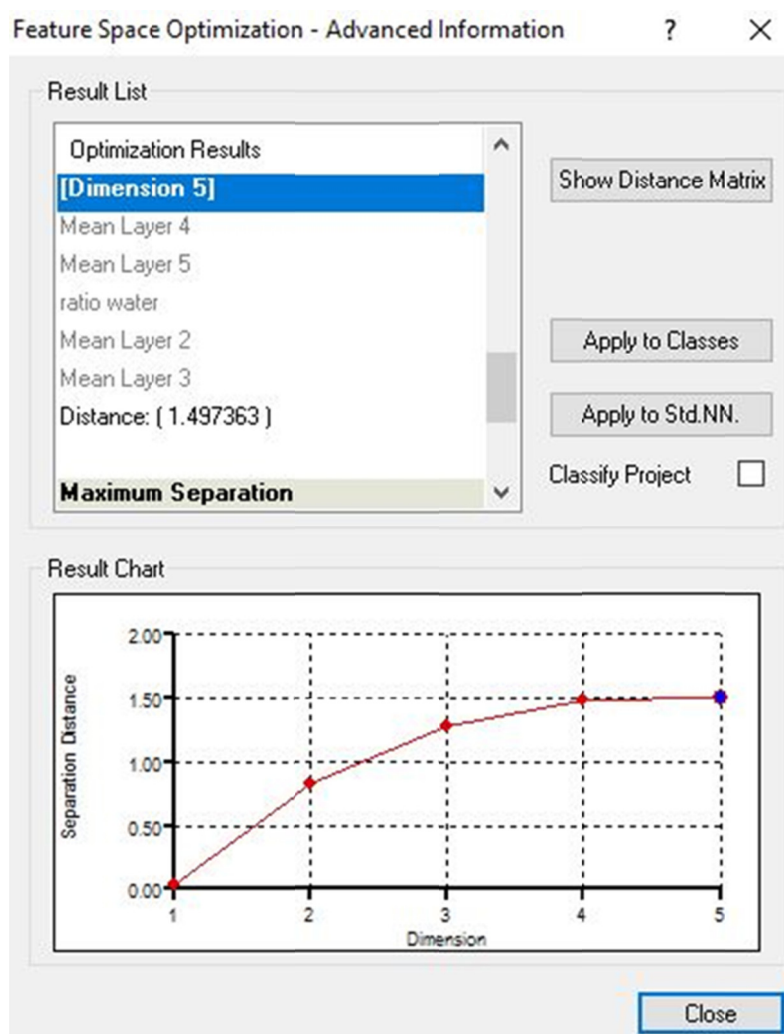


Figure 12: An example of the Feature Space Optimization tool results, indicating which Features best separate the classes to be classified

The FSO output indicates the features that allow for the greatest distance between the classes. The combination of features that provides the greatest distance in a feature space can then be used in a Nearest Neighbour Classification.

Class Separation Distance Matrix

Class/Class	water	Veg	Urban	LowVeg
Dimension: 5				
Urban	2.484804	2.066916	0.000000	4.917704
Veg	7.704090	0.000000	2.066916	1.497363
water	0.000000	7.704090	2.484804	17.890950
LowVeg	17.890950	1.497363	4.917704	0.000000

Figure 13: The Class Separation Distance Matrix indicating the distance between classes, within the feature space

Figure 12 shows an example of the Class Separation Distance Matrix which indicates the average distance between the land-cover classes, using the features selected by the FSO analysis. This can be used to evaluate the results from the FSO process before applying the results to a nearest neighbour classification process.

For this study, 13 features were used and evaluated in the FSO before the nearest neighbour classification step was performed, features used in this study is shown in table 5.

Table 5: Table of all the features (bands and indices) used in this study

Features (bands and indices)	Used for identification of	Landsat satellite	
		Landsat 4-7	Landsat 8
Normalized Difference Vegetation Index (NDVI)	Vegetation	$(\text{NIR-Red}) / (\text{NIR+Red})$	
Band Ratio for Built-up Area (BRBA)	Built-up and bare soil	Red / SWIR-1	
Enhanced Built-Up and Bareness Index (EBBI)	Built-up and bare soil	$(\text{SWIR-1} - \text{NIR}) / 10\sqrt{(\text{SWIR-1} + \text{TIR})}$	
Normalized Difference Built-up Index (NDBI)	Built-up and bare soil	$(\text{SWIR-1} - \text{NIR}) / (\text{SWIR-1} + \text{NIR})$	
Modification of Normalized Difference Water Index (NDWI)	Water	$(\text{Green} - \text{NIR}) / (\text{Green} + \text{NIR})$	
Mean Blue		B1	B2
Mean Green		B2	B3
Mean Red		B3	B4
Mean NIR		B4	B5
Mean SWIR-1		B5	B6

3.3.5. Classifying image objects using a nearest neighbour classification method

A nearest neighbour image classification method is a relatively simple non parametric algorithm. This is useful considering the fact that data aren't always normally distributed (e.g. Gaussian) and cannot be linearly separated (Boiman, Shechtman and Irani, 2008).

The principle of a nearest neighbour image classification method is similar to a supervised classification method. Training areas for each land-cover class is selected and then used to classify the rest of the image (Yan, 2003). The algorithm assigns a class to all the unclassified image objects based on their distance from sampled objects within a multidimensional feature space (Wenxia, *et al.*, 2005).

eCognition allow specific features (bands and indices) or combinations of features to be used in a nearest neighbour image classification method that allows for the best separation of classes within a feature space, these features were identified with the FSO tool.

Figure 13 is an illustration of how the Nearest Neighbour classification method works within a two dimensional space.

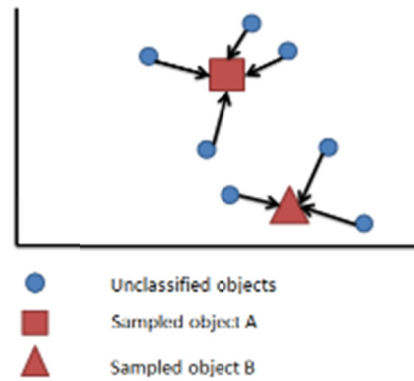


Figure 14: An illustration of the way a nearest neighbour classification works within a 2D space. The blue points are unclassified objects that are classified based on their distance from classified objects (image derived from Wenxia *et al.*, (2005), Figure 6, p3)

The formula to identify the objects closest to a sampled object, as set out by Wenxia, et al (2005) is:

$$d = \sqrt{\sum_f \left[\frac{v_f^{(s)} - v_f^{(o)}}{\sigma_f} \right]^2}$$

Where:

d : distance between sample object s and image object o ;

$V_f^{(s)}$: feature value of sample object for feature f ;

$V_f^{(o)}$: future value of image object for feature f ;

σ_f : standard deviation of the feature values for feature f .

3.3.6. Accuracy assessment of image classification

The accuracy of the classification process was assessed by using an error matrix (Campbell, 2011). An error matrix is a way to determine how accurate a classification

process is compared with ground trothing points. Also it can be used to calculate the commission errors and omission errors. A kappa coefficient ($\hat{K}$) can also be produced, which is the difference between the observed accuracy and the change agreement. $\hat{K} > 0.8$ represent good accuracy, $\hat{K} < 0.8$ and > 0.4 represent a middle accuracy and $\hat{K} < 0.4$ is a poor accuracy (Campbell, 2011).

The $\hat{K}$ statistic can be calculated using:

$$\hat{K} = \frac{N \sum_{i=1}^k y - \sum_{i=1}^k (x_{-i} \times x_{+i})}{N^2 - \sum_{i=1}^k (x_{-i} \times x_{+i})}$$

Because accurate historical field observations are not readily available, for the all the areas and years covered in this study, Landsat images used in the classification process were also used for accuracy assessment. For the classifications done with Landsat 5 images, the accuracy assessment was done using the 30m X 30m Landsat images. The accuracy assessment for the classification done with Landsat 7 and Landsat 8 images, were done using pan-sharpened images (15m X 15m). This was used to better identifying land-cover classes contained within sample objects.

eCognition do provide an accuracy assessment function, in which a percentage of sampled objects are selected and used as test data. This function was not used in this study, because it fails to measure the accuracy of the objects created and only measures the accuracy of the classification compared to the test dataset.

To test the accuracy of the image objects along with the classification results 50 classified objects, from each classified class, were selected randomly within QGIS. These objects were used for accuracy assessment (referred to as accuracy objects). The observed land-cover type, within each accuracy object boundary, from the original Landsat images (Landsat 5 images) and pan-sharpened Landsat images (Landsat 7 and 8 images) was assigned as an observed class for each of the

accuracy objects. If an object contained more than one observed land-cover class, the observed class was assigned for the land-cover class that is in majority.

The observed land-cover class and the classified class was used in an error matrix, created in Microsoft Excel, to calculate the overall accuracy, kappa coefficient, commission errors and omission errors.

In addition, to identify the observed land-cover classes for the randomly selected accuracy objects, the object accuracy was also identified. If an accuracy objects contained 90% or more of a single observed land-cover class, a value of 1 was assigned to the objects, indicating that it is correctly created. However, if an object contained less than 90% of a single observed land-cover type, a value of 0 was assigned to the object. This is to indicating that the object was not correctly created. This process aimed to ensure that the accuracy assessment not only reflects the accuracy of the classification results but also the accuracy of the objects created.

3.4. Analysing the relationship between urban growth, population estimates and GDP growth

To meet the aims and objectives set out for this study, an analysis was done on the population growth and the urban area growth for each city.

To assist in the analysis, the rate of growth (in %), be it for population, economic and urban growth, were also calculated and used in the comparison of the different datasets.

Rate of growth was calculated as follows:

$$\text{Rate of growth (\%)} = ((y_2 - y_1)/y_1) * 100$$

Where:

y_1 = year 1 e.g. 1990

y_2 = year following year 1 e.g. 1995

Once the rate of growth was calculated, A parametric (Pearson's correlation) and a non-parametric (Spearman's rank correlation) test for correlation were performed, both of which indicated a significantly positive relationship.

For all the Pearson's and Spearman's rank correlation tests, the results indicated a positive relationship ($R > 0.9$ and $\rho = 1$) between urban growth and GDP as well as urban growth and population estimates.

A linear regression model was used to analyse the direction and strength of correlation between UN population estimates and the expanding urban footprint for each of the cities. The same was used to identify the nature of the relationship between the expansion of the urban footprint and GDP growth.

It needs to be highlighted that statistical tests, like a linear regression model, on the data from this study was subject to noise due to the small number of observations. Additionally, if an outlier or outliers are identified, using the Bonferroni test for outliers, it was not removed as this would severely influence the results of the analysis of such a small dataset. Moreover, since the data were measured over time, the models were tested for the influence of autocorrelation, the data being correlated with itself (DeCarlo & Tryon, 1993). Usually a time series analysis is used to compensate for autocorrelation. However it was not used because it is recommended that a minimum of 50 to 100 observations is needed for a time series analysis (Box and Jenkins, 1994). A Durbin Watson test (Durbin & Watson, 1951) for autocorrelation was performed, for each regression model.

The linear regression models residuals were tested to establish if the model is influenced by heteroskedasticity, violating one of the key assumptions of linear models. If the model does show any heteroskedasticity, it might result in the model being biased.

The UN population estimates for urban areas are not measured in the same manner for all the urban areas. Most of the estimates are based on population censuses data for the city proper area, the city administrative region, mega city (metropolitan area) or the urban agglomeration (continuous urban, suburban and town areas). However, some population estimates are not based on census data, like those for Lagos. In cases like these data like mortality and fertility rates, supplied by independent agencies are used to inform interpolation models (Bloch *et al.*, 2015)

The population estimates for Cairo, Egypt are based on census data for 1960, 1966, 1976, 1985, 1996 and 2006. The estimates are for the entire metropolitan area, which includes Cairo (Al-Qahirah), Giza (Al-Jizah) and Qalyubia (Al-Qalyübyah).

In the city of Dhaka, the UN population estimates are based on the census data for the years 1951, 1961, 1974, 1981, 1991, 2001 and 2011. This is measured for the entire Mega city (Metropolitan area).

The UN population estimates for Delhi are based on Censuses data for the years 1951, 1961, 1971 and 1981 along with estimates for 1991, 2001 and 2011. The estimation by the UN takes into consideration the urban agglomeration which refers to Contiguous suburban cities and towns, including Faridabad, Gurgaon, and Ghaziabad along with New Delhi. For Lagos, the UN population estimates are not based on census data and the estimates refer only to Lagos state and not the continuous urban environment or the larger metropolitan area. Shanghai's UN population estimates are based on the census data for the years 1953, 1964, 1982, 1990, 2000 and 2010 as well as population register data for 1957, 1959, 1965 and 1977. The estimates are composed of population in all urban areas of sixteen city districts (Baoshan, Changning, Fengxian, Hongkou, Huangpu, Jiading, Jing'an, Jinshan, Minghang, Pudong, Putuo, Qingpu, Songjiang, Xunhui, Yangpu, and Zhabei)

CHAPTER FOUR – RESULTS

This chapter puts forth the results from the analysis done during this study. Firstly, the results from the object creation process are presented. Secondly, the overall accuracy and kappa coefficient of the classification process are discussed in detail for each city by year. Then the urban area size measurements, from the image classification results, are shown along with the calculated rate of growth. The results from the analysis on the relationship between UN population estimates and urbanisation and those from the analysis on the relationship between GDP and urbanisation are shown.

4.1. Results from the segmentation weight tests

Initially, two tests were done to establish the weights to be used, for the scale and shape parameter, in the multi-resolution segmentation algorithm. The results, as indicated by figure 14 and 15 show that the accuracy of the objects decreasing as the shape parameter is increased; this is due to the increase in the size of the objects. The optimum Shape value of 0.25 was selected; smaller values resulted in very small objects that were not practical. Using the best Shape settings, the results for the Scale parameter tests indicated that as the scale value increases, the accuracy decreases. An optimum Scale value of 0 was selected with a compactness of 0.

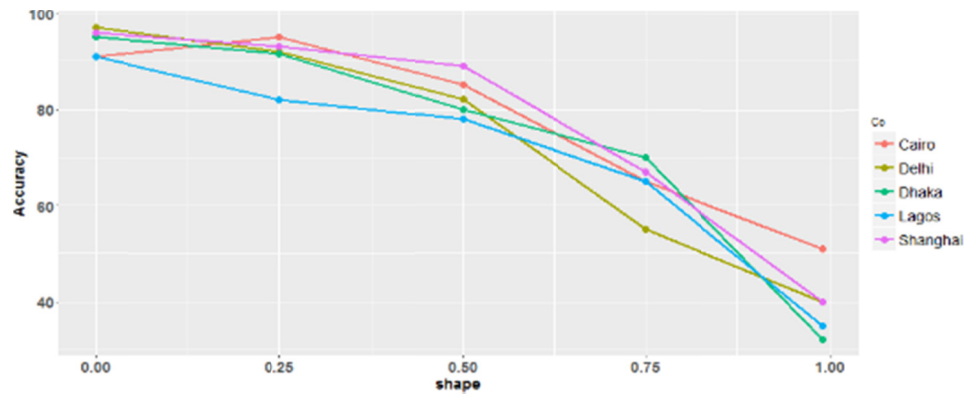


Figure 15: The accuracy of image objects, using different Shape weights values. The results indicated a decreasing accuracy as Shape weight increases

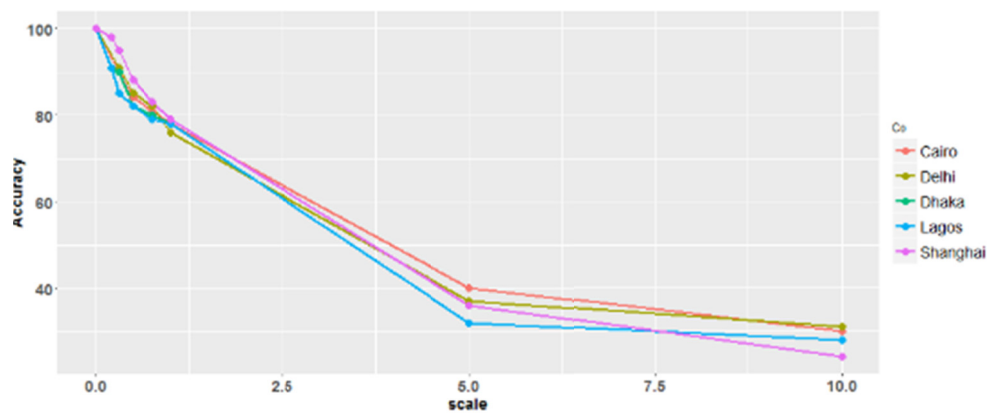


Figure 16: The results from testing different weight settings for image segmentation. The accuracy of the objects decrease as the weight values set for the Scale parameter is increased

Figure 16 is a visual representation of the results from testing the various segmentation weight values. The object accuracy test results for each year by city are shown in table 6. An example of the decreasing accuracy of the image objects, as the weights increase, is shown in figure 16. Figure 17, 18 and 19 shows examples of the image objects created.

Table 6: The accuracy of the image objects created, using the optimum weight settings (Shape:0.25, Scale:0)

	<u>1990</u>	<u>1995</u>	<u>2000</u>	<u>2005</u>	<u>2010</u>	<u>2015</u>
Cairo	95.50%	92.00%	89.90%	91.10%	94.00%	92.00%
Delhi	94.00%	98.00%	89.90%	89.80%	91.70%	91.00%
Dhaka	92.00%	93.20%	89.00%	89.50%	92.00%	92.00%
Lagos	92.00% (1984)		87.00%	89.00%	92.00%	87.40%
Shanghai	95.00%	94.00%	92.00%	95.00%	92.50%	87.00%

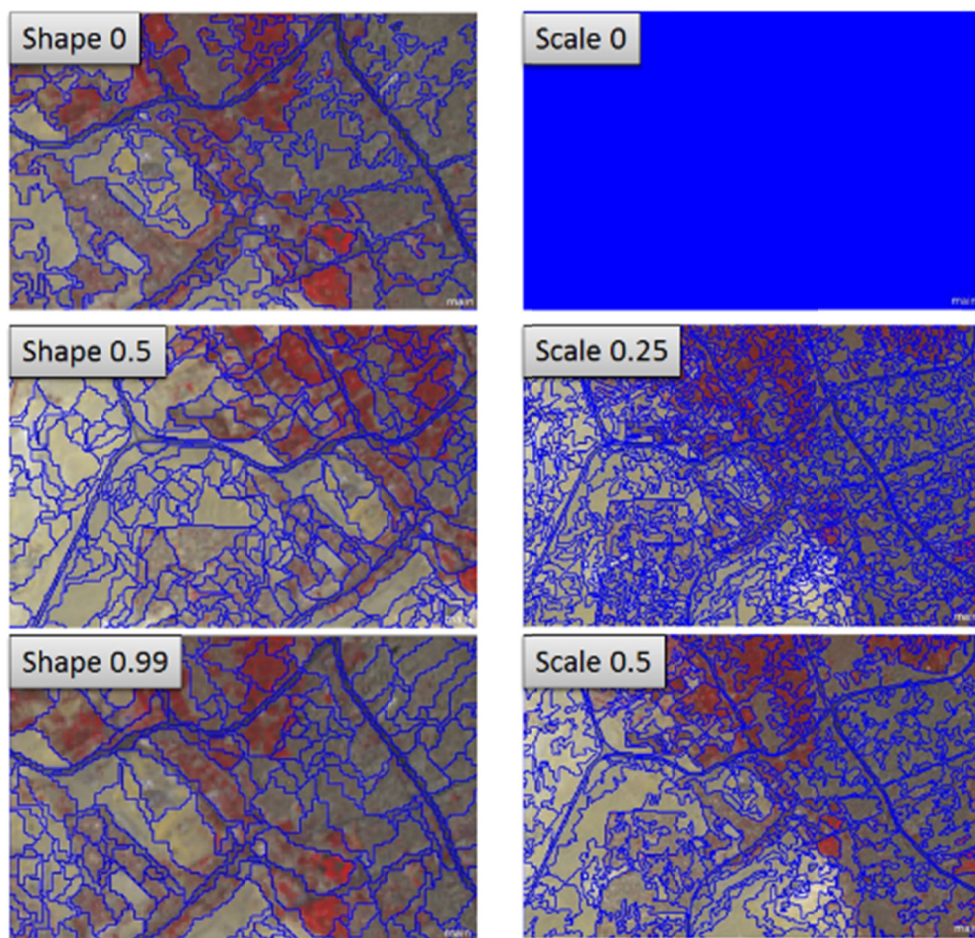


Figure 17: An example of the decreasing accuracy of the image objects created during the segmentation process. As shape (left) increase the object contain mixtures of land use types. As the Scale (right) increases the object size increases, at Scale 0 the objects as the size of individual pixels, at scale 0.5 the objects start to contain a mixture of land use types.



Figure 18: An example from an elongated image object created for a section of road in Cairo, Egypt. (Landsat 7 ETM+, B=B1, G=B4, R=B3)

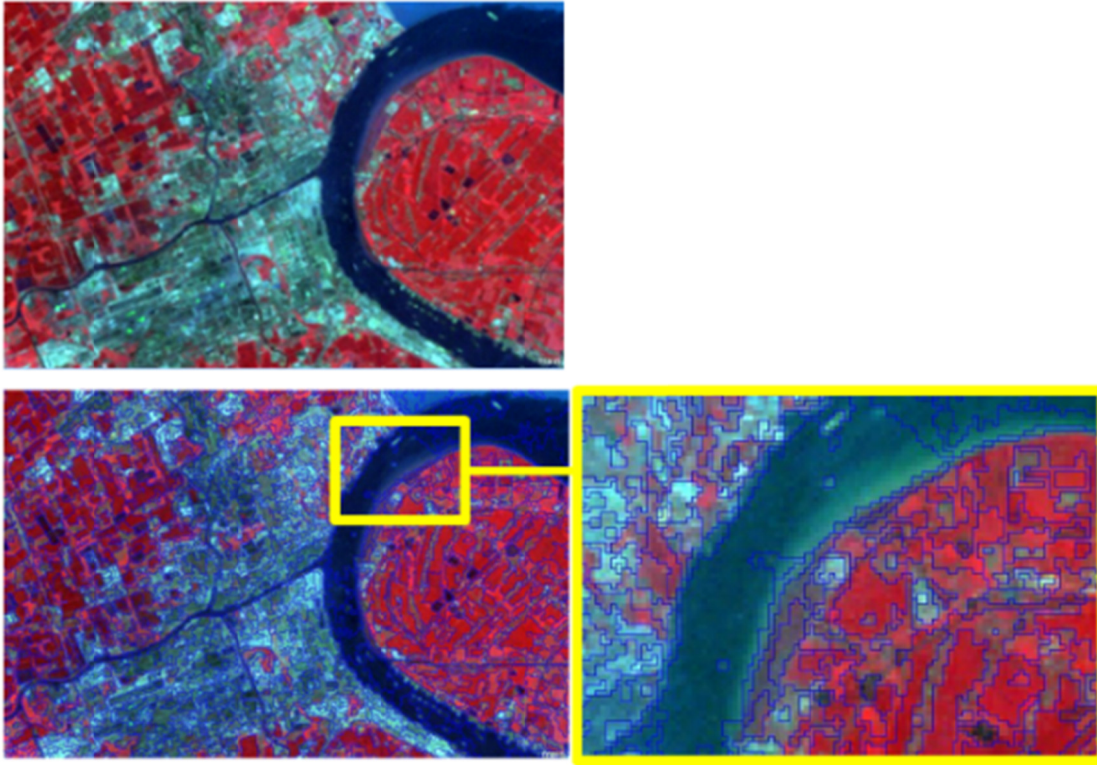


Figure 19: An example of image objects created along the Huangpu River, Shanghai, China (Landsat 5 TM, B=B1, G=B3, R=B2)



Figure 20: An example of image objects created on the edge of the urban areas of Shanghai, China (Landsat 5 TM, B=B1, G=B3, R=B2)

4.2. Analysis of the expanding urban footprint, as estimated from the image classification results

Using the classified Landsat images, it was possible to calculate the size of the urban footprint for each of the cities for each year studied. Table 7 shows the urban area size for each city by year. Figure 20 is a visual representation of the data shown in table 7.

Table 7: The urban area size (km²) and the rate of urban area growth (%) for each of the five cities by year

Year	<u>Cairo</u>		<u>Delhi</u>		<u>Dhaka</u>		<u>Lagos</u>		<u>Shanghai</u>	
	<u>Urban area (km²)</u>	<u>Growth rate (%)</u>	<u>Urban area (km²)</u>	<u>Growth rate (%)</u>	<u>Urban area (km²)</u>	<u>Growth rate (%)</u>	<u>Urban area (km²)</u>	<u>Growth rate (%)</u>	<u>Urban area (km²)</u>	<u>Growth rate (%)</u>
1990	491.3		474.5		97.6		274.2 (1984)		600.0	
1995	818.0	66.5	564.6	19.0	99.0	1.4			898.9	49.8
2000	1013.7	23.9	663.9	17.6	106.7	7.8	702.9	60.9	1319.7	46.8
2005	1208.4	19.2	938.6	41.4	122.8	15.1	1029.2	46.4	1694.2	28.4
2010	1397.7	15.7	1062.8	13.2	190.2	54.9	1431.9	39.1	2461.5	45.3
2015	1631.2	16.7	1647.6	55.0	355.2	86.7	2269.9	58.5	3845.2	56.2

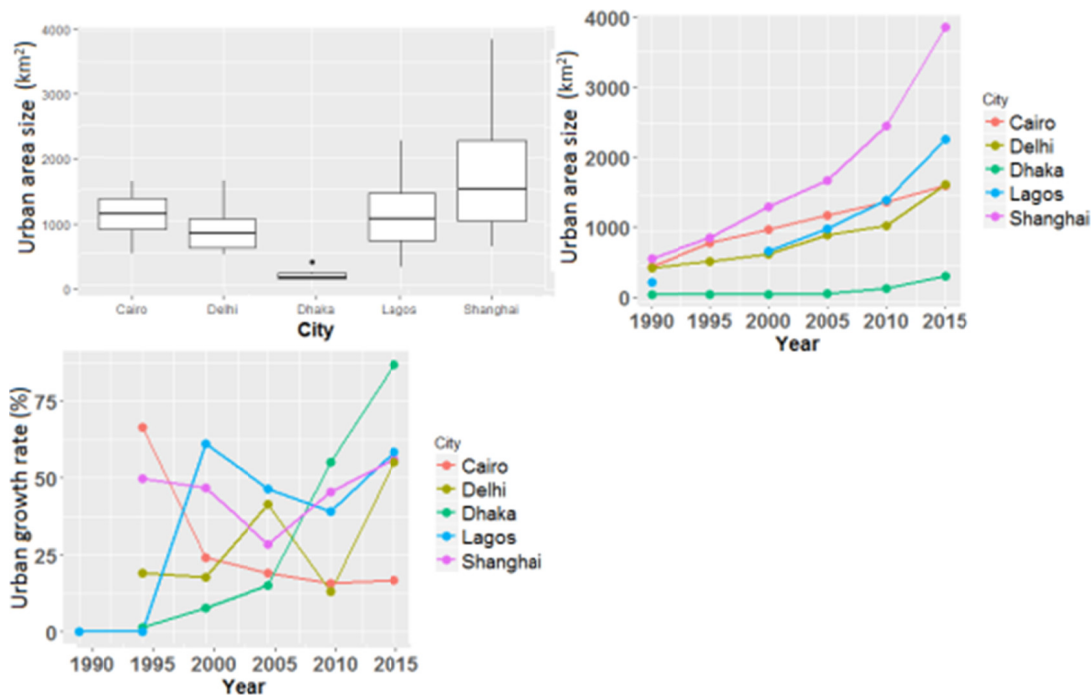


Figure 21: (Top Left) A box plot indicating the urban growth experienced by each city from 1990 to 2015. (Top Right) A line plot indicating the urban growth experienced by each city from 1990 to 2015. (Bottom Left) A line plot indicating the urban growth rate (%) experienced by each city from 1990 to 2015.

For all 5 the cities the urban area more than doubled in size from 1990 to 2015. The city that experienced the least amount of growth was Cairo, which grows 3.32 times from its original size in 1990. It is followed by Delhi, which grew 3.47 times in the same time period. Dhaka grew 3.63 times from 1990 to 2015. By 2015 Shanghai has grown to be 6.4 times in size from 1990. Lagos experienced a growth of 8.27 times from 1990 2015, starting at 274.2km² in 1990 and growing to 2269.94km².

For all five cities, a decrease in the rate of growth is seen between 1995 and 2000. Shanghai's rate of growth starts at 49.82% in 1995 and slows down to 46.81% in 2000 and 28.38% in 2005. From 2005 to 2015 Shanghai's rate of growth continues to increase from 28.38% to 45.29% in 2010 and 56.21% in 2015. Delhi's rate of growth varies over time, starting at 18.98% in 1995 and decreasing to 17.6% in 2000. In 2005 the rate of growth increases to 41.37% but slows down to 13.23% in 2010 and increases again in 2015 to 55.03%

4.2.1. Cairo, Egypt

Cairo grew from 491.3 km², in 1990, to 1931.2 km² in 2015, this relates to an increase of 3.93 times. From 1990 to 1995 the urban area footprint grew at a rate 66.5% however, since 1995 up until 2010 the rate of growth declines to 15.7% and increase again to 16.7% in 2015. The results showed that the city expanded towards the east and west of the city into the desert regions, along transportation corridors. Figure 21 illustrates the growth of Cairo from 1990 to 2015.

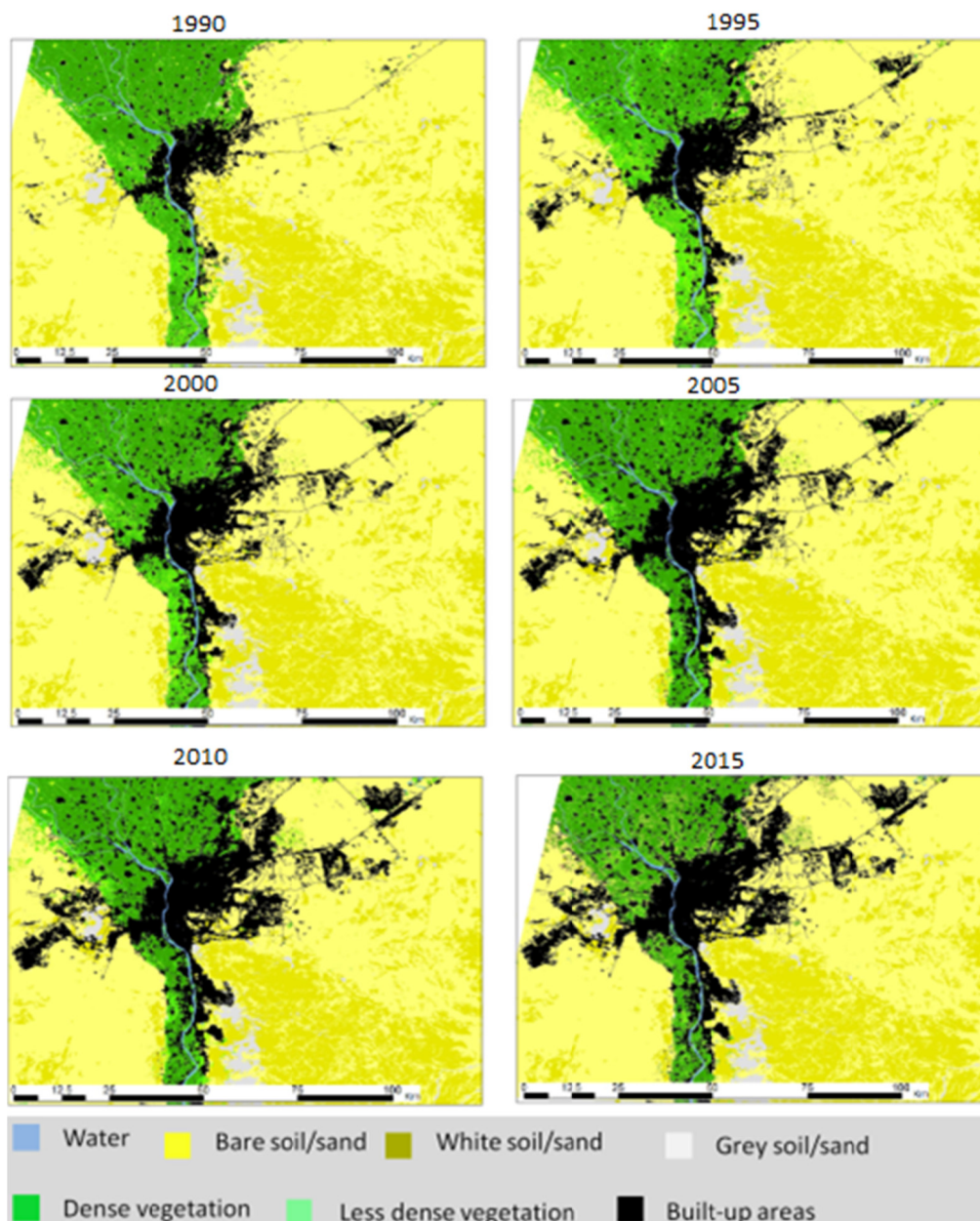


Figure 22: Maps indicating the classification results for Cairo for the years 1990, 1995, 2000, 2005, 2010 and 2015

4.2.2. Delhi, India

Delhi covered an area of 474.5 km² in 1990 and grew to 1647.6km² in 2015, an increase of 3.47 times.

The rate of increase is below 20% from 1990 to 2000 and increases to 41.4% in 2005 but decreases to 13.2% in 2010 only to show a large rate of increase from 2010 to 2015. The results indicated that the urban areas expand mostly towards the south and along transportation corridors towards the East. Figure 22 illustrates the growth of Delhi from 1990 to 2015.

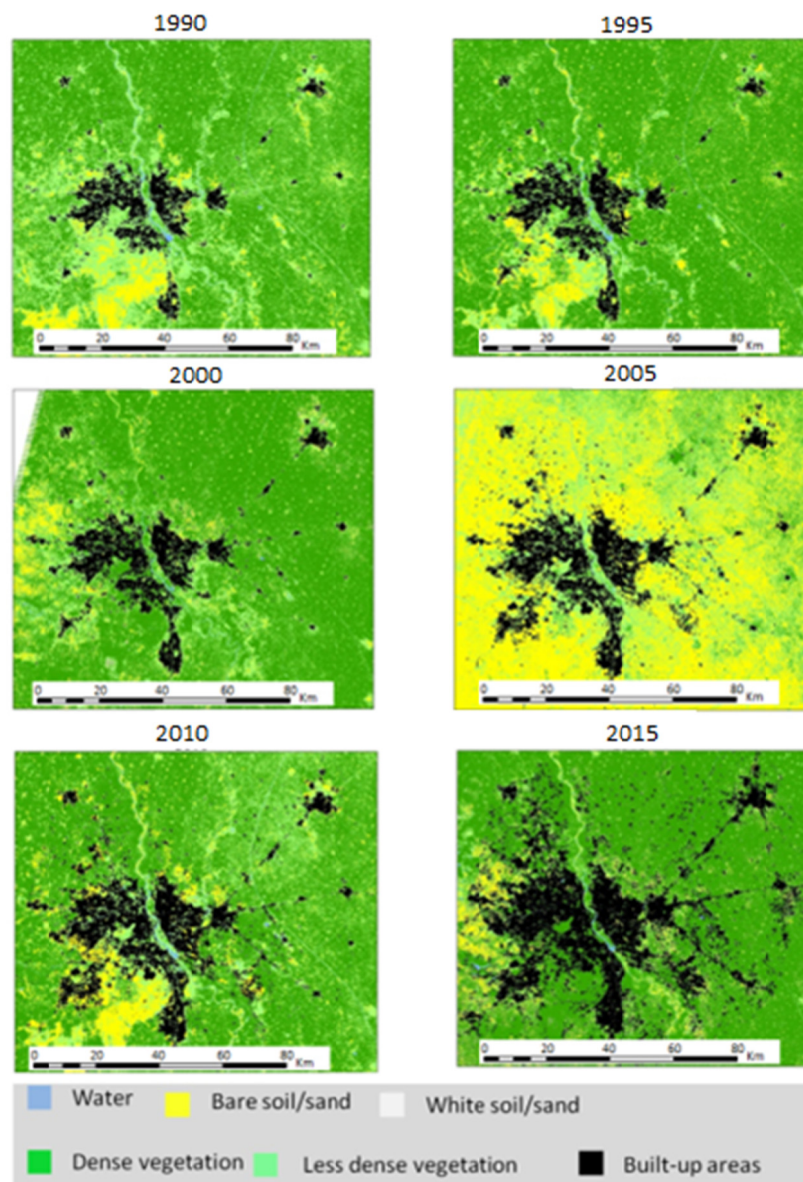


Figure 23: Maps indicating the classification results for Delhi for the years 1990, 1995, 2000, 2005, 2010 and 2015

4.2.3. Dhaka, Bangladesh

Dhaka started with a relatively small urban footprint, at 97.6km² and increased to 355.2km².

The rate of increase is low during the 1990's and increases over time. A number of physical geographical constraints limit the growth of the city. During the rainy season large areas surrounding the city is flooded; as a result most of the growth observed is concentrated towards the north and south of the city. Figure 23 illustrates the growth of Dhaka from 1990 to 2015.

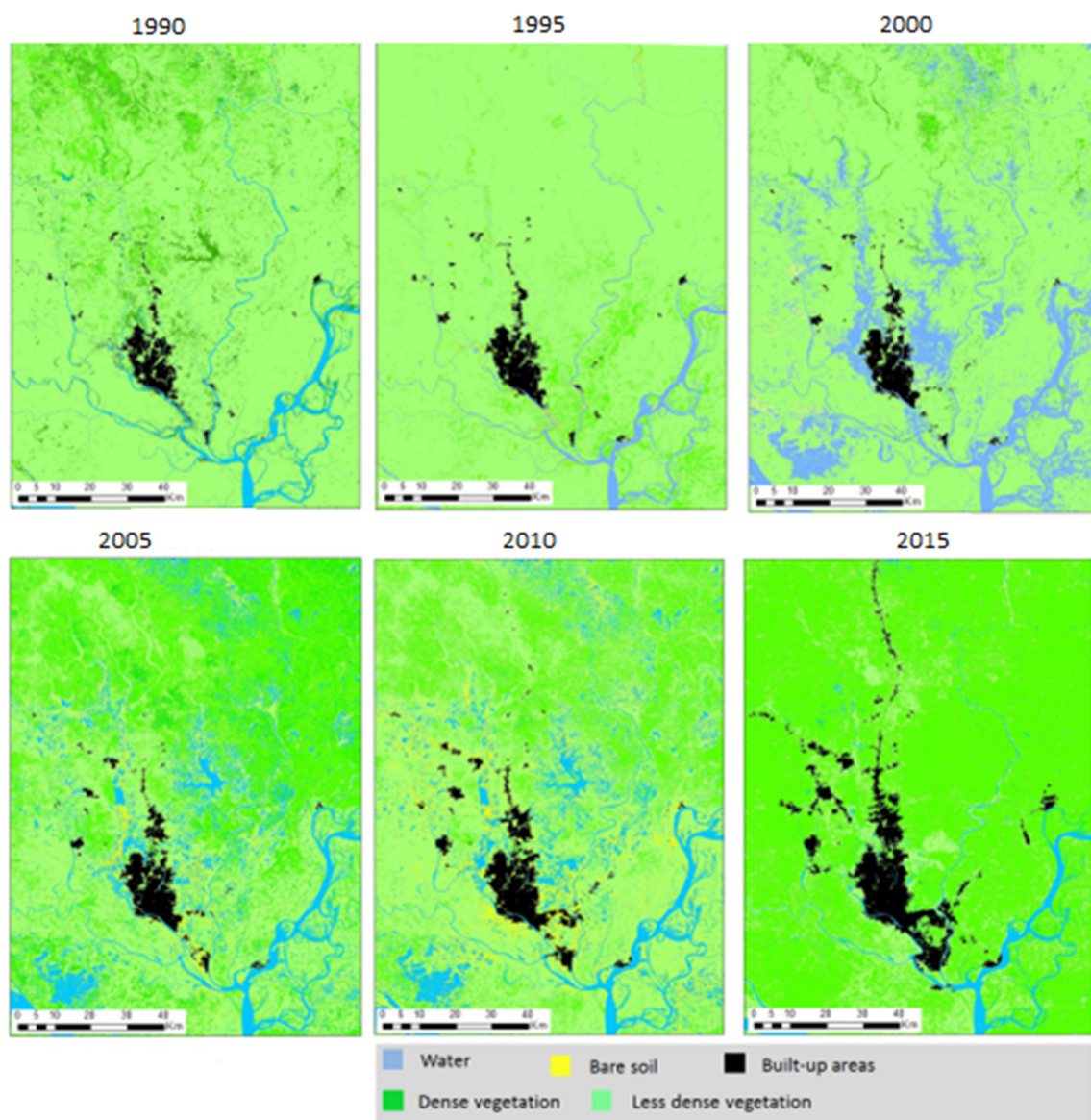


Figure 24: Maps indicating the classification results for Dhaka for the years 1990, 1995, 2000, 2005, 2010 and 2015

4.2.3. Lagos, Nigeria

Lagos starts at 274.2km² and increased to 2269.9km², this resulted in a huge increase in the urban footprint of 8.27 times. The rate of growth is constantly high with growth rated close to or above 40%.

Due to a lack of Landsat images in the 1990's for Lagos, it is difficult to compare the growth of Lagos to the other cities in this study. However the urban areas footprint increased by 60.9% from 1984 to 2000, indicating a large increase during this time. Most of the expansion in the urban footprint occurred towards the north and east of the city, this might be a result form wetland areas surrounding the urban area. Figure 24 illustrates the growth of Lagos from 1984 to 2015 (excluding 1995).

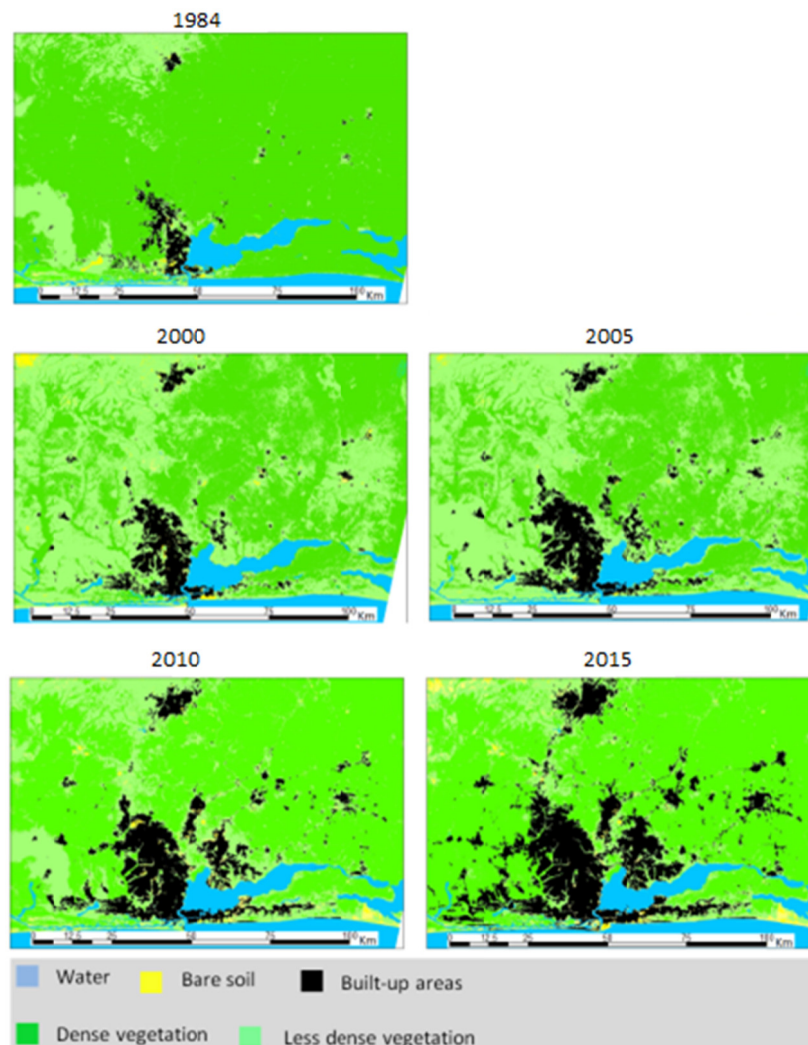


Figure 25: Maps indicating the classification results for Lagos for the years 1984, 2000, 2005, 2010 and 2015

4.2.4. Shanghai, China

Shanghai started at 600km² and increased to 3845.2km², resulting in an increase of 6.4%. The rate of increase remained high from 1990 to 2015, with a rate above 40%., the 2000 to 2005 rate of growth being an exception at 28.4%.

The majority of growth occurred towards the west, inland. Another observation is that the growth is predominantly along transportation networks towards smaller urban cores. Figure 25 illustrates the growth of Shanghai from 1990 to 2015.

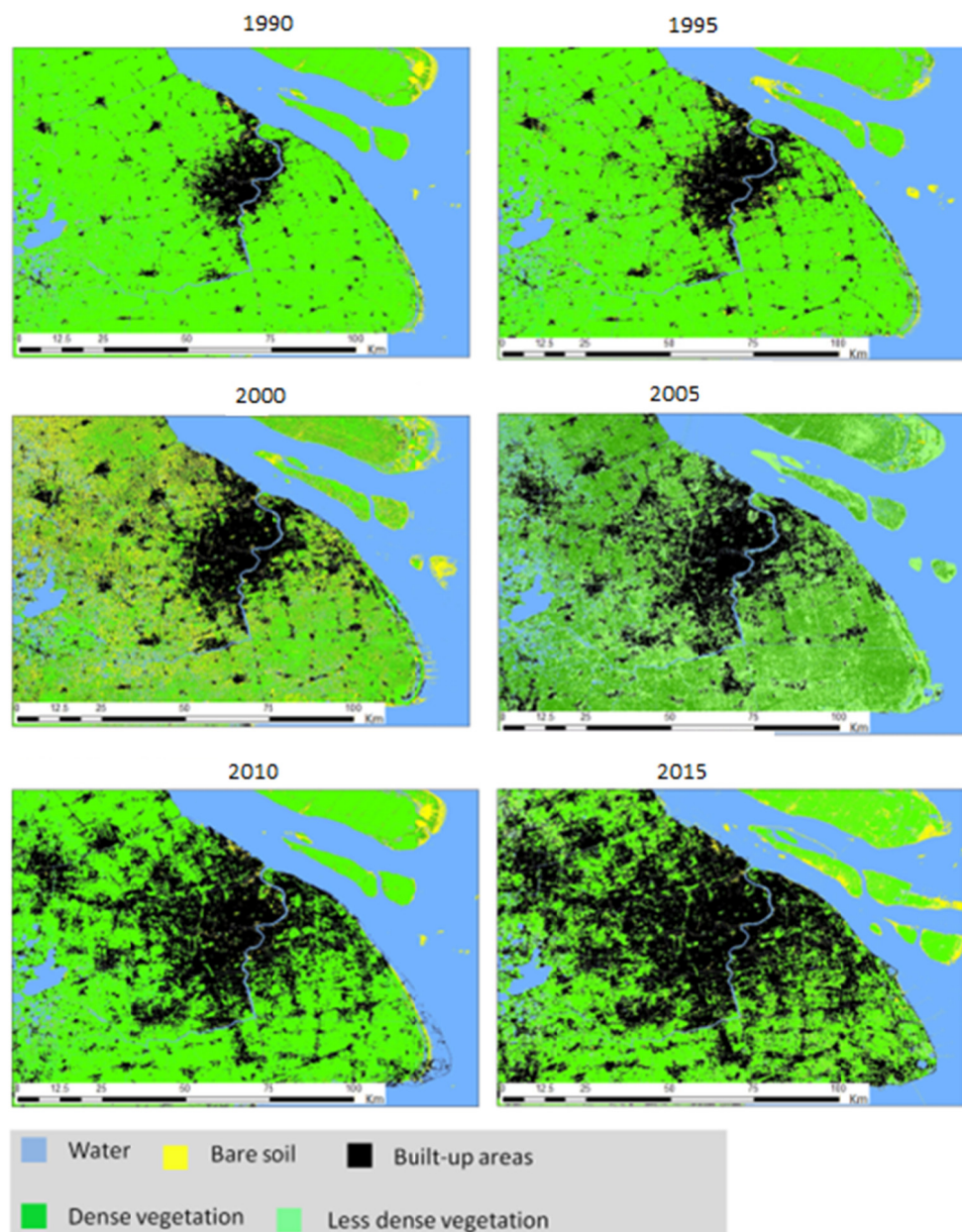


Figure 26: Maps indicating the classification results for Shanghai for the years 1990, 1995, 2000, 2005, 2010 and 2015

4.3. Accuracy results from the classification process

4.3.1. Overall accuracy and kappa coefficient for the object oriented classification method

The accuracy of the classification results was analysed using an error matrix, which allows for the calculation of an overall accuracy, kappa coefficient, omission (users) error and commissioned (producers) error. The classification accuracy differed for each of the cities and each of the years. This could be due to different environmental and manmade conditions influencing the classification results; it might also be due to inaccurate object creation or inaccurate sample selection.

The overall accuracy for each of the cities indicates that the highest average overall accuracy was achieved in Delhi, at 86.73% and the lowest in Lagos, at 75.16%. Table 8 shows the overall accuracy and kappa score for each of the cities by year. Figure 26 is a visual illustration of the results shown in table 8.

Table 8: The overall accuracy and kappa score for each city by year

<u>Year</u>	<u>Cairo</u>		<u>Shanghai</u>		<u>Delhi</u>		<u>Dhaka</u>		<u>Lagos</u>	
	<u>Overall accuracy</u>	<u>kappa</u>	<u>Overall accuracy</u>	<u>kappa</u>	<u>Overall accuracy</u>	<u>kappa</u>	<u>Overall accuracy</u>	<u>kappa</u>	<u>Overall accuracy</u>	<u>kappa</u>
1990	84.27	81.12	79.7	74.6	84.21	81.58	78	72.5	76.51 (1984)	70.5
1995	86.55	83.8	81.7	77.2	85.71	83.33	80.6	75.2		
2000	84.39	81.28	79.2	73.9	79.43	74.97	84.7	80.7	80.82	76.19
2005	77.78	73.2	83.5	79.4	81.11	77.93	87	83.7	76.97	71.23
2010	80.79	76.9	82	77.5	83.25	80.44	76.5	70.5	75.16	68.96
2015	86.52	83.83	84.6	80.8	86.73	84.52	78.5	73.2	82	77.5

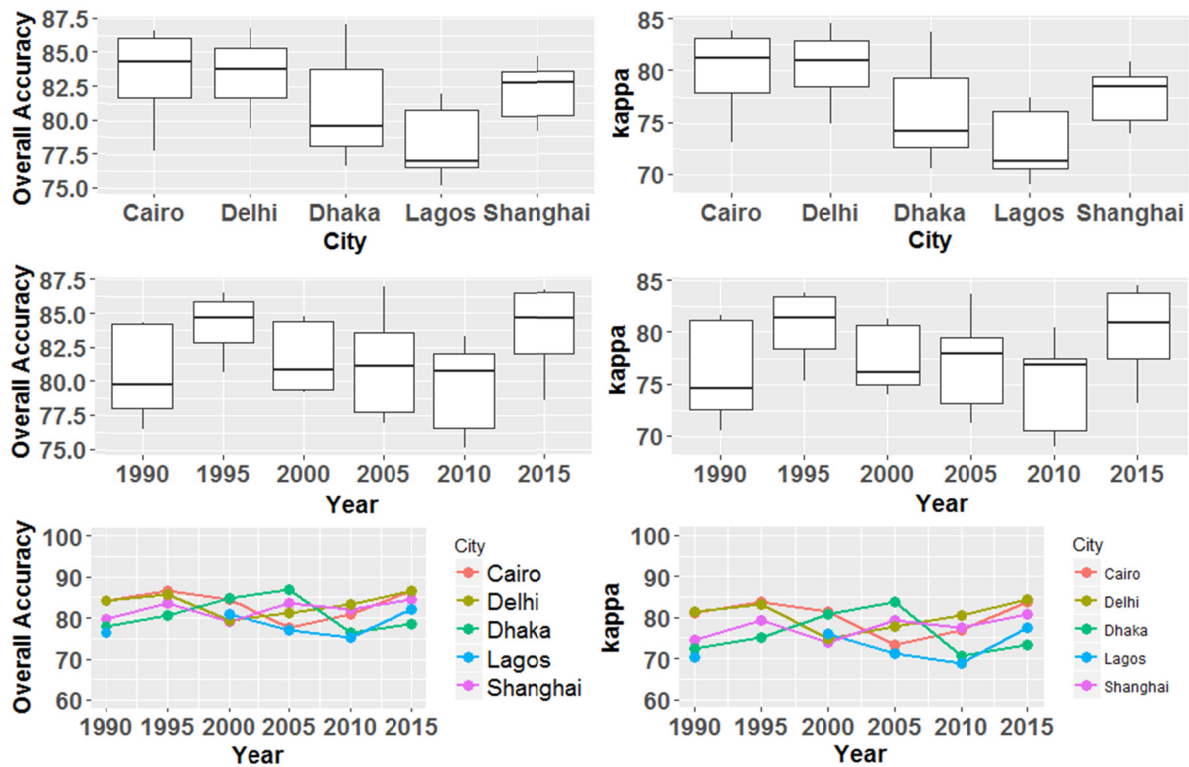


Figure 27: (Top left) A box plot of the overall accuracy measured for each city. (Top right) A box plot of the kappa coefficient measured for each city. (Middle left) A box plot showing the overall accuracy measured for each year of study. (Middle right) A box plot of the kappa coefficient measured for each year. (Bottom left) A line plot showing the overall accuracy for each city by year. (Bottom right) A line plot showing the kappa coefficient measured for each city by year.

4.3.1.1. Cairo, Egypt

An average overall accuracy of 83.38% was achieved for Cairo, and an average kappa of 80.02%. The lowest overall accuracy, at 77.78% and lowest kappa, 73.20% was measured for 2005. A maximum overall accuracy of 86.5%, with a kappa of 83.80% was measured for the 1995 classification. Figure 21 illustrates the classification results for Cairo.

4.3.1.2. Delhi, India

The accuracy assessments for Delhi showed that on average the overall accuracy was 83.41% with an average kappa of 80.46%. A minimum overall accuracy measurement of 79.43% was measured in 2000 with the maximum of 86.73% in 2015. Figure 22 illustrates the classification results for Delhi.

4.3.1.3. Dhaka, Bangladesh

An average overall accuracy of 80.8% was achieved for Dhaka, with an average kappa of 75.96%. A minimum overall accuracy measurement of 78.0% was measured in 1990 with the maximum of 84.76% in 2000. Figure 23 illustrates the classification results for Dhaka.

4.3.1.4. Lagos, Nigeria

The accuracy assessments for Lagos indicated that on average the overall accuracy was 78.29% with an average kappa of 72.87%. A minimum overall accuracy measurement of 75.16% and a kappa of 68.96%, was measured in 2010. The maximum overall accuracy was measured for 2015 at 82.0% with a kappa of 77.5%. Figure 24 illustrates the classification results for Lagos.

4.3.1.5. Shanghai, China

In the case of Shanghai, an average overall accuracy of 81.77% was achieved with an average kappa of 77.23%. The lowest overall accuracy measurement was 79.7%, for 1990 and a maximum of 84.6% in 2015. Figure 25 illustrates the classification results for Shanghai.

The box plots in Figure 21, indicates the overall accuracy by year, this shows that the lowest average overall accuracy was measured for 2010 (79.54%) and the highest average overall accuracy for 2015 (83.67%).

4.3.2. Built-up area land-cover class accuracy assessment

Because this study focuses on urban expansion, this section will only discuss the accuracy of the urban land-cover class. See Appendix E for detailed error matrix for each city at each of the years of study. Table 9 shows the user's accuracy and producer's accuracy for each of the years by city. Figure 27 is a visual representation of the data in table 9.

Table 9: The user's and producer's accuracy for each city by year

Year	<u>Cairo</u>		<u>Shanghai</u>		<u>Delhi</u>		<u>Dhaka</u>		<u>Lagos</u>	
	<u>user's accuracy</u>	<u>produce accuracy</u>	<u>user's accuracy</u>	<u>produce accuracy</u>	<u>user's accuracy</u>	<u>producer accuracy</u>	<u>user's accuracy</u>	<u>producer accuracy</u>	<u>user's accuracy</u>	<u>producer accuracy</u>
1990	100	90	82.1	76.7	83.9	92.9	80.6	83.3	65.9 (1984)	84.4
1995	93.1	90	81.2	86.66	72.7	77.4	88.8	80		
2000	86.2	80.6	81.5	73.3	77.1	81.8	85.3	92.1	88.5	76.7
2005	92.6	83.3	79.3	79.3	80	77.4	96.6	87.5	77.8	70
2010	88.5	76.7	85.7	80	85.2	74.2	80	80	76.7	71.9
2015	96.3	86.7	80.6	78.1	79.4	90	80.6	86.3	80	80
avg.	92.8	84.6	81.7	79	79.7	82.3	85.3	84.9	77.8	76.6

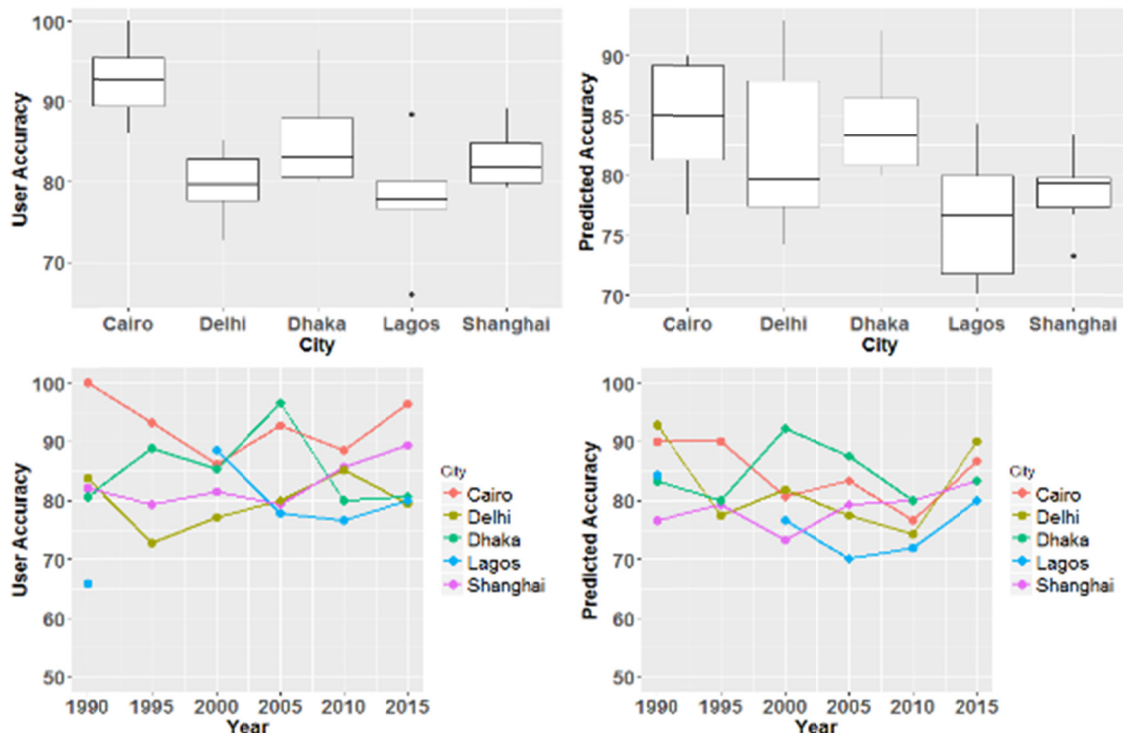


Figure 28: (Top Left) A Built-up land-cover class user's accuracy box plot by city. (Top right) a Built-up land-cover class producer's accuracy box plot by city. (Bottom left) a line plot, indicating the Built-up land-cover class user's accuracy, for each city by year. (Bottom right) a line plot, indicating the Built-up land-cover class producer's accuracy, for each city by year.

4.3.2.1. Cairo, Egypt

An average user's accuracy of 92.78% was achieved for Cairo, with the highest accuracy of 100% for 1990. The lowest accuracy was measured for 2000 at 86.21%. An average producer's accuracy of 84.55% was achieved. With the highest was achieved in 1990 and 1995 at 90% and the lowest for 2010 at 76.67%. Table 10 shows that producer's accuracy for Cairo for each year.

Table 10: Producer's accuracy for Cairo, by year of image classification

<u>Year</u>	<u>Urban</u>	<u>water</u>	<u>Vegetation</u>	<u>Low density vegetation</u>	<u>Soil</u>	<u>White soil</u>
1990	27	0	0	1	2	0
1995	25	0	0	3	2	0
2000	25	0	2	3	1	0
2005	25	0	0	5	0	0
2010	23	2	0	5	0	2
2015	26	0	0	1	0	4

4.3.2.2. Dhaka, Bangladesh

An average user's accuracy of 85.3% was achieved for Dhaka, with the highest accuracy of 96.6% for 2005 and the lowest accuracy at 80% for 2010. An average producer's accuracy of 84.9% was achieved. With the highest achieved for 2000 at 92.1% and the lowest for 1995 and 2010 at 80%. Table 11 shows that producer's accuracy for Dhaka for each year.

Table 11: Producer's accuracy for Dhaka, by year of image classification

<u>Year</u>	<u>Urban</u>	<u>water</u>	<u>Vegetation</u>	<u>Low density vegetation</u>	<u>Soil</u>
1990	25	0	1	3	1
1995	24	0	2	3	1
2000	35	0	1	1	1
2005	28	0	1	2	1
2010	25	0	0	5	1
2015	24	0	0	2	4

4.3.2.3. Delhi, India

An average user's accuracy of 79.7% was achieved for Delhi, with the highest accuracy of 85.2% for 2005 and the lowest accuracy at 72.7% for 1995. An average producer's accuracy of 82.3% was achieved. With the highest achieved for 1990 at 92.9% and the lowest for 2010 at 74.2%. Table 12 shows that producer's accuracy for Delhi for each year.

Table 12: Producer's accuracy for Delhi, by year of image classification

<u>Year</u>	<u>Urban</u>	<u>water</u>	<u>Vegetation</u>	<u>Low density vegetation</u>	<u>Soil</u>	<u>White soil</u>	<u>Rock</u>
1990	26	2	0	1	1	0	0
1995	24	0	0	3	3	0	1
2000	27	1	0	1	3	0	1
2005	24	0	2	1	3	0	1
2010	23	0	1	3	4	0	0
2015	27	0	0	2	1	0	0

4.3.2.4. Lagos, Nigeria

An average user's accuracy of 77.75% was achieved for Lagos, with the highest of 88.46% for 2000 and the lowest accuracy at 65.85% for 1990. An average producer's accuracy of 76.58% was achieved. With the highest achieved for 1990 at 84.38% and the lowest for 2010 at 70%. Table 13 shows that producer's accuracy for Lagos for each year.

Table 13: Producer's accuracy for Lagos, by year of image classification

<u>Year</u>	<u>Urban</u>	<u>water</u>	<u>Vegetation</u>	<u>Low density vegetation</u>	<u>Soil</u>
1984	27	0	5	0	0
1995					
2000	23	0	0	0	7
2005	21	2	0	0	7
2010	0	3	1	5	23
2015	24	0	1	3	2

4.3.2.5. Shanghai, China

An average user's accuracy of 81.1% was achieved for Shanghai, with the highest of 85.7% for 2010 and the lowest accuracy at 79.3% for 2005. An average producer's accuracy of 79.0% was achieved. With the highest achieved for 1995 and 2005 at 86.6%, respectively, and the lowest for 2000 at 73.3%. Table 14 shows that producer's accuracy for Shanghai for each year.

Table 14: Producer's accuracy for Shanghai, by year of image classification

<u>Year</u>	<u>Urban</u>	<u>water</u>	<u>Vegetation</u>	<u>Low density vegetation</u>	<u>Soil</u>
1990	23	0	1	5	1
1995	26	0	1	2	1
2000	22	0	1	3	4
2005	23	1	1	5	2
2010	24	0	2	3	1
2015	23	0	1	2	4

4.4. Analysis of the relationship of UN population estimates and the measured growth of the urban footprints

Table 15 shows the urban area size for each city by year, as estimated from the classification results, and the rate of urban area growth along with the estimated population size and rate of population increase. Figure 28 is a visual representation of the results shown in table 15.

Table 15: The urban area size (km²), rate of urban area growth (%), UN population estimates (1000 and rate of population growth (%) for each of the cities by year

Year	<u>Cairo</u>				<u>Delhi</u>				<u>Dhaka</u>			
	<u>Urban Size (km²)</u>	<u>Growth Rate (%)</u>	<u>Pop. est. (1000)</u>	<u>Pop. growth rate (%)</u>	<u>Urban Size (km²)</u>	<u>Growth Rate (%)</u>	<u>Pop. est. (1000)</u>	<u>Pop. growth rate (%)</u>	<u>Urban Size (km²)</u>	<u>Growth Rate (%)</u>	<u>Pop. est. (1000)</u>	<u>Pop. growth rate (%)</u>
1990	491.3		9892.0		474.5		9726.0		97.6		6621.0	
1995	818.0	66.5	11962.0	20.9	564.6	19.0	12407.0	27.6	99.0	1.4	8332.0	25.8
2000	1013.7	23.9	13626.0	13.9	663.9	17.6	15732.0	26.8	106.7	7.8	10285.0	23.4
2005	1208.4	19.2	15174.0	11.4	938.6	41.4	18670.0	18.7	122.8	15.1	12331.0	19.9
2010	1397.7	15.7	16899.0	11.4	1062.8	13.2	21935.0	17.5	190.2	54.9	14731.0	19.5
2015	1631.2	16.7	18772.0	11.1	1647.6	55.0	25703.0	17.2	355.2	86.7	17598.0	19.5
Year	<u>Lagos (area of analysis)</u>				<u>Shanghai (area of analysis)</u>							
	<u>Urban Size (km²)</u>	<u>Growth Rate (%)</u>	<u>Population est. (1000)</u>	<u>Population growth rate (%)</u>	<u>Urban Size (km²)</u>	<u>Growth Rate (%)</u>	<u>Population est. (1000)</u>	<u>Population growth rate (%)</u>				
1990	254.61 (1984)		4764.0		488.9		7823.0					
1995			5983.0	25.6	737.6	33.7	10450.0	33.6				
2000	448.02	47.6	7281.0	21.7	1033.8	28.7	13959.0	33.6				
2005	586.58	23.6	8859.0	21.7	1227.9	15.8	16763.0	20.1				
2010	745.88	21.4	10781.0	21.7	1782.0	31.1	19980.0	19.2				
2015	987.24	24.4	13123.0	21.7	2513.0	29.1	23741.0	18.8				

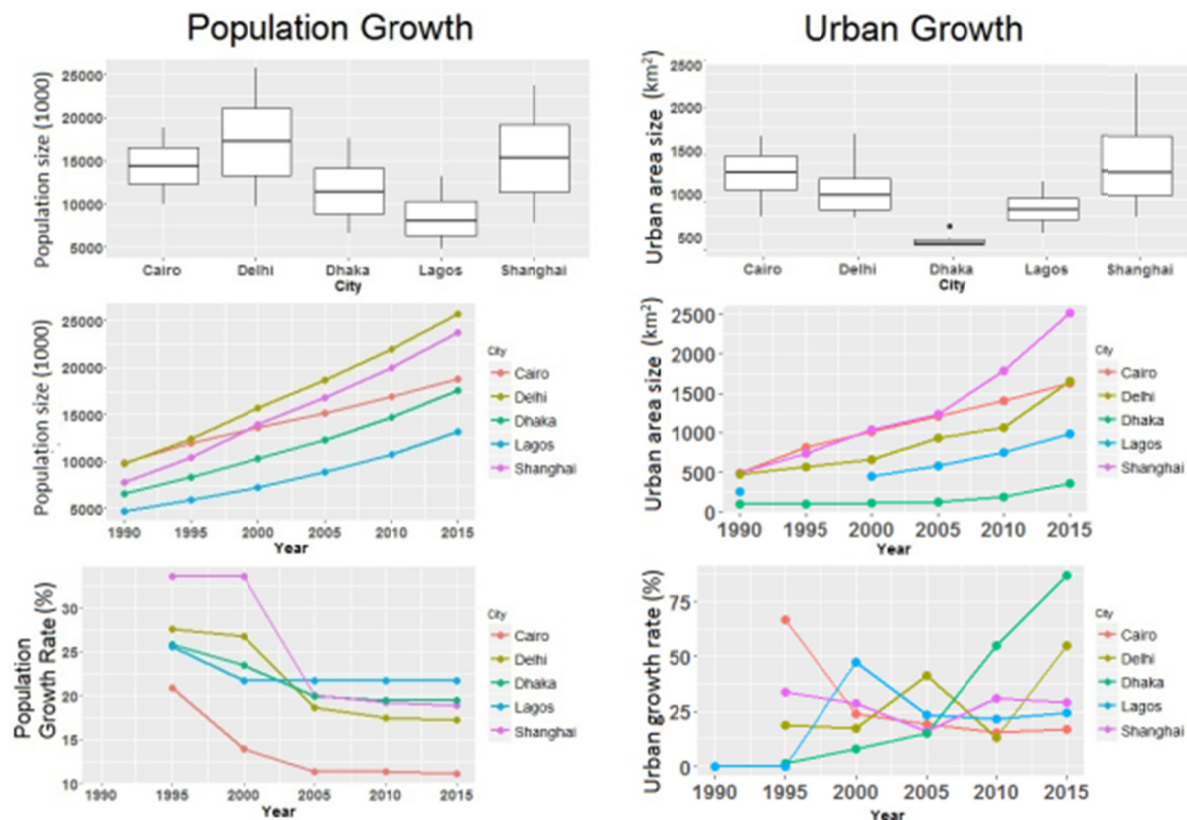


Figure 29: (Top right) A box plot indicating the population growth experienced by each city from 1990 to 2015. **(Top left)** A box plot indicating the urban growth experienced by each city from 1990 to 2015. **(Middle left)** A line plot indicating the growth in population estimates for each of the five cities by year. **(Middle right)** A line plot indicating the growth in urban area size for each of the five cities by year. **(Bottom left)** A line plot indicating the rate of growth in population estimates for each of the five cities by year. **(Bottom right)** A line plot indicating the rate of urban area growth for each of the five cities by year.

The population estimates increased at a steady rate for all five cities from 1990 to 2015, to a point where estimates more than doubled for all 5. Lagos experienced the largest increase in population, from 7.8 million to 23.7 million and increase of 3.034 times). This was followed by Dhaka with a 2.75 times increase, Delhi increased 2.67 times, Shanghai increased 2.64 times and Cairo 1.89 times.

Delhi's population surpasses Cairo's in the early 1990's, and by the late 1990's it was surpassed by Shanghai. This makes Cairo the only city's population estimates to be surpassed by the other cities.

The rate of population, in %, slowed down for all five cities from 1990. The rate of population growth decreases noticeable from 1995 to 2000, especially from 2000 up

until 2005. Shanghai experienced the sharpest drop in growth rate from 2000 to 2005.

When comparing the estimated population numbers with the growing urban footprint, by analysing these results, a number of points are highlighted. For one the population estimates for Delhi is higher than any of the other cities, yet the physical urban size does not reflect this and is only the third largest city. This might reflect a densely populated urban area.

The same is true for Dhaka; the physical urban size is much smaller than the other cities at 355.2km² in 2015. Yet it has a large estimated population close to 17 million. Again this might point to a highly dense urban area, however it might also be that a lot of people live in sparsely built up areas around the Dhaka urban area. Due to the scattered nature of these settlements and dense vegetation, it is possible that they could not be properly detected on the Landsat images with a resolution of 30m.

A parametric (Pearson's correlation with an $R > 0.9$) and a non-parametric (Spearman's rank correlation with $\rho = 1$) test for correlation was performed, both of which indicated a significantly positive relationship. A linear model was created for each city to analyse the strength and direction of relationship between the population estimates and physical urban growth. The results indicated that there is a linear relationship between these two variables for all 5 cities, though the strength of the relationship differs significantly between the five cities. All the regression tests resulted in a significant p-values, for Cairo the p-value was 0.000005, for Dhaka it was 0.02, for Delhi it was 0.0288, for Lagos it was 0.00203 and for Shanghai it was 0.000761, see table 16 for detailed test results.

The model indicated that if the estimated population increases by one unit (1000) the physical urban area for Cairo will increase by 0.1259 km², 0.02176 km² for Dhaka and 0.06936km² for Delhi. The analysis for Lagos and Shanghai only took into consideration the urban growth within the administrative boundaries in which the population estimates are estimated. For Lagos (Lagos State) the urban area will increase by 0.0234 km² for each unit of increase in population and 0.12213 km² for Shanghai. Table 16 shows the model results for each of the cities.

From these results, we can observe that the strongest relationships between the two variables are seen for Cairo, Lagos and Shanghai. Compared to the other three cities, a weaker relationship is observed.

Table 16: Results from the regression models to test the relationship between population growth and urbanisation for each of the five cities

	<u>Cairo</u>	<u>Dhaka</u>	<u>Delhi</u>	<u>Lagos</u>	<u>Shanghai</u>
Pearson's correlation	0.9981	0.868	0.955	0.9936	0.965144
Spearman's correlation	1	1	1	1	1
p-value	0.00277	0.00278	0.00277	0.01667	0.00277
Intercept Estimation	-717.4	91.7073	-312.25008	-955.39	-589.965
Intercept Pr (>t)	0.000213 ***	0.2662	0.18276	0.0021*	0.0526.
Pop Estimate	0.1259	0.02176	0.06936	0.0234	0.12213
Pr (>t)	0.000005 ***	0.0200*	0.00288**	0.00203**	0.000761***
R-squared	0.9964	0.77	0.9137	0.9718	0.9553
Adjusted R-squared	0.9954	0.072	0.8921	0.962	0.9441
DF	4	4	4	3	4
P-value	0.00000499 ***	0.01996*	0.00288**	0.002028***	0.0007613***
Slope in degrees	7.1734°	0.396°	3.967°	13.1704°	6.96295°
Durbin Watson Autocorrelation Test P-value	0.284	0.074	0.342	0.204	0.034
Testing for heteroskedasticity P-value	0.1897	0.30127	0.33825	0.5365	0.4456
Bonferroni Outlier test	0.00424	0.01477	0.01876	0.0853	0.327

As explained in the research methodology section, due to the small sample size these models are subject to noise. The small sample size also makes it impossible to perform a time series analysis and as a result, a Durbin Watson test was performed to test if the models were influenced by autocorrelation.

4.5. Analysis of GDP growth and physical urban growth estimates

Table 17 shows the urban area size for each city by year and the rate of urban area growth along with the estimated level of GDP and rate of GDP increase. Figure 29, visually representations the data shown in table 17.

Table 17: The estimated urban size and rate of urbanisation, derived from the image classification process, along with the estimated GDP (\$1000.00) and rate of GDP increase

<i>Year</i>	<i>Cairo</i>				<i>Delhi</i>				<i>Dhaka</i>			
	<i>Urban Size (km²)</i>	<i>Growth Rate (%)</i>	<i>GDP est. (\$1000)</i>	<i>GDP est. growth rate (%)</i>	<i>Urban Size (km²)</i>	<i>Growth Rate (%)</i>	<i>GDP est. (\$1000)</i>	<i>GDP est. growth rate (%)</i>	<i>Urban Size (km²)</i>	<i>Growth Rate (%)</i>	<i>GDP est. (\$1000)</i>	<i>GDP est. growth rate (%)</i>
1990	491.3		43130.4	23.3	474.5		326608.0	38.0	97.6		30128.8	35.2
1995	818.0	66.5	60159.2	39.5	564.6	19.0	366599.6	12.2	99.0	1.4	37939.8	25.9
2000	1013.7	23.9	99838.5	66.0	663.9	17.6	476609.1	30.0	106.7	7.8	47124.9	24.2
2005	1208.4	19.2	89685.7	-10.2	938.6	41.4	834215.0	75.0	122.8	15.1	60277.6	27.9
2010	1397.7	15.7	218887.8	144.1	1062.8	13.2	1708458.9	104.8	190.2	54.9	115279.1	91.2
2015	1631.2	16.7	301499.0	37.7	1647.6	55.0	2048517.4	19.9	355.2	86.7	172886.6	50.0

<i>Year</i>	<i>Lagos</i>				<i>Shanghai</i>			
	<i>Urban Size (km²)</i>	<i>Growth Rate (%)</i>	<i>GDP est. (\$1000)</i>	<i>GDP est. growth rate (%)</i>	<i>Urban Size (km²)</i>	<i>Growth Rate (%)</i>	<i>GDP est. (\$1000)</i>	<i>GDP est. growth rate (%)</i>
1990	274.2 (1984)		30757.1	6.5	600.0		356937.3	16.1
1995			28547.0	-7.2	898.9	49.8	728007.5	104.0
2000	702.9	60.9	46386.0	62.5	1319.7	46.8	1198474.9	64.6
2005	1029.2	46.4	112248.3	142.0	1694.2	28.4	2256902.6	88.3
2010	1431.9	39.1	369062.4	228.8	2461.5	45.3	5930502.3	162.8
2015	2269.9	58.5	568508.3	54.0	3845.2	56.2	10354831.7	74.6

The GDP growth for the five countries showed a significant growth from 1990 to 2015. The country that has experienced the largest increase in GDP was China, which had grown 33.676 times from 1990 to 2015. Nigeria grew 18.483 times from 1990 to 2015. Egypt and India follows with a growth of 6.99 times and 6.272 times, respectively. Bangladesh has seen the least amount of growth in GDP, with growth of 5.738 times.

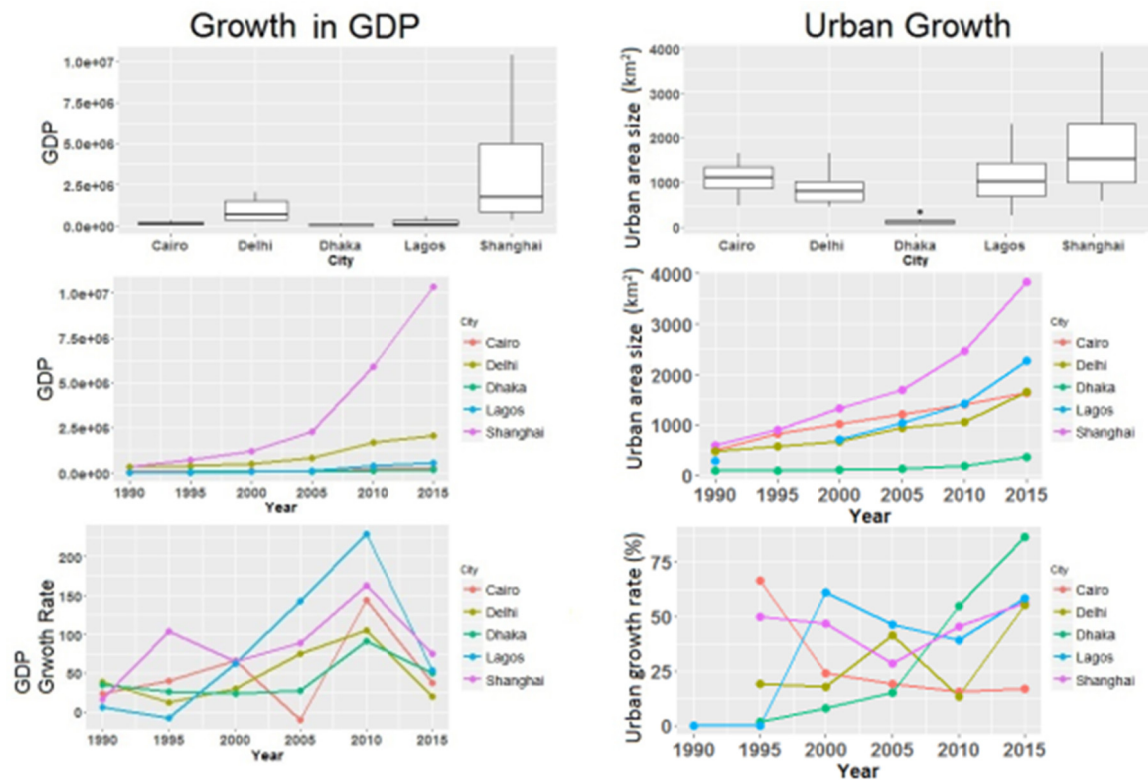


Figure 30: (Top right) A box plot indicating the economic growth experienced by each city from 1990 to 2015. (Top left) A box plot indicating the urban growth experienced by each city from 1990 to 2015. (Middle left) A line plot indicating the growth in GDP estimates for each of the five cities by year. (Middle right) A line plot indicating the growth in urban area size for each of the five cities by year. (Bottom left) A line plot indicating the rate of growth in GDP estimates for each of the five cities by year. (Bottom right) A line plot indicating the rate of urban area growth for each of the five cities by year.

The rate of GDP growth, growth upon the previous year in %, were below 50% for all five countries from 1990 to 1995 with China being the only exception, seeing a GDP growth rate of 100% from 1990 to 1995. By 2000 China, Nigeria and Egypt experienced a growth rate above 50%, while Bangladesh and India was still below 50%. From 2005 to 2010 all the countries experienced a GDP growth rate above 90%, with Nigeria experiencing the largest % increase at 228.79%. In 2015 the rate of GDP growth slowed down to below 75% for all 5 countries, with Egypt decreasing the most from 144.06% in 2010 to 37.74% in 2015.

Egypt's GDP varies substantially from 1990 to 2015. The GDP grew by 39.48% from 1990 to 1995 and 65.95% from 2000 to 2005. From 2000 to 2005 the GDP contracted by -10.16% but increased again from 2010 to 144.06% and 37.74% by 2015. Cairo's urban growth increased sharply between 1990 and 1995 by 66.5% but decreased to 23.93% in 2000 and continues to decrease to 19.2% in 2005, 15.67%

in 2010 and 16.71% in 2015. Due to this it is difficult to say whether there is a linear relationship.

Bangladesh has seen a slow increase in GDP growth, with a GDP growth below 36% from 1990 to 2005. However, in 2010 there is a sharp increase in GDP of 91.24% from 2005 but decreased to 49.97% between 2010 and 2015. Dhaka's urban growth continued to increase from 1990 to 2010. The lowest growth rate was 1.4% from 1990 to 1995 and the highest of 86.7% between 2010 and 2015.

India's GDP had a continuous growth rate year upon year from 1990 to 2010. From 1990 to 1995 the GDP grew by 12.24%, and 30.0% from 1995 to 2000, 75.03% from 2000 to 2005 and 104.798% between 2010 from 2005. The GDP growth rate was only 19.904% from 2010 to 2015. Delhi's urban growth varies significantly over the twenty five years covered in this study; 17.6% from 1990 to 1995 and 18.98% from 1995 to 2000.

Nigeria's GDP grew from \$30.75 billion to \$521.803 billion from 1990 to 2015. Nigeria's GDP growth rate contracted from 1990 to 1995 by -7.19%, but increased to 62.49% in 2000, 141.99% in 2005 and 228.79% in 2010. The rate of growth did however decrease in 2015 to 41.39%. Between 1984 and 2000 Lagos increased by 60.2%, the GDP increased by 50.81% from 1990 to 2000. From 2000 to 2010 the GDP growth rate increased by 141.99% in 2005 from 2000 and 228.79% by 2010 from 2005. For the same period Lagos's urban area growth rate declined. By 2005 the urban growth rate decreased to 46.42% from 2000 and decreased to 39.12% from 2005 to 2010.

China has the largest GDP of the five countries, and displayed a continuous increase in % over time. From 2000 to 2005 the GDP growth showed a steep increase compared to the previous five years. A steeper increase is observed in the physical urban area expansion from 2005 to 2015, almost the same as what was observed in the GDP growth for the same period.

A parametric (Pearson's correlation) and a non-parametric (Spearman's rank correlation) test for correlation was performed, both of which indicated a significantly positive relationship. To analyse the relationship between urban growth and GDP

growth a simple linear regression was used. From the regression analysis, we see that the relationship, between GDP and physical urban growth, varies significantly between the five cities included in this study.

The regression model indicated that for one unit of increase in GDP (\$1000.00) the urban size for Cairo increases by 0.003621 km² (R² 0.81), 0.001761 km² for Dhaka (R² 0.92), 0.0005508 km² for Delhi (R² 0.89), 0.003527 km² for Lagos (R² 0.89) and 0.0013 km² for Shanghai (R² 0.97).

All the models resulted in a significant P-value < 0.05, with little influence of heteroscedastic and autocorrelation. The Bonferroni test for outliers did, however, identify that the model for Shanghai was influenced by outliers. Due to the small sample size of 6, the outlier variable/variables cannot be removed from the model.

Table 18: Results from the regression models to test the relationship between GDP growth and urbanisation for each of the five cities

	<u><i>Egypt (Cairo)</i></u>	<u><i>Bangladesh (Dhaka)</i></u>	<u><i>India (Delhi)</i></u>	<u><i>Nigeria (Lagos)</i></u>	<u><i>China (Shanghai)</i></u>
Pearson's correlation	0.901	0.963	0.943	0.95	0.986
Spearman's correlation	1	1	1	1	1
p-value	0.0166	0.00277	0.00277	0.01667	0.00277
Intercept Estimation	602.7	161.9	363.2	567.4	764.4
Intercept Pr (>t)	0.0135 *	0.0000992 ***	0.03273 *	0.00118* *	0.003501 **
GDP Estimate	0.003621	0.001761	0.0005508	0.0013	0.0002993
GDP Pr (>t)	0.0140 *	0.000993 ***	0.00465 **	0.01396 *	0.000271 ***
R-squared	0.8131	0.949	0.8907	0.89	0.9733
Adjusted R-squared	0.7663	0.936	0.8634	0.866	0.9666
DF	4	4	4	3	4
P-value	0.01402 **	0.00099 ***	0.004652 **	0.01396 *	0.0002706 ***
Slope in degrees	0.2074454*	0.100903°	0.06472°	0.2021114°	0.01714834°
Durbin Watson Autocorrelation Test P-value	0.082	0.594	0.452	0.208	0.078
Testing for heteroskedasticity P-value	0.2525471	0.20602	0.1050717	0.2369	0.3135984

CHAPTER FIVE - DISCUSSION OF RESULTS

In some circumstances, an object-oriented classification method has been shown to be more accurate than a pixel based classification (Li and Chen, 2009). However, the occasional low accuracy measurements do highlight the shortcomings when applying an object-oriented method to Landsat images.

The relatively high classification accuracy results achieved highlights the usefulness and practicality of an object-based classification method. The classification results allowed for the successful analysis of the relationship between population estimates, GDP growth and physical urban growth.

5.1. Results and short comings of using the seasonal based Landsat images

The selection of Landsat images based on seasonality resulted in less bare soil being classified as urban. However, it did make the process of image acquisition difficult since during or after high rainfall seasons the majority of Landsat images were found to have a high percentage of cloud cover.

In the case of Dhaka, Bangladesh, the high levels of rainfall, during the rainy season, seems to result in large areas of land being flooded. As such the plant growth is dense and little bare soil is visible. However less densely built areas on the outskirts of the city is obscured by vegetation. This resulted in the little to no built-up areas to be classified in the rural areas outside the city. The same is true for Lagos, Nigeria, where the high rainfall conditions result in low dense urban areas not being classified properly due to dense vegetation cover.

For the other cities the results from using images from seasons with high rainfall was successful in limiting misclassification between bare soil and urban areas.

5.2. Results from the object oriented classification

In this study, an object oriented classification method was used to classify various Landsat images to identify urban areas with the aim of measuring physical urban growth over time. Overall the accuracy of the image segmentation process was

good. For the image segmentation process, the overall accuracy was above 87%. The accuracy of the image objects was fundamental to ensure accurate classification results. The results are close to that observed by other studies like where an accuracy of close to or more than 90% was observed (Frohn *et al.*, 2008, Taubenbck, 2012). The classification results varied substantially for each of the cities, even though some good accuracy results were achieved there were still some low accuracy measurements.

A study on land cover type in for Delhi by (Ahmad *et al.*, 2016) found that, in 2001, the built-up area size in the state of Delhi was 754.09km². This study did consider a larger region, but found that the total built-up area size for 2000 was 663.9 km². Considering the fact that the scale differs between the two studies, these results are relatively close, confirming that relatively similar results were found by other others.

The majority of the urban area classification results in user accuracy and producer's accuracy above 80%. This indicates that the urban area size measurements made was sufficient to meet the aims and objectives of this study. The low accuracy observed in the classification of Lagos and Dhaka was due to the scattered nature of human settlements in rural villages surrounding the urban areas. This relatively low measurement might also be due to the high density vegetation in these areas. An object orientated classification done on Jakata by Taubenböck (2012) resulted in an overall accuracy of 81% for Landsat 5 image and 92% for Landsat 7 images. This might indicate a similar problem in which the classification of urban areas is influenced by high density vegetation covers. These low accuracy measurements for urban land-cover classification might have caused inaccurate measurement of urban area size.

5. 3. Discussion of the analysis on the relationship between physical urban growth, UN population estimates and GDP growth

Using the classification results, this study was able to analyse the relationship between population estimates, GDP growth and urban growth.

For the five cities studied, the rate of urban area growth is higher than the rate of population change. This might indicate an inconsistency in the population estimates

or the urban areas becoming less dense over time. Nevertheless, the relationship isn't clear and further research is needed.

The relationship between GDP and physical urban growth isn't clear either. Overall, the trends of increase or decrease in physical urban growth do not exactly correspond to the trends seen in GDP growth. However, an observation can be made that there is a lag effect between the two variables. This observation isn't true for all five cities studied, as each of the cities and their economies are unique. Chen *et al.*, (2014) identified that a short to medium term increase in the speed of urbanisation has little to no effect on economic growth. Thus urbanisation on its own does not lead to economic growth (Chen *et al.*, 2014)

The observation made by Angel *et al.*, (2005), that a city's area size triples as the urban population doubles, was tested on the results from this study. The results (shown in Table 19) seem to correspond to the observation made by Angle *et al.*, (2005). This does indicate that urban areas tend to become less densely populated over time, if we consider the population estimates used in this study to be reliable.

Table 19: This table indicates if the urban area doubled in size (from "Year from" up until "Year to"). The table also indicates by how much the population has grown in the same period as the urban area doubled.

			<i>Population est. (1000)</i>	<i>Urban Size (km2)</i>
<u>Cairo</u>	<i>Year from</i>	1990	9892.0	491.3
	<i>Year to</i>	2015	18772.0	1631.2
	<i>Increase</i>		1.9	3.3
<u>Delhi</u>	<i>Year from</i>	1995	12407.0	564.6
	<i>Year to</i>	2015	25703.0	1647.6
	<i>Increase</i>		2.1	2.9
<u>Dhaka</u>	<i>Year from</i>	1995	8332.0	99.0
	<i>Year to</i>	2015	17598.0	355.2
	<i>Increase</i>		2.1	3.6
<u>Lagos</u>	<i>Year from</i>	2000	7281.0	702.9
	<i>Year to</i>	2015	13123.0	2269.9
	<i>Increase</i>		1.8	3.2
<u>Shanghai</u>	<i>Year from</i>	1990	7823.0	600.0
	<i>Year to</i>	2005	16763.0	1694.2
	<i>Increase</i>		2.1	2.8

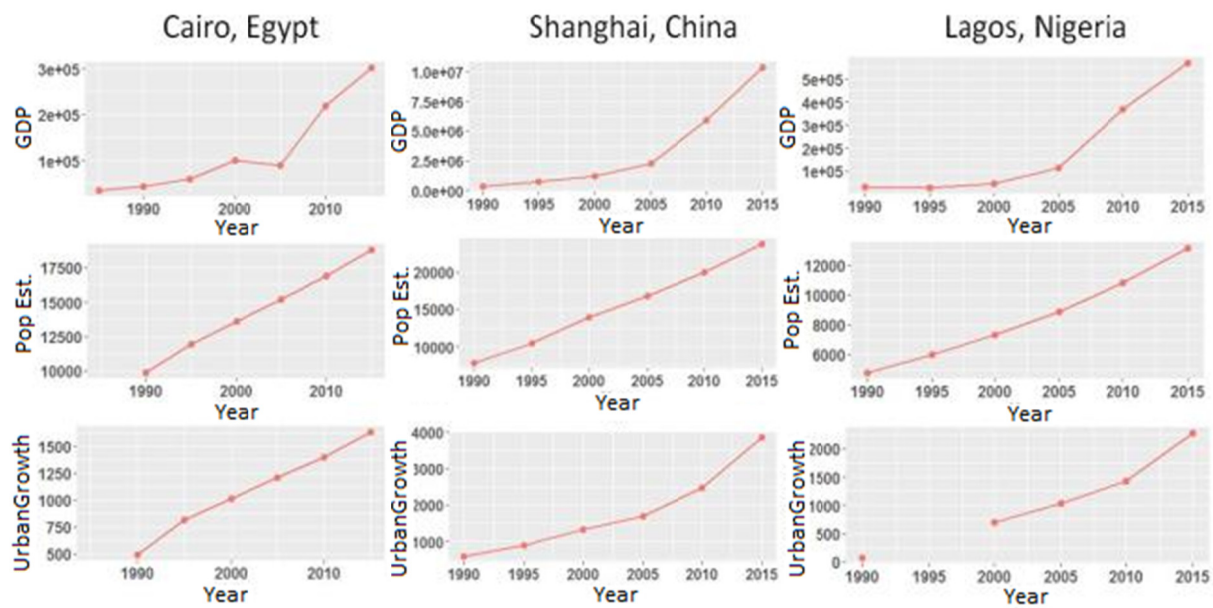


Figure 31: Line charts indicating the growth in GDP, population estimates (popEst) and urban area size (urbanGrowth) for Cairo, Shanghai and Lagos.

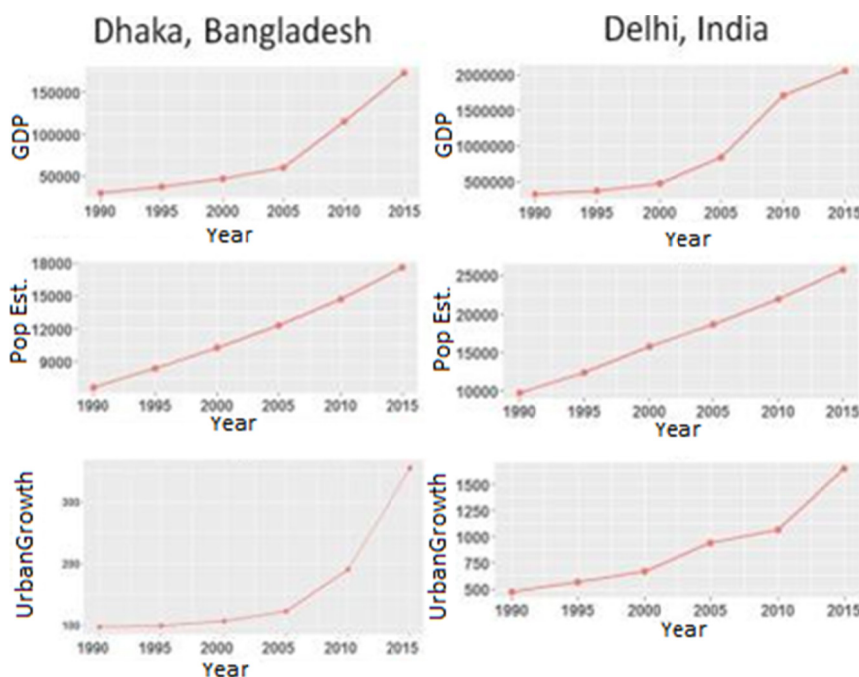


Figure 32: Line charts indicating the growth in GDP, population estimates (popEst) and urban area size (urbanGrowth) for Dhaka and Delhi.

For Cairo, the urban area growth rate increased between 15.67% and 23.9% from 1995 to 2015 and population growth rate increased from 11.08% to 13.9% in the same period. This might point to the city area growing faster than the population estimates and a decreasing population density over time. The 1996 national census

indicated that the rate of population growth for the city of Cairo has slowed from 2.74% in the 1970's and 1980's to 1.6% (Sutton and Fahmi, 2001). Furthermore Cairo's current population growth is mainly due natural population growth (Allen *et al.*, 2004). Despite these observations of a slowdown in the population growth, the regression model indicated that the built-up area would increase by 0.1259km² for every unit of increase in population (1000). Due to Cairo being surrounded by desert, land for development is limited, as a result linear development along the river Nile might be more predominant.

Egypt's GDP and Cairo's urban growth do not follow the same trends. During the period 2000 to 2005 Egypt's GDP growth slowed down and even contracted, with a growth rate of -10.17% for 2000 to 2005. However, this slowdown in GDP had little to no real effect on Cairo's urban expansion, which only slowed from a rate of 23.93%, from 1995 to 2000, to 19.2%, from 2000 to 2005. The regression model did, however, indicate that there is an increase of 0.00362km² for every one unit (\$1000.00) of increase in GDP.

Dhaka is a relatively small city, compared to the other cities in this study, yet it has a high estimated population. The city's population estimates showed a relatively constant rate of increase between 21% and 26%. However, the urban area only grew by 1.4% from 1995 to 1995, 7.8% from 1995 to 2000 and 15.1% from 2000 to 2005, but from 2005 to 2015 the urban area growth rate increased to 54.9% in 2010 and 86.7% in 2015. This point to the rate of physical urban growth which is more than that of the population estimates. From the regression analysis, the city of Dhaka has grown only by 0.02176 km² for every unit (1000) of increase in population. A weak relationship between night time NTL and urban population growth, for the period 1999 to 2010 was identified by Zhou *et al.*, (2015). Dewan and Yamaguchi (2009) found a 37% urban area increase in Dhaka increased 1993 to 2003. However this study found that from 1995 to 2005 the built-up area only increased by 24.04%. It needs to be noted that it is difficult to compare the results as the study by Dewan and Yamaguchi (2009) only considered the main urban area. A possible reason for the slow urban growth, compared to the population growth estimates, from 1990 to 2005 might be ascribed to densification of the urban population. Only after 2005 the urban areas started to increase to accommodate the increased population. It need to

be highlighted that during the image classification process it became clear that Dhaka is subject to large areas being covered in water during the rainy season. This severely limits the area of urban expansion.

Between 1995 and 2005 Bangladesh's GDP grew at a steady rate of 24% and 27%. Between 2005 and 2010 the economy grew at a rate of 91.25% before slowing down to 30.11% in 2015. The urban growth from 1995 to 2005 was low and only increased from 2005 to 2010 but the rate slowed down from 2010 to 2015. The biggest increase in GDP occurred in from 2005 to 2010. However the largest increase in urban area growth was only observed from 2010 to 2015, 5 years after the increase in GDP. The regression model predicted that the urban area would increase by 0.001761 km² for every unit of growth in GDP (\$1000.00). A report done for the World Bank indicated that the urban areas in Bangladesh only contribute around 36% of the country's GDP and 9% of the population living in Dhaka (Hussain *et al*, 2013). The population growth continued to increase at a steady rate throughout the 25 years with the urban growth only rely increasing after 2005, this might be due to the increase in GDP after 2005 which increased investment and allowed for more development to take place. This statement can be linked to a report on the availability of jobs in Bangladesh by The World Bank. According to the World Bank, Bangladesh experienced a decline in poverty of 1.8% from 2000 to 2005 and a decline of 1.7% from 2005 to 2010. This was mostly due a changing demography e.g. declining in fertility rates and a shift in the the economy which provided more jobs in the services and manufacturing sectors (World Bank, 2015).

Delhi's population estimates are more than those of Shanghai for all the years in this analysis, yet the urban size is significantly less than that of Shanghai, indicating a much denser urban environment. This finding is supported by other studies that also found that Delhi is a highly densely populated urban area (Taubenböck *et al.*, 2013). It can be argued that the larger economy of China and Shanghai's greater access to international markets through seaports resulted in more industrial related areas to develop in Shanghai that is not found in Delhi. These factors might explain the higher density observed in Delhi, compared to Shanghai, as there is less investment in industrial activities that form part of the built-up environment. The regression model for Delhi indicated that the built-up area would grew by 0.06936 km² for every unit of

increase in population (1000), with a population density of 15 600 people per square km in 2015.

India's GDP increased steadily from 1990 to 2010 but contracted after 2010 up until 2015. Delhi contributed more towards India's GDP than other mega cities in India, this is because businesses have started to move their head offices to New Delhi to be closer to government (Kamdar, 2010). The urban areas of Delhi continued to show a high growth rate after the slowdown in GDP growth, experienced between 2010 and 2015. When looking at the rate of growth, a relatively weak relationship exists. The increase in the rate of economic growth isn't reflected in the rate of urban growth. The regression model showed that the built-up area will increase by 0.003527 km² for each unit of increase in GDP (\$1000.00). As with Dhaka, the population increased steadily with little urban development up until 2005. After 2000 the GDP started to increase which might have provided investment in new developments. According to a report by the Reserve Bank of Australia, India experienced an increase in GDP from 2000. This increase was mostly due to economic reforms e.g. privatising state owned industries, which led to an opening of the economy which in turn encouraged investment (Cagliarini and Baker, 2010).

For Lagos, the population estimates decreased in its rate of growth over time with 33.58% growth from 1990 to 1995 and a minimum of 18.82% between 2010 and 2015. It has also been found that Nigeria's reluctance to improve rural economies have resulted in a high rural urban migration (Emordi and Osiki, 2008). Bloch *et al.*, (2015) pointed out that Lagos's rapid population growth can be ascribed to a high fertility, declining mortality and rural urban migration. The urban area footprint increased by 56.21% between 2010 and 2015, from 39.12% observed between 2005 and 2010. It has been shown that the traditional Nigerian urban settlement is characterised by a decentralized population and economic activities, furthermore urban/metropolitan areas get consolidated through corridors, e.g. Lagos-Ibadan (Bloch *et al.*, 2015). Thus the relationship between population estimates and physical urban growth isn't clear. The regression model indicated that the urban area would increase by 0.0977 km² for every unit (1000) of increase in population. Due to the fact that Nigeria's census data aren't publically available, it is difficult to get exact population numbers (Bloch *et al.*, 2015). For example, the UN estimated that the

urban population in Nigeria to be 69 million, however Africapolis estimated the urban population to be 50 million. Furthermore the projected population growth varies substantially, the UN anticipate a growth rate of 4.3%, while Africapolis anticipate a rate of 2.1% (Bloch *et al.*, 2015). This highlights inconsistencies in population estimates, these inconsistencies are potentially highlighted in the weak relationship between urban growth and population estimates. However the UN statistics provide the best estimations of population numbers, considering the limited data available to demographers (Bloch *et al.*, 2015).

Interestingly, the average rate of urban area increase for Lagos was 47.66% for the period 2000 to 2015. If the average rate of growth, from 1990 to 2000, was 47.66% the city would have reached an estimated size of $+223\text{km}^2$ by 2000. But the measured size was 702.98 km^2 for 2000, from the 274.2 km^2 and not the predicted $+497\text{ km}^2$. This indicates that the urban areas study did experience a rapid increase in the rate of growth from 1989 to 2000. A possible cause of this increase was identified by Braimoh and Onishi (2005), who found a positive correlation between the increase in manufacturing between 1984 to 2000 and a rapid increase in residential area growth.

Nigeria's GDP growth rate remained low from 1990 to 2005. However, between 2005 and 2010 the rate increased to 228.79% compared to the 141.99% between 2000 and 2005. Between 2010 and 2015 the rate of increase did however slowed down to 41.39%. The increase in economic growth and eventual decrease can, in part, be explained by Nigeria's reliance on oil as a major source of economic growth (Idemudia, 2012). Nigeria oil output exploded between 1960 and 2012 with an estimated 5100 barrels a day. About 40% of Nigeria's GDP and 83% of government revenue did come from it's oil and gas industry in 2012 (Idemudia, 2012). The rate of physical urban area growth does not follow the same trend, with the rate of physical urban growth slowing to 39.12% between 2005 and 2010 and increasing again between 2010 and 2015 to 58.53%. This might indicate that the physical urban area growth does not follow the rate of GDP growth. The regression model showed that the urban area will increase by 0.003527 km^2 for each unit of increase in GDP (\$1000.00).

For the city of Shanghai, the population estimates are relatively constant with the lowest growth rate of 17.18% from 2010 to 2015 and a high of 27.57% between 1990 and 1995. But, the urban area growth rate reached a high of 56.21% from 2010 to 2015 and a low of 28.38% from 2000 to 2005. This indicates that the urban growth rate does not follow the population estimates. It needs to be noted that China's larger economy and Shanghai's location and access to shipyards, along the Yangtze River and seaports, might have caused a large increase in industrial and manufacturing land use. In 2001 50.7% of the cities GDP were generated from the tertiary sector, which includes financial services and shipping (Yang, 2002). This points to an urban area that grows faster than the growth in population estimates. However this can possibly be explained by the shift in the socio-economic landscape after 1990. The national and regional governments implemented a strategy to transform the economy of the city. The focus was on the tertiary sector, which includes financial, information and shipping services. This resulted in the local government starting to introduce policies aimed at the decentralization of densely populated areas (Zhang *et al.*, 2013). The regression model indicated that for every one unit of increase in population estimates (1000) the urban area would increase by 0.1259 km².

China's GDP growth remained relatively constant from 1990 to 2005, however, from 2005 to 2010 the economy experienced an increase of 162.77% from 88.31%. The urban areas grew by 28.38% from 2005 to 2010 and 45.29% from 2010 to 2015. This growth rate follows the increase in GDP. The fact that Shanghai's urban growth rate might follow the increase in China's GDP might be due to it's access to international and domestic markets via the Yangtze River and East China Sea. Furthermore Zhu (1995) found that due to the change to secondary and tertiary economic activities, Shanghai experienced an increase of 160% in industrial growth in the suburban areas, from 1982 to 1990. The author also found that an increase of 156.6% was observed in the outskirts of the city. This combined with other factors like decentralization of population policies has had an effect where the city footprint increase not just due to population growth, natural or migration or both, but also due soci-economic policies. Thus Shanghai's manufacturing, industrial and logistics sectors might be closely linked to China's GDP.

CHAPTER SIX - CONCLUSION AND RECOMMENDATIONS

Summary

This study set out to establish if there is a relationship between physical urban growth and the UN population estimates. The relationship between physical urban growth and economic growth, measured in the form of GDP, was explored and analysed. The rate of urban growth was measured using an object orientated image classification method.

Images, to be used in the image classification process, were selected based on season. The aim was to limit the possible misclassification of bare soil as urban areas. This process was successful, but the time allocated to selecting cloud free images during or just after rainy seasons proved to be an extremely time consuming process. However, the positive results potentially achieved in the classification process outweigh the time spent searching of images that meet all the criteria.

The advantages of object based image classification methods are undeniable, it allows for the analysis of objects rather than individual pixels. In addition, the contextual information of each object, like average reflectance values of the neighbouring object, allow for a more innovative approach to classification. The accuracy results achieved in the classification process was high, and allowed accurate measurement of total urban area size. However, the accuracy assessment method followed resulted in the identification of objects that contained mixed land use classes, indicating that there were wrongfully created/classified objects. As a result, the use of an object based classification method on Landsat images need to be approached with care. The testing of the weight settings for the image segmentation process was vital, but this was a time-consuming exercise.

This study aimed to identify if there is a relationship between population estimates and physical urban growth, and if there is a relationship, how strong is that relationship. Theoretically, as an urban areas population grows, either through natural growth or migration or both, an urban area should expand as more housing is developed and more economic activities are concentrated in the urban areas.

The regression models indicated that there is indeed a positive relationship between the two variables for all five cities. However, the population estimates grew at a steady rate overtime for all five cities, while the urban areas grew at different rates over time. This might point to some under or over prediction of population numbers.

This study presumed that the fastest growing city, by population, would react more to GDP growth than other cities. This was under the assumption that more working opportunities might lead to an increase in population, through natural growth or rural urban migration, or a combination of both and the increase in availability might stimulate more economic growth.

When comparing the growth in GDP and physical urban growth, it is difficult to identify a clear pattern for each of the individual cities. The fact that this study only selected 5 cities and only 6 time-based measurements per city makes it difficult to identify a clear trend.

The regression analysis showed that there is a weak positive relationship between GDP growth and urban growth.

An important observation made, was that there might be a lag effect present in how urban growth reacts to the increase or decrease in GDP. The rate of GDP growth, for all 5 countries decreased in 2015, a study comparing the rate of physical urban area growth in 2020 might yield better information and be able to identify if the lag effect is present. The main issue in identifying this lag effect is that urban areas are complex entities. A reaction to a slowdown in GDP might only be observed in 5 or 10 years, but an increase in GDP might have a more immediate effect. This will also need to be tested.

It can also be argued that a decreasing economy might result in an increase in rural to urban migration, as more people search for employment opportunities. Also a weak link between urban growth and GDP growth might be caused if a country's key economic sectors isn't linked to industrial or manufacturing done in urban areas. This results in more people staying in rural areas to supply labour, for example to mining, oil or gas drilling. This might result in less urbanisation than what is expected if there is a strong link between urban growth and GDP.

Bloom *et al.*, (2008) theorised that urban primacy, the formation of a main urban core that has obtained a great level of dominance over smaller areas, impacts negatively on economic growth. They also pointed out in their study that urban growth is more of an indicator of economic growth rather than an instrument that drives economic growth. In the case of all five cities, we see the main urban core growing substantially, resulting in urban primacy. The effect of this might be debated; on the one hand the concentration of industry, businesses and labour might result in cost saving due to an agglomeration of the economic sector. However if the theory is proven to be true, the impact of the five cities studied on a region's economic growth must be kept in mind to ensure that the urban area and the country's economy is sustainable.

This study showed that the link between GDP growth and urbanization is not strong. Some of the urban areas studied continued to grow even after a slowdown in the growth of GDP. This highlights a much more complex relationship between the two factors, which can potentially result in unpredictability in urbanisation. The five cities studied have only started to become true global cities from the late 1990's. The long-term trend will most likely also show a strong relationship between economic growth and urbanisation, as seen in most of the developed countries, however in the short to medium term the relationship is not as clear.

Local governments in developing countries mostly have a resistance to urban growth (Angel *et al.*, 2005). For example, the reluctance of service provision to informal areas in the hope of discouraging the expansion of these informal areas. But as pointed out by Bloom *et al.*, (2008), to control urbanisation through the means of policies, either by inhibiting or supporting urban growth would most likely fail. Angel *et al.*, (2005) also came to the same conclusion that policies designed to control population is unworkable and unrealistic.

Recommendations

Object orientated image classification is powerful, despite this the classification results showed that some objects were wrongfully classified due to objects containing a mixture of land-cover types. A proposed solution is to test and apply alterations to the weight values for image segmentation algorithm. Another issue

identified was the extensive amounts of time spend on testing weight values for the image segmentation process. For a study of this size, It is recommendation that alternative classification method should be used. More advanced pixel based classification algorithms, like random forest, support vector machine learning or artificial neural networks might produce better classification results. More powerful cloud based platforms, like Google Earth Engine, have become available in recent years. These platforms allow for the analysis of images without the need to download them. In addition they can utilize large amounts of computing power that allows for fast data processing.

A more detailed study, in which the different land-cover classes, e.g. residential, industrial or commercial areas, are identified, might yield more detailed measurements. These can then be used to study the relationship between economic growth and the rate at which industrial and commercial areas grew. It might be recommended that remote sensing of urban areas should carry more weight in population estimates.

Due to the relatively small number of observations, it is impossible to conduct proper statistical test to establish strength and direction of the relationships between the variables. It is recommended that a larger number of cities for each country is selected and more measurements are made over time.

A detailed study of environmental and geographical factors influencing urban growth should be incorporated in a urban growth model. For example rivers, flood plains, mountains and climatic conditions like rainfall. A good example would be Dhaka, the rivers and lowlands surrounding the city are subject to high water levels during high rain seasons. This limits the availability of suitable land to develop. Another example would be the extensive desert surrounding Cairo, despite the fact that the majority development have observed away from the already crowded Nile area, the dry sand conditions still limit development. These all play an important role in urban growth and it is recommended that these factors should be considered in a urban growth model.

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Appendix A

Rank	Country	City	Country that have experienced war since 1990	Sample	UN population estimates (thousands)		
					1990	2015	2015 - 1990
1	India	Delhi	No	Yes	9725.9	25703.2	15977.3
2	China	Shanghai	No	Yes	7823.0	23740.8	15917.8
3	China	Beijing	No	No	6787.7	20384.0	13596.3
4	Bangladesh	Dhaka	No	Yes	6620.7	17598.2	10977.5
5	China	Shenzhen	No	No	875.0	10749.5	9874.5
6	Pakistan	Karachi	Yes	No	7147.1	16617.6	9470.6
7	China	Guangzhou, Guangdong	No	No	3072.1	12458.1	9386.0
8	China	Chongqing	No	No	4010.6	13331.6	9321.0
9	Egypt	Al-Qahirah (Cairo)	No	Yes	9892.1	18771.8	8879.6
10	India	Mumbai (Bombay)	No	No	12436.4	21042.5	8606.1
11	Nigeria	Lagos	No	Yes	4764.1	13122.8	8358.7

Table A.1: The list of 11 cities that have experienced the largest growth in population from 1990 to 2015 (UN population estimates).

Appendix B

List of data sources used

- World Administrative Divisions – ESRI**
<http://www.arcgis.com/home/item.html?id=d86e32ea12a64727b9e94d6f820123a2>
 Licencing: http://www.esri.com/~media/Files/Pdfs/legal/pdfs/redist_rights_103.pdf?la=en (allowed to use but cannot redistribute data)
- GDP data – World Bank Databank**
http://databank.worldbank.org/data/reports.aspx?Code=NY.GDP.MKTP.CD&id=af3ce82b&report_name=Popular_indicators&populartype=series&ispopular=y
 File: ny.gdp.mktp.cd_Indicator_v2.xls
 Licencing: <http://data.worldbank.org/summary-terms-of-use> (free to use cannot redistribute or sell)
- Urban population data – UN**
<http://esa.un.org/unpd/wup/DataQuery/>
 File: Annual-Population-of-Urban-Agglomerations-(thousands)-20150712092122.xls
 Licencing: free to use
- ISO codes – UN ECONOMIC COMMISSION FOR EUROPE**
<http://www.unece.org/cefact/locode>
 File: 2015-1 UNLOCODE CodeList.mdb
 Licencing: free to use
- Conflict data**
<http://www.pcr.uu.se/data/>
 Licencing: free to use cannot redistribute or sell
- City Locations – United Nations Code for Trade and Transport Locations**
<http://www.unece.org/cefact/locode/welcome.html>
 Licencing: free to use cannot redistribute or sell

7. Landsat images – NASA

<http://earthexplorer.usgs.gov/>

Licencing: free to use cannot redistribute or sell

8. Climate Data- World Bank climate knowledge portal

<http://sdwebx.worldbank.org/climateportal/index.cfm>

Accessed via rWBclimate <- R package (<https://github.com/ropensci/rWBclimate>)

Licencing: free to use

List of software packages used

1. ArcGIS 10.1
2. eCognition 9
3. ERDAS 2014
4. QGIS 2.6
5. R 3.2
6. MS Access 2010

Appendix C

R script for acquiring climate data for each of the five cities

```
#-----load libraries-----
library("rWBclimate")
library("ggplot2")
library("gridExtra")
#-----get climate data-----
CHN<-get_historical_precip("175", "month")
Ind<-get_historical_precip("105", "month")
Nig<-get_historical_precip("460", "month")
Eg<-get_historical_precip("395", "month")
Ban<-get_historical_precip("100", "month")
#-----create a ggplots for each region-----
pCHN<-ggplot(CHN,aes(x=month,y=data))
+geom_bar(stat="identity")+geom_text(aes(label=round(data,2),vjust=1.5,colour="white"))+ggtitle("Shanghai , China (area 175)")
pIND<-ggplot(Ind,aes(x=month,y=data))
+geom_bar(stat="identity")+geom_text(aes(label=round(data,2),vjust=1.5,colour="white"))+ggtitle("Delhi , India (area 105)")
pNIG<-ggplot(Nig,aes(x=month,y=data))
+geom_bar(stat="identity")+geom_text(aes(label=round(data,2),vjust=1.5,colour="white"))+ggtitle("Lagos, Nigeria (area 460)")
pEg<-ggplot(Eg,aes(x=month,y=data))
+geom_bar(stat="identity")+geom_text(aes(label=round(data,2),vjust=1.5,colour="white"))+ggtitle("Al-Qahirah (Cairo) , Egypt (area 395)")
pBan<-ggplot(Ban,aes(x=month,y=data))
+geom_bar(stat="identity")+geom_text(aes(label=round(data,2),vjust=1.5,colour="white"))+ggtitle("Dhaka ,Bangladesh (area 100)")

#-----plot all charts-----
grid.arrange(pBan,pCHN,pEg,pIND,pNIG, ncol=2)
```

Appendix D

Table of all the images used for image classification during this study

Main images used								Landsat 7 (SLC-Off) gap fill			
Country	City	Path	Row	Year	LANDSAT_SCENE_ID	Landsat Satellite	Image Date	LANDSAT_SCENE_ID	Image Date		
China	Shanghai	118	38	1990	LT51180381989223HAJ01	Landsat 5	11/08/89				
				1995	LT51180381995224HAJ00	Landsat 5	12/08/95				
				2000	LT51180382000142BJC00	Landsat 5	21/05/00				
				2005	LT51180382004201BJC00	Landsat 5	19/07/04				
				2010	LT51180382011012BJC00	Landsat 5	12/01/11				
				2015	LC81180382015215GLN0	Landsat 8	03/08/15				
		118	39	1990	LT51180391989223HAJ01	Landsat 5	11/08/89				
				1995	LT51180391995224HAJ00	Landsat 5	12/08/95				
				2000	LT51180392000158HAJ03	Landsat 5	06/06/00				
				2005	LT51180392003358BJC00	Landsat 5	24/12/03				
				2010	LT51180392011012BJC00	Landsat 5	12/01/11				
				2015	LC81180392015215LGN00	Landsat 8	03/08/15				
India	Delhi	146	40	1990	LT51460401991073ISP00	Landsat 5	14/03/91				
				1995	LT51460401995068ISP00	Landsat 5	09/03/95				
				2000	LE71460401999343SGS00	Landsat 7	09/12/99				
				2005	LE71460402005167ASN00	Landsat 7 (SLC-Off)	16/06/05	LE71460402005151ASN00	01/06/05		
				2010	LT51460402009234KHC00	Landsat 5	22/08/09	LE71460402006234PFS00	22/08/06		
				2015	LC81460402015251LGN00	Landsat 8	08/09/15				
				Egypt	Cairo	176	39	1990	LT51760391990216XXX03	Landsat 5	04/08/90
1995	LT51760391996158AAA01	Landsat 5	06/06/96								
2000	LE71760392000236EDC00	Landsat 7	23/08/00								
2005	LE71760392006236ASN02	Landsat 7 (SLC-Off)	24/08/06					LE71760392006268ASN00	25/09/06		
2010	LE71760392009212ASN00	Landsat 7 (SLC-Off)	31/07/09					LE71760392011218ASN00	06/08/11		
2015	LC81760392015221LGN00	Landsat 8	09/08/15					LE71760392010151ASN00	31/05/10		
Bangladesh	Dhaka	137	43	1990	LT51370431991314BKT02	Landsat 5	10/11/91				
				1995	LT51370431995325BKT00	Landsat 5	21/11/95				
				2000	LE71370432000299SGS00	Landsat 7	25/10/00				
				2005	L71137043_04320051210	Landsat 7 (SLC-Off)	07/12/06	LE71370442005360PFS00	26/12/05		
								LE71370442005328SGS00	24/11/05		
				2010	L71137043_04320090324	Landsat 7 (SLC-Off)	24/03/09	LE71370442010358PFS00	24/12/10		
				2015	LC81370432014089LGN00	Landsat 8	30/03/14	LE71370432010294SGS00	21/10/10		
		137	44	1990	LT51370441991314BKT02	Landsat 5	10/11/91				
				1995	LT51370441995325BKT00	Landsat 5	21/11/95				
				2000	LE71370442000299SGS00	Landsat 7	25/10/00				
				2005	L5137044_04420061205	Landsat 5	05/12/06				
				2010	L5137044_04420091111	Landsat 5	11/11/09				
				2015	LC81370442014089LGN00	Landsat 8	30/03/14				
Nigeria	Lagos	191	55	1984	p191r055_5dt19841218_z31	Landsat 4	18/12/84				
		NO IMAGE FOR THIS DATE									
		191	55	2000	LE71910552001343SGS00	Landsat 7	09/12/01				
				2005	L71191055_05520061207	Landsat 7 (SLC-Off)	07/12/06	LE71910552005354ASN00	20/12/05		
								LE71910552005322ASN00	18/11/05		
				2010	L71191055_05520110103	Landsat 7 (SLC-Off)	03/01/11	LE71910552009333ASN00	29/11/09		
				2015	LC81910552015342LGN00	Landsat 8	08/12/15	LE71910552010320ASN00	12/11/10		

Appendix E Additional information of each city

Egypt, Cairo (Al-Qahirah)



Contextual information



Figure 33: map indicating the location of Cairo within Egypt

Landsat image location

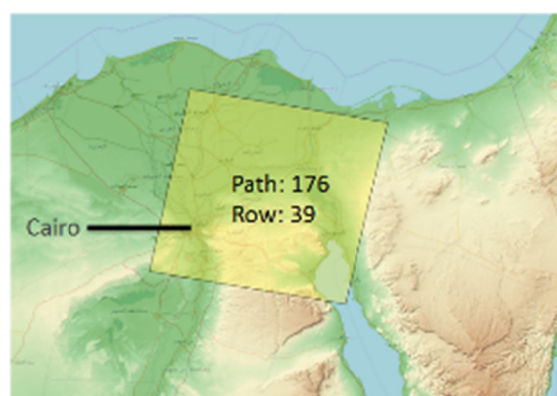


Figure 34: A map indicating the location of Cairo within the Landsat image Path and Row.
Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Urban class classification map

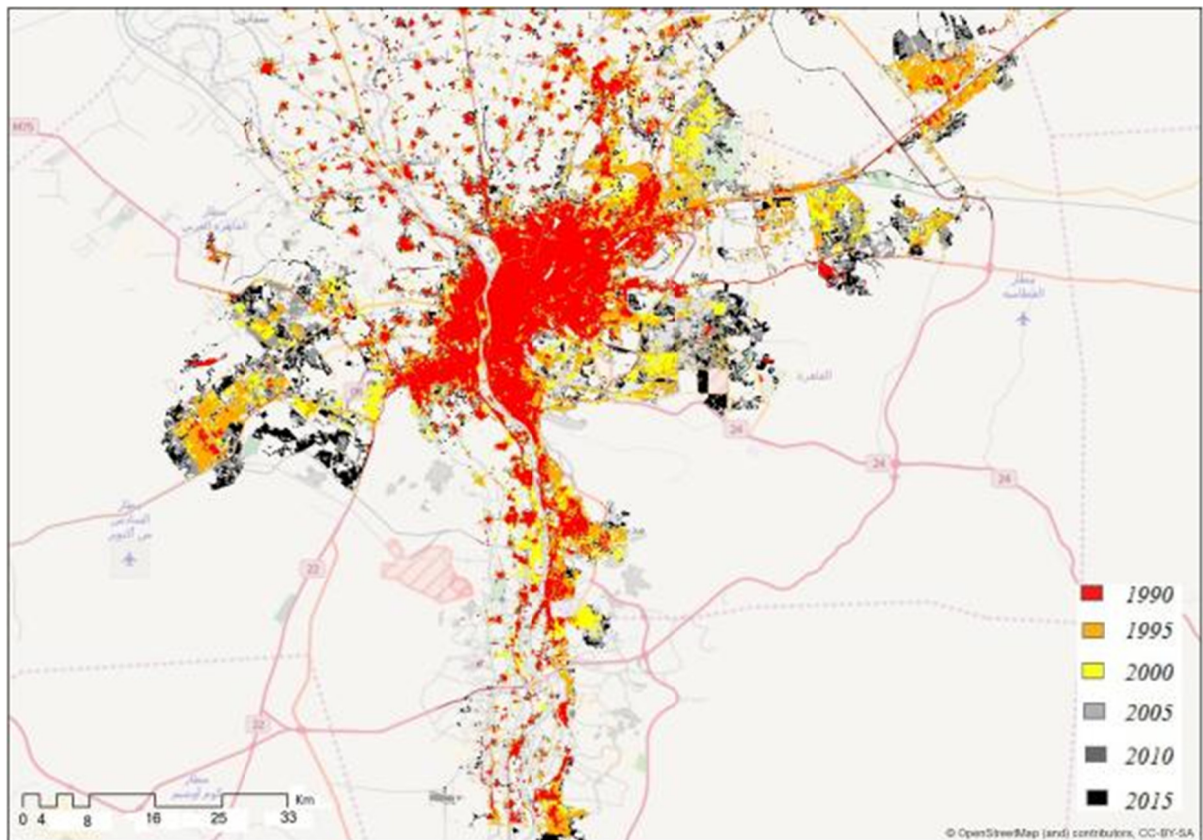


Figure 35: A map showing the Built-up (Urban) area for each year, classified from Landsat images. Background image from OpenStreetmap, API: OpenLayers Plugin QGIS



Error matrices for Cairo for each of the years studied

1990	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	White Sand	Total
	water	28	0	0	0	0	0	28
	Veg	0	21	0	0	8	0	29
	Urban	0	0	27	2	1	0	30
	Soil	0	0	0	24	5	3	32
	Low Veg	0	5	0	3	22	0	30
	White Sand	0	0	0	1	0	28	29
	Total	28	26	27	30	36	31	178

Overall accuracy	84.27
kappa	81.12

1995	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	WhiteS and	Total
	water	20	0	0	0	0	0	20
	Veg	0	24	0	0	6	0	30
	Urban	0	0	25	2	3	0	30
	Soil	0	3	2	23	2	1	31
	Low Veg	0	2	0	3	25	0	30
	White Sand	0	0	0	2	0	28	30
	Total	20	29	27	30	36	29	171

Overall accuracy	84.80
kappa	81.69

2000	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	White Sand	Total
	water	28	0	1	0	0	2	31
	Veg	0	25	0	0	5	0	30
	Urban	0	2	25	1	3	0	31
	Soil	0	0	3	25	0	0	28
	Low Veg	0	2	0	0	21	0	23
	White Sand	0	0	0	8	0	22	30
	Total	28	29	29	34	29	24	173

Overall accuracy	84.39
kappa	81.28

2005	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	White Sand	Total
	water	19	0	0	0	0	0	19
	Veg	0	20	2	3	5	0	30
	Urban	0	0	25	0	5	0	30
	Soil	0	0	0	25	5	2	32
	Low Veg	0	5	0	3	22	0	30
	White Sand	0	0	0	5	3	22	30
	Total	19	25	27	36	40	24	171

Overall accuracy	77.78
kappa	73.20

2010	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	White Sand	Total
	water	22	0	2	0	0	0	31
	Veg	0	25	0	0	5	0	30
	Urban	0	0	23	0	5	2	32
	Soil	0	0	1	26	5	0	30
	Low Veg	0	2	0	6	22	0	30
	White Sand	0	0	0	6	0	25	24
	Total	27	37	38	26	27	22	177

Overall accuracy	80.79
kappa	76.90

2015	User Class \ Sample	water	Veg	Urban	Soil	Low Veg	White Sand	Total
	water	30	0	1	0	0	0	30
	Veg	0	22	0	0	8	0	31
	Urban	0	0	26	0	4	0	30
	Soil	0	0	0	27	2	1	30
	Low Veg	0	5	0	1	21	0	30
	White Sand	0	0	0	2	0	28	27
	Total	29	30	27	27	30	35	178

Overall accuracy	86.52
kappa	83.83

User's accuracy and produce accuracy for each of the land-cover types classified for Cairo



Year		1990	1995	2000	2005	2010	2015
High density Vegetation (veg)	<i>user's accuracy</i>	80.77	82.76	86.21	80.00	92.59	81.48
	<i>produce accuracy</i>	72.41	80.00	83.33	66.67	83.33	73.33
Low density Vegetation (Veg Low)	<i>user's accuracy</i>	61.11	75.76	72.41	55.00	59.46	60.00
	<i>produce accuracy</i>	73.33	83.33	91.30	73.33	73.33	77.78
Bare soil (Soil)	<i>user's accuracy</i>	80.00	77.42	73.53	69.44	68.42	90.00
	<i>produce accuracy</i>	75.00	77.42	89.29	78.13	81.25	90.00
Built-up (Urban)	<i>user's accuracy</i>	100.00	93.10	86.21	92.59	88.46	96.30
	<i>produce accuracy</i>	90.00	90.00	80.65	83.33	76.67	86.67
Water	<i>user's accuracy</i>	100.00	100.00	100.00	100.00	100.00	100.00
	<i>produce accuracy</i>	100.00	100.00	90.32	100.00	91.67	96.77
White sand/ soil (white sand)	<i>user's accuracy</i>	90.32	96.55	91.67	91.67	92.59	96.55
	<i>produce accuracy</i>	96.55	93.33	73.33	73.33	80.65	93.33

India, Delhi



Contextual information



Figure 36: Map indicating the location of Delhi within India

Landsat image location

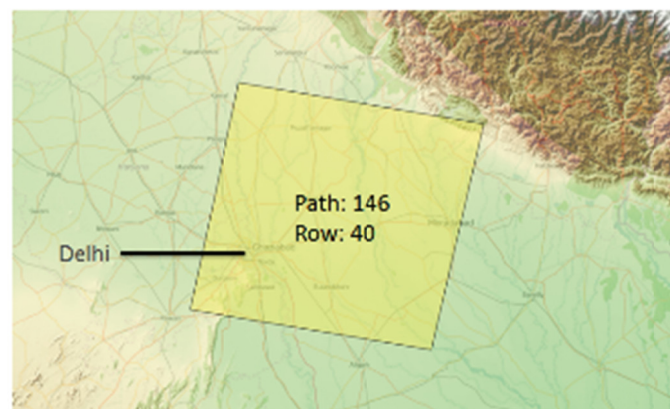


Figure 37: A map indicating the location of Delhi within the Landsat image Path and Row.
Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Urban class classification map

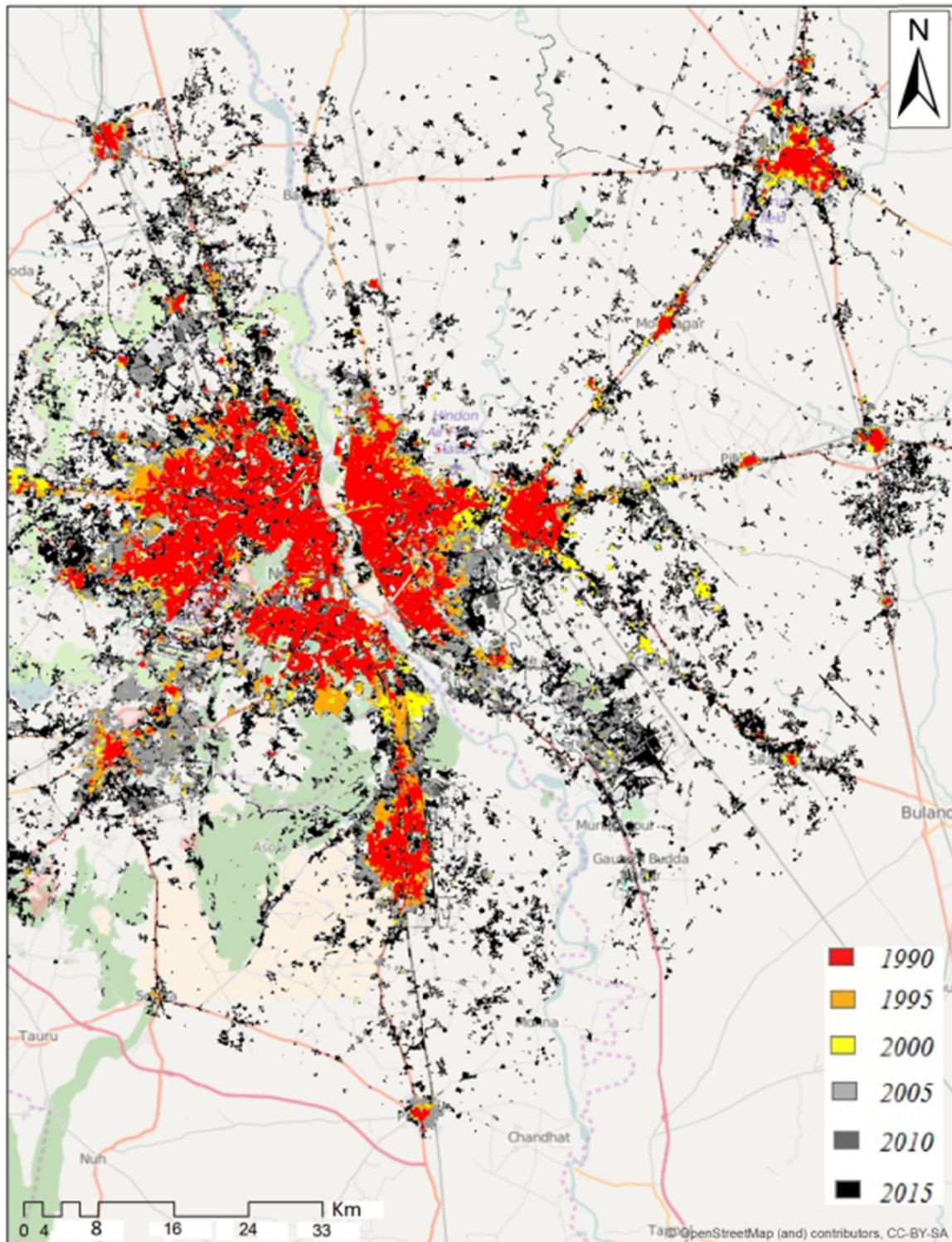


Figure 38: A map showing the Built-up (Urban) area for each year, classified from Landsat images. Background image from OpenStreetmap, API: OpenLayers Plugin QGIS



Error matrices for Delhi for each of the years studied

1990	User Class \ Sample	water	Veg	Urban	Soil	WhiteSand	Rock	Low Veg	Total
	water	28	0	2	0	0	0	0	30
	Veg	0	27	0	0	0	0	5	32
	Urban	2	0	26	0	0	0	0	28
	Soil	0	4	3	22	0	0	0	29
	WhiteSand	0	0	0	8	22	0	0	30
	Rock	0	0	0	5	0	25	0	30
	Low Veg	0	4	0	0	0	0	26	30
	Total	30	35	31	35	22	25	31	209

Overall accuracy	84.21
kappa	81.58

1995	User Class \ Sample	Low Veg	water	Veg	Urban	Soil	WhiteSand	Rock	Total
	Low Veg	23	0	3	4	0	0	0	30
	water	0	28	0	1	0	0	0	29
	Veg	4	0	26	0	0	0	0	30
	Urban	3	0	0	24	3	0	1	31
	Soil	3	0	0	4	23	0	0	30
	WhiteSand	0	0	0	0	1	28	1	30
	Rock	0	0	0	0	2	0	28	30
	Total	33	28	29	33	29	28	30	210

Overall accuracy	85.71
kappa	83.33

2000	User Class \ Sample	Low Veg	water	Veg	Urban	Soil	WhiteSand	Rock	Total
	Low Veg	22	0	7	0	1	0	0	30
	water	0	24	3	3	0	0	0	30
	Veg	6	0	22	0	1	0	0	29
	Urban	1	1	0	27	3	0	1	33
	Soil	1	0	0	5	24	0	0	30
	WhiteSand	0	0	0	0	7	20	0	27
	Rock	0	0	0	0	3	0	27	30
	Total	30	25	32	35	39	20	28	209

Overall accuracy	79.43
kappa	75.97

2005	User Class \ Sample	Low Veg	water	Veg	Urban	Soil	WhiteSand	Rock	Total
	Low Veg	22	0	8	0	1	0	0	31
	water	0	27	0	3	0	0	0	30
	Veg	4	0	24	1	2	0	0	31
	Urban	1	0	2	24	3	0	1	31
	Soil	1	0	0	2	31	0	0	34
	WhiteSand	5	0	0	0	2	23	0	30
	Rock	2	0	0	0	3	0	25	30
	Total	35	27	34	30	42	23	26	217

Overall accuracy	81.11
kappa	77.93

2010	User Class \ Sample	Low Veg	water	Veg	Urban	Soil	WhiteSand	Rock	Total
	Low Veg	23	0	3	1	3	0	0	30
	water	0	28	0	1	0	0	0	29
	Veg	3	0	24	1	2	0	0	30
	Urban	3	0	1	23	4	0	0	31
	Soil	1	0	1	1	27	1	0	31
	WhiteSand	0	0	0	0	4	28	0	32
	Rock	0	0	0	0	5	0	21	26
	Total	30	28	29	27	45	29	21	209

Overall accuracy	83.25
kappa	80.44

2015	User Class \ Sample	Low Veg	water	Veg	Urban	Soil	WhiteSand	Rock	Total
	Low Veg	23	0	2	3	2	0	0	30
	water	0	28	0	1	1	0	0	30
	Veg	4	0	25	1	0	0	0	30
	Urban	2	0	0	27	1	0	0	30
	Soil	2	0	0	2	26	0	0	30
	WhiteSand	0	0	0	0	2	26	0	28
	Rock	0	0	0	0	5	0	28	33
	Total	31	28	27	34	37	26	28	211

Overall accuracy	86.73
kappa	84.52

User's accuracy and produce accuracy for each of the land-cover types classified for Delhi



Year		1990	1995	2000	2005	2010	2015
High density Vegetation (veg)	<i>user's accuracy</i>	77.1	89.7	68.8	70.6	82.8	92.6
	<i>produce accuracy</i>	84.4	86.7	75.9	77.4	80.0	83.3
Low density Vegetation (Veg Low)	<i>user's accuracy</i>	83.9	69.7	73.3	62.9	76.7	74.2
	<i>produce accuracy</i>	86.7	76.7	73.3	71.0	76.7	76.7
Bare soil (Soil)	<i>user's accuracy</i>	62.9	79.3	61.5	73.8	60.0	70.3
	<i>produce accuracy</i>	75.9	76.7	80.0	91.2	87.1	86.7
Built-up (Urban)	<i>user's accuracy</i>	83.9	72.7	77.1	80.0	85.2	79.4
	<i>produce accuracy</i>	92.9	77.4	81.8	77.4	74.2	90.0
Water	<i>user's accuracy</i>	93.3	100.0	96.0	100.0	100.0	100.0
	<i>produce accuracy</i>	93.3	96.6	80.0	90.0	96.6	93.3
White sand/soil (white sand)	<i>user's accuracy</i>	100.0	100.0	100.0	100.0	96.6	100.0
	<i>produce accuracy</i>	73.3	93.3	74.1	76.7	87.5	92.9
Exposed rock / mountain (Rock)	<i>user's accuracy</i>	100.0	93.3	96.4	96.2	100.0	100.0
	<i>produce accuracy</i>	83.3	93.3	90.0	83.3	80.8	84.8

Bangladesh, Dhaka



Contextual information



Figure 39: map indicating the location of Dhaka within Bangladesh

Landsat image location

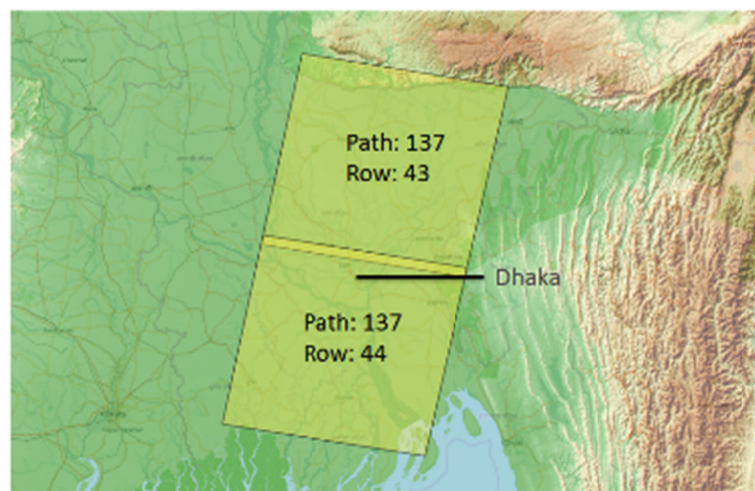


Figure 40: A map indicating the location of Dhaka within the Landsat image Path and Row.
Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Urban class classification map

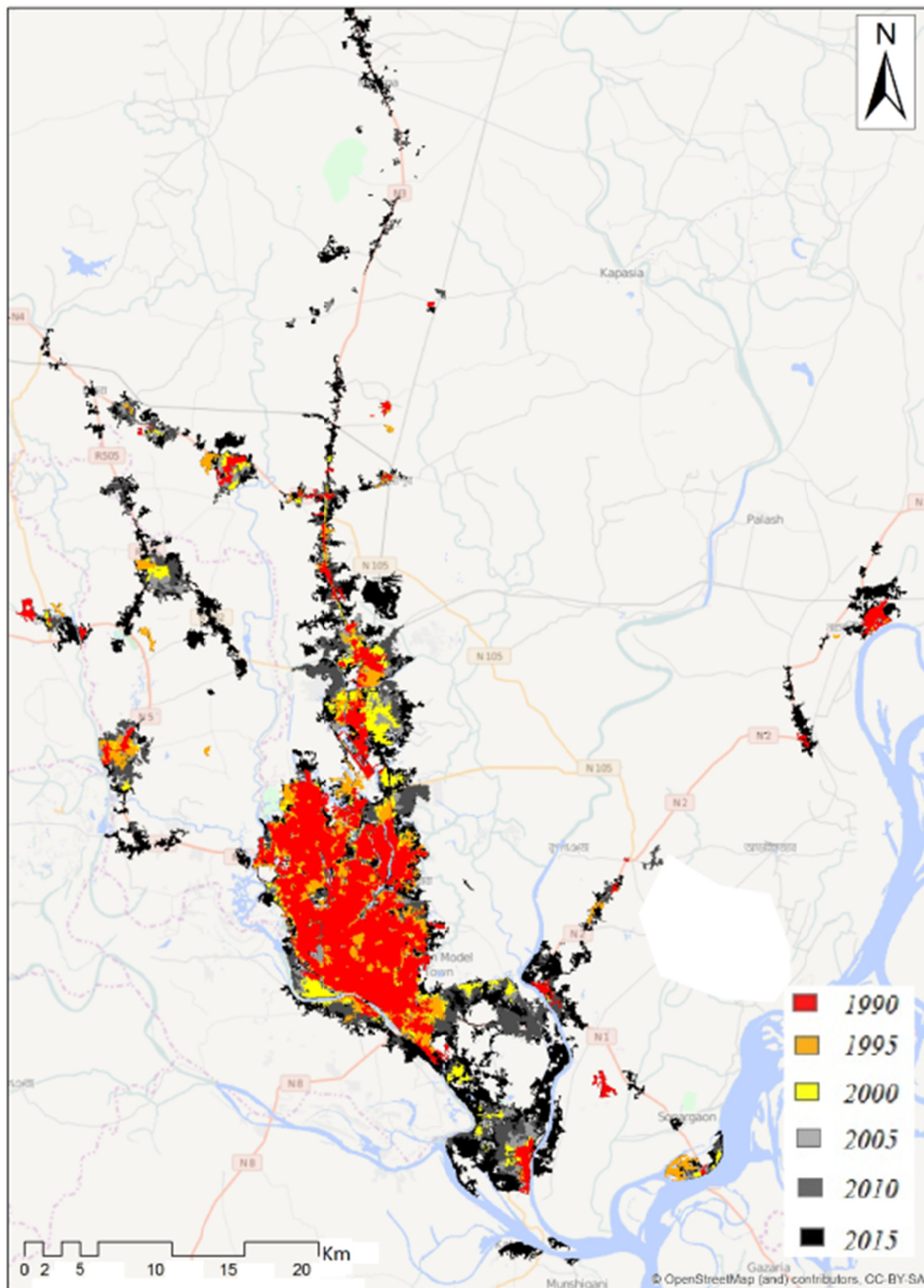


Figure 41: A map showing the Built-up (Urban) area for each year, classified from Landsat images. Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Error matrices for Dhaka for each of the years studied



1990	Row Labels	water	veg	veg low	urban	soil	Total	Overall accuracy	78.05
	water	32	2	4	0	3	41	kappa	72.58
	veg	2	23	5	0	5	35		
	veg low	0	2	23	5	0	30		
	urban	0	1	3	25	1	30		
	soil	0	0	2	1	25	28		
	Total	34	28	37	31	34	164		
1995	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	80.69
	water	36	2		2	0	40	kappa	75.25
	veg	2	25	1	2	4	34		
	urban	0	2	24	1	3	30		
	soil		3	0	7	1	11		
	low veg	0	2	2	1	25	30		
	Total	38	34	27	13	33	145		
2000	Row Labels	water	veg	veg low	urban	soil	Total	Overall accuracy	84.76
	water	25	2		0	0	27	kappa	80.71
	veg	1	24	4	1	0	30		
	veg low	1	7	34	4	1	47		
	urban		1	1	35	1	38		
	soil	0	0	0	1	21	22		
	Total	27	34	39	41	23	164		
2005	Row Labels	water	veg	veg low	urban	soil	Total	Overall accuracy	87.01
	water	28	1	3	0	1	33	kappa	83.79
	veg	0	26	2	1	5	34		
	veg low	1	0	27	0	0	28		
	urban	0	1	2	28	1	32		
	soil	0	2	0	0	25	27		
	Total	29	30	34	29	32	154		
2010	Row Labels	water	veg	veg low	urban	soil	Total	Overall accuracy	76.58
	water	21	0	0	3	0	24	kappa	70.6
	veg	4	23	8	1	1	37		
	veg low	0	3	28	2	2	35		
	urban	0	0	5	24	1	30		
	soil	0	5	2	0	25	32		
	Total	25	31	43	30	29	158		
2015	Row Labels	water	veg	veg low	urban	soil	Total	Overall accuracy	73.55
	water	27	0	0	1	0	28	kappa	66.92
	veg	4	22	4	1	4	35		
	veg low	0	5	23	2	0	30		
	urban	0	0	8	18	4	30		
	soil	0	5	0	3	24	32		
	Total	31	32	35	25	32	155		

User's accuracy and produce accuracy for each of the land-cover types classified for Dhaka



Year		1990	1995	2000	2005	2010	2015
High density Vegetation (veg)	<i>user's accuracy</i>	82.1	73.5	70.6	86.7	74.2	68.8
	<i>produce accuracy</i>	65.7	73.5	80.0	76.5	62.2	64.7
Low density Vegetation (Veg Low)	<i>user's accuracy</i>	62.2	75.8	87.2	79.4	65.1	76.7
	<i>produce accuracy</i>	76.7	83.3	72.3	96.4	80.0	76.7
Bare soil (Soil)	<i>user's accuracy</i>	73.5	53.8	91.3	78.1	86.2	80.0
	<i>produce accuracy</i>	89.3	63.6	95.5	92.6	78.1	75.0
Built-up (Urban)	<i>user's accuracy</i>	80.6	88.9	85.4	96.6	80.0	80.6
	<i>produce accuracy</i>	83.3	80.0	92.1	87.5	80.0	83.3
Water	<i>user's accuracy</i>	94.1	94.7	92.6	96.6	84.0	87.1
	<i>produce accuracy</i>	78.0	90.0	92.6	84.8	87.5	96.4

Nigeria, Lagos

Contextual information



Figure 42: map indicating the location of Lagos within Nigeria

Landsat Path and Row Map covering the study area

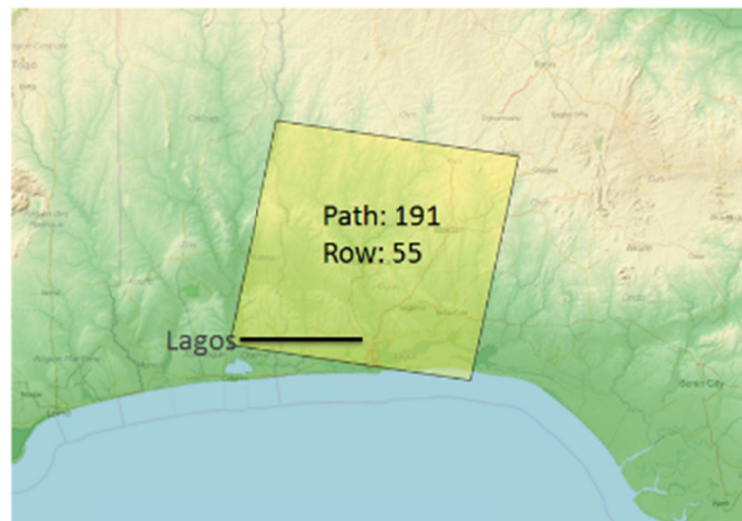


Figure 43: A map indicating the location of Lagos within the Landsat image Path and Row.
Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Urban class classification map

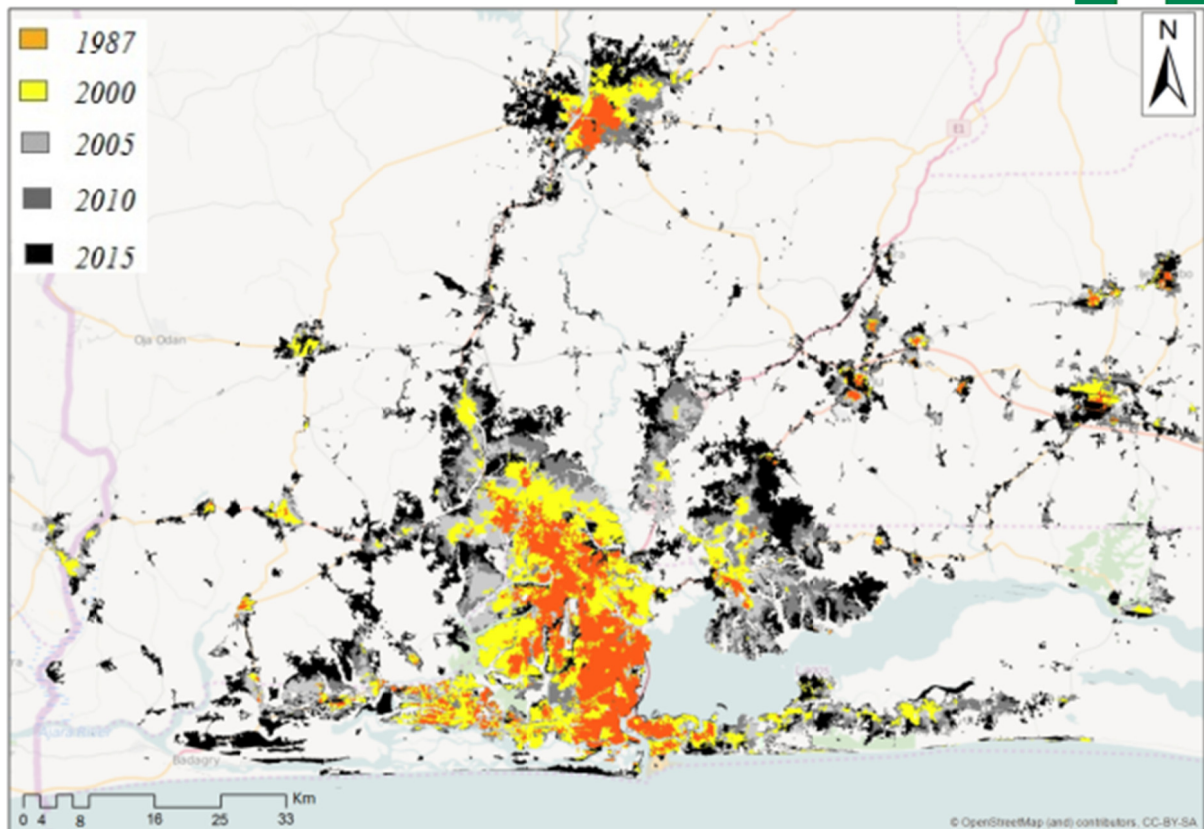


Figure 44: A map showing the Built-up (Urban) area for each year, classified from Landsat images. Background image from OpenStreetmap, API: OpenLayers Plugin QGIS

Error matrices for Lagos for each of the years studied

1984	User Class \ Sample	water	Veg	Urban	Soil	LowVeg	Total	Overall accuracy	76.51
	water	27	0	1	0	2	30	kappa	70.5
	Veg	0	20	3	2	5	30		
	Urban	0	5	27	0	0	32		
	Soil	0	0	10	15	0	25		
	LowVeg	1	5	0	1	25	32		
	Total	28	30	41	18	32	149		
1995								Overall accuracy	
		No Data						kappa	
	2000	User Class \ Sample	water	Veg	Urban	Soil	LowVeg	Total	Overall accuracy
water		28	0	0	0	2	30	kappa	76.19
Veg		5	22	3	0	5	35		
Urban		0	0	23	7	0	30		
Soil		0	0	0	25	0	25		
LowVeg		1	5	0	1	25	32		
Total		34	27	26	33	32	152		
2005	User Class \ Sample	LowVeg	water	Veg	Urban	Soil	Total	Overall accuracy	76.97
	LowVeg	25	0	5	0	0	30	kappa	71.23
	water	0	28	0	3	0	31		
	Veg	12	0	18	1	0	31		
	Urban	0	2	0	21	7	30		
	Soil	3	0	0	2	25	30		
	Total	40	30	23	27	32	152		
2010	User Class \ Sample	LowVeg	water	Veg	Urban	Soil	Total	Overall accuracy	75.16
	LowVeg	20	0	7	0	3	30	kappa	68.96
	water	0	28	0	2	0	30		
	Veg	7	0	22	2	0	31		
	Urban	3	1	0	23	5	32		
	Soil	5	0	0	3	22	30		
	Total	35	29	29	30	30	153		
2015	User Class \ Sample	LowVeg	water	Veg	Urban	Soil	Total	Overall accuracy	82
	LowVeg	25	0	5	0	0	30	kappa	77.5
	water	0	29	0	1	0	30		
	Veg	5	0	23	2	0	30		
	Urban	3	0	1	24	2	30		
	Soil	5	0	0	3	22	30		
	Total	38	29	29	30	24	150		

User's accuracy and produce accuracy for each of the land-cover types classified for Lagos



Year		1990	1995	2000	2005	2010	2015
How density Vegetation (veg)	<i>user's accuracy</i>	66.7		81.5	78.3	75.9	79.3
	<i>produce accuracy</i>	66.7		62.9	58.1	71.0	76.7
Low density Vegetation (Veg Low)	<i>user's accuracy</i>	78.1		78.1	62.5	57.1	65.8
	<i>produce accuracy</i>	78.1		78.1	83.3	66.7	83.3
Bare soil (Soil)	<i>user's accuracy</i>	83.3		75.8	78.1	73.3	91.7
	<i>produce accuracy</i>	60.0		100.0	83.3	73.3	73.3
Built-up (Urban)	<i>user's accuracy</i>	65.9		88.5	77.8	76.7	80.0
	<i>produce accuracy</i>	84.4		76.7	70.0	71.9	80.0
Water	<i>user's accuracy</i>	96.4		82.4	93.3	96.6	100.0
	<i>produce accuracy</i>	90.0		93.3	90.3	93.3	96.7

China, Shanghai



Contextual information



Figure 45: map indicating the location of Shanghai within China

Landsat image location

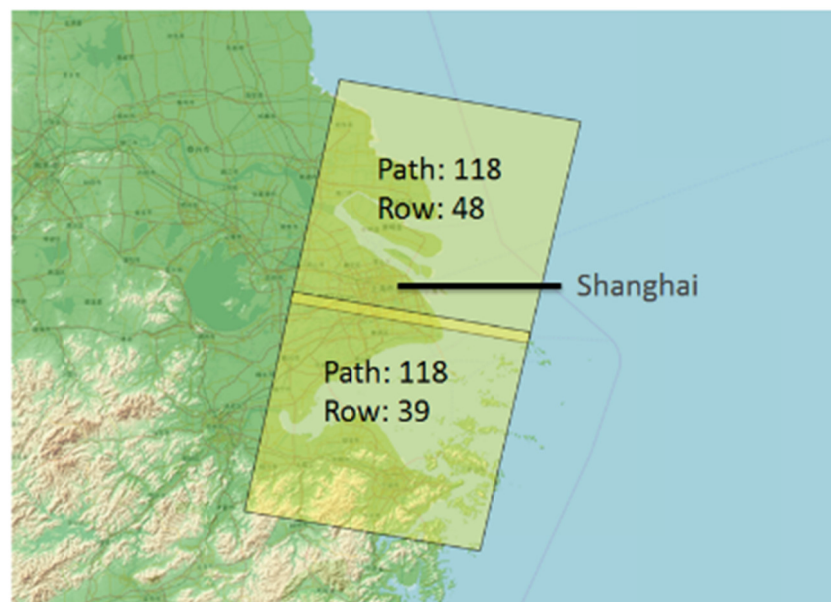


Figure 46: A map indicating the location of Shanghai within the Landsat image Path and Row.
Background image from OpenStreetmap, API: OpenLayers Plugin QGIS



Urban class classification map

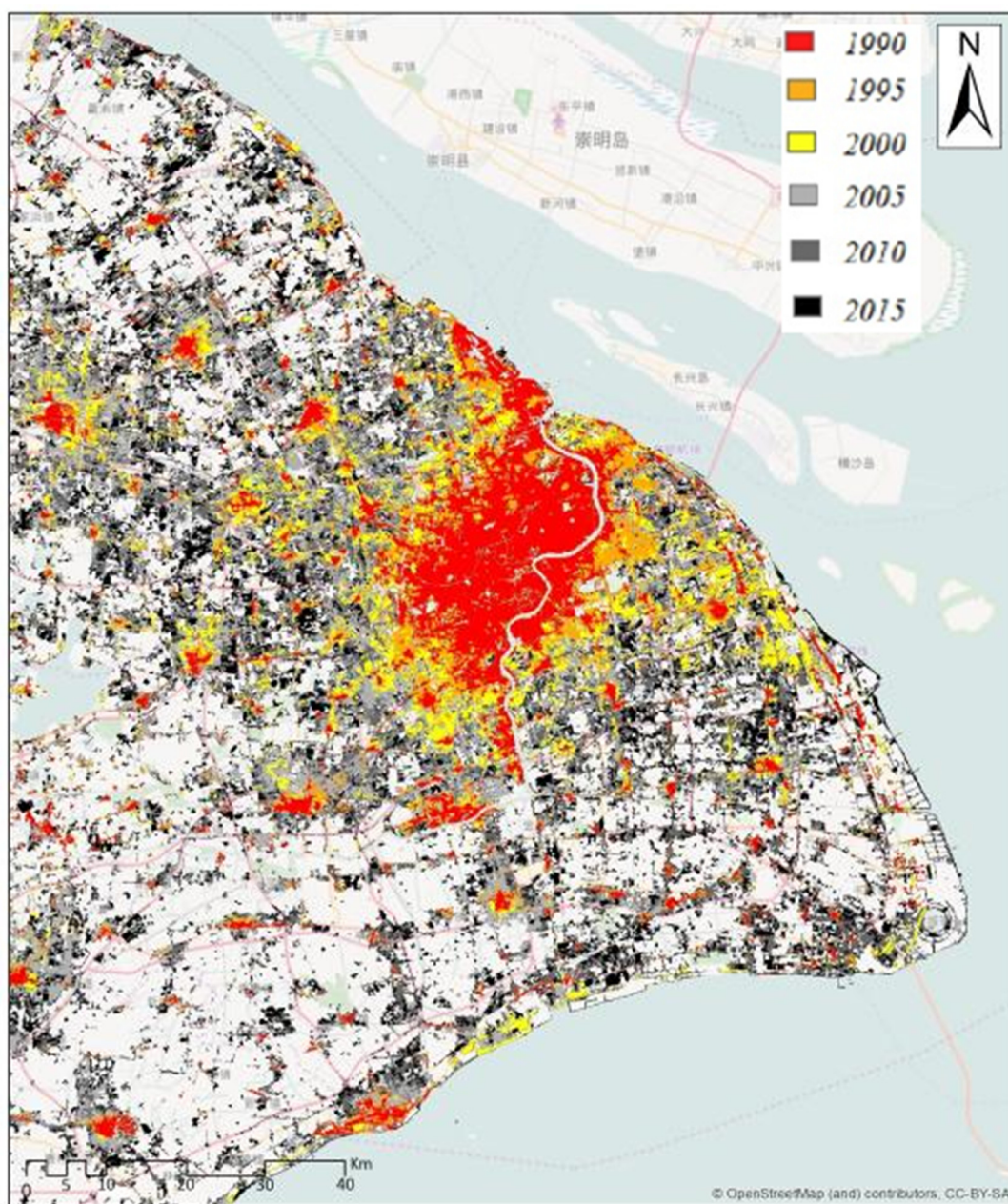


Figure 47: A map showing the Built-up (Urban) area for each year, classified from Landsat images. Background image from OpenStreetmap, API: OpenLayers Plugin QGIS



Error matrices for Shanghai for each of the years studied

1990	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	79.73
	water	28	2		0	0	30	kappa	74.65
	veg	1	24	1	1	3	30		
	urban	0	1	23	1	5	30		
	soil	1	1	2	21	3	28		
	low veg	0	4	2	2	22	30		
	Total	30	32	28	25	33	148		
1995	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	81.76
	water	28	0	0	0	0	28	kappa	77.19
	veg	0	24	1	0	5	30		
	urban	0	1	26	1	2	30		
	soil	0	1	2	26	1	30		
	low veg	0	6	3	4	17	30		
	Total	28	32	32	31	25	148		
2000	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	79.19
	water	26	0	1	0	2	29	kappa	73.99
	veg	0	25	1	0	4	30		
	urban	0	1	22	4	3	30		
	soil	0	1	1	28	0	30		
	low veg	0	7	2	4	17	30		
	Total	26	34	27	36	26	149		
2005	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	80.13
	water	27	0	4	0	0	31	kappa	75.15
	veg	0	25	4	1	0	30		
	urban	1	1	23	2	5	32		
	soil	0	1	2	25	2	30		
	low veg	0	4	2	1	21	28		
	Total	28	31	35	29	28	151		
2010	Row Labels	water	veg	urban	soil	low Veg	Total	Overall accuracy	82.00
	water	28	0	1	0	1	30	kappa	77.50
	veg	2	22	1	1	4	30		
	urban	0	2	24	1	3	30		
	soil	0	1	0	26	3	30		
	low Veg	0	4	2	1	23	30		
	Total	30	29	28	29	34	150		
2015	Row Labels	water	veg	urban	soil	low veg	Total	Overall accuracy	82.00
	water	28	0	0	0	2	30	kappa	77.50
	veg	3	24	0	1	2	30		
	urban	0	1	23	4	2	30		
	soil	0	1	4	25	0	30		
	low veg	0	6	1	0	23	30		
	Total	31	32	28	30	29	150		

User's accuracy and produce accuracy for each of the land-cover types classified for Shanghai



Year		1990	1995	2000	2005	2010	2015
High density Vegetation (veg)	<i>user's accuracy</i>	75.00	78.79	73.53	78.79	75.86	75.00
	<i>produce accuracy</i>	80.00	89.66	83.33	89.66	73.33	80.00
Low density Vegetation (Veg Low)	<i>user's accuracy</i>	66.67	75.00	65.38	75.00	67.65	79.31
	<i>produce accuracy</i>	73.33	75.00	56.67	75.00	76.67	76.67
Bare soil (Soil)	<i>user's accuracy</i>	84.00	86.21	77.78	86.21	89.66	90.00
	<i>produce accuracy</i>	75.00	83.33	93.33	83.33	86.67	90.00
Built-up (Urban)	<i>user's accuracy</i>	82.14	79.31	81.48	79.31	85.71	89.29
	<i>produce accuracy</i>	76.67	79.31	73.33	79.31	80.00	83.33
Water	<i>user's accuracy</i>	93.33	100.00	100.00	100.00	93.33	90.32
	<i>produce accuracy</i>	93.33	90.00	89.66	90.00	93.33	93.33