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Object-Based Image Analysis of VHR Satellite Imagery for Population Estimation in Informal Settlement Kibera-Nairobi, Kenya

Tatjana Veljanovski[1,2], Urša Kanjir[1], Peter Pehani[1,2], Krištof Oštir[1,2] and Primož Kovačič[3]
[1]Scientific Research Centre of the Slovenian Academy of Sciences and Arts
[2]Space-SI – Centre of Excellence for Space Science and Technologies
[3]Map Kibera Trust
[1,2]Slovenia
[3]Kenya

1. Introduction

Cities in Africa and developing countries in general are having a difficult time coping with the influx of people arriving every day. Informal settlements are growing, and governments are struggling to provide even the most fundamental services to their urban populations.

Kibera (edge region within the Nairobi) is the biggest informal settlement in Kenya, and one of the biggest in Africa. The population estimates vary between 170,000 and 1 million and are highly debatable. What is certain is that the area is large (roughly 2.5 km^2), host at least hundreds of thousands people, is informal and self-organized, stricken by poverty, disease, population increase, environmental degradation, corruption, lack of security and - often overlooked but extremely important – lack of information which all contribute to lack of basic services such as access to safe water, sanitation, health care and formal education.

In Africa, but also in other continents, urban growth has reached alarming figures. Informal settlements formation has been associated with the rapid growth of urban population caused by rural immigration, triggered by difficult livelihood, civil wars and internal disturbances. The result of this very rapid and unplanned urban growth is that 30% to 60% of residents of most large cities in developing countries live in informal settlements (UNHSP, 2005). Nowadays, informal residential environments (slums) are an important component reflecting fast urban expansion in poor living conditions.

Densely populated urban areas in developing countries often lack any kind of data that would enable the monitoring systems. Monitoring systems joining spatial (location) and social data can be used for the monitoring, planning and management purposes. New methods of monitoring are required to generate adequate data to help link the location and socioeconomic data in urban systems to local policies and controlling actions. In the past, rapid urban growth was quite difficult to manage and regulate when processes were in progress. Available census data barely accounts for the reality, as in most cases, they are based on figures extrapolated from old census, carried out in the 1970s or, if recent, they are obtained with poor accuracy, as informal settlements are difficult to survey (Sartori et al., 2002). More can now be done at least to monitor the extent and consequences of rapid urban growth. Where accurate maps of informal settlements and relevant census data completely lack, answers can be found using independent survey, derived from satellite or aerial technologies. Usage of satellite imagery nowadays enables rather quick answers to questions such as: where informal settlements are, what was the dynamics of their growth, how many people potentially live there, what basic services inhabitants need. Among the main issues to be addressed in informal settlements are the needs for potable water, waste evacuation, energy, education and health care facilities, and crime control. It is believed these actions can be planned based on quality mapping of the phenomena.

The spatial resolution of space-borne remote sensing has improved to such extent that their products are comparable with the ones provided by aerial photography. Satellite images taken with very high resolution (VHR) sensors, i.e. resolution around and below 1 m, enable skilled user to identify and extract buildings, trees, narrow paths and other objects of comparable size. A side effect of higher resolution is larger quantity of data which require more storage capacities and processing costs. Detection of informal residential settlements from satellite imagery is especially challenging task due to the microstructure, merged/overlapping rooftops and irregular shapes of buildings in slum-like areas. High spatial resolution is essential to facilitate extraction of individual buildings that are characterized by small, densely packed shanties and other structures. Informal settlement Kibera is composed of varying sizes of houses, where roofs can be a combination of many different materials, and mainly unpaved road and path network. Typically this can produce a spectral response on satellite imagery that is difficult to interpret and makes it difficult for traditional classification strategies to differentiate across object class type.

Various approaches enable to extract data from imagery in urban environments. Simultaneously with expansion of VHR satellite systems an object-based image analysis (OBIA) was developed to answer new technological opportunities. OBIA approach works in similar way as human brain perceives nature/environment, namely (high detailed) image is segmented into homogeneous regions called segments or "image objects" (Benz et al., 2004), which are then classified into meaningful classes, following the specific context of the study.

1.1 Objectives of the research

Objective of the work perform was to help Map Kibera Trust initiative with satellite data processing. Studies on Kibera informal settlement had two aims: first, to derive detailed land use/cover map that can further supply population estimation, and second, to analyse the potential of VHR imagery for detecting changes and settlement growth in recent past.

Since object-based classification of VHR satellite data has been argued as the most appropriate method to obtain information from urban remote sensing applications, this approach was used to derive accurate land cover map. The study involved GeoEye and QuickBird satellite images acquired between 2006 and 2009. Object-based approach was used to determine detailed urban structure in informal settlements area. Urban expansion was analyzed through comparison of images taken on different dates, using contextual multi-level pixel based approach. The results of object-based analysis based on morphology attributes were further explored to estimate the potential population. There is a big discrepancy among estimations on Kibera population, thus different density parameters were tested to approach the potential population scenario.

The first, introductory chapter sets the informal residential settlement issue in the wider context of the remote sensing possibilities framework, highlighting the methodology of the study. Chapter 2 gives an overview of research and applications of informal residential environments monitoring. Chapter 3 reviews existing conditions in Kibera, Nairobi's informal residential settlement, bringing into perspective the historical development of the slum, and its current characteristics. Chapter 4 consists of a set of specific procedures performed at two spatial extents, to attain both aims of the study. Entire Kibera settlement was being reviewed, to map the general state and dynamics of housing (change detection) between years 2006 and 2009. Raila village was studied in detail using object-based analysis to derive precise map of the village land cover/use to derive population estimation models in a given situation. Chapter 5 collects the results of mapping and population estimations. Chapter 6 discusses the data and analyses involved in managing monitoring aspects of the slums. The last chapter concludes the study with some suggestions for future work.

2. Informal residential environments monitoring

Although there is a strong need to obtain spatial information about informal settlements in order to increase living conditions for its residents and regarding the fact that remote sensing images offer a well suited data source, studies on informal settlements with VHR data are not frequent. Nevertheless, in Hoffman (2001), first results of detecting informal settlements from IKONOS data in Cape Town showed the principle feasibilities using object-oriented approach. The results were promising but seemed to be very dependent on the data. Later on Hoffman et al. (2006) showed that several adaptations were necessary to OBIA algorithm improvement when applying their extraction methods to the QuickBird scene. Automatic image analysis procedures for a rapid and reliable identification of refugee tents from IKONOS imagery over the Lukole refugee camp in Tanzania was made by Giada et al. (2002). Sliuzas and Kuffer (2008) analyzed the spatial heterogeneity of informal settlements using selected high resolution remote sensing based spatial indicators such as roof coverage densities and a lack of proper road network characterized by the irregular layout of settlements. Cooperation between KeyObs, UNOSAT, OCHA and Metria resulted in digitalization of VHR GeoEye satellite image of Afgooye corridor (Somalia) from 2009, where all temporary shelters were identified (UNHCR, 2010). Different methods to detect and monitor spatial behaviour of informal settlements were presented also by Lemma et al. (2005), Radnaabazar et al. (2004), Kuffer (2003), Sartori et al. (2002), Dare & Fraser (2001) and Mason et al. (1998).

3. Study area description

Kibera is a division of Nairobi area, Kenya, within Langata constituency. Located southwest of the city centre of Nairobi, Kibera encompasses an area of 2.5 km^2, accounting for less than percent of Nairobi's total area while containing more than 25% of its population. It is the largest informal settlement in Nairobi, and the second largest urban slum in Africa, with population number varying with the season. The settlement is divided into a number of villages, including Kianda, Soweto West, Raila, Gatwekera, Kisumu Ndogo, Lindi, Laini Saba, Siranga, Kamdi Muru, Makina, Mashimoni and Soweto East (Fig. 1).

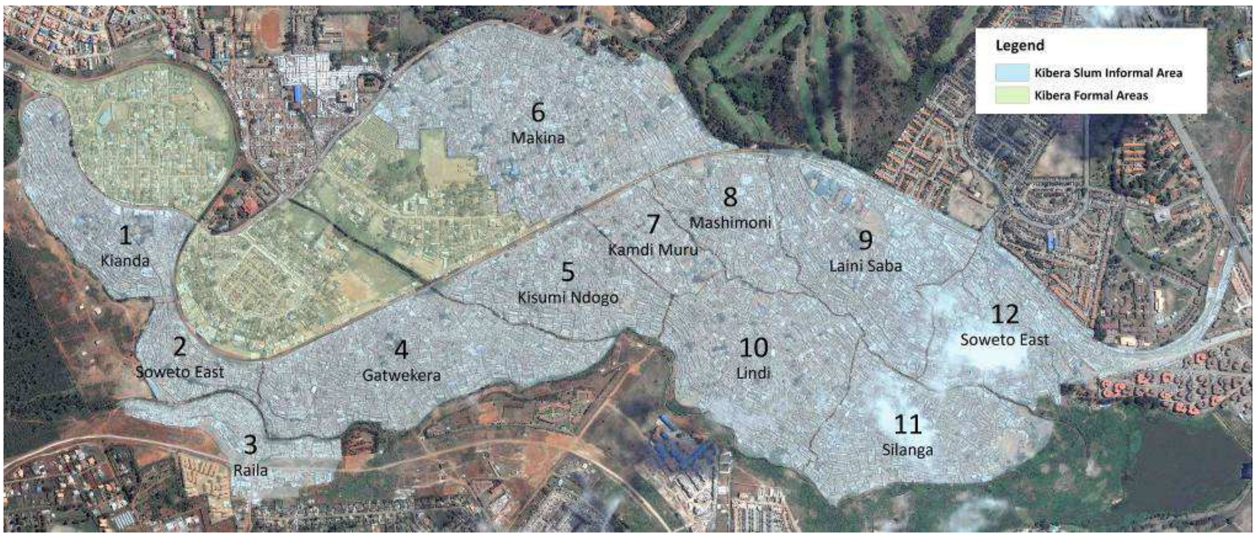


Fig. 1. Kibera settlement is divided into three formal and 12 informal villages.

3.1 General background of Kibera, Nairobi

Kibera emerged in 1912 when the British East African army, known as the King's African Rifles, granted temporary rights to a group of 300 former soldiers from the Nubian community, who had served in the army, to settle on a small piece of land near Nairobi's city centre. Temporary structures were put in place but as the Nubian soldiers grew older and became unable to continue their military service, they began to set up more permanent residence on the land (A history of Kibera, 2011). Turbulent years after the independence combined with socioeconomic factors brought a dramatic increase in the population of Kibera's residents.

Today Kibera consists of 15 villages out of which just 3 are formal and thus connected to the city's utility grids (water, sewage, electricity, waste collection etc.), however the rest (12) are informal and "disconnected" from the rest of the city. Apart from lacking basic services and adequate infrastructure it is also affected by population growth, the illegal construction of infrastructure, and the increasing degradation of the environment. Unclear land-tenure arrangements in informal settlements discourage investments in proper infrastructure and repair; structures are often owned and rented by people, who mostly do not have any rights to the land on which the structures stand. This leads to the lack of legal security of tenure for most of the residents.

Because of this lack of the legal security of tenure and neglectfulness from the city and the government there's little initiative from the residents to improve their living conditions. That is why most of the structures in Kibera are temporary, wooden, mud houses covered with corrugated iron sheets (Fig. 2) and most of the service providers are self-organized groups or cartels which drive up the prices of service delivery – in some cases residents pay 10 times as much as those in the rest of the city.

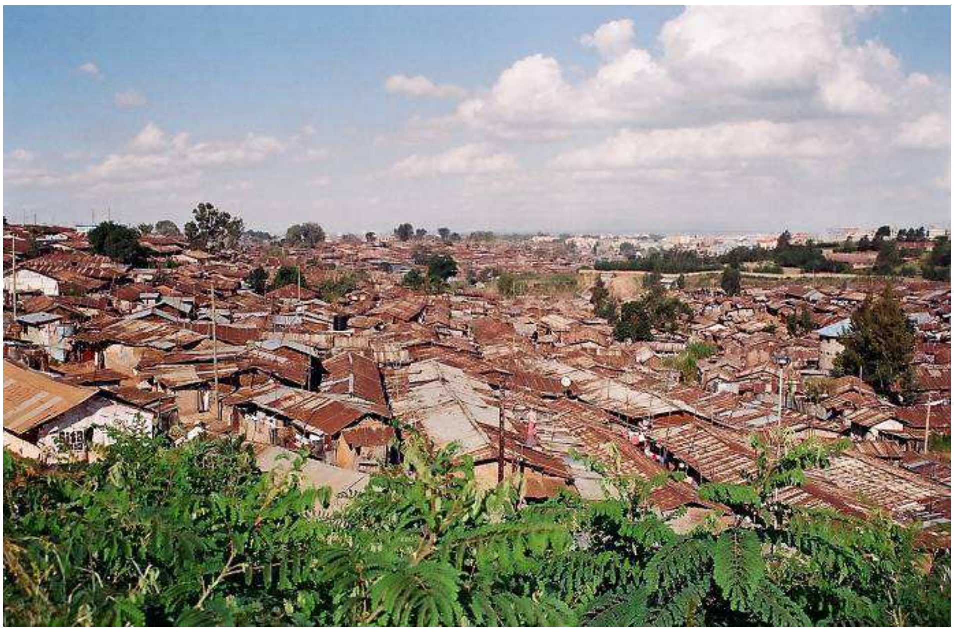


Fig. 2. View over Kibera informal settlement (Photo: Primož Kovačič).

All these reasons lead to, as one resident of Kibera put it, “survival tactics”. These “survival tactics” engulf communities, the provincial administration and the government, leading them into a vicious cycle of under the table dealings, vandalism, lack of engagement, threats, and price controls with no clear perspective or solutions.

3.2 Map Kibera Project and Map Kibera Trust

Kibera is likely one of the most photographed, researched, and well-known slums in the world but the complete and mapped information was not shared and not easily (if at all) accessible. Before October 2009, Kibera did not even appear on any of the online maps. Map Kibera Project (MKP) was first initiated in response to the lack of available data. The initiative wanted to produce reliable data and maps showing the actual physical and socio-demographic features of the Kibera informal settlement, making them publicly available through a digital geo-referenced data base (MKP, 2011).

Map Kibera Project trained 13 youth from the slum in GPS system and basic GIS techniques to map points of interest in their community: clinics, schools, water sources, toilets, street lights, hot spots, businesses and other landmarks. The youth uploaded the data themselves to OpenStreetMap (www.openstreetmap.org), a volunteer-built map of the world.

The Map Kibera Trust (MKT) offers organizational support for the mapping work, as well as other youth driven programmes such as video production and other new media tools (blog, twitter, SMS platforms). The mission of the MKT is to contribute to a culture where digital story-telling, open data and geographic information lead to greater influence and representation for marginalized communities in Kenya. MKT has since grown into a platform specializing in community-driven data for informal settlements and on community based development.

American Association for the Advancement of Science supports the operation of MKT and other NGO activities and has donated several satellite images of the area. MKT activities include various Kibera specific phenomena mappings (www.mappingnobigdeal.com), though the assessment of potential of VHR satellite imagery for mapping purposes presents one of the recent examinations of their use for Kibera community.

3.3 Available VHR satellite data

Six VHR satellite images were available for our research (Table 1): one GeoEye image and five QuickBird images. Satellite images were partly (pre)processed. This means images were roughly georeferenced and corrected for sensor radiometry, also pan-sharpened, and provided as a stack of three visible bands only.

Date	Sensor	Bands used	Spatial resolution	Cloud coverage	Analysis performed
2006-03-27	QuickBird	R-G-B	0.6 (pansharpened)	minor	Change detection
2006-07-31	QuickBird	R-G-B	0.6 (pansharpened)	free	
2007-01-22	QuickBird	R-G-B	0.6 (pansharpened)	present	
2008-01-07	QuickBird	R-G-B	0.6 (pansharpened)	free	
2008-08-10	QuickBird	R-G-B	0.6 (pansharpened)	present	Change detection
2009-07-25	GeoEye	R-G-B	0.5 (pansharpened)	free	Land use/cover Change detection

Table 1. List of available satellite images and their main characteristics.

Besides different inherent spatial resolution the main differences among GeoEye and QuickBird images were sensor viewing angles, causing higher objects roof prints and shadows to have different positions among images. As Kibera informal settlement lies in a hilly terrain, the positional accuracy fit of geographical entities among images was not reached because much of distortion comes from the terrain as well. For the study no digital elevation model was available, thus ortorectification was not possible. However, GPS field walks tracks were available for the main roads and path-network in the area.

4. Methods

Study of Kibera informal settlement has two main aims: to derive detailed land use/land cover map that can supply population estimation, and to analyse the settlement growth and changes between 2006 and 2009.

Extracting data of urban land use structure from remote sensing imagery require methods that are able to provide appropriate level of details observed. Object based classification has been successfully implemented to obtain land cover information from urban VHR remote sensing applications. Thus, this approach was selected in the land use/cover classification of Kibera settlement with main aim to delimitate well residential objects from open areas, and potentially to obtain informal settlement structure in the microstructure level (distinguish individual houses). In addition to determination of detailed urban structures we were also interested in locating the step-wise expansion of informal residential areas, which was analyzed through comparison of images taken in different time using pixel-based multi-level image differencing approach.

Object based classification of the Kibera informal settlement was performed on GeoEye image since its characteristics (close to nadir viewing angle, good spatial resolution, and fine contrast) were most promising to obtain adequate details on object recognition within the informal settlement area. Rooftops are covered with different materials, ranging from new to rusty sheets, bricks and other materials, each of them having specific reflectance characteristics (spectral representation) on satellite image (Fig. 3, Fig. 6a). For population estimation study we need to differentiate well rooftops, unpaved roads and non-build land and therefore discriminate residential areas from open soils, respectively. Object based segmentation automatically delimits satellite image into homogeneous elements (segments), where close correspondence to the real (geographical) objects on the Earth's surface is expected. Usage of thus obtained image elements (segments) has a number of benefits, one of them is ability to incorporate spatial and contextual information such as size, shape, texture and topological relationships (Blaschke et al., 2004; Benz et al., 2004) in contextual classification. In the stage of classification all these segments are classified according to their attributes into most appropriate classes (representing various geographical objects under study consideration), while obtaining detailed classification of urban area land cover/use.

QB 2006-03-27 QB 2008-08-10 GE 2009-07-25

Fig. 3. Examples of rooftops, rooftops renovations and buildings constructions on VHR satellite imagery from three different dates.

With object-based analysis on rooftops morphology attributes we expected to improve the assessment of the potential population in slum areas. Since no complete and relevant field survey (official census) was recently performed, different density parameters were tested to approach the potential population and compared to other available population assessments.

4.1 Data pre-processing and preparation

Data preprocessing is important procedure in remote sensing technology. It meets issues that have to be carefully understood and solved before any data analysis process starts. In order to be able to compare satellite images taken for the same scene at different acquisition dates they have to be co-registered and radiometrically adjusted. Recent automatic registration algorithms can accomplish the task well when similar acquisition geometry among sensor systems is provided. Global geometric transformations are mostly appropriate for positional corrections in such cases. However, this was not the case with the imagery obtained for Kibera study (see section 3.3).

Obtained images were rectified but not precisely aligned one to another. Due to agitated terrain in Kibera and lack of any digital elevation model, semi-automated rigorous procedures of co-registration could not be applied. The non-linear rubber-sheeting method was the only possibility to obtain mutually aligned images. This procedure is effective, but very time consuming, since it demands manual selection of hundreds of control points for each image.

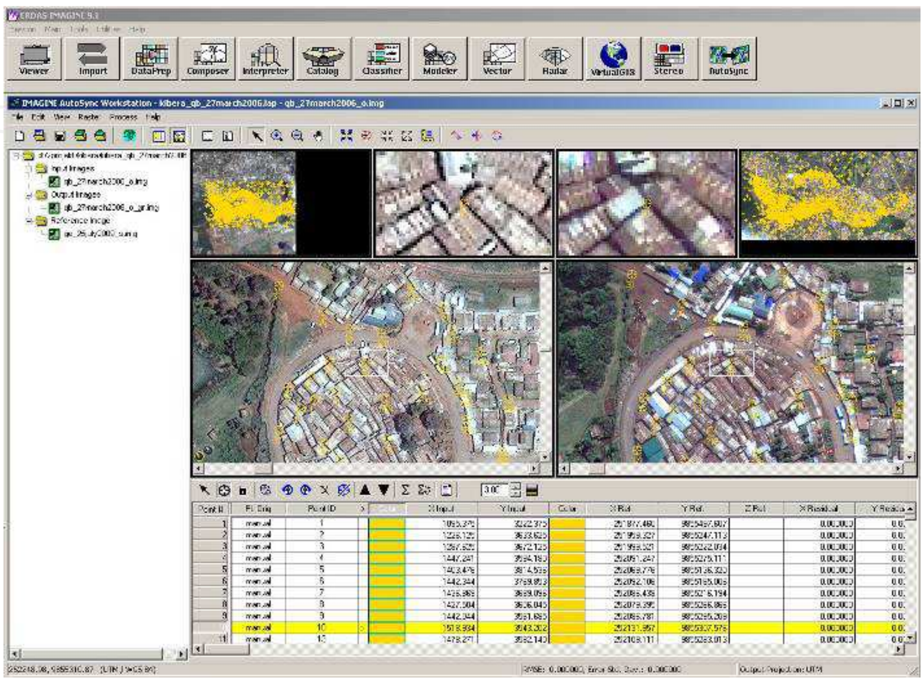


Fig. 4. Selecting the control points for rubber-sheeting method for image geo-referencing (AutoSync module of ERDAS Imagine).

GeoEye image taken on 25th of July 2009 was selected as the reference image considering its highest spatial resolution, good matching with GPS path-network tracks and the fact it is most recent. Then QuickBird images selected for analysis were manually registered to the reference, based on cca. 1,400 manually selected control points per image and using a piecewise transformation based on triangles formed from the tie points (Fig. 4). Resampling was nearest neighbour. An average RMSE is not reported as this is local approximation technique. Geo-corrected images were evaluated through detailed visual control.

Geometrically matched GeoEye and QuickBird images were then used for OBIA. Finally three images were selected for change detection due to their best results in geo-correction phase: GE2009-07-25, QB2008-08-10 and QB2006-03-27. For change detection analysis images were resampled to uniform 1 m resolution, to be prepared for radiometric standardisation.

After geometric adjustments there are still differences amongst the spectral properties of satellite images (spectral bands from the same or different images are not adjusted to each other). Hence, before pixel-based image comparisons (image differencing) the radiometric standardisation is needed. Most standardisation procedures derive from adjustments of invariant objects or from the least squares method (linear regression). The problem with the first method is that invariant areas should be verified with field measurements. Furthermore, the generally recognised invariant objects, such as deserts or light sandy beaches, do not come into play, since they cannot be found in Kibera area. The principle of the second approach is that it tries to globally adjust the given (to-be-adjusted) image or a chosen area with the reference image or a subset through a statistical approach. We applied linear regression for the relative adjustment of spectral bands between the images. Relative radiometric normalisation was done through local adjustments of QuickBird images onto GeoEye reference image, for Kibera settlement with 30 m buffer subset only.

4.2 Land cover classification

Since GeoEye image of the whole Kibera informal settlement contains lots of information and the analysis of the total area would be too demanding in terms of computer processing, we divided image of Kibera into 12 smaller parts (according to 12 informal villages). The complete process of segmentation and classification was applied systematically for each informal village separately, with same parameter settings at each phase. This was possible due to relatively homogenous landscape over Kibera settlement. Thus we obtained 12 regional classification outputs, which were then merged in the final stage. To avoid erroneous classification on the edges of the splitted images, we applied 30 meter buffer when masking the village fragments out from the whole GeoEye image (Fig. 5).

Fig. 5. A buffer of 30 meters around the village border.

Object based classification consists of two stages. Image is first segmented into a set of segments (regions) that are considered to be homogeneous in terms of one or more spectral or spatial properties. Then follows classification where each segment is classified into belonging object class.

Supervised segmentation within software used (ENVI EX, Feature Extraction module) is defined by two segmentation parameters that influence an average size of segments: segmentation and merging. Setting different values for these two parameters causes change of size of segments, allowing for an image to be segmented at many different scales, so both parameter values influence classification results. Since structure of the Earh's surface is similar throughout the whole settlement, same general segmentation parameters were used for each of the 12 villages. Visual example of segment structures are shown on Fig.6.

While classifying Raila village we adapted segmentation parameters to best extract shapes of individual buildings inside informal settlement. Since segmentation parameters were adequate for one particular land use only (i.e. buildings), others were expected to be under- or over-segmented. There is no single "optimal" scale for analysis of remote sensing images, rather there are many optimal scales that are specific to the image-objects that exist within a scale (Hay et al., 2003) and this is why using a multi-scale approach may often be preferable (Johnson and Xie, 2011). All spectral bands were used and given equal weight for image segmentation and all available attributes were calculated for all segments.


a b c

Fig. 6. Original GeoEye image (a), objects segmented (b), objects merged (c) (Feature Extraction module of ENVI EX).

The objects extracted during the segmentation were then classified using Support Vector Machine (SVM) classification algorithm in an object-oriented framework along with training sets, selected by experienced user. Nine land cover classes were used all together (Table 2).

Land use / cover classes	**Description**
Buildings_blue	Residential houses with blue spectral reflectance on image.
Buildings_light	Residential houses with white or bright spectral reflectance.
Buildings_brown	Residential houses with brown or dark spectral reflectance.
Buildings_red	Residential houses with red spectral reflectance.
Roads	Traffic connection between villages, usually unpaved.
Shadows	Shadowed areas around high objects (high vegetation and buildings).
Soil	Areas of unvegetated soil, mudded ground.
Vegetation 1	Green vegetated areas, low vegetation (grass).
Vegetation 2	Green vegetated areas, high vegetation (trees).

Table 2. Land cover classes anticipated with object-based classification.

These nine urban land use/cover classes included four types of residential housing. Sub-classes were choosed because of their different spectral signature inside the same land cover class (e.g. instead of selecting only class "buildings" we selected four subclasses "buildings_blue", "buildings_light", „buildings_brown" and "buildings_red", Fig. 7). This way we obtained better results than we would have using one general class only. More detailed classification of residential housing was made only in Raila village.

Classification results were obtained as a raster image and a vector file. Vectors were exported to a single layer and later processed for the need of post-classification in ESRI ArcMap software (all polygons smaller than 2 m^2 were merged with neighbouring larger polygons).

Fig. 7. Selecting training samples for supervised classification (Feature Extraction module of ENVI EX).

4.3 Change detection

Satellite data offers unique utility for monitoring and quantifying land cover change over time. Consequently, change detection has become a significant part of the remote sensing research over the last decades. The goal of remote sensing change detection is to detect the geographic location of changes, identify their type (if possible) and quantify their amount. If long term imagery time series are handled, trends can be recognised. A large number of change detection methods have been evolved and they differ in their refinement, robustness and complexity (Hall and Hay, 2003). Nowadays a three level systematisation system is proposed that differentiates change detection methods by introducing the notion of pixel, feature and object level image processing (Deer, 1998). In general change detection techniques can be grouped into two major types (Jianya et al., 2008; Coppin et al., 2004; Lu et al. 2004; Singh 1989): image differencing techniques and post-classification comparison techniques. The main difference between the two types is that image differencing methods can identify the location and the magnitude of change but can not identify the type of land use or surface changes taken place in the area. Post-classification techniques can identify the location and provide the change character. Recent advances in change detection mostly involve high resolution data and consequently object-oriented and/or multi-scale approaches, with a range of techniques to approach contextual modelling (Lang et al., 2006; Blaschke et al., 2008; Addink & Van Coillie, 2010).

4.3.1 Change detection of Kibera informal settlement

The use of VHR satellite image time series may provide a reliable approach to detect dense urban growth in detail (Hofmann et al., 2006). A generically applicable and rapid operational land cover mapping of these settlements has generally proven difficult (Netzband & Rahman, 2010). Object-based classification and land use mapping of Kibera settlement from GeoEye image (section 4.2 and 5.2) highlighted some typical problems for object delineation in slum-like areas that can be corrected only with a lot of manual work. Main difficulties are associated with informal area outer-homogenity but inner-heterogenity due to the microstructure of urban agglomeration. Object-based classification is thus very demanding in terms of methodology adaptation to informal residential areas specifics, especially when accounting for their direct relation to representation on different satellite data sources. Thus within the limited framework of this case study pixel-based approach to identify outline of urban growth was preferred. The procedure was implemented on radiometrically adjusted time series (section 4.1). GeoEye 2009-07-25 and QuickBird 2006-03-27 images were compared for the changes over whole Kibera, and GeoEye 2009-07-25, QucikBird 2008-08-10 and 2006-03-27 images were analysed for the observation of sequential urban growth of Raila village.

The simple thresholding of difference images is a well-known method that leads to the delimitation of changes and no-changes. The advantage of this method is that it can be fully automatic. However main disadvantage is that it heavily depends on consistency of datasets. Regardless of the carefully performed data preparations certain unwanted effects remains, which may drastically burden the imagery comparisons. This data variability behaves as a detected change and may well be enclosed within identified pattern of changes, although not all of the identified differences belong to real changes (false, non-intrinsic changes). Such false effects result in over-estimation of change pattern and can cause the quantitative evaluation fail. Since this data noise originates from the pre-processing algorithms as well as the natural and technological conditions during data acquisition, it can not be completely removed with data radiometric corrections (Veljanovski & Oštir, 2011).

To overcome this drawback a contextual multi-level change detection approach was applied that can efficiently treat most of the unwanted differences and suppress sensor related noise (Veljanovski, 2008). Taking into account the neighbourhood and change information by joining two spatial scales (Fig. 8), approach reduces amount of small size false differences.

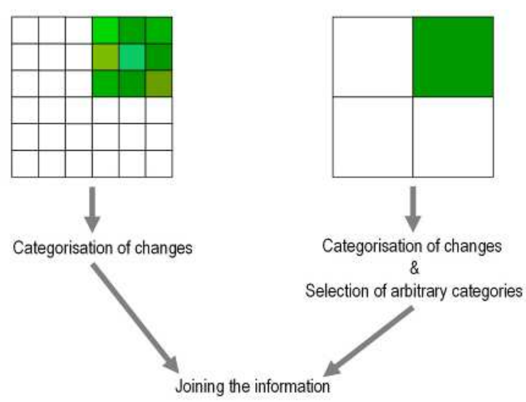


Fig. 8. Change detection approach takes into account the neighbourhood and change information by joining different spatial scales.

The model is based on focal information logic that gives averaged change information in a slightly reduced spatial scale – within the specified neighbourhood. It is based on the fact that in a larger geographic area (e.g. a 3 x 3 pixel window or 3 m spatial resolution for resampled VHR data) the information of the changes will tend to level abrupt change information if a small spatial scale change is present, and will show the averaged difference if the majority of pixels in the observed window are subjected to change. Computing the piecewise change information between two time-successive data sets provides valuable information regarding the location and numeric change value derived from contextual information within the specified neighbourhood.

The procedure was implemented as follows. First, spectral information for a slightly coarser scale (i.e. 3 m spatial resolution) was computed for images or areas of interest. This may be accomplished with a specified neighbourhood mean value annotation. Second, change differentiation between images is performed on a coarser resolution scale and change magnitude categorisation is applied (see below for categorisation classes and their definition). Third, upper positive and negative changes are reclassified so that the mask of important changes based on the neighbourhood context characteristics is prepared. Fourth, change differentiation is calculated on the original data scale (i.e. GeoEye and QuickBird data in 1 m spatial resolution), then categorisation is applied, and finally a mask (or a mask with a buffer) of an arbitrary specified magnitude of changes (obtained in the previous step) is overlaid in order to restrict merely the contextually supported changes.

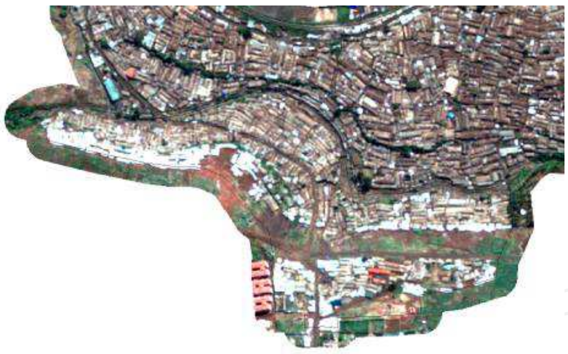
Normally, if there is no substantial unwanted effects (noise) due to meteorological or sensor influences in images, changes obtained from the difference image (image differentiation) are distributed normally and symmetrically, with the average at 0. Abrupt changes (objects or land cover transformations) can then be defined by thresholding the distribution tails, giving the pattern of positive and negative changes in reflectance (spectral) space. We have calculated change magnitude (transition class category) intervals for every 0.5 standard deviation. Then the criterion of 2.5 standard deviations for negative changes and 2.0 for positive changes was applied to enclose the majority of detected transformations in both real and spectral world situations. Result of such categorisation of image difference is a pattern of abrupt changes (locations of appearance, disappearance of objects), with no association to change characterisation (type of change, from-to).

Each output from the above automatic threshold procedure is finally refined to an arbitrary degree, depending on case study objective. For entire Kibera informal settlement changes were obtained from comparison of GeoEye 2009-07-25 and QuickBird 2006-03-27 images. Change patches smaller than 5 m^2 were eliminated for the purpose of this example, mainly to reduce the impact of change artefacts belonging to small patches of rooftop renovations (Fig. 3). False changes identified due to differences in viewing angle (location of buildings and trees shadows, buildings boundaries due to different original resolution of imagery) were also removed using the results obtained from object based classification (state of land use in 2009, section 4.2). Where shadow or vegetation object class were present, change pattern was corrected in the given context. Described and implemented step-wise change pattern refinement is shown in Fig. 9, for a subset of Raila village and northern neighbourhood. In other words, with simple generalisation we could control many aspects of the change pattern for study's specific aims.

Results were visually examined and evaluation of change pattern characteristics (over- and under-estimations) was done throughout the area using complementary comparison of satellite images involved.

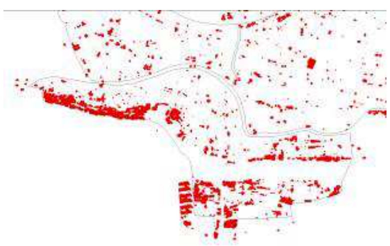
4.3.2 Raila village change detection

Raila village is known to have undergone extensive development during recent years (Kibera Wikipedia, 2011; MKP, 2011). Thus temporally detailed examination was performed observing its urbanisation. Change detection procedure described in section 4.3.1 was in addition implemented for Raila village only, but for two time sequences: 2006-2008 and 2008-2009. QB 2006-03-27, 2008-08-10 and GE 2009-07-25 images were used for this example.



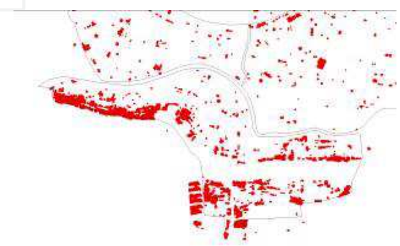
2006-2009 3-band difference image for Kibera subset (Raila village).

Change pattern over 2006-2009 3-band difference image.



Change pattern after automatic multi-level threshold procedure.

Change pattern after eliminating false changes due to shadows differences.



Change pattern after eliminating small patches due to rooftop renovations.

Fig. 9. Overview of change pattern intermediate results through implemented processing steps.

4.4 Population estimation

Population statistics gives very important information for understanding of modern society. Demographic research is one of the main research directions of social science for a better understanding of the interactions between population growth and social, economic and environmental conditions. The collection of population data depends mainly on the census, which is labour-intensive, time-consuming and demands high financial resources. The 2009 Kenya Population and Housing Census reported Kibera's population to be 170,070 (Karanja, 2010). This report was far from the belief of that time that Kibera slum was of the biggest informal urban settlements in the world. Several actors had provided and published over the years increasing estimations of the size of its population, most of them stating that it was the largest slum in Africa with the population exceeding 1 million. According to Davis (2006), a well known expert on urban slums, Kibera had a population of about 800,000 people. International Housing Coalition (IHC, 2007) talked about more than half a million people. UN-Habitat (2004) had released several estimations ranging between 350,000 and 1 million people. These statistics mainly come from analyses of aerial images of the area. IRIN (2006) estimated a population density of 2000 residents per hectare. In 2008 an independent team of researchers began a door-by-door survey named Map Kibera Project (MKP, 2011). A trained team of locals, after having developed an ad-hoc surveying methodology, has so far gathered census data of over 15,000 people and completed the mapping of 5000 structures, services (public toilets, schools), and infrastructures (drainage system, water and electricity supply) in the Kianda village. Considering data collected for Kianda village, the population of the whole Kibera slum can be estimated between 235,000 and 270,000 people.

Nonetheless, no estimation so far guessed by the MKP, or the UN, or the Government of Kenya or by other actors can be taken for granted and does not represent the real dimension of the population of Kibera. In general, no estimation can be proved nor refuted until an exhaustive census will be taken throughout the whole slum (Kibera Wikipedia, 2011).

Because population is not directly related to land cover surface reflectance, population estimation is still a challenging task based purely on remote sensing spectral signatures. Although population is not directly measurable on the remote sensing images this technology may provide good approximation of population estimation by measurement of visible variables, e.g. the number of residential buildings and/or the area of build-up zone (Zhang, 2003). There exist many studies using different approaches on remote sensing data for population estimation. Studies date from the early 1970s onward, where air photos were utilized for manual counts of dwelling units. There are three most used methods of population estimation by remote sensing: residence count method, area (density) method and regression model method (Zhang, 2003). Residence count method was mostly done in first period of studies on this topic on the western urban environment (Horton, 1974, Barrett & Curtis, 1986). Area density method was used by H.H. Wang (1990), F.Z. Wang (1990), P. Sautton (1998), Langford et al. (1994), Z.J. Lin (2001) and others. Regression model method is currently also often used (Galeon, 2010, Dengsheng et al., 2006, Zhang, 2003). With each type of method some ancillary field survey data are needed.

Considering the above situation and the fact that for Kibera we lack other potential socio-geographic data (elsewhere applied to predict population with regression technique), we decided to assess the population on residential land cover class information obtained from object-based classification with density per area method solely. For each village a total area of buildings was calculated and different occupation scenarios (i.e. persons/living area) were tested to observe the range of possible population fluctuation.

5. Results

With object-based (contextual) classification performed on GeoEye image with Feature Extraction module of ENVI EX, it was possible to obtain accurate land cover map and following this, total residential area of Kibera slum and its divisions (villages) with very high accuracy. From this data, those related to build-up areas, were used for population estimation. With multi-level contextual change detection implemented in Erdas Imagine, it was possible to obtain representative change pattern reflecting where in informal settlement intensive urbanisation processes have taken place. Results are presented in the following order: land cover mapping, change pattern identification and population estimation, for Kibera informal settlement (section 5.1) and Raila village (section 5.2), respectively.

5.1 Kibera

5.1.1 Kibera land cover map 2009

Object based classification and post-classification on GeoEye 2009-07-25 image was performed for each village in Kibera informal settlement separately. Finally individual results were joined in a land cover map of Kibera informal settlement (Fig. 10).

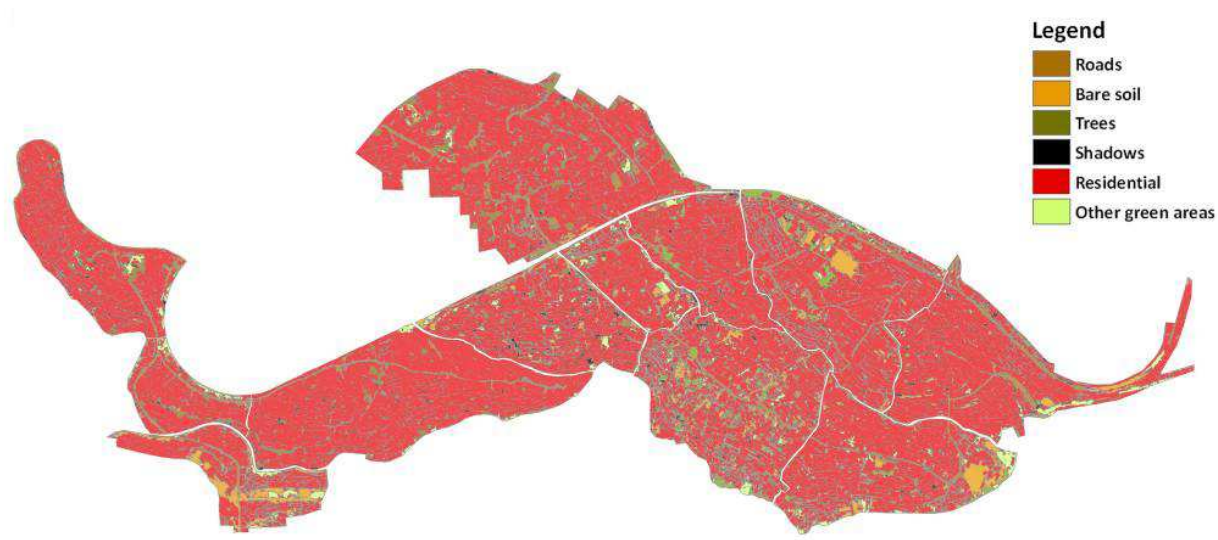


Fig. 10. Merged final classification results of GeoEye image where all 6 selected land cover classes are shown for all 12 Kibera villages (ESRI ArcGIS).

Vectorized classes of entire Kibera were merged together in order to be able to calculate area of total land use/land cover. As it is seen from Table 3, residential areas cover 2/3 (66%) of the whole Kibera area and are prevailing when compared to other land uses. This can be well confirmed from the visual examination of the satellite images of the discussed area.

Accuracy assessment was done by comparing results of supervised classification with manually digitalized objects. Comparison was done on the area 200 x 300 m in the village

Land use [m²] / village	Residential	Trees	Green areas	Soils (roads, bare ground)	Shadows	Total
Kianda	117,710	8,144	9,511	16,775	18,005	170,145
Soweto West	49,620	4,089	6,455	15,001	6,177	81,343
Raila	45,657	8,835	17,066	30,886	6,139	108,583
Gatwekera	234,609	17,634	11,718	19,682	23,878	307,520
Kisumi Ndogo	111,472	6,979	6,944	10,891	28,432	164,717
Makina	303,599	53,844	11,992	40,474	34,801	444,710
Kamdi Muru	51,248	1,829	7,541	12,123	8,670	81,412
Mashimoni	96,287	5,520	2,018	7,628	16,900	128,355
Laini Saba	181,211	17,400	13,141	45,545	20,490	277,786
Lindi	159,112	2,5826	11,885	48,215	26,630	271,668
Silanga	150,058	21,569	19,975	34,833	17,298	243,733
Soweto East	174,200	6,238	15,618	29,302	22,823	248,181
SUM [m²]	**1.674,784**	**177,906**	**133,863**	**311,354**	**230,245**	**2.528,152**
SUM (%)	**66.25**	**7.04**	**5.29**	**12.32**	**9.11**	**100,00**

Table 3. Area of different land use types for 12 informal villages and the total sum in Kibera.

Lindi. Only residential segments were estimated. Since with ENVI EX classification the outline of individual residential objects could not be extracted, we compared only the total sums of areas classified as *residential*. Results are shown in Table 4. The best result (error of 3%) was obtained when choosing parameter values for segmentation/merge: 85/85.

All (semi)automatic classification methods display some errors, but as an approximate solution object based classification on VHR data yielded very good results upon selection of proper segmentation parameter values. Different shapes and colours in informal settlements determine a complex urban formation, which is difficult to differentiate from other land cover types, especially from bare soils and unpaved streets. With the object-based classification dwelling zones were found with high accuracy all over the image, in spite of their spectral similarities with streets and other urban features, especially bare soils.

	Area [m²]	**Coverage [%]**
Testing rectangle (200m x 300m)	60,000	
Manual digitalization	37,913	
Supervised classification ENVI EX (segmentation 85, merge 85)	**36,663**	**97**
Supervised classification ENVI EX (segmentation 85, merge 65)	42,172	111
Supervised classification ENVI EX (segmentation 85, merge 45)	41,174	109

Table 4. Comparison of results of ENVI EX supervised classification using different segmentation parameters with manual digitalization. The total areas were compared for residential classes only.

5.1.2 Kibera change detection

The multi-level contextual change detection method we used in this case study was first developed for monitoring various greater and intensive processes on the Earth's surface with middle resolution imagery (i.e. Landsat, SPOT). The result on Kibera proved same contextual logic is efficient also when implemented on very high spatial resolution imagery.

Change detection applied to Kibera informal settlements aimed to obtain an outline of the distribution and extent of major urbanisation processes. Comparison was made for QB 2006-03-27 and GE 2009-07-25 images. Method has proven to be suitable for monitoring changes related to various processes (buildings construction, buildings collapse or disappearance, rooftop renovation, increase/decrease in vegetation) and/or of the coincident description of their trends (see section 5.2.2 for identified informal settlement growth in Raila village area). Although quantitative assessment of change occurrences was not performed due to lack of independent reference data, a detailed visual control was made through comparison of before and after images and, nevertheless, several conclusions can be derived.

Identified pattern of changes (Fig. 11) clearly draw attention to spots where urbanisation between years 2006 and 2009 was most intensive: Kianda north-east, Raila southern border, Mashimoni and Laini Saba northern border and Soweto East eastern tail. According to the density of change pattern elements, in addition to the edges of Kibera informal settlement, several changes occurred in the eastern part of Kibera. These are mainly due to larger new buildings constructions or complete rooftops renovations. Additional socio-economic data or bigger events information (like flooding) would be welcomed to associate the rate of more intensive rooftops renovations at some of Kibera villages and compared to the other parts of the settlements.

With external data, for example land cover for a reference point in time, a fairly reliable "from-to" change statistics could be extracted. However in rather homogenous land use areas like Kibera informal settlement is, where most of the land use is residential (section 5.1.1) and where urbanisation direction limits are well known due to formal residential settlement boundaries, such information would not additionally characterize the change pattern. On the example of Raila village change detection in section 5.2.2 we comment some difficulties observed related to detection of change in slum-like areas in a more detail.

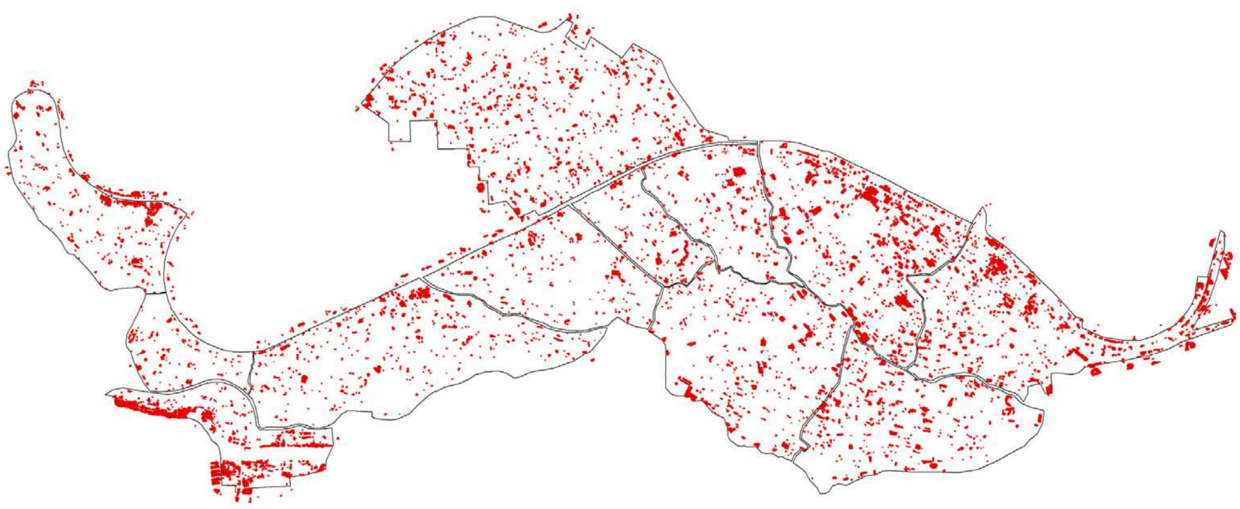


Fig. 11. Identified changes between years 2006 and 2009 (Erdas Imagine). Change pattern enclose changes due to new buildings construction, buildings disappearance and larger rooftop renovations.

5.1.3 Kibera population estimation in 2009

Total surface of Kibera was calculated as a sum of housing areas of all 12 villages throughout whole Kibera from vector results obtained with object-based classification. All the vectorized structures have been computed using ArcGIS software and we assumed that all the structures are used for habitat purposes.

Sum of the residential areas show that total residential area of Kibera is around 1.646,883 m^2, which is 358,706 m^2 more than total surface from year 1993 given by Sartori et al. (2002), where residential area was 1.333,834 m^2. We can see that informal settlement population density has increased from year 1993. Since Kibera is surrounded by well-defined residential boundaries and its drastical expansion therefore was not possible, we can assume that the increase of residential area can attribute to denser housing inside the informal settlements through years.

As we can see from Table 5, population estimation of Kibera can vary from 150 thousand up to 650 thousand people living in the informal settlements according to different population density sources. Nevertheless, both limits are high taking into account Kibera is spread on 2.5 km^2 only.

Source	Density [people/m^2]	People living in Kibera
MapKibera Project (2008)	0.0951	156,652
IRIN (2006)	0.2000	329,377
AHI US (2005)	0.3000	494,065
Sartori et al. 1 (2002)	0.3300	543,471
Sartori et al. 2 (2002)	0.3900	642,284

Table 5. The estimation of population according to the density acquired from different sources. Housing area of Kibera was calculated from results obtained with object classification of GeoEye image from 2009.

5.2 Raila village

5.2.1 Detailed land cover map of Raila village 2009

We made a detailed classification focused on residential housing only on image subset covering the area of Raila village. The main idea was to automatically obtain polygon shapes of each individual residential object or settlement. Although on VHR image individual objects in general can be distinguished, due to the complexity and variety of dense roof surface there was impossible to extract the shape of every individual residential object or each group of objects (settlements). Roofs and their elements themselves present heterogeneity, resulting in distinct spectral variation within areas of homogeneous land cover. Class „buildings_bright“ were possible to detect since they had a very distinct morphological pattern that was contrasted by surrounding (built-up) land cover. Segments of class „buildings_brown“ were sometimes integrated with their surroundings (soil) so they could not be readily distinguished. Some urban elements (like rooftops) are a combination of many different surface materials; this produced a spectral response that was difficult to interpret with routine procedures.

Automatic shape detection of each individual residential object would enable good total population estimation. Two approaches to get classified vector shapes closer to individual buildings were considered:

- Manual correction of the shapes of obtained polygons: Small test showed that this is extremely time consuming. Correction took more time than it would take if one would manually digitize the whole image.
- Use of additional attributes that are automatically created in the phase of ENVI EX segmentation: Investigation showed that there is no useful relation within additional attributes of all sub-classes of buildings. Therefore additional attributes could not assist to semi-automatic reclassification of some segments in order to obtain better shapes of individual object in build-up zones.

Finally, focused to residential build-up objects in Raila area four major object classes were modelled and mapped (Fig. 12).

Fig. 12. Detailed object based classification results for residential areas in Raila village.

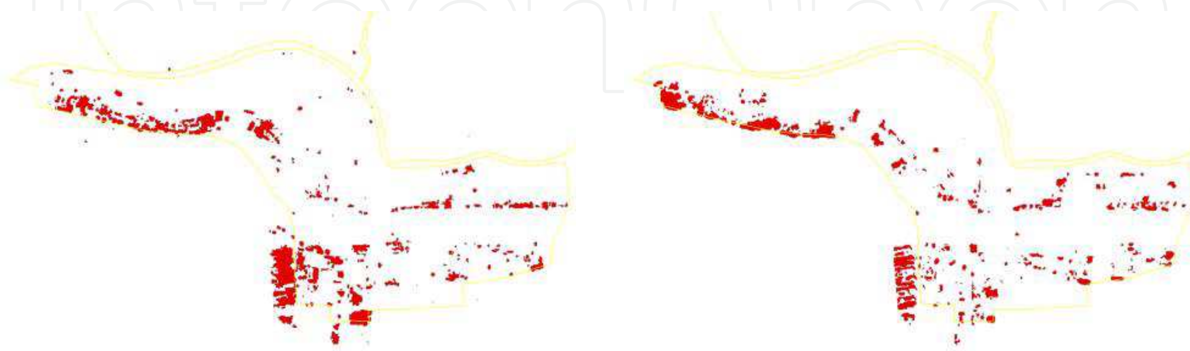
5.2.2 Raila village urban growth

Multi-level contextual change detection approach was applied to Raila village to highlight the extent of major urbanisation processes that can take action even in a short time span. As expected the development on southern border of the village is well recognised (Fig. 13) and different time sequences analysed outlined where and when the growth has taken place.

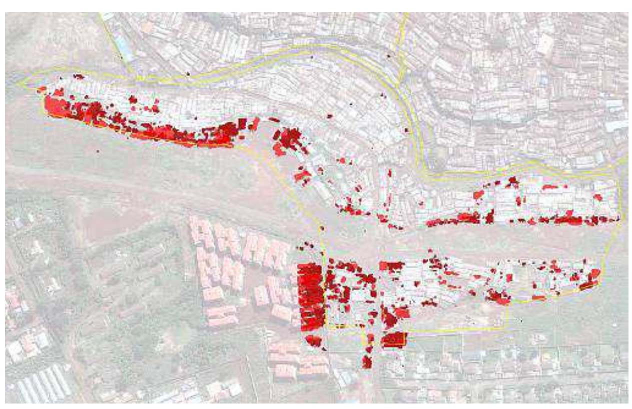
Method incorporates spatial neighbourhood dependence to control the false change information (i.e. inherent changes due to locally based variability in data). As a result it gives a change pattern of positive and negative changes in imagery spectral space. Positive changes correspond to an increase in digital number values at the same location and negative changes to a decrease in spectral values. Method was developed for middle resolution imagery, but its application to Kibera informal settlement data proved this concept to be efficient on VHR imagery as well. In general, majority of objects transformations regardless of their size (small patches to entire buildings) was identified. The results were evaluated with visual control or before-after imagery comparison. Although quantitative assessment was not possible as more detailed independent data were not available, we estimate that more than 90% of changes associated to buildings appearance and disappearance are captured.

Hence, detailed inspection of identified changes outlined several difficulties related to detect change in slum-like areas. First of them is preservation of shape. Because of the use of multi-level information the objects edges may be shrinked to some degree, causing that change is not recognised at entire object extent but only at part of it. Second, the level of change recognition (detection rate) is different in positive and negative spectral space. New materials (i.e. metal plates) used to cover houses have very strong reflection, so difference from low reflecting brown soil to new buildings with bright cover is obvious and unproblematic. In contrast, for example from rusty rooftops to bare soil this difference is not

QB2006-03-27 QB2008-08-10 GE2009-07-25



Change pattern from years 2006-2008. Change pattern from years 2008-2009.



Urban growth pattern through years 2006, 2008 and 2009 for Raila village.
Dark red corresponds to 2006-2008 and light red to 2008-2009 period.

Fig. 13. Results of change detecion for urban growth pattern through years 2006, 2008 and 2009 for Raila village, Kibera.

great and consequently buildings disappearance is more difficult to detect. Same applies if new building has dark colour rooftop covers (for example, often used blue colour plates). Main change missing occurrences therefore apply to the just described situations, making difficulties for automatic approaches. To some extent this problem was solved so that the threshold for negative changes was reduced during transformation categorisation step.

5.2.3 Raila village population estimation in 2009

According to the total residential area in Raila village obtained from object based classification (section 5.1.1, Table 3), population estimation was calculated based on different density per area parameters (Table 6). Additionaly we illustrate this information also in terms of typical size of houses in the Raila village (Fig. 14).

Source	Density [people/m²]	Density [people/32m²]	Estimated population of Raila
MapKibera Project (2008)	0.0951	3.04	4,343
IRIN (2006)	0.2000	6.40	9,131
AHI US (2005)	0.3000	9.60	13,697
Sartori et al. 1 (2002)	0.3300	10.56	15,067
Sartori et al. 2 (2002)	0.3900	12.48	17,806

Table 6. Density of people living in Raila village according to different sources and total residential area obtained from object-based classification of GeoEye 2009-07-25 image.

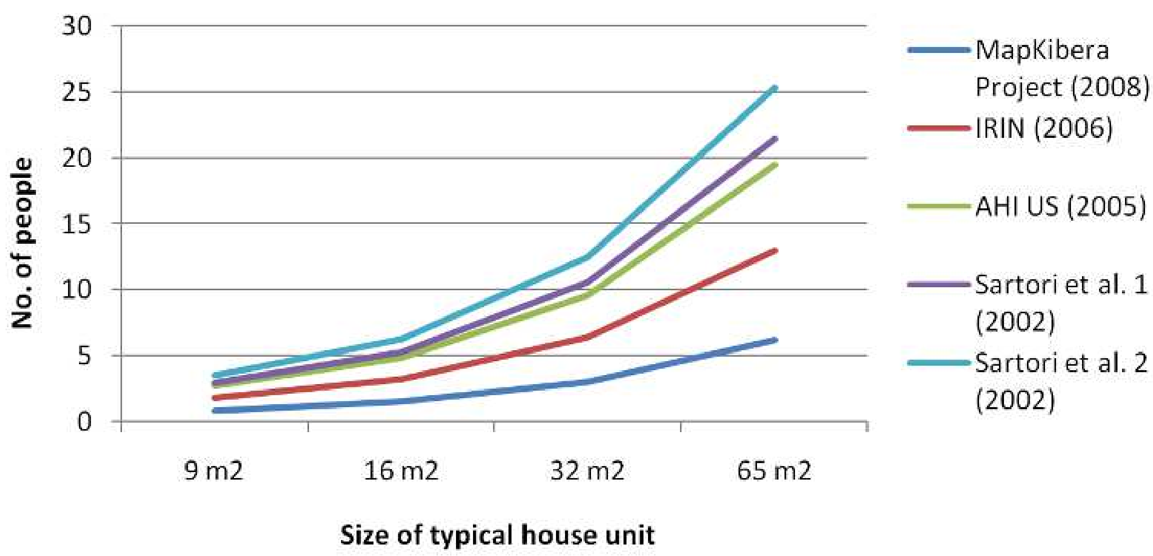


Fig. 14. Density of people according to different sources per typical size of houses in Raila village.

In Table 6 we presented also the density on 32 m² unit since this size of house was measured to be a most typical and frequent (medium range size) housing unit in Raila village. It was also observed that size of small buildings is approximately 16 m², while large buildings reach on average 65 m². Fig. 14 summarise in addition the above relationship.

When perfoming such population estimation it is assumed that all of the build-up area is used for dwelling, which is not allways true as houses may be also used for other activities. For the possible calibration of the above population densities field survey sampling would be required. Nevertheless, Table 6 clearly outlines how population estimation based on critera of simple density per area based modelling can propose up to 4-times higher (different) population estimation.

6. Discussion

Informal settlements are a very dynamic phenomenon in space and time and the number of people living in these areas is growing worldwide. The reasons for this are many-sided and were not under detailed examination of this study. Informal settlements represent a particular housing and living conditions which is from a humanitarian point of view in most cases below acceptable standards (UN-HABITAT, 2004; MKP, 2011; Sartory et al. 2002). Due to informal character and low governmental management services in the past, reliable and accurate data about informal settlements and their population is rarely available. On the other side there is a strong need to transform informal into formal settlements and to gain more control about the actual urbanisation progress. Thus, obtaining spatially and temporally accurate information is a first step to establish proper actions in terms of local or regional planning. For these tasks, conventional data sources, such as maps, statistics or even GIS data are usually obsolete, not available, not as accurate as needed or do not hold the information needed (MKP, 2011; Sartory et al. 2002). The case study presented demonstrates how informal settlements can be approached from VHR satellite image data. Using an object based approach of image analysis detailed land cover/use within informal settlements can be obtained to facilitate GIS-based management tasks and population modelling. The application of automatic, even if simple pixel-based, change detection proved to support real-time observation of informal settlement areas whenever appropriate VHR satellite data are available with relatively low processing costs.

Merits of object-based image analysis in dense informal settlements analysis with VHR remote sensing data have been confirmed in several studies (section 2). However some drawbacks still resist. In case of residential land cover/use map derivation main unsolved difficulty is automatic detection and separation of individual houses. Although small differences in heights of rooftops create visually well distinguished boundaries of objects, the heterogeneity of rooftop material and its small scale changeability often overrule the value of neighbourhood houses boundaries relationship. Current limit of object based analysis is also that still requires substantial post-classification routines and check-over that can be done mainly manually through visual control. What characterise this procedure as time demanding whenever geometrically and semantically correct information is aimed.

Change detection applied revealed great potential for long-term monitoring and informal settlements urbanisation growth analysis. Hence more research is needed to provide sufficient detection rate of spectrally lower magnitude changes that are typical for informal settlements specifics and its reflectance intensity representation on satellite imagery. Due to rooftop material used bright (metal) materials are unproblematic to distinguish from soils, however dark rooftop materials (blue, brown colour) are spectrally closer to bare, unpaved (brown) or vegetated (green) soils. Here object based approaches would prove better option as sub-object attributes could be explored and used.

Valuable population estimation can be made with a relatively low cost if residential area if accurately estimated from high-resolution images, although some considerations exist. Area based population estimation model can be used for the informal settlements in other images of similar resolution knowing the number of people living per surface unit. Zhang (2002) exposed some problems of selection of the scales of remote sensing imagery, reduction of influence of plant cover on remote sensing data, stability of the correlation between population and remote sensing indicator variables and correction of building count. In this research we met all mentioned problems in order to accurately estimate population out of VHR satellite data. Nevertheless, if a clear understanding of mentioned issues is considered, reliable population model of population estimation by remote sensing data can be created. Thus, the application of satellite data information (such as accurate information on land use extent and other measures of surface or environmental characteristics) along with socio-economic data may well facilitate complex modelling to estimate population trends.

In terms of remote sensing technology contribution it is necessary to continue to develop new techniques for complex densely packed urban environments such as informal settlements. Emphasis on spectral properties should be considered but also emphasis on the characteristics of the shape, texture, context, and relationship with neighbouring pixels (and/or objects) information needs to be enhanced; as well as integration of the knowledge on corresponding socio-economic drivers should not be neglected.

7. Conclusion

Effective methods of monitoring informal settlements are required to generate appropriate data fast enough to assist to local policies and their controlling actions. Remote sensing data are especially powerful in that respect since, apart they are up-to date, they assist to link the geographic location with the accurate socio-economic data.

The results of change detection confirmed that VHR imagery is very promising for immediate monitoring of dense informal residences in the areas where much information is lacking. The results of object-based (contextual) classification of the land use in informal settlements of Kibera were highly accurate, especially if taking into consideration that informal settlements are difficult to be interpreted with automatic or semi-automatic routines. On the other side, the results indicate the problem of the ratio between spectral and spatial heterogeneity of objects in slum-like areas when viewed only from the above (satellite) perspective. Overall, the use of the object-based image analysis holds great promise for dense urban environments and was proved useful for studies of urban change structure and corresponding population estimation.

Satellite derived information can greatly complement the information that is traditionally collected by field observations (UNHCR, 2000). Quantitative information that can be derived from it should not be underestimated. The production of maps with geometrical shapes of settlements can contribute to recover the management of informal settlements, especially when interfaced with database that has information collected on the field. Although several challenges have not been yet solved adequately, e.g. delimitation of individual objects in slum-like areas, we can notice that applications are being developed. Thus (automatic) analysis of objects enables tremendous opportunities for population estimation in informal settlements.

8. Acknowledgment

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9. References

A History of Kibera (2011). Available from www.brianekdale.com/?p=230.

Addink, E.A., Van Coillie, F.M.B. (Eds.) (2010). *GEOBIA 2010: Geographic Object-Based Image Analysis*, Ghent, Belgium, 29. June - 2. July 2010. ISPRS Vol.No. XXXVIII-4/C7, Archives ISSN No 1682-1777. Available from http://geobia.ugent.be/proceedings/html/papers.html.

AHI US (2005). Affordable housing institute. Available from http://affordablehousinginstitute.org/blogs/us/2005/07/kibera_africas.html.

Barrett, E., Curtis, L. (1986). *Introduction to Environmental Remote Sensing,* pp. 238-241. London: Chapman and Hall.

Benz, U.C., Hofmann, P., Willhauch, G., Lingenfelder, I., Heynen, M. (2004). Multi-resolution, object-oriented fuzzy analysis of remote sensing data for GIS-ready information. *ISPRS Journal of Photogrammetry and Remote Sensing*, Vol. 58, pp. 239-258.

Blaschke, T., Burnett, C., Pekkarinen, A. (2004). New contextual approaches using image segmentation for object-based classification. In: *Remote Sensing Image Analysis: Including the spatial domain*, De Meer, F. and de Jong, S. (Eds.), Kluver Academic Publishers, Dordrecht, pp. 211-236.

Blaschke, T., Lang, S., Hay G.J. (eds.) (2008). *Object-Based Image Analysis: Spatial Concepts for Knowledge-Driven Remote Sensing Applications* (Lecture Notes in Geoinformation and Cartography). Springer.

Dare, P.M., Fraser, C.S. (2001). Mapping informal settlements using high resolution satellite imagery. In: *Int. J. of Remote Sensomg*, Vol. 22, No. 8 pp. 1399-1301.

Davis, M. (2006). The Planet of Slums.

Deer, P. (1998). *Digital change detection in remotely sensed imagery using fuzzy set theory*. Ph.D. thesis, Departments of Geography and Department of Computer Scoence, University of Adelaide, Australia.

Dengsheng, L., Qihao, W., Guiying, L. (2006). Residential population estimation using a remote sensing derived impervious surface approach. *International Journal of Remote Sensing*, Vol. 27, No. 16, pp. 3553-3570.

Galeon F. (2008). Estimation of population in informal settlement communities using high resolution satellite image. *The International Archives of the Photogrammetry: remote sensing and spatial information sciences*, Vol. 37, Beijing.

Giada, S., De Groeve, T., Ehrlich, D. (2003). Information extraction from very high resolution satellite imagery over Lukole refugee camp, Tanzania. *International Journal of Remote Sensing*, Vol. 24, pp. 4251-4266.

Hay, G. J., Blaschke, T., Marceau, D.J., Bouchard, A. (2003). A comparison of three image-object methods for the multiscale analysis of landscape structure. *ISPRS Journal of Photogrammetry & Remote Sensing 57*, pp. 327-345.

Hoffman, P., Strobl, J., Blaschke, T., Kux, H., (2006). Detecting informal settlements from Quickbird data in Rio de Janeiro using an object based approach. Available from http://ispace.researchstudio.at/downloads/2006/165_Hofmann_et_al.pdf

Hofmann, P., 2001. Detecting urban features from IKONOS data using an object oriented approach. *Fist Annual Conference of the Remote Sensing & Photogrammetry Society*, pp. 28-33.

Horton, F. (1974). Remote sensing techniques and urban acquisition. In: *Remote Sensing Techniques for Environmental Analysis,* Estes, J., Senger L. (Eds.) , pp. 243-276. Santa Barbara: Hamilton Publishing Co.

IHC (2007). International Housing Coalition. Urban Investments and Rates of Return: Assessing MCC's Approach to Project Evaluation. Available from http://www.intlhc.org/docs/urban-investment.pdf.

IRIN (2006). Humanitarian news and analysis. A project of the UN Office for the Coordination of Humanitarian Affairs (09/13/2006), "KENYA: Kibera, The Forgotten City". Available from http://www.irinnews.org/Report.aspx?ReportId=62409.

Jianya, G., Haigang, S., Guorui, M., & Qiming, Z. (2008). A review of multi-temporal remote sensing data change detection algorithms. *The International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*.

Johnson, B., Xie, Z. (2011). Unsupervised image segmentation evaluation and refinement using a multi-scale approach. *ISPRS Journal of Photogrammetry & Remote Sensing* 66, pp. 473-483.

Karanja, M. (2010). Myth shattered: Kibera numbers fail to add up. Daily Nation. Available from http://www.nation.co.ke/News/Kibera%20numbers%20fail%20to%20add%20up/-/1056/1003404/-/13ga38xz/-/index.html

Kibera Wikipedia (2011). Available from http://en.wikipedia.org/wiki/Kibera.

Kuffer, M. (2003). Monitoring the Dynamics of Informal Settlements in Dar Es Salaam by Remote Sensing: Exploring the Use of SPOT, ERS and Small Format Aerial Photography. In: *Schrenk, M. (Ed.): Proceedings CORP 2003*, pp. 473-483.

Lang, S., Blaschke, T., Schöpfer, E. (2006). *1st International Conference on Object-based Image Analysis*. http://www.isprs.org/proceedings/XXXVI/4-C42/papers.htm.

Langford, M., Unwin, D.J. (1994). Generating and mapping population density surfaces within a geographical information system. *The Cartographic Journal*, Vol. 31, No.1, pp.21-26.

Lemma, T. et al. (2005). A Participatory Approach to Monitoring Slum Conditions. Available from http://www.itc.nl/library/papers_2005/conf/sliuzas_par.pdf

Lin, Z., Jin, Y., Li, C. (2001). Urban population geographical information systems. *Proceedings of the 20th International Cartographic Conference*, pp. 1279-1282, Beijing, China, August 6-10, 2001.

Lu, D., Mausel, P., Brondizio, E., Moran E. (2004). Change detection techniques. *International Journal of Remote Sensing 20 (25)*, 2365–2407.

Mason, O.S.., Fraser, C. (1998). Image sources for informal settlement management. In: *Photogrammetric Record*, Vol. 92 (1998), No. 16, pp. 313-330.

MKP (2011). Map Kibera Project. Available from http://mapkibera.org, http://www.mapkiberaproject.org, http://mapkiberaproject.yolasite.com

Netzband, M., Rahman, A. (2010). Remote Sensing for the mapping of urban poverty and slum areas. Panel contribution to the Population-Environment Research Network Cyberseminar, "What are the remote sensing data needs of the population-environment research community?", May 2010.

Radnaabazar, G. et al. (2004). Monitoring the development of informal settlements in Ulanbaatar, Mongolia. http://www.schrenk.at/CORP_CD_2004/archiv/papers/CORP2004_radnaabazar_kuffer_hofstee.pdf (accessed 2006).

Sartori, G., Nembrini G. & Stauffer, F. (2002). Monitoring of Urban Growth of Informal Settlements and Population Estimation from Aerial Photography and Satellite Imaging. http://www.thirstycitiesinwar.com/files/informalsettlements.pdf

Singh, A. (1989). Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing 10*, pp. 989–1003.

Sliuzas, R.V. and Kuffer, M. (2008). Analysing the spatial heterogeneity of poverty using remote sensing : typology of poverty areas using selected RS based indicators. In: *Remote sensing : new challenges of high resolution, EARSeL*, joint workshop, 5-7 March 2008 Bochum, Germany / ed. by C. Jürgens. Bochum : EARSeL, 2008. pp. 158-167.

Sutton, P. (1997). Modeling population density with night-time satellite imagery and GIS. *Computers, Environment and Urban Systems*, Vol. 21, No.3-4, pp. 227-244.

UN-Habitat (2004). Africa on the Move. An urban crisis in the making. Available from http://www.unhabitat.org/downloads/docs/4626_83992_GC%2021%20Africa%20on%20the%20Move.pdf

UNHCR (2000). Population estimation and registration. In: *Handbook for Emergencies*, 2nd edition, pp. 118–131, Geneva: UNHCR Publications.

UNHCR (2010). IDP Population Assessment of the Afgooye Corridor – January 2010.

UNHSP (2005). United Nations Human Settlements Programme (UN-HABITAT), Nairobi. Situation analysis of informal settlements in KISUMU, Kenya slum upgrading programme. Available from http://www.unhabitat.org, http://www.unhabitat.org/pmss/listItemDetails.aspx?publicationID=2084

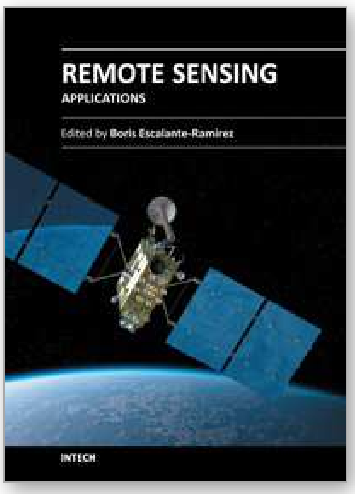
Veljanovski, T. (2008). The problem of false (non-intrinsic) changes in pixel-based change detection on Landsat imagery. *Geodetski vestnik, Vol. 52, No. 3*, pp. 457-474.

Veljanovski, T., Oštir, K. (2011). Influence of radiometric pre-processing on image properties and comparability consistency. *International Conference on Sensors and Models in Photogrammetry and Remote Sensing: SMPR2011*, May 18-19, Tehran-Iran.

Wang, F.Z. (1990). Urban population estimation – multispectral imagery analysis. *Urban Environment and Urban Ecology*, pp. 34-42.

Wang H.H. (1990). City population estimation method with satellite imagery. *Remote Sensing technology*, pp. 48-54.

Zhang, B. (2003). Application of remote sensing technology to population estimation. *Chinese geographical science*, Vol. 13, No.3, pp.267-271.



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Nowadays it is hard to find areas of human activity and development that have not profited from or contributed to remote sensing. Natural, physical and social activities find in remote sensing a common ground for interaction and development. This book intends to show the reader how remote sensing impacts other areas of science, technology, and human activity, by displaying a selected number of high quality contributions dealing with different remote sensing applications.