*Urban expansion and its impact on urban agriculture – remote sensing based change analysis of Kizinga and Mzinga Valley – Dar Es Salaam, Tanzania*

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## ABSTRACT

Urban agriculture is a phenomenon that can be observed world-wide, particularly in cities of developing countries. It is contributing significantly to food security and food safety and has sustained livelihood of the urban and peri-urban low income dwellers in developing countries for many years. Population increase due to rural-urban migration and natural, coupled with formal as well as informal urbanization are competing with urban farming for available space and scarce water resources. A multitemporal multisensoral urban change analysis over the period of 25 years (1982-2007) was performed in order to measure and visualize the urban expansion along the Kizinga and Mzinga valley in the South of Dar es Salaam. Airphotos and VHR satellite data were analyzed by using a combination of a composition of anisotropic textural measures and spectral information.

The study revealed that unplanned built-up area is expanding continuously and vegetation covers and agricultural lands decline at a fast rate. The validation showed that the overall classification accuracy varied depending on the database. The extracted built-up areas were used for visual interpretation mapping purposes and served as information source for another research project. The maps visualize an urban congestion and expansion of nearly 18% of the total analyzed area that had taken place in the Kizinga valley between 1982 and 2007. The same development can be observed in the less developed and more remote Mzinga valley between 1981 and 2002. Both areas underwent fast changes where land prices still tend to go up and an influx of people both from rural and urban areas continuously increase density with the consequence of increasing multiple land use interests.

## INTRODUCTION

Urbanisation is one of the major problems of mankind in the near future. In 2008, for the first time in history, more than half the world's population lived in urban areas. The world's urban population is expected to double from 3.3 billion in 2007 to 6.4 billion by 2050, and it is predicted that by 2030, over 56% of the world's population will live in cities (i). This urban population growth will be most significant in low income countries, notably in Africa and Asia (ii). Sub-Saharan African countries have the world's highest rates of urban growth and the highest levels of urban poverty. The slum population in these countries doubled in the period 1990 to 2005, when it reached 200 million (iii).

As cities expand, so do the food needs of urban families. The capacity of local municipalities to manage this urban growth is threatened in many developing countries, or already on the decline. The identification of ways to provide food, shelter and basic services to the city residents and create "sustainable cities" are challenges for many city authorities around the world. The phenomenon that a growing number of urban dwellers are engaging in agricultural activities, especially in the less developed countries has been witnessed all over the world. It is estimated that 800 million people are engaged in urban (intra-urban and peri-urban) agriculture world-wide and play an important role in feeding the world's cities (iv, v).

The urbanisation process in many developing countries goes hand in hand with increasing urban poverty, growing food insecurity and malnutrition, especially of the urban poor. Food production in the city is in many cases a response of urban poor to inadequate, unreliable and irregular access to food and inadequate access to formal employment opportunities (vi). Therefore the contribution

of urban agriculture to enhancing urban food security, healthy nutrition, poverty alleviation, and social integration, especially of the poorer sections of the urban population, is of high importance.

Despite substantial growth, urban agriculture received very limited recognition from the authorities in the past. The uncertain legal status of urban agriculture is such that official projects or programmes aimed at improving urban agriculture have been rare. Typically urban agriculture is not taken into account in the urban planning process. In the case of Dar Es Salaam the city government has recognised the need to develop strategies that can enhance urban agriculture in order to ensure sustainable human development. In 1992 the city has integrated urban agriculture in urban planning through a bottom-up approach, under the Environmental Planning and Management (EPM) Process and the Strategic Urban Development Plan (SUDP) has officially set apart several areas to be used for large and medium scale urban agriculture (vii).

However, rapid urbanization means that city boundaries as defined by administrative jurisdictions may be overtaken by new expansion almost as soon as they have been redrawn to account for previous spread (viii). Locations that are rural at one moment become peri-urban the next, and urban soon after. For this reason the fringes of most African cities are unstable with respect to settlement patterns, population density and land use (ix). Of late, professionals and politicians have realised that if urban agriculture is taken seriously and properly organised, it can be effective land management (vii).

Remote sensing is an important tool to provide information about land use and its development over time. It has been used to investigate urban environments, urban land cover changes and city growth in particular. Many publications illustrate the automatic or semi-automatic spectral analysis of medium to high spatial resolution data, e.g., Landsat TM, SPOT HRV. Spectrally derived land cover classifications are further enhanced by visual interpretation of either airphoto, or more recently, of very fine spatial resolution (VHR) optical satellite imagery, e.g., IKONOS or Quickbird [x-xv].

Aerial photographs as well as VHR data provide very fine spatial but coarse spectral resolution data, by comparison with medium and fine spatial and spectral resolution satellite data. So far, these kinds of data were analyzed mainly by analogue, visual interpretation, which is very time consuming, which has led to the new challenge of finding ways to successfully extract and classify urban areas in a more automated way. Single buildings, roads, gardens and lawns that make up the complex heterogeneous urban fabric [xvi] are visible in detail and VHR imagery provides an opportunity for their classification and delineation. Carleer and Wolff [xvii] combined spectral information on VHR imagery together with spectral, textural and morphological features for the improvement of urban land cover classification. The features were calculated after previously segmenting the image into meaningful objects. Herold *et al.* [xviii] conducted a similar segmentation or object based classification of an urban area in California based on IKONOS data. Another approach is the use of image textural information to discriminate built-up structures. Zhang *et al.* [xix] successfully merges spectral and textural information for improving urban recognition by analysing SPOT panchromatic data. Another methodology was developed by Pesaresi [xx] and is based on a fuzzy rule-based composition of anisotropic textural measures, based on the gray-level co-occurrence matrix (GLCM). This method was successfully applied with medium resolution data of different source and quality dealing with built-up area discrimination in urban and suburban areas [xxi-xxiii, xxvi], therefore it was tested in this study to successfully derive built-up areas on b&w aerial photographs and VHR satellite data, in order to map the remaining agricultural areas suitable for urban agriculture. The maps will then be used as important information source for a project on the suitability of wastewater irrigated agriculture in the Kizinga and Mzinga valleys in the South of Dar es Salaam.

**METHODS**

Aerial photographs of 1981, 1982, 2003 and VHR satellite data of 2007 was used to monitor urban development in two valleys of high importance for urban agriculture of Dar Es Salaam (Table 1, Figure 1).

*Figure 1: Overview of Dar Es Salaam and the two analyzed areas: Kizinga (a) and Mzinga (b) valleys.*

Two sample data subsets are shown in Figure 2. Vector features of building footprints of a 1km x 1km area were available for validation purposes. All remote sensing data was mosaiked and geo-referenced and resampled to a spatial resolution which is considered optimal for the discrimination of built-up areas using the proposed textural approach. It was applied to the black and white and red-green-blue coloured areal photographs as well as to the visible-near-infrared VHR satellite data.

*Table 1: Remote sensing data.*

| Acquisition date/Year | Sensor | Approx. Resolution of texture kernel used [m] | Area Coverage |
|---|---|---|---|
| 1981 | B&W analogue camera | 2.0 | Mzinga |
| 1982 | B&W analogue camera | 0.7 | Kizinga |
| 2002 | RGB colour analogue camera | 1.8 | Mzinga |
| 2007 | RGB, NIR Quickbird | 2.4 | Kizinga |

*Figure 2: Sample subset area (1km x 1km) of Quickbird data acquired in 2007 (left) and b&w aerial photograph of 1982. The urban congestion and expansion towards Kizinga river in the South are clearly visible.*

The anisotropic rotation-invariant built-up presence index [xxii] was applied to delineate urban and non-urban regions. The main component of the workflow computes the contrast textural statistic based on the grey-level co-occurrence matrix (GLCM) as introduced by Haralick *et al.* [xxiv]. The method is based on image texture and therefore is advantageous for multisensor and multitemporal image analysis. The efficiency of this method to delineate built-up areas has been shown to work for optical panchromatic images [xxii] as well as SAR images [xxv]. Pesaresi [xxi,xxiii] has shown that the GLCM contrast statistic is the most efficient at discriminating between built-up and non-built-up areas. To determine good contrast statistics between building roofs, shadows and background, the input imagery must have a spatial resolution that is equal to or better than the dimensions of the discernable built-up objects. Different displacement vectors are used to compute the contrast statistic to take advantage of the anisotropic nature of the urban texture. The directional components of the contrast statistic are used to produce a single texture layer using the intersection and union operators (xxii).

The result provides structural information on the urban regions, including buildings and tarmac areas, such as roads, squares or other open spaces. The final binary built-up mask is produced by interactively choosing a threshold value that delineates the image into built-up and non built-up areas. These thresholds were chosen by comparing the built-up area result with the natural color input imagery to maximize urban area overlap.


**RESULTS**

The validation of the resulting built-up mask is not easy, since the procedure classifies not only buildings but also sealed, open spaces and roads as built-up areas. Still, a validation was conducted for a randomly selected area of 1km x 1km in the suburbs of Dar Es Salaam, close to the Kizinga river. First, the roads in the generated built-up mask were excluded from the validation. Second, buildings in the validation area were digitized and buffered by 2.5m to assure the generation of a comprehensive buildings reference layer. The validation was done for two remote sensing datasets used for the analysis of the Kizinga valley area: the Quickbird dataset as well as the aerial photographs acquired in 1982. The achieved accuracies are listed in Table 2.

*Table 2: Validation results of built-up (BU) and non-built-up (NBU) classes for a subset area of 1km x 1km in the Kizinga valley.*

|  | 2007 | | 1982 | |
|---|---|---|---|---|
|  | BU | NBU | BU | NBU |
| Overall Accuracy | 80.85 | | 82.63 | |
| Kappa Coefficient | 0.56 | | 0.42 | |
| Producer Accuracy | 64.50 | 89.70 | 47.08 | 91.49 |
| User Accuracy | 77.22 | 82.36 | 58.48 | 87.13 |

The classification accuracy varied depending on the database, with the Quickbird data of 2007 achieving a better result than the b&w aerial photograph of 1982. Figure 3 clearly shows that a lot of buildings in the aerial photograph were not recognized as such leading to a high omission error. Additionally, areas of high contrast such as trees and bare soil in the background, along roads, and areas around buildings identified as buildings lead to a high commission error. Another reason contributing to the omission error is the fact that the reference contains only buildings whereas the presented methodology classifies also bare soil areas, parking lots, construction sites, side roads or dumps as built-up areas (Figure 3).
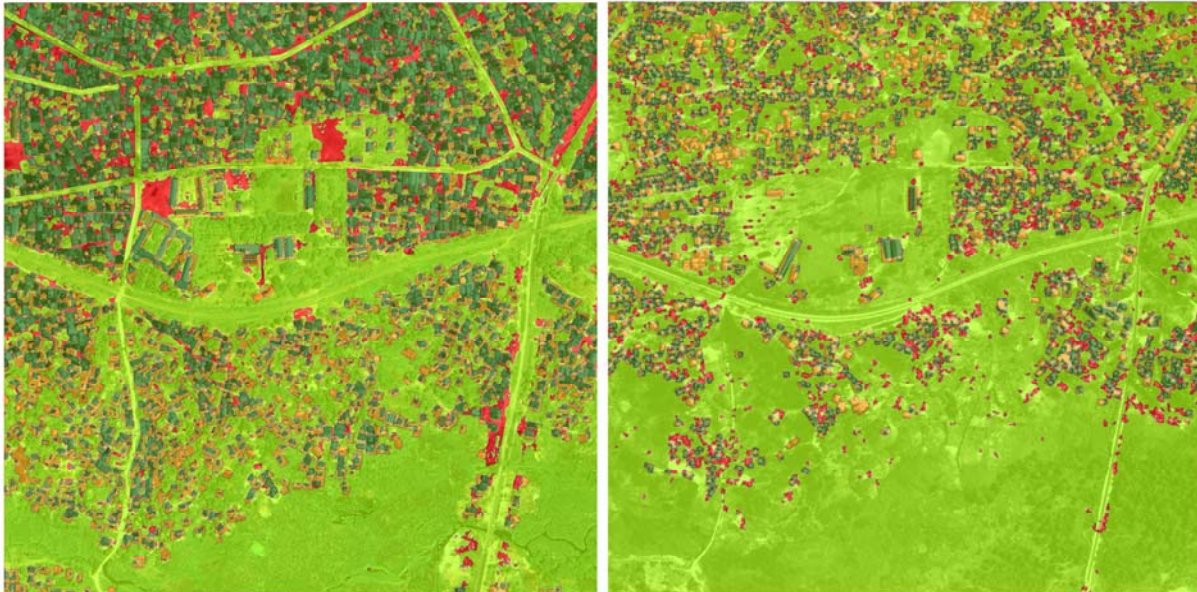


*Figure 3: Validation area in the Kizinga valley for the built-up mask derived from Quickbird data (left) and b&w aerial photographs (right). Correctly classified built-up (BU) (dark green) and non-built-up (NBU) (light green). Errors of omission are presented in (orange) and errors of commission in (red).*

The same reasons lead to classification errors when applying the methodology to the Quickbird dataset but due to a better radiometric resolution and a generally better quality of the data the accuracy is generally higher than that of the b&w aerial photograph dataset. Actually, most buildings are detected as such only that the areas of detection are smaller than the actual built-up area. This is clearly visible in the South of the subset area where a lot of new buildings had been constructed in recent years. The performance of the methodology, basing on textural contrast, depends not only on the materials used for the roof but also on the surroundings of buildings. If roofs are made of red adobe, rusty corrugated iron sheets or are surrounded or partially covered by large trees

leading to little contrast between the buildings and the soil background the detection of buildings may fail.

However, the results show that the methodology works with b&w aerial photographs of reduced quality as well as high-resolution VHR satellite data. Built-up masks may be extracted in a fast and uncomplicated way and built-up maps may be generated that, on a smaller scale, e.g. on regional or city level, offer the possibility to recognize and address the challenges of uncontrolled urban sprawl and its consequences for peri-urban and urban farming.

## CONCLUSIONS

The anisotropic rotation-invariant built-up presence index [xxii] was applied to delineate urban and non-urban regions. So far the method had been applied mainly on medium resolution data of 5 -10 m geometric resolution. In this study VHR data as well as b&w and rgb aerial photographs with higher geometric resolution but some of them of lower quality, served as input data. The validation showed that some of the generated built-up/non-built-up masks contain rather larger errors. The reasons of which have been discussed in the results section. However, the extracted areas can still be used for a visual interpretation of change analysis and mapping purposes (Figure 4). Additional manual editing could further improve the results in a way that statistical data may be derived. It could also be tried to geometrically further resample the data in order to derive more generalized built-up/non-built-up classifications suitable for urban change analysis on a larger scale. However, Figure 4 visualizes well the urban congestion and expansion that had taken place in the Kizinga valley between 1982 and 2007. The same can be observed in the Mzinga valley between 1981 and 2002. Both areas undergo rapid changes where land prices tend to go up and an influx of people both from rural and urban areas increase density with the consequence of multiple land use interests. Both valleys, for example, are also prone to flooding and serve as water reservoirs. They also have the potential of becoming important recreational areas and function as "green lungs". All these multiple interests call for a coordinated urban land use management officially integrating urban agriculture and strengthening its role as a sustainable source of income, employment and food.
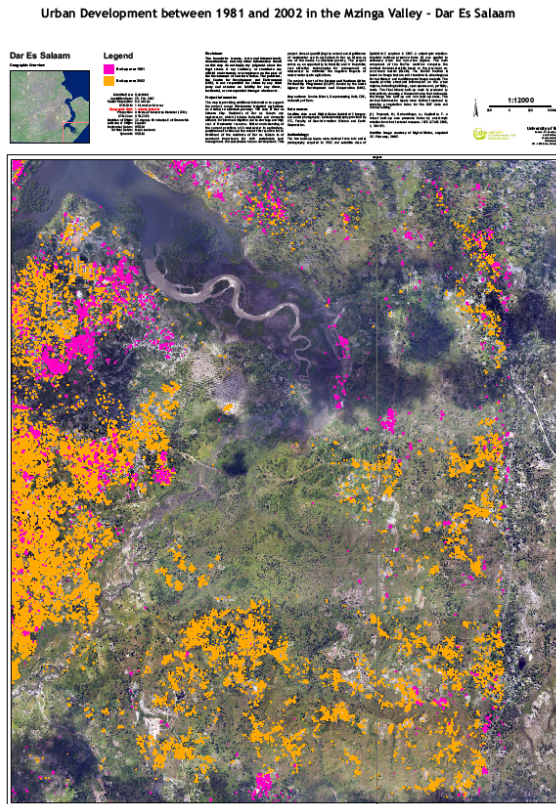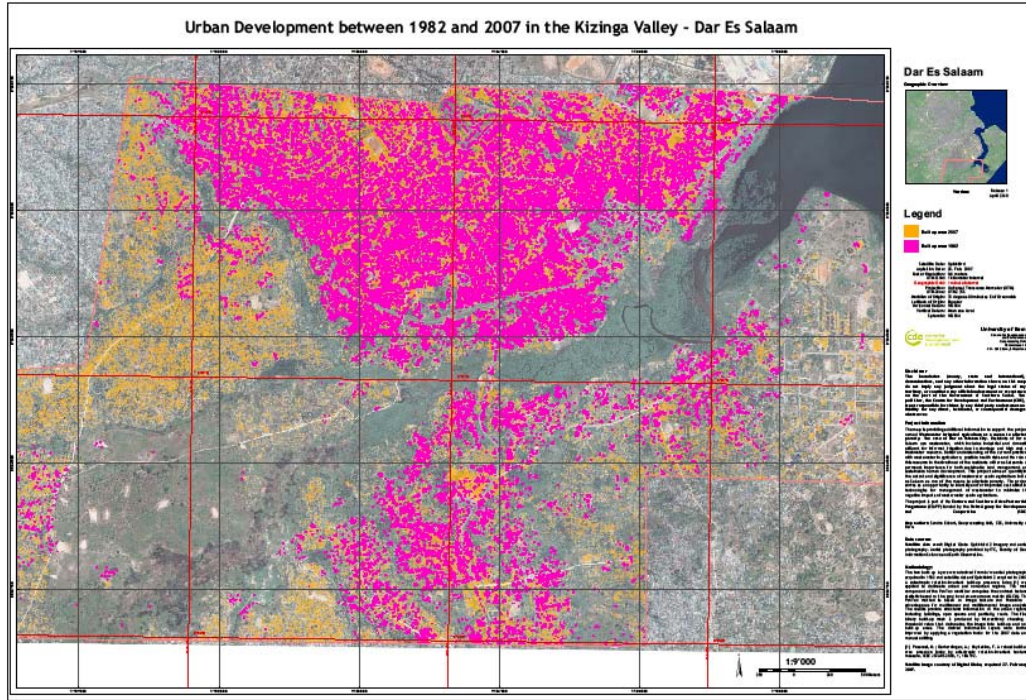
*Figure 4: Generated maps representing urban development in the Kizinga valley (top) and the Mzinga valley (bottom), where pink represents built-up areas in 1982/1981 and orange in 2007/2002 respectively. The delineation of the analysed areas was determined by the geographic overlap of the remotely sensed data.*

## ACKNOWLEDGEMENT

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