ASSESSING THE QUALITY OF URBAN FOOTPRINT COVERAGES OF KAMPALA

GEWA LI
February, 2014

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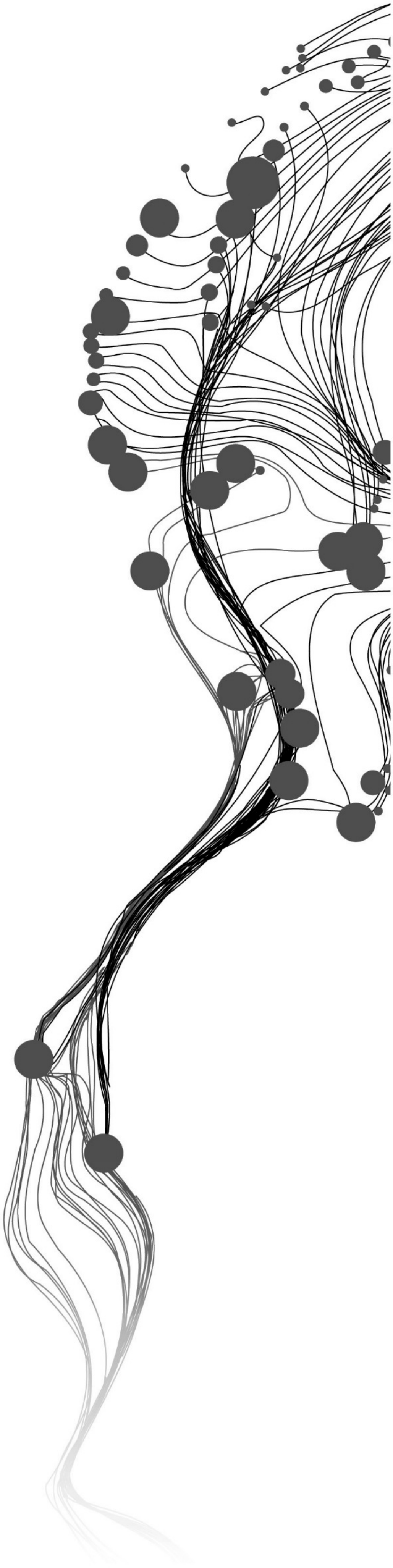

ASSESSING THE QUALITY OF URBAN FOOTPRINT COVERAGES OF KAMPALA

GEWA LI
Enschede, The Netherlands, February, 2014

Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation.
Specialization: Urban Planning and Management

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ABSTRACT

Assessing the accuracy of land-cover classifications is a major challenge in remote sensing. This is due to the absence of reliable, highly accurate, and temporal-comparable reference data. The main objective of this research was to assess the quality of urban footprint products of Kampala (2010) with the reference data from Kampala Capital City Authority (KCCA). This was done using the Global Human Settlement Layer (GHSL) and Urban Footprint Classification (UFC) products. The Global Human Settlement Layer (GHSL) was developed and maintained by the Joint Research Centre (JRC). Urban Footprint Classification (UFC), which is a fully-automated and operational image analysis product resulting in a binary settlement masks was developed and maintained by the German Aerospace Centre (DLR).

This research attempted to assess the quality of both urban footprint products with available reference data in order to identify the factors that may result to wrong classification of some areas as well as reflect on what kind of urban planning applications could benefit from these urban footprint products.

The research approaches involved checking the quality of the reference data; processing the reference data to make it comparable with the target data; accuracy assessment by error matrix table and statistical comparison of the reference data and the urban footprint products via SPSS (Statistical Package for Social Sciences); and finally structuring of possible factors that may influence data quality by overlaying the products with available reference data and image Mosaic.

Generally, the results showed that both products generated acceptable results with an overall accuracy of $\geq$75. The factors influencing the quality of extracting urban footprint were first identified from reference points with errors and secondly from wrongly classified areas. There were no significant differences between both products on the possible factors of influence. Two groups of factors were identified as main influencers; built environment factors and natural environment factors. The statistical comparison between both products and their corresponding reference data sets illustrated a high relationship. On the other hand, comparison with contrasting reference data sets (that is, GHSL with building and roads; and UFC with only buildings) showed highly uncorrelated results.

Urban densification, land use and land cover applications were discussed in this research. Since the GHSL is a continuous data with ranging values, it tested better at describing urban densification; UFC on the other hand was considered better for land cover analysis than for land use analysis. However, the only data available for this research was for one year; this limited a further temporal analysis that could further explain the suitability of these products for urban planning dynamics.

Key words: Quality assessment; urban footprint products; factors; urban planning applications

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Blessings Gewa Li
Enschede, Febaray, 2014

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ACRONYMS

JRC: Joint Research Centre

GHSL: Global Human Settlement Layer

DLR: German Aerospace Centre

UFC: Urban Footprint Classification

ICT: Information and Communication Technologies

HR: High Resolution

MR: Medium Resolution

VHR: Very High Resolution

SAR: Synthetic Aperture Radar

TSX: TerraSAR-X

TanDEM-X: TerraSAR-X add-on for Digital Elevation Model

RMSE: Root Mean Square Error

GCP: Ground Control Points

DEM: Digital Elevation Model

KCCA: Kampala Capital City Authority

GUF: Global Urban Footprint

SPSS: Statistical Package for Social Sciences

UFP: Urban Footprint Processor

ERS: European Remote Sensing

ESA: European Space Agency

LU: Land use

1. INTRODUCTION

1.1. Urban Footprint Mapping

Urbanization represents one of the most dynamic processes in the context of global urban land use change. Rapid urban growth has over time contributed to various problems such as climate change, increasing levels of poverty and population growth. Mapping of urban extensions and monitoring of fast growing cities is therefore important for the management of cities and urban areas. "A frequent and reliable delineation of the city footprints is a basic requirement for the analysis and understanding of the urban dynamics worldwide" (Taubenbock et al., 2011, p. 1). Previous studies show that most of the existing footprint products were mainly derived from Medium Resolution (MR around 30 m) sensor data (Potere et al., 2009). For example, Angel et al. (2005) established a random-stratified global assessment dataset (drawing a stratified global sample of 120 cities with population in exceed of 100,000) derived from MR (28.5 m) Landsat-based city maps. Those maps have often been used for comparison with some coarse-resolution global urban maps to check their accuracy. However, one of the setbacks of MR layers is that they cannot be used to accurately identify structures, buildings, and housing patterns and can therefore not provide important information that would allow an accurate characterization of built-up and non-built areas. This is due to the fact that these datasets have relatively large pixel sizes; one-pixel conversion for instance can result to displacement in the order of kilometres. In the recent past, efforts have been made to improve the quality of urban footprint products based on High Resolution (HR1-10 m) and Very High Resolution (VHR <=1 m) earth observation data.

Joint Research Centre (JRC) and German Aerospace Centre (DLR) have recently developed image based global urban footprint coverage from VHR optical called Global Human Settlement Layer (GHSL) and VHR radar data called Urban Footprint Classification (UFC) respectively. There is however insufficient knowledge on the quality of the global urban footprint coverage (Esch et al., 2011). It is therefore important to examine the quality of such datasets by comparing them with the available ground reference data (e.g. topography data); this would help to draw conclusion on the main factors that determine the accuracy of urban footprint images.

Study area

The study area is Kampala City; it is the largest city and capital of Uganda. The city is built on seven hills and is situated on the northern shores of Lake Victoria. Since 1970, Kampala has experienced exponential population growth from 330,000 to 1.5 million in the year of 2009. The average population density is 6100 persons per km^2 with slum areas increasing to 30,000 persons per km^2 (Vermeireren et al., 2012).

The city of Kampala was selected for this research due to three main reasons: first, ITC (Faculty of Geo-Information Science and Earth Observation) has an on-going project on Integrated Flood Management; so this readily availed data that was important for this study. Secondly, Kampala is one of the fastest growing cities in Africa (with an annual growth rate of 5.6% according to Vermeireren) and it is therefore an important city to monitor its growth and expansion. Furthermore, the unprecedented growth and expansion of this city instigated some past studies; Makita et al. (2010) for instance, focused on the rapid urban growth phenomena in the city of Kampala by analysing and mapping the urbanization characteristics. Abebe (2013) analysed the spatio-temporal growth pattern of the Kampala and quantified the underlying spatial pattern of the urban landscape. The third reason why Kampala was selected for this study is that both JRC and DLR are interested to have an accuracy test of their products on a city in a non-western country- this makes Kampala a good study location.

Main characteristic of VHR optical data and VHR radar data

Several airborne and satellite sensors provide VHR data that is used for monitoring, mapping and management tasks in various research areas (Peters et al., 2011). VHR optical imagery (with a resolution of 0.5 m, e.g. Geoeye, Worldview) can reveal sufficient details of the built-up environment for manual or automated building change detection. However, in highly dense urban areas with very small buildings it is extremely difficult to extract buildings and other features (such as roads) accurately. VHR data can also offer inclined textural information, allowing for both improved interpretation and classification based on the texture and shape of the ground objects (Mansouri et al., 2011).

With a spatial resolution of up to 1 m, the German radar satellite TerraSAR-X has significantly increased the usability of space borne Synthetic Aperture Radar (SAR) imagery in the context of urban applications (Esch. et al., 2010). This is in contrast to the European Remote Sensing (ERS) satellites (provided by European Space Agency (ESA)), which have a resolution of only up to 30 m (Grey et al., 2003). TSX offers space-based observation capabilities that were previously unavailable. When compared to the optical data, the primary advantage of SAR systems is that they can acquire data during day time and at nights, independent of the weather and environmental conditions. However, considering factors such as limited spectral resolution and the complexity of signal interpretation in the geometrically urban landscape, SAR sensors are barely used for detailed urban monitoring nowadays (Schenk et al., 2011).

Global Human Settlement Layer

The GHSL is a continuous project of the European Commission that aims at delivering a globally consistent representation of all human settlements around the world at HR and even VHR. In 2011, a first test of the JRC image information query system to produce the GHSL was performed. It demonstrated a systematic differentiation between built-up and non-built areas that were computed in an unsupervised and fully automated technique (Ouzounis et al., 2013). The distinct characteristics for the GHSL technology does not require too much human intervention because it extracts information from satellite images automatically; it therefore very suitable for monitoring urban change (Pesaresi et al., 2013).

The general workflow of creating the GHSL is described by Pesaresi et al. (2013). According to Pesaresi, the methods of creating GHSL can generally contain image information query, feature detection, classification, quality control and validation, and after the mosaic-tilling process comes the output. In short there are two steps of feature extraction; derivation of textural image features from grey-level co-coccurrence matrix contrast textural measurements and a multi-scale morphological analysis.

The GHSL built-up structures are defined as "enclosed constructions above ground which are intended or used for the shelter of humans, animals, things or for the production of economic goods; it refers to any structure constructed or erected on a site"(Pesaresi et al., 2013, p. 10). Thus GHSL is a kind of product that approximates building stock, with their geographic locations, but not other physical elements of the built-up patterns. The "built-up area" and "non-built-up area" in GHSL is represented as a continuous value that is threshold to provide information on the presence of buildings. The JRC experimented through a quantitative analysis on built-up area of GHSL over the city of Luneburg, Germany (Pesaresi et al., 2013). The agreement measures between the GHSL built-up areas output and reference data can be seen by table 1:

Table 1 Agreement measures between the GHSL built-up areas output and the reference layer

	Overall accuracy	*BU_accuracy*	*BU_agreement*	*X_fit (50)*	*X_fit (500)*
Mean	90.82%	86.64%	87.46%	86.75%	96.17%
Standard deviation	3.33%	7.10%	12.49%	8.09%	5.11%

The *overall accuracy* is the number of pixels in agreement with the BU/NBU classification divided by the sum of all the pixels analysed in the scene. The *built-up (BU) accuracy* is the number of pixels in agreement with the BU class divided by the sum of all BU reference pixels analysed in the scenes. The *built-up agreement* is a per scene global measurement expressing the agreement on the total surface classified as BU class. The *x fit* measurement is the per-pixel R-square linear regression fit (correlation) between the GHSL output and the reference layer. The calculation was done using two different scales or spatial resolutions: 50x50 meters, and 500x500 meters.

Figure 1 (left) shows the GHSL of Kampala (2010), at a 10 m resolution. The image was extracted from Quick bird Orthophoto image and transformed into a continuous map with image value range of 0-255 approximately (progression of the values (higher) mean there is a more likelihood that the pixel is built-up area).

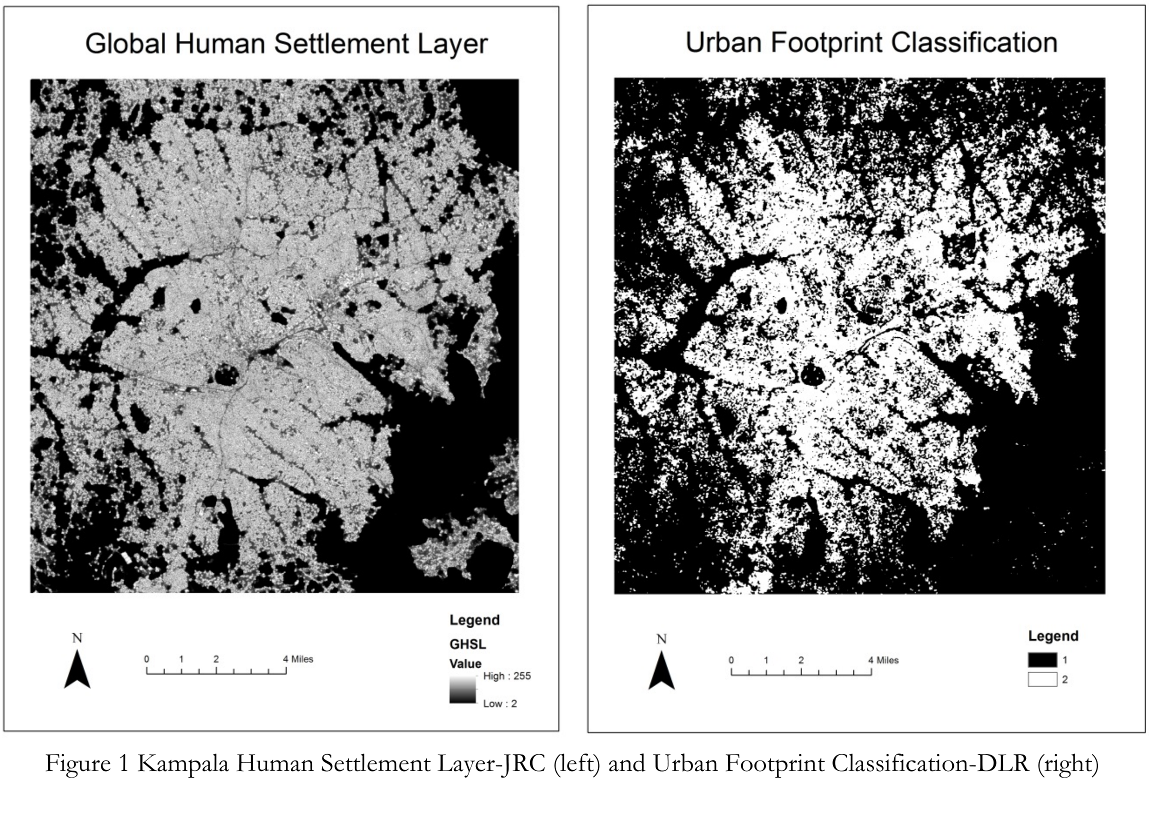


Figure 1 Kampala Human Settlement Layer-JRC (left) and Urban Footprint Classification-DLR (right)

Urban Footprint Classification

The DLR deploys the potential of the TanDEM-X (TerraSAR-X add-on for Digital Elevation Model) mission and develops the Urban Footprint Processor (UFP) based on TanDEM-X data (offers a spatial resolution up to 1 m) to form a global map of human settlements (that is the UFC), they propose semi-automated detection of built-up areas based on single-polarized TSX images for extracting the urban footprints (Felbier et al., 2012). The UFC reflects the distribution of man-made structures with a vertical component (strong scattering due to double bounce). This includes all kinds of buildings and constructions. (Esch et al., 2011).

The UFC shows a processing chain to map human settlements from world-wide SAR data. It contains the basic product generation and the final production generation. The former one includes amplitude calculation, texture analysis and classification, and multilooking (preparation of image components), and the latter one includes generalization, geocoding and slope correction, and mosaicking (Felbier et al., 2012). However, compared to the classification approach described in the previous section, they applied an enhanced method (fully-operational training and classification using support vector data description-one-class classifier), but this is more due to performance issued and the results and underlying effects are quite similar to the ones described in the papers by Esch et al. (2013). The author assessed the quantitative accuracy of urban footprint by comparing 1500 randomly distributed reference points to topographic reference information, the mean overall accuracy (based on 12 urban regions, including Europe, Asia and Australia countries) was 88.5% with a kappa value of 0.77. The mean producer accuracy was 88% and the user accuracy was 91%.

Figure 2 below shows processed results for the greater Kampala data set (2010); the red colour shows the built-up areas while the black colour shows the non-built areas. DLR generated the UFC for Kampala (figure 2) in a spatial resolution of 20 m; the UFC is a binary map, the non-built-up area means that there is very low possibility of existence of buildings, while the built-up area means that there is a high possibility that buildings exists. To compare with the GHSL, the right side of figure 1 (UFC) shows a binary map which value 1 indicates non-built-up area and value 2 shows built-up area, they all show the same area and same scale.

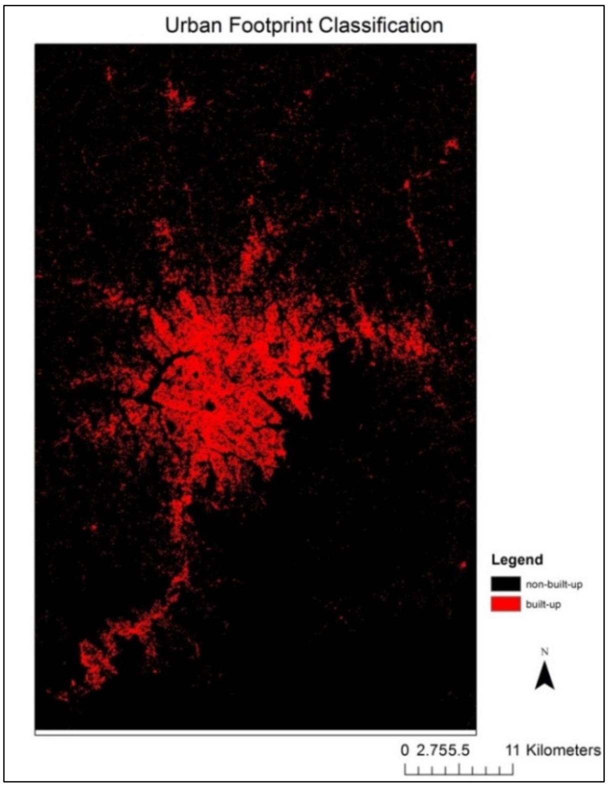


Figure 2 Urban Footprint Classification of Greater Kampala (DLR, 2010)

The general information to compare the two footprint products is shown in table 2 below. As shown by the table 2, the GHSL data is different from the UFC with respect to the original images, images types, resolution, map type and values.

Table 2 Summary of basic characteristics of the GHSL and UFC data sets

Data set	***GHSL***	***UFC***
Source	JRC	DLR
Reference year	2010	2010
Original images	Quickbird, MODIS, etc.	TanDEM-X
Image type	Optical	Radar
Resolution	10 meter	20 meter
Values	Image 2~255	Image1 'non-built-up'; Image2 'built-up'
Map type	Continuous (percent urban)	Binary (built-up/non-built-up)
Overall accuracy	90.82%	88.5%
Already tested cities	Brussels, Luneburg, Brasilia	New Delhi, Buenos Aires, Munich, Nairobi, Padang, etc.

1.2. Research Problem

The main research problem was to develop an appropriate methodology to assess the quality of VHR urban footprint products (GHSL and UFC) as well as analyse topographic data and other spatial factors influencing their quality. Currently, there is insufficient knowledge on the quality of global urban footprint coverage (Esch et al., 2011). The main factors that have popularly been researched by other authors are the main characteristics of optical data and radar data; this research however made an addition by including topographical features and land patterns in assessing the quality of urban footprint.

1.3. Research Objectives

General objective:

The main objective of this study was to assess the quality of two new urban footprint products derived from VHR optical and radar satellite images for Kampala city.

Specific objectives:

1. To develop an assessment method to determine the quality of the urban footprint products.
2. To identify possible factors that would influence the quality of the two products and assess the extent to which the quality of the two products are affected by such factors.
3. To reflect on the suitability of urban footprint products for urban planning applications.

1.4. Research questions

Based on the above research objectives, the following research questions were also posed to assist in analysis:

Questions for sub objective 1:

1) What is the quality of the available topographic reference data?

2) How to compare the reference data with the footprint products?

3) Which urban footprint product shows a better accuracy?

Questions for sub objective 2:
1) What factors could determine the quality of the products in general?
2) What types of land use patterns may influence the quality of the products?
Questions for sub objective 3:
1) Which urban planning applications could be considered and in which ways?

1.5. Structure of the thesis

This thesis is structured into five different chapters; the first chapter introduces the research topic and also addresses the statement of problem, research objectives, research questions and organization of the thesis. The second chapter contains review of related literature where the quality assessment methods and factors influencing the quality of extracting the urban footprint have been addressed. Chapter three explains about data and the methodology used in the study, including data analysis, accuracy assessment procedures and methods used for identifying the factors that provides information about the quality of the images. Chapter four presents results of this study derived from data analysis and discussions. Chapter five presents the conclusions of this research, study limitations, recommendations and future research directions proposed by this study.

2. LITERATURE REVIEW

2.1. Introduction

This chapter reviews important literature that is relevant to this study including definitions of concepts, quality assessment methods, remote sensing and factors influencing the quality of the remote sensing data.

2.2. Definition of urban areas and built-up areas

In urban remote sensing, there is currently no generally accepted definition of urban areas (Potere et al., 2009), and the challenge of providing a consistent, practical definition of "urban areas" places a limit on the accuracy of urban maps that is probably as important as sensor-based errors. Specifically, urban areas have been described as "places dominated by the built environment, where the built environment incorporates all non-vegetative, human-constructed elements, including roads, buildings, runways, industrial facilities, etc. and 'dominated' implies coverage greater than or equal to 50% of a given landscape unit (here, the pixel)."(Potere et al., 2009, p. 6539). For binary thematic class, urban areas show that urban pixels are places where the built-environment covers the majority (more than 50%) of the pixel, and for continuous map pixels with a majority of built environment are labelled "urban area".

At the same time, there are several ways to define the built-up area since it contains heterogeneous land use types and implies heterogeneous functional aspects of the area. Congalton (1991) defined the built-up area as "a discrete area measurement that records the presence of buildings and the space in between buildings. The spaces in between buildings are defined by the spatial rule that defines the distance from the building. That distance is either a 1) buffer built around the building footprint or by 2) the grid cell size of the grid cell that intersect the buildings". It is worth noting that based on chapter 1 the built-up area of GHSL means only buildings should be included, however, for UFC the built-up area contains not only buildings but also other urban features which have an elevation (such as roads, railways and bridges). Actually, in remote sensing, Pesaresi et al. (2013) mentioned that urban areas and built-up areas have the same meaning. The main difference is for example, when 'green space' or 'open space' (e.g. a golf course or park) dominates a pixel, these areas are not considered built-up area even through –in terms of land use- they may function as urban space.

2.3. Quality assessment methods

Accuracy assessment is an important part of classification, since measurement errors are generally described in terms of accuracy. It is usually done by comparing a classified image output with some reference data that is believed to reflect the true land cover accurately. Sources of reference data include ground truth, higher resolution images, and maps.

A range of methods used for assessing the quality of remote sensing classification data have been developed to meet land management and decision maker's needs. For describing the spatial data quality, Alkema et al. (2012) mentioned five aspects that should be considered:

(1) Positional accuracy: the accuracy of a feature's database coordinates;
(2) Temporal accuracy: the accuracy of the temporal information held in a database;
(3) Attribute accuracy (classification accuracy): the accuracy of attributes listed for a database feature;
(4) Completeness: are there any gaps in the coverage of the data;
(5) Lineage: the history of a data set; and

(6) Logical consistency: the correctness of relationships between database features and those found in the real world.

All of these six aspects can influence many aspects of quality. For example, the temporal information could determine the positional accuracy in terms of land use change.

Two common methods used to represent the accuracy of image or raster map classifications are the error matrix and the kappa coefficient (a measure of the proportion of agreement after chance agreement is removed from consideration). The error matrix includes a table with the reference data filled in columns and the classified products filled in rows. The accuracy assessment process contains different statistical calculations (Congalton, 1991), such as tables 3, A~D, which refer to the reference classes and a~d which refers to the classes in the classification result; the overall accuracy can be calculated by (35+11+38+2)/163=53%, which is shown in table 3, the producer's accuracy which measures the probability of a reference pixel being correctly classified and the user's accuracy which measures the probability that a pixel classified on the image actually represent that category on the ground.

Table 3 Example of an error matrix with derived errors and accuracies expressed as percentages

	A	**B**	**C**	**D**	**Total**	**Error of commission (%)**	**User accuracy (%)**
A	*35*	*14*	*11*	*1*	61	43	57
B	*4*	*11*	*3*	*0*	18	39	61
C	*12*	*9*	*38*	*4*	63	40	60
D	*2*	*5*	*12*	*2*	21	90	10
Total	53	39	64	7			
Error of omission	34	72	41	71	163		
Producer accuracy	66	28	59	29			

Kappa statistics is another measure of accuracy and is defined as a measure of the actual agreement of the cell values minus the random agreement. Kappa statistics can be used to statistically determine 1) if the remotely sensed classification is better than a random classification, and 2) if two error matrices are significantly different from each other. The interpretation of kappa statistics is shown in table 4. The kappa coefficient can be calculated by Equation(1) where Pr(a) is the relative observed agreement among raters, and Pr(e) is the hypothetical probability of chance agreement, using the observed data to calculate the probabilities of each observer randomly saying each category. If the raters are in complete agreement then $\varkappa = 1$. If there is no agreement among the raters other than what would be expected by chance (as defined by Pr(e)), $\varkappa = 0$ (Congalton, 1991).

$$\boxed{\kappa = \frac{\Pr(a) - \Pr(e)}{1 - \Pr(e)},} \quad (1)$$

Table 4 Interpretation of Kappa statistics (Congalton & Green, 2008)

Interpretation of Kappa

	Poor	Slight	Fair	Moderate	Substantial	Almost perfect
Kappa	0.0	.20	.40	.60	.80	1.0

Kappa	Agreement
< 0	Less than chance agreement
0.01–0.20	Slight agreement
0.21– 0.40	Fair agreement
0.41–0.60	Moderate agreement
0.61–0.80	Substantial agreement
0.81–0.99	Almost perfect agreement

Another method used for quantifying positional accuracy is Root Mean Square Error (RMSE); this is used to measure the difference between values predicted by a model and the values actually observed from the environment that is being modelled. "The value of the RMSE is normally calculated from a set of check measurements (coordinate values from an independent source of higher accuracy for identical points). The differences at each point can be plotted as error vectors for a single measurement, as shown in figure 3. The positional error of a measurement can be expressed as a vector, which in turn can be viewed as the vector addition of its constituents in the x-and y-directions." (Alkema et al., 2012, p. 299).

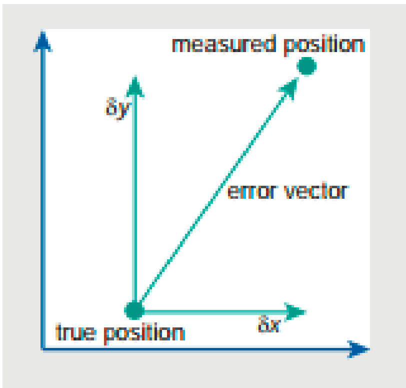


Figure 3 The positional error of a point (source: (Alkema et al., 2012, p. 299))

These individual differences from the above definition are also called residuals, and the RMSE serves to aggregate them into a single measure of predictive power (Alkema et al., 2012). The RMSE of a model prediction with respect to the estimated variable X_{model} is defined as the square root of the mean squared error (Equation 2):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(X_{obs,i} - X_{model,i})^2}{n}} \qquad (2)$$

Where X_{obs} is observed values and X_{model} is modelled values at time/place *i*.
This method was be used to check the position accuracy of the topographic data (reference digital building polygons, railway lines and roads) for this study.

Hussain et al. (2013), indicated that various techniques for remotely sensed data have been developed, the most common methods are the traditional pixel-based and the more recently object-based assessing method. Object based methods represent more features than pixel based, such features as spectrum, shape, texture and context; pixel-based on the other hand is limited to spectrum and textural. Figure 4 below shows an example of these two methods in comparison to classified image data. At the pixel level, the feature value of a single pixel is extracted for comparison; at the object level, the feature value of an object is the average of all included pixels. Esch et al. (2010), showed an object-based image analysis, in which the texture layer is used along with original intensity information to extract settlements automatically: "the technique is tested on the basis of 12 TSX scenes covering representative urban agglomerations distributed throughout the world. Overall, accuracies between 76% and 96% for the derived city footprints demonstrated the high potential of both the TSX imagery and the proposed analysis approach in detecting built-up areas" (Esch et al., 2010, p. 1). A pixel-based approach is described by Mayaux et al. (2006). They provided two methods for accuracy assessment: quality control based on a comparison with ancillary data and a quantitative accuracy assessment based on a stratified random sampling of reference data, however, final results of this validation was not shown in detail.

In this research, both urban footprint products were provided in raster layer type, converting from raster type to vector type for object-based accuracy assessment map may cause uncertainty of results and also data information limitations.

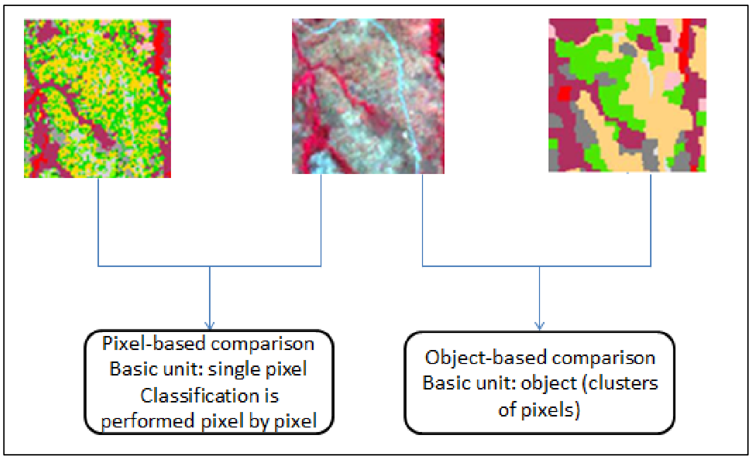


Figure 4 Pixel-based and object-based approaches

2.4. Possible factors influencing the quality of extracting urban footprint

From previous studies conducted by various researchers, for instance, Angel et al. (2005), Ouzounis et al. (2013) and Esch et al. (2010), three types of factors have been shown to affect image classification accuracy (figure 5). These include sensor related factors; factors belonging to the data extraction process; and topographic factors and physical factors. Some details of these factors are shown in table 5 below.

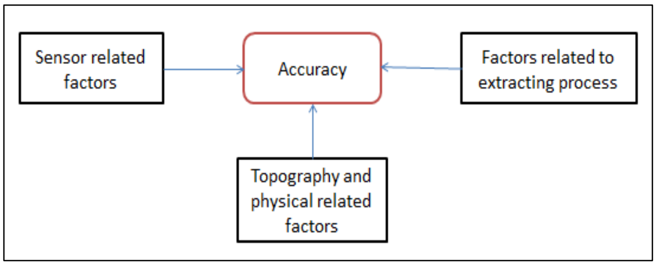


Figure 5 Framework of factors influencing the accuracy

The generation of the first group of factors (as shown by the first row of table 5 below) is based on the nature and knowledge of remote sensing sensors; the second group is based on the methods used to determine effects from the literature review and the last group of potential factors was generated from the assessment process and the current situation of the city of Kampala (some of these factors from different groups can be used interchangeably).

Table 5 Factors influencing the quality of the urban footprint

Factors	Radar data (UFC)	Optical data (GHSL)
Factors that cannot exam based on the already given urban footprint products	Sensor characteristics; signal interpretation; direction of the antenna; satellite position; wavelength; number of looks, etc.	Sensor characteristics; weather condition; day-night factors; illumination; cloud coverage; viewing angles, etc.
Factors already investigated by previous studies about the footprints accuracy (they should also be re-examined in this work)	Training sample size; slope angle; classifier type; building density and volume; resolution; interpreter's experience; surface roughness; terrain and object-geometry, etc.	Training sample size; slope angle; resolution; knowledge of study area; terrain and object-geometry; shadow; roof materials, etc.
Potential factors (to be explored in the this work)	Road systems (surface, size, orientation); buildings (density, size, orientation, height); land cover pattern; railway lines; wetland (maybe), etc.	Road systems (surface, size, orientation); buildings (density, size, orientation, height); land cover pattern; railway lines, etc.

Radar data is different from optical data with respect to the surface parameters they measure and in the way the information in coded in the image (Angel et al., 2005). Thus the sensor-specific image characteristics have to be taken into consideration during factors analysis. Esch et al. (2013), asserted that the factors influencing the properties of the SAR image are system-specific imaging parameters, such as wavelength, polarization and acquisition geometry including orbit direction, local incidence angle, and aspect of the target with respect to sensor position. Other parameters are object-specific imaging parameters such as surface roughness, material of building and surrounding area and terrain-and object-geometry. When it comes to optical images, Ouzounis et al. (2013) highlighted that the problems associated with images are overlap in spatial domain, repeated image acquisitions during time line, specific sensor characteristics, local landscape and some operational parameters which also influence the image quality. In conclusion, topographic factors do not influence optical data as much as they influence radar data.

2.5. Urban planning applications provided by urban footprint products

Urban planning is a technical and political process concerned with the utility of land and design of the urban environment, including transportation networks, infrastructures, and land use, to guide and ensure the sequential development of settlements and communities (Pesaresi et al., 2013). In order to reach the purpose of planning urban environment, a series of urban footprint information needs to be acquired, such as calculating the growth rate of urbanization and the urban density. In this research the main focus is on the analysis of urban footprint products analysis based on optical and radar data.

"Nowadays, the remote sensing technology can be used to investigate urban terrain, physiognomy, lakes, plants, sights, traffic, land utilization and building distribution quickly"(Verma et al., 2009, p. 3), and remote sensing techniques are especially useful for change detection analysis, land use and land cover mapping, urban sprawl/urban spatial growth and selection of sites for specific facilities, such as school, restaurants, hospital and industry. For example, Angel et al. (2005) used optical and radar remote sensing data in the Mekong Delta to test settlement detection and impervious surface estimation.

Henderson and Xia (1997), presented a report on the urban planning applications of radar data, which mentioned that it can generally contribute to human settlement detection, population estimation, human activities assessment on the physical landscape, mapping and analysing urban land use patterns and change, and interpretation of socioeconomic conditions. Among them, the settlement analysis is an important element in studying and evolution of present and previous cultures.

Pesaresi et al. (2013) proposed that the optical data would contribute to population disaggregation and risk and disater management applications, as well as support regional planning in general. In addition, Valero et al. (2008) used VHR optical data to estimate the nature of the roof of every building in the frame of seismic vulnerability assessment in urban areas and especially present a feature extraction processing aiming at discriminating between flat roofs and gable ones.

In conclusion, radar systems offer some distinct advantages over optical sensors as well as contributing to potential synergistic benefits of merged data sets (Henderson & Xia, 1997). The information on acquired from the urban footprint products could be useful in urban planning application such as mapping urban land use and land cover changes, for calculating the number of buildings that could be required for a predicted future population increase and for analysis of transportation systems. Among these applications, the socioeconomic aspect can only be derived from housing types, building densities, environmental characterizes, and spatial relationships between residential areas and other land use categories that are observable on remote sensing imagery (Henderson & Xia, 1997).

3. DATA AND METHODOLOGY

3.1. Introduction

This chapter presents the available data used in this research, the overall methods, techniques and approaches used to achieve the research objectives. It primarily expresses the data sources, methods of reference data used for assessing the quality of the urban footprint products, identification of possible factors that have influence on the quality of the urban footprint products and reflect the suitability of the urban footprint products for urban planning applications.

3.2. Research design and methodology

This research was conducted in three phases: pre accuracy assessment, accuracy assessment and post accuracy assessment phase. The first phase was a preliminary phase which involved development of research proposal, including problem structuring, generation of research objectives and associated research questions and defining methods. The main tasks of the second phase were data processing and accuracy assessment through error matrix and kappa coefficient. The last phase involved structuring of possible factors affecting the image accuracy and reflecting on urban planning applications that GHSL and UFC would provide. Figure 6 below is a flow chart of the research design process employed in this research.

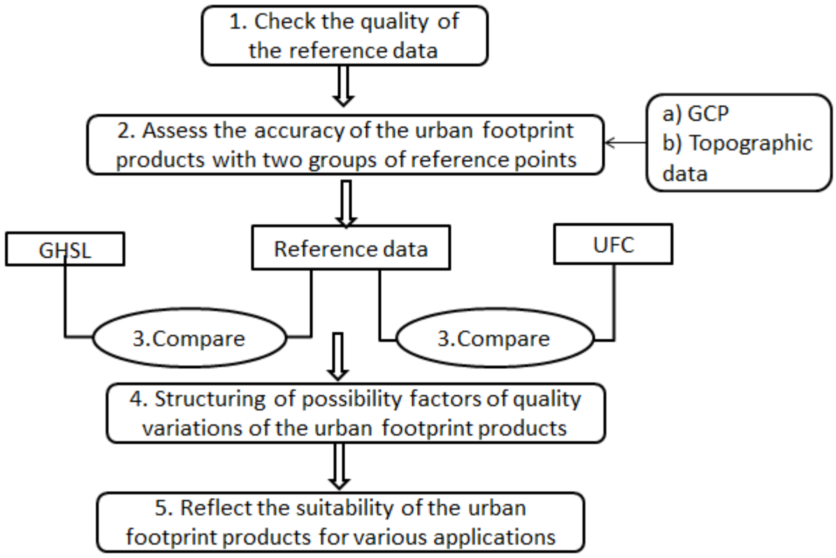


Figure 6 Research design

As shown by figure 6 above, the research process was carried out in five steps; the first step was to check the quality of reference data and improve the reference data; these would then be compared with the urban footprint products. The second step was to perform the accuracy assessment using error matrix and kappa coefficient table; this was done using GCP data obtained from Abebe (2013) and Vermeireren et al. (2012). At this step, comparison with a set of randomly selected points from topographic data (as further discussed in section 3.3.1) was also done. The third step as shown by figure 6 above was to compare the reference data with urban footprint products followed by the fourth step which was to identify possible factors influencing the data quality. The final step was to reflect on urban planning applications that the two products can provide.

3.3. Data source and type

This study made use of data collected from Secondary sources. The main source of data was Kampala Capital City Authority (KCCA). This data was sufficient for this study and there was therefore no need for field visits. Table 6 below is a summary of the spatial data needs and their corresponding data sources.

Table 6 Data needs and data sources

Spatial data	Year	Source
Building footprints	2010	KCCA
Roads	2010	KCCA
Railway lines	2010	KCCA
Wetlands	2010	KCCA
Land use map	2012	KCCA
Administrative region	2010	KCCA
DEM(Digital Elevation Model)	2010	KCCA
GCP(Ground Control Points)	2012 and 2013	Vermeireren and Abebe
GHSL	2010	JRC
UFC	2010	DLR
Image Mosaic	2010	KCCA

3.3.1. Available reference data

The first step was to identify and list available reference data (existing data) that was used for comparison for accuracy assessment. For this study, four reference data sets were available: (1) topographic data 2010 (as shown in table 7) collected from KCCA; (2) ground-truth samples (shown by figure 7); these were coordinates of 100 selected ground control points (GCP) which were collected from the field by Abebe (2013) and 170 GCP obtained from Vermeireren et al. (2012), bringing the total to 270 GCP; (3) Land use map of Kampala 2012 (shown by figure 8 left); the summary of the land use type is shown in table 8. Figure 8 right shows the land use map of Kampala reclassified into two classes, urban and non-urban. The urban areas accounts for 79% (188 km^2) of the total area. The non-urban areas on the other hand, which consists of agriculture, environmental and open spaces land uses covers 54 km^2 (21%); and (4) Digital elevation model 2010 (DEM) shown by figure 9 (left) obtained from KCCA. The resolution of the layer is 5 meter and it is a continuous map ranging from 1097.49~1306.14. However, some DEM data for the study area was unavailable as shown by figure 9 (left); the data that was available did not exclusively cover the study area. Figure 9 (right) shows distribution of the elevation value. DEM provided information on elevation, aspect and slope which was useful to check why the urban footprint products and the reference data did not match.

Table 7 List of reference data

Spatial data	Format/type	Source
Building footprints	Shape file	Derived
Roads	Shape file	Derived
Railway lines	Shape file	Derived
Wetlands	Shape file	Derived

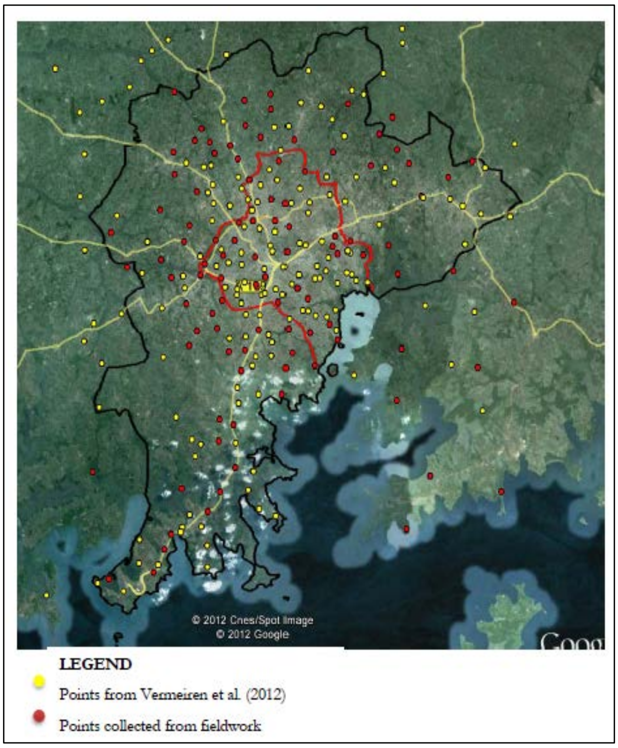


Figure 7 Location of reference data (Kampala) collected from previous research [source:(Abebe, 2013)]

Table 8 Area of each land use type and urban class (source from: KCCA)

Land use	Shape area(km^2)	Percentage(%)	Urban(see figure 8)
Agriculture	11	4.5	No
Commercial	15	6	Yes
Construction	0.4	0.2	Yes
Cultural	0.8	0.3	Yes
Environmental	38	16	No
Extraction	0.3	0.2	Yes
Industrial	7	2.9	Yes
Institutional	11	4.5	Yes
Mixed use	15	6	Yes
Open space	5	2	No
Recreation	0.3	0.2	Yes
Residential	138	57	Yes
Transportation	0.2	0.1	Yes
Utilities	0.1	0.1	Yes
Total	**242**	**100**	

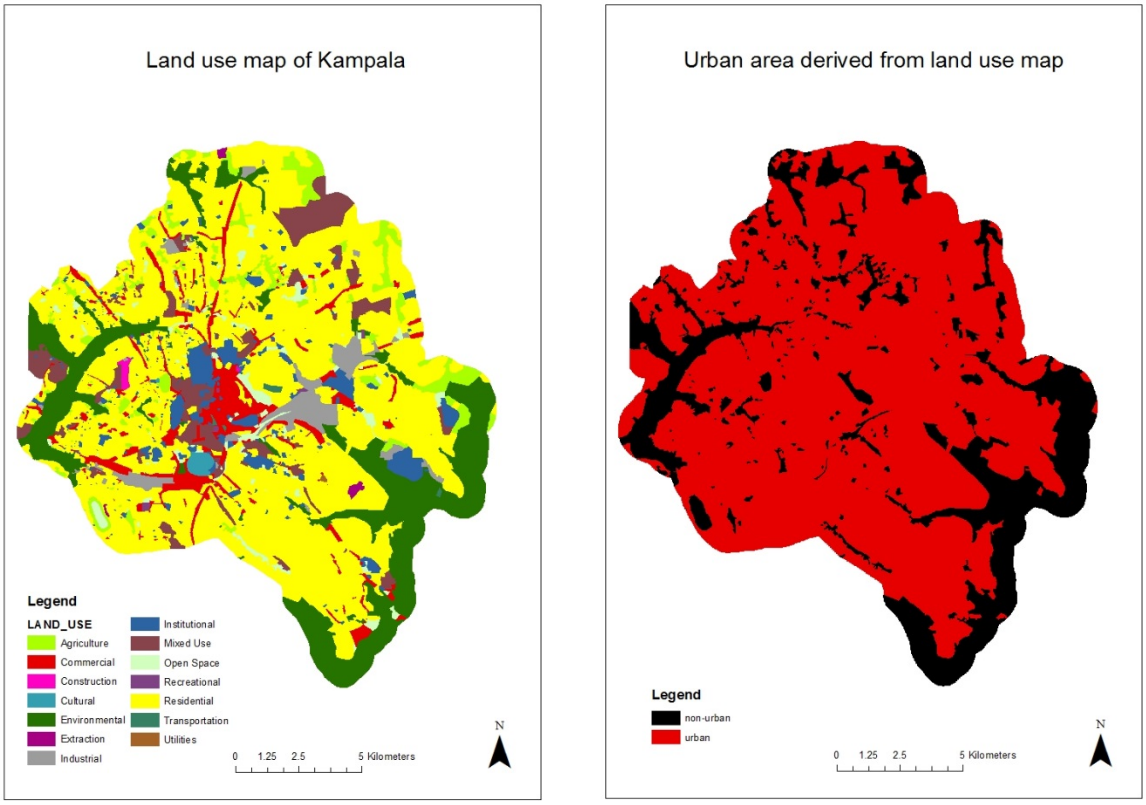


Figure 8 Land use map (left) and urban area derived from land use map (right) of Kampala in 2012

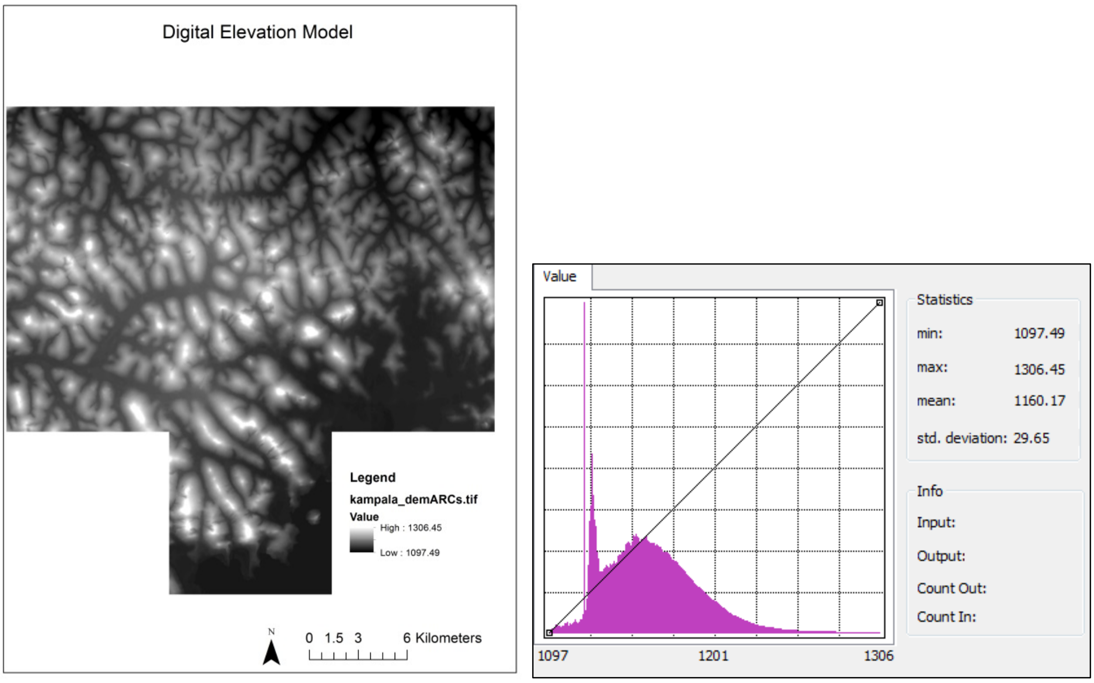


Figure 9 DEM (left) and histogram of elevation values (right)

3.4. Step 1: Checking the quality of reference data

There are many issues to be considered in an accuracy assessment (Congalton, 1991); the first thing is to ensure that accurate data is used as reference for accuracy assessment. If the ground truth reference data contains errors, the misclassification is not reflected as a mistake in the classified map. Thus, it is important to check the quality of the reference data before comparing with the urban footprint products.

Checking the quality of the ground truth points

The ground truth reference points were collected from two heterogeneous sources (mentioned in 3.3.1); so after merging them into one data set, they were overlaid with the image mosaic (figure 10 (left)). These points were either representing built-up area or non-built-up area, thus the quality of these points mainly concerned positional accuracy. Figure 10 (right) shows an example of a reference point representing non-built-up area (as shown by the legend); however, the accurate position on the image (figure 10 right side) is built-up, so this point needs to be changed to represent built-up area before accuracy assessment is conducted. Each of these points was manually zoomed in to a large extent to ensure accurate position on the image. In total, there were three points that were wrongly positioned in non-built-up area, which were changed to built-up.

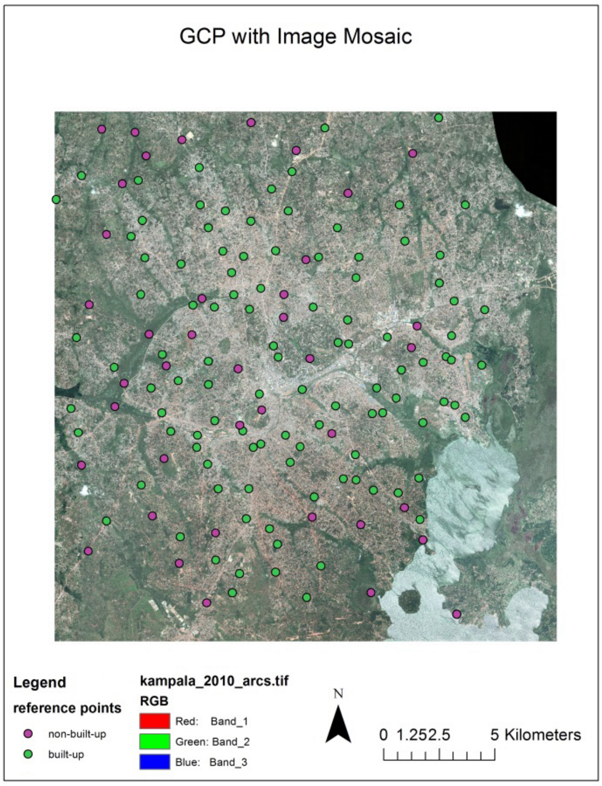


Figure 10 GCP with Image Mosaic (left) and example of GCP with error (right)

Checking the quality of the topographic data

At this step, the topographic data consisting of digital building footprints and roads (including railways) was overlaid with the image mosaic to check whether it was complete or if it contained any geometric problems (commission and omission). As earlier discussed in section 2.3, the quality of spatial data includes four aspects, as discussed below;

(1) Temporal accuracy:

Since the digital buildings dataset was collected in 2010, the same as the image mosaic, the temporal accuracy was deemed reasonable. The roads and railways datasets were collected in 2004, even though, with the exception of the construction of the Northern by-pass, these have changed very minimally. Railways remained unchanged from 2004. The ring roads did not exist in 2004; but appeared in the 2010 dataset (figure 11). So the ring roads were digitised manually based on image Mosaic of the year 2010.

Figure 11 Ring roads in Kampala (white part shows the situation in 2010, green part shows the planned road)

(Source: Google Earth Image)

(2) Completeness:

1) Based on the manual comparison with the image mosaic of 100 sampling test building polygons, there were 3 of the polygons omitted (b, c, d in figure 12; the blue boxes shows the buildings that were not digitised). One of them was located on a vegetated area; figure 12 (a), the blue box shows an already digitized building that is located on the wrong area. Figure 13 shows overlapping building polygons which if not corrected may affect the accuracy result during pixel by pixel comparison with the urban footprint products. To correct this problem, the polygons were first converted to raster format and thereafter reconverted to vector data (polygons) - this solved the problem of overlapping. Initially, there were 279151 building polygons, but after the conversion process there were 252252 left.

(a)

(b) (c) (d)

Figure 12 Building polygons with errors on the image

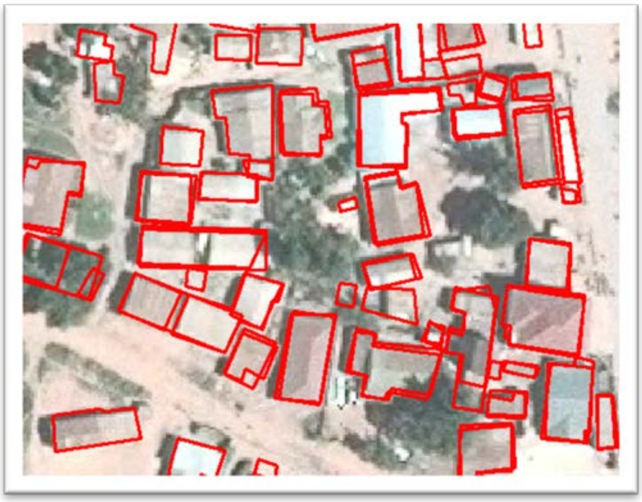
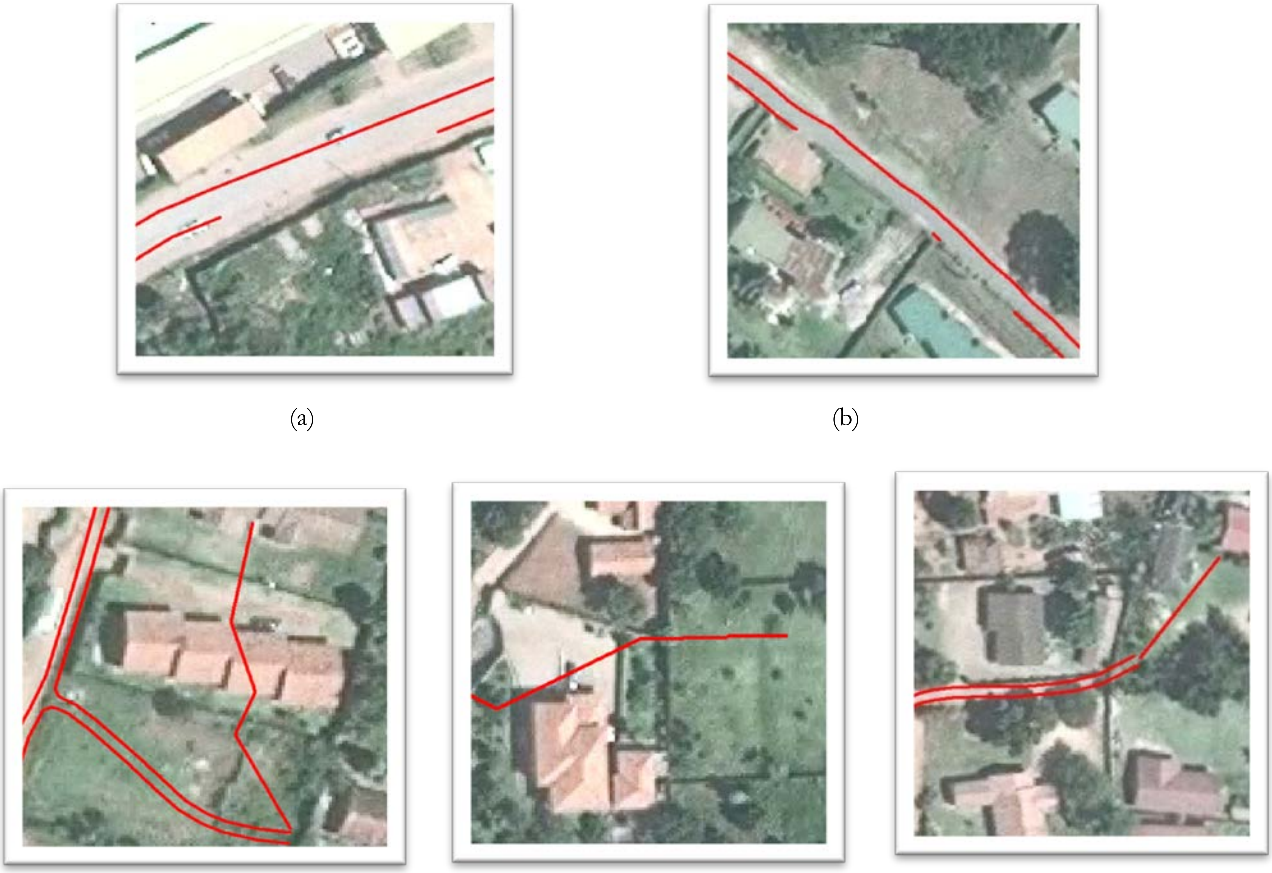


Figure 13 Part of overlapping building polygons

2) As for the road lines, after checking the 100 test sampling lines there were two lines that were not fully connected (a and b in figure 14) and three lines that were wrongly located on either vegetated areas or on buildings (c, d, e in figure 14). These examples should be better classified. Some are partially digitized, some show roads where no roads where no roads can be seenon the image.



(a) (b)

(c) (d) (e)

Figure 14 Roads with errors on the image

(3) Positional accuracy:

1) In order to check the positional accuracy of the digital building polygons, 20 randomly selected building polygons were used. Kernels were thereafter chosen for each polygon (as shown by the blue point on figure 15), which were compared with the image mosaic point (as shown by the purple point figure 15) and the two points were used to calculate the RMSE. The same method was used to calculate the RMSE for roads. Figure 16 shows the position of the 20 random points for the test building polygons and road lines that were selected for checking the positional accuracy (the image is blown to full extent to show the position of all the random points and so the test polygons and the road lines could not be seen clearly on the image).

Figure 15 Examples of RMSE calculation: building polygon (left) and one road line (right)

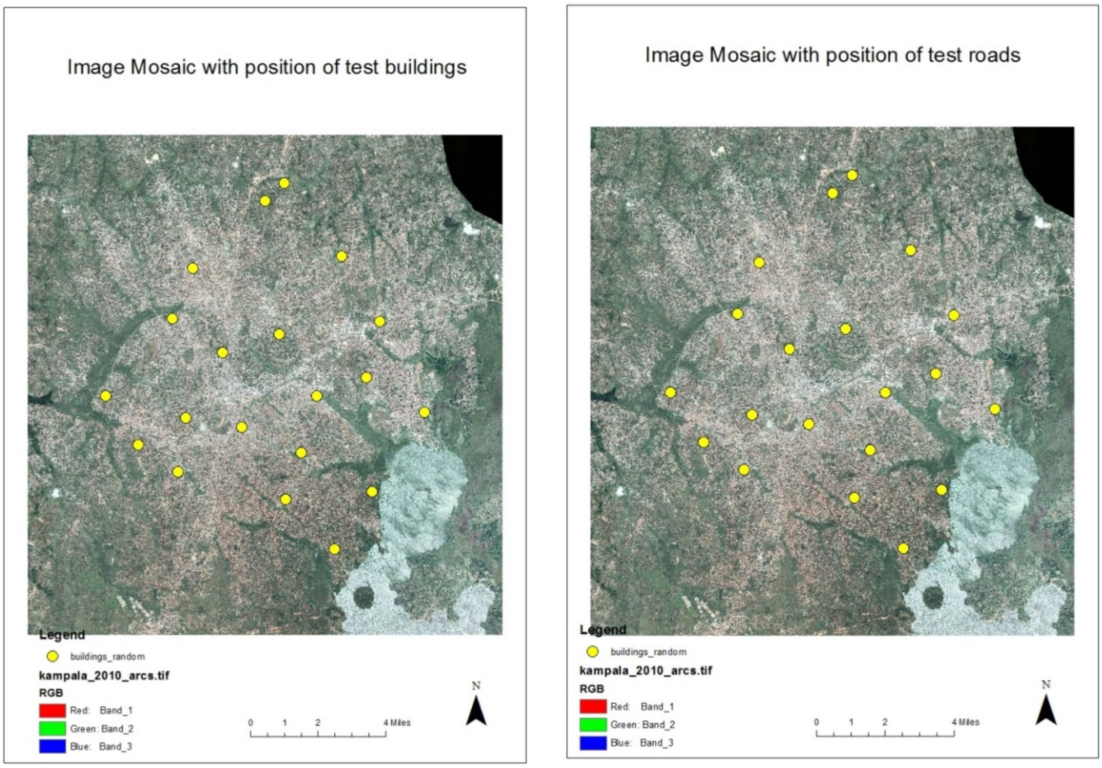


Figure 16 Positions of tested buildings and road lines for RMSE calculation

Table 9 RMSE for building polygons (x,y-source means the position of the buildings footprints, x,y-map means the position of buildings on the image)

Checking points	*x-source(m)*	*y-source(m)*	*x-map(m)*	*y-map(m)*	*Residuals(m)*
1	457323.716116	40203.728057	457323.755803	40203.807433	0.0474893
2	455609.090758	40220.878824	455609.090758	40220.878824	0.0114957
3	455547.098759	40202.305037	455547.098759	40202.305037	0.0115133
4	454869.300388	40635.625935	454869.300388	40635.625935	0.0522711
5	454447.035845	40658.255606	454447.024543	40658.327230	0.0259466
6	450734.398603	36181.271195	450734.143155	36180.451085	0.095372
7	455723.727150	33661.337634	455723.496710	33660.365988	0.041237
8	457723.803316	29797.795427	457723.481076	29796.324212	0.0278812
9	451492.150380	32411.877152	451491.711729	32410.726360	0.0560886
10	453933.977513	36790.083380	453933.699498	36789.590046	0.108143
11	450516.886252	40118.952157	450516.726688	40118.795670	0.0735019
12	447524.356349	34018.183993	447523.798384	34017.058614	0.009605
13	453820.646632	30675.796186	453820.214721	30674.367804	0.0326654
14	461787.169180	32831.446962	461787.093274	32830.559273	0.00942067
15	459310.731218	35932.095108	459310.558819	35931.518948	0.051118
16	452665.229733	44365.471975	452665.287945	44365.990710	0.0234963
17	448591.472758	32137.382880	448590.930029	32136.127320	0..0158899
18	457703.904853	26371.702343	457703.419724	26369.766327	0.0145262
19	448777.737582	38240.184506	448777.305408	38239.663324	0.0487522
20	452165.081015	39392.505413	452164.917244	39392.291261	0.0138632

As Shown in table 9 the total RMS error for the digital building polygons was: 0.0475332 m, since there were 20 sampling points for test and the accuracy was more than 95% (1-4.7%), it meant the positions of the digital building footprints matched well with the image mosaic.

2) For checking the position accuracy of the roads, a similar method was applied. 20 road lines were randomly selected then the edge of the each line was compared with a point on the image perpendicular with the edge of each line on the edge of the road.

Table 10 RMSE for road lines(x,y-source means the position of the road networks, x,y-map means the position of road lines on the image)

Checking points	*x-source(m)*	*y-source(m)*	*x-map(m)*	*y-map(m)*	*Residuals(m)*
1	452754.076490	42876.295541	452754.076490	42876.295541	0.0268306
2	459686.997563	34403.520533	459686.997563	34403.520533	0.0491434
3	448324.428414	33119.583674	448324.322581	33119.689507	0.0930526
4	455435.263365	30269.977097	455435.161941	30270.078520	0.10078
5	453755.162128	36075.975243	453755.110314	36076.027057	0.0483869
6	452078.223191	31638.533550	452078.171377	31638.585364	0.17385
7	450324.709714	39224.534935	450324.578524	39224.110498	0.217952
8	457409.142850	40870.434952	457409.079696	40870.418731	0.084838
9	457082.112066	27443.127130	457081.916621	27443.110908	0.0230618
10	456941.281725	35068.733152	456941.203872	35068.716930	0.134736
11	455152.731059	35649.898971	455152.653206	35649.882749	0.0788069
12	448057.336533	37372.109983	448057.364514	37372.093762	0.075033
13	453434.688569	40298.702365	453434.487244	40298.686144	0.0913253
14	451158.296824	35915.328254	451158.217615	35915.312033	0.0470672
15	458997.711015	40474.639085	458997.631806	40474.622863	0.0272228
16	457768.379650	38407.963692	457768.300441	38407.947470	0.0807057
17	456918.992456	34092.681168	456919.310123	34092.585572	0.252445
18	452461.838209	39056.174990	452461.782346	39056.154099	0.131709
19	448740.768474	36239.527158	448740.580318	36239.638559	0.160773
20	451058.034002	31567.192571	451057.574300	31567.178643	0.157958

As shown in table 10 the total RMS error for the roads was: 0.120294 m, the error is larger than for building polygons. This is most likely because of the temporal difference between the image mosaic and the road network (2004 and 2010). Also it was difficult to define the position of a kernel on the road line (compared with simply the first point on the polygon) for comparing with the image. However, due to the fact that no field work was conducted and also due to data limitation these data sets were considered to be acceptable given pixel sizes being used (i.e. 10 m and 20 m).

(4) Attribute accuracy: all of these reference data sets are buildings, roads and railways, so the attribute accuracy is not an issue of concern.

After manual improvement of the reference data, it was considered a good match with the image mosaic and was therefore suitable for accuracy assessment with the two urban footprint products.

3.5. Step 2: Conducting a general assessment of urban footprint products quality

The main purpose of accuracy assessment is to ensure classification quality and user confidence on the product (Congalton, 1991). In this study, in order to measure the agreement between the two footprint products and the reference, two strategies were adopted: i) directly compared the products with the ground control points by error matrix and kappa statistics analysis, and ii) compared the products with other types of reference data (topographic reference data sets converted to a set of random points) by error matrix and kappa statistics analysis.

3.5.1. Making accuracy assessment with the ground truth points

Before making the assessment at this stage, the first step was to define the built-up and non-built-up area for both groups of comparing data sets. For the GHSL which was a continuous layer with higher value, indicated a more possibility of existence of built-up area; by assumption, it was direct and easier to set the middle of the ranging value as cutting point to define the built-up and non-built-up area. On the other hand, the radar data was already set as two categories, thus it was used directly for the assessment.

The following four steps show the procedure that was used for making accuracy assessment with ground truth points;

(1) The first step was to delete part of the original GHSL data which contained missing values; as shown by figure 17, the area in the orange box shows the data with missing value. Because the UFC data covered a larger area of Kampala than GHSL data, the geographic extent of GHSL was used to clip the UFC dataset in order to make them the same size for comparison (figure 18).

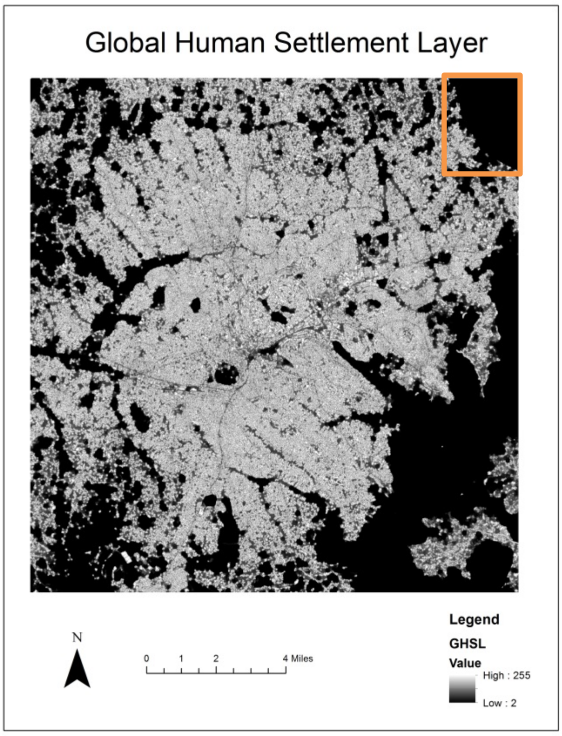


Figure 17 Original GHSL with orange window showing the area with missing values

(2) The second step was reclassification of the GHSL data from continuous value (0~255) to 2 classes; 0 value which indicated non-built-up area and value 1 which indicated built-up area. During the reclassification process the "Equal Interval" method was used and the breaking point was at 127.5. Since the comparison was with reference points, which contained only two classes (built-up and non-built), the GHSL needed to be comparable with them and was therefore converted from continuous format to binary format.

(3) The third step was to analyse the ground control points (GCP) in order to check what land use type they are represented. Both data sets from Vermeireren et al. (2013) and Abebe (2013) showed that value 0 meant non-built-up area (containing wetlands, water body, bare soil, forest, open space and vegetation)

and value 1 meant built-up area (include buildings and roads). The ground control points covered a larger area than the study area in this research, so the outside ones were excluded before calculating the accuracy of the products (originally there were 270 GCP, but after deleting 146 GCP remained; of this, which 106 GCP represented the built-up area and 40 of them represented the non-built-up area). Figure 18 below shows the distribution of these reference points within the study area overlaid on the GHSL and UFC. It is also important to note that the GCP were acquired from two different sources and merged into one layer. To ensure that the points were at exactly the same location as the classified raster image, the geographic position of the reference points (WGS1984_UTM_Zone_36N) was re-projected to the same geographic position as the two urban footprint products (WGS1960_UTM_Zone_36N).

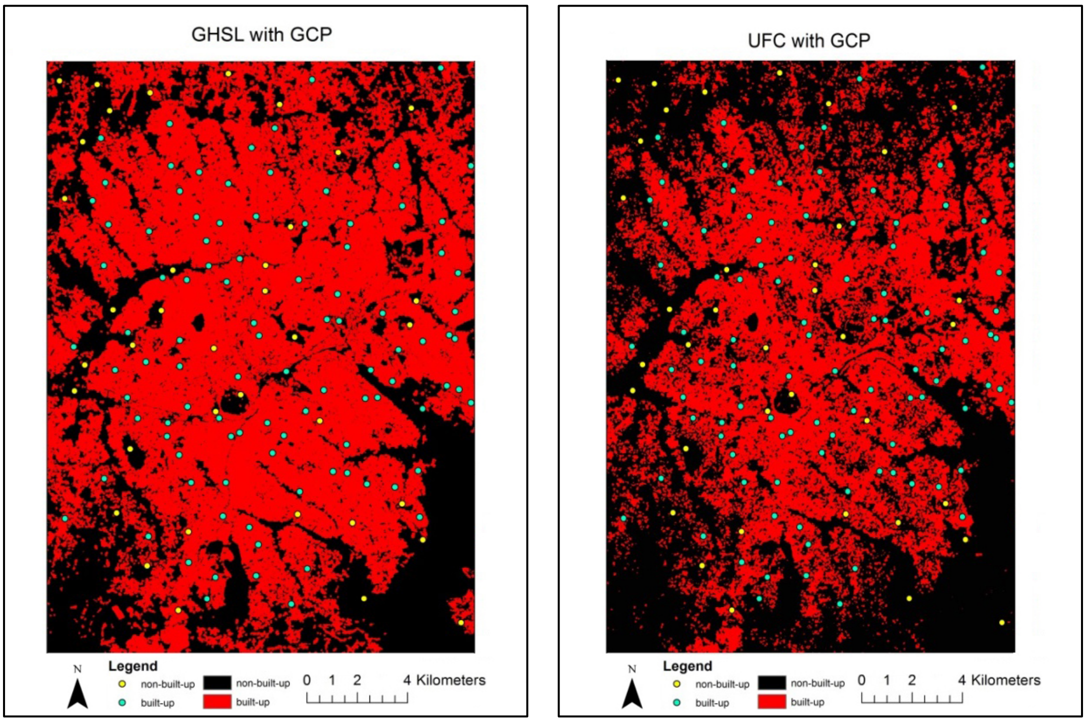


Figure 18 Location of reference data in the GHSL (left) and UFC (right)

(4) To assess the accuracy of the two products based on the GCP, it was also important to determine whether their land use types (built-up and non-built-up) matched or not. The assessment process was performed in ERDAS with "Raster-Supervised-Accuracy assessment" by comparing the position (x and y showing the value of meters) of each ground control point with the two footprint products correspondingly. The final outcomes provide the accuracy assessment report which shows the table of error matrix and kappa coefficient.

3.5.2. Making accuracy assessment with the topographic data

Quantitative accuracy assessment of maps involves the comparison of a site on a map against reference information for the same site. When it comes to the assessment with the topographic reference data, it is known that the footprint products and the topographic reference data have different layer types and resolutions, so they first needed to be converted to the same layer type and resampled to the same resolution before comparing. In this research building footprints and also building footprints plus road networks (reference data) were converted to a fine resolution of 1 m in raster format at the beginning.

The following section details out the process used for making accuracy with topographic data:

(i)Assessing the accuracy of GHSL with topographic data:

Chapter 2 gave a definition of built-up area based on GHSL, which stated that only buildings are contained in the built-up class; the other elements belong to the domain of non-built-up. Thus the digital building footprints were used as reference data for the GHSL.

(1) Figure 19 (left) shows the raster layer after converting from digital building polygons. The black area shows non-built-up land and the red area indicates built-up land. The study area is the same with Kampala administrative region shown in figure 21(left).

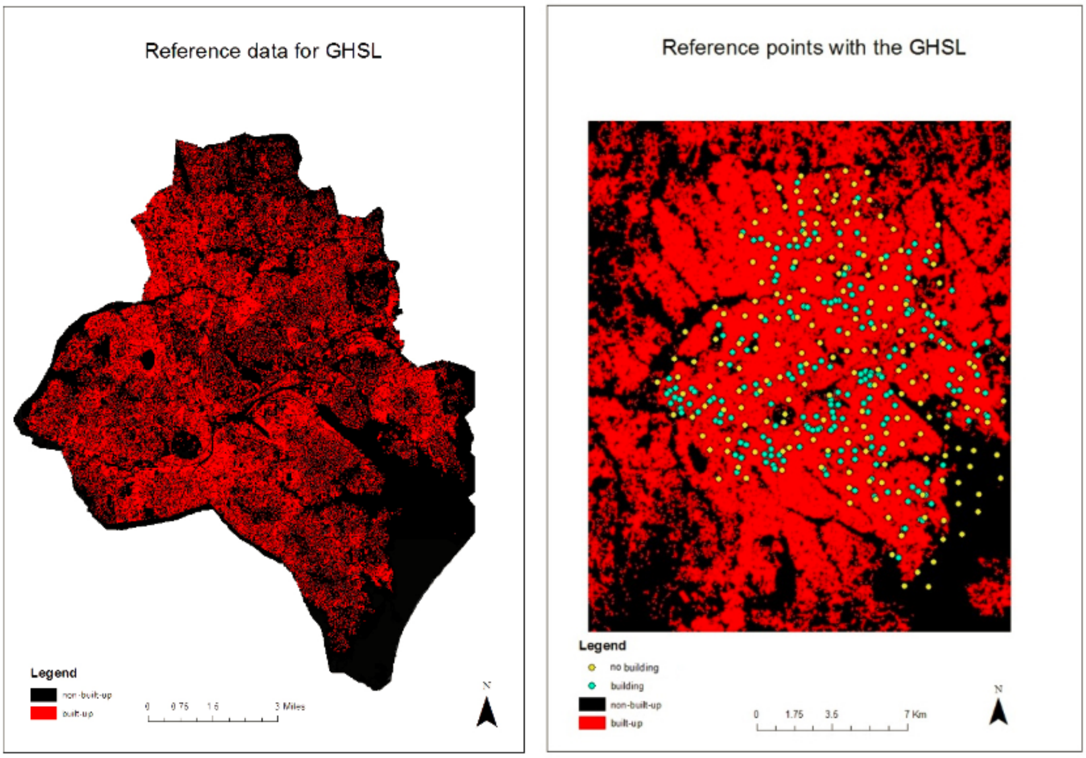


Figure 19 Topographic reference data (1 m resolution) for comparing with GHSL in Kampala (left) and Reference points distributed on the GHSL (right)

(2) In order to create an error matrix table (which only uses point data for accuracy assessment), the reference raster data was first converted to points. Four hundred random sampling reference points were thereafter chosen (with 200 representing the built-up area (blue points) and 200 representing the non-built area (yellow points)) as shown in figure 19 (right) above.

(3) For assessing the accuracy based on these random sampling points, the procedures are the same with the previous accuracy assessment methods which compared with ground control points in ERDAS.

(ii) Assessing the accuracy of UFC with topographic data:

For UFC, the Global Urban Footprint (GUF) algorithm is mainly sensitive towards all structures with vertical components (buildings, poles, etc.). Impervious areas such as big squares in towns will therefore most likely not be detected. Of course there might be some part of a railway or street mapped as built-up in GUF, but this is due to local ambiguities in the signal. However, due to data limitation and because no field work conducted, all the roads, railways and buildings were assumed to be elevated and belonged to the built-up class. The following procedure was used to assess the accuracy of UFC with topographic data:

(1) Since all the roads and railways were polylines, there was needed to make a make a buffer around them before converting them to raster format as a reference layer. The buffer was created by first creating a centreline for all these roads and the railway; making a buffer directly would cause several overlapping polygons. A 4 m buffer was finally created for all the road lines and railway; the buffer measurements were obtained from the image mosaic.

(2) The next step was to merge all the roads, railways and buildings (polygons) into one layer which was defined as the reference of built-up area of UFC; this layer was then converted to raster format with two class types: built-up area and non-built-up area.

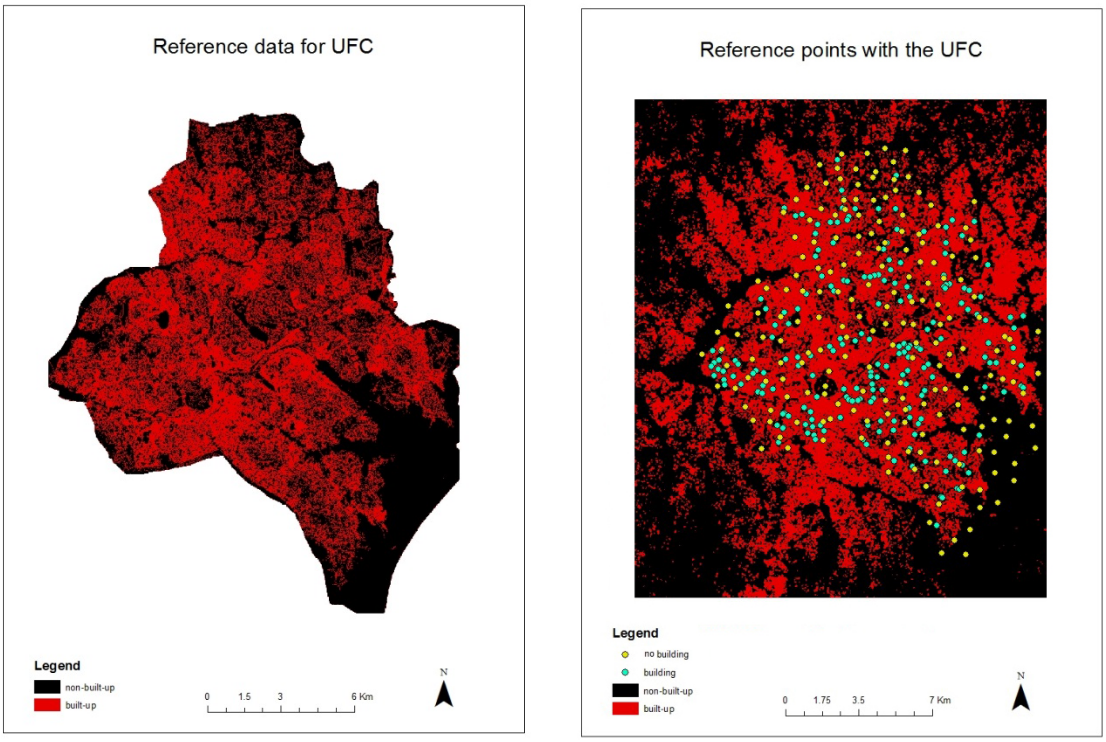


Figure 20 Topographic reference data (1 m resolution) for comparing with UFC in Kampala (left) and Reference points distributed on the UFC (right)

(3) The same methodology (as earlier described for converting reference data for GHSL) was used for converting the raster data set of UFC into a set of points; after a random sampling of 400 points with 200 points for built-up area (blue points) and the rest of 200 points for non-built-up area (yellow points) (figure 20 right).

(4) For assessing the accuracy based on these random sampling points, the procedures are the same with the previous accuracy assessment methods with ground control points in ERDAS.

Comparing the GHSL with the building footprints and the UFC with the building footprints plus roads may not be the best way; there is also need to interchange the reference data by testing GHSL data with buildings footprints plus roads and UFC data with buildings to see whether it would give different results.

It was also important to test the relationship between the two products with their reference data quantitatively. This was done through a pixel based approach. When making a pixel by pixel comparison with the urban footprint products, the reference data should be converted to the same layer type and resolution as the urban footprint products (10 m and 20 m). The process of creating these reference maps is explained below.

3.6. Step 3: Comparing the reference data with the GHSL and the UFC

After assessing the accuracy of the two urban footprint products (the preceding steps of data processing), clusters of wrongly classified areas are extracted in order to find the possible factors influencing the quality of the urban footprint products. There was need to statistically compare the two products with the same kinds of reference data to better understand the relationship between the reference data and the urban footprint products. By just comparing the urban footprint products with random sampling points may not be accurate enough, so building footprints together with road lines were also used as reference data to compare with both products.

Comparing the reference data with GHSL

(1) The first step was to generate the processing extent; this was done to avoid analysing data sets with no values. The processing extent was generated by overlaying the original administrative region (figure 21, left side)), of Kampala with building polygons and roads layer. This was done by manual digitization to cover the areas with buildings and roads; however, not all buildings and roads were covered. Figure 21 (right) was the final processing extent generated.

(2) The next step was to generate a 10 by 10 grid fishnet in ArcGIS (this equals the 10 m resolution of GHSL). A union between the fishnet and digital building polygons (called Union reference GHSL) was done to calculate the percentage coverage of the buildings in each grid cell. Because each cell measured 100 square meters, it also meant that the shape area of each polygon ranged between 0-100; with 0 meaning that there was no building polygon coverage in the grid, while 100 meant that the grid was fully covered by the building polygon. Therefore the original GHSL resized from the original values of between 0-255 to values ranging between 0-100 in order to be comparable.

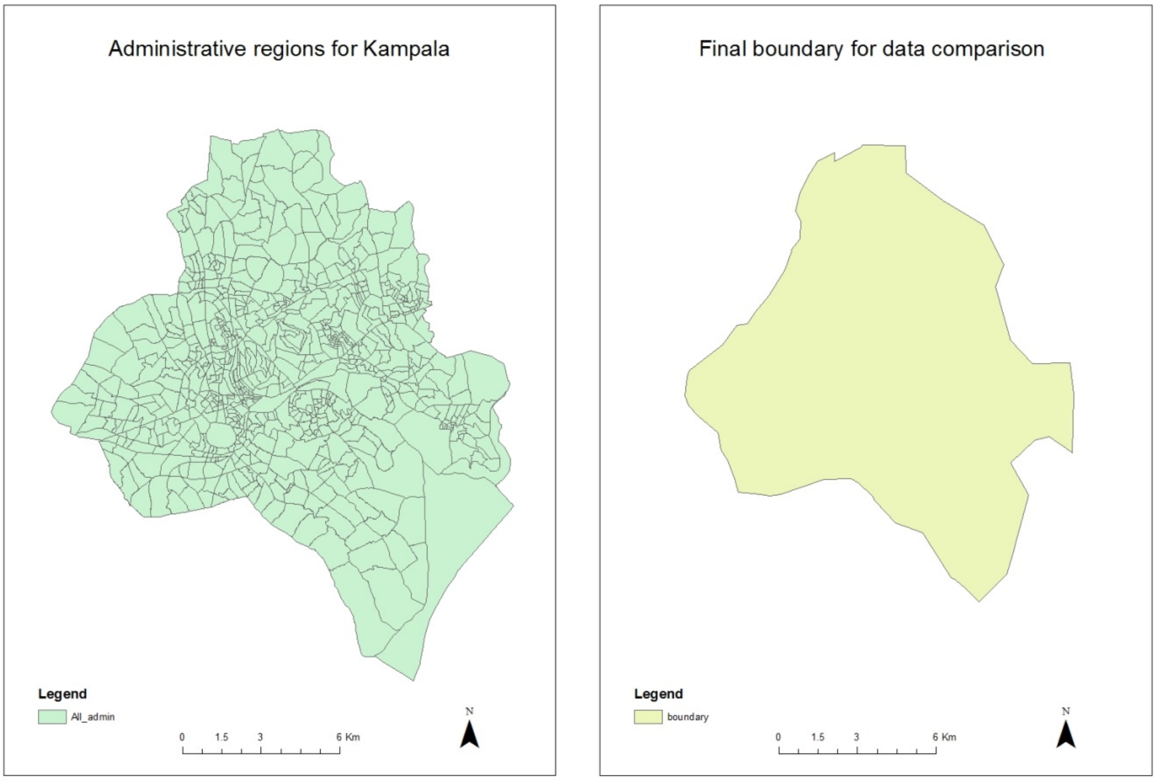


Figure 21 Administrative regions of Kampala in 2010 (left) and final boundary for data comparison (right)

(3) The second step generated a scatter plot in SPSS to see the relationship between the urban footprint products and the reference data. After reclassifying the GHSL into values ranging between 0~100 (in step 1 above), the GHSL was thereafter converted from raster format to vector format (polygons). A union between vector GHSL and the "Union reference GHSL" was thereafter performed in order to see the relationship between both reference data and the target data.

As there were plenty of values in the study area, there was a need to do a random selection in SPSS to make the scatter plot easily visible. Therefore 5% of the total values were selected for random selection (theses constituted 143864 values out of the total 5759686 values).

(4) The same steps (1 and 2 above) was used to change the reference data that contained the building footprints plus the roads and the railways and was used to determine which kind of reference data matched better with the GHSL.

Comparing the reference data with UFC

The following procedure was used to compare the reference data with UFC:

(1) In ArcGIS a 20 by 20 grid fishnet was generated (UFC resolution equals 20 m). The fishnet was set to the same processing extent as the study area. A union between the built-up reference polygons (including buildings, roads and railways) with fishnet was thereafter done; this was to calculate the percentage of the built-up reference polygons' shape area contained in each grid cell. If the percentage was bigger than 50%,

the cell was considered built-up area and given a value 1 and, if the coverage in the grid cell was less than 50%, the cell was considered non-built-up area and given a 0 value.

(2) The next step was to define a distinct cut-off value to delineate built-up vs. non-built-up areas. The chosen cut-off value or threshold influenced the delineation of the built-up area and had to be adjusted carefully, ideally employing reference data. Therefore UFC was converted from raster format to vector format with binary geocodes; a spatial join with the reference data was thereafter made.

T-test values were calculated in SPSS based on the geocodes (land use type) for the UFC and the corresponding shape area for the reference data in order to set the appropriate cutting-off value between the built-up and non-built-up area for the reference data. T-test means that there are two groups, and their means are being compared (Nie et al., 1975).

(3) The third step was analysing the statistic correlation between the UFC and the corresponding reference data based using chi-square in SPSS. Chi square is a versatile statistical test used to examine the significance of relationships between two (or more) nominal-level variables (Nie et al., 1975). In this case, the UFC is a binary map with two values and the reference also contained two nominal values.

(4) The same method was also done for the reference data containing only building footprints to check their relationship.

3.7. Step 4: Structuring possible factors of quality variations for the GHSL and the UFC

Imaging radar gets an image in which each pixel contains a digital number according to the strength of backscattered radiation received from the ground. There are 3 main factors that influence the strength of the backscattered radiation received: (1) radar system properties, i.e. wavelength, antenna and emitted power; (2) radar imaging geometry, i.e. beam width, incidence angle and range; (3) characteristics of interaction of the radar signal with objects, i.e. surface roughness and composition, and terrain relief (Alkema et al., 2012).

For the optical image there are 4 characteristics that can affect the data quality: noise (a spurious chaotic pattern carrying no information about the object), contrast (the difference of appearance of a feature or a structure in an image from its surrounding), sharpness (concerned with sudden blackening changes at the boundary between adjacent parts) and resolution (which refers to ability of an image to show small structures separately).

However in this research, the factors discussed in the preceding paragraph could not be analysed, thus based on the available reference data the following two types of factors (table 11) were used to make comparisons.

Table 11 Main factors used for comparing urban footprint products with reference data

Natural Environment Factors	Built Environment Factors
Slope	Buildings
Aspect (radar data)	Roads
Elevation	Railways
Wetlands	
Vegetation(trees, bush lands, forests, park gardens)	

3.7.1. Structuring possible factors of quality variations by comparing with GCP

At this stage, the factors which influenced the quality of urban footprint products were assessed. After the assessment process, there were a series of points which did not match with the classified images; (both GHSL and UFC). DEM, land use map for Kampala (2012), topographic data (roads, railways, buildings and wetlands), and image mosaic of the year 2010 were used as reference data. The points with errors were used to summarize the possible factors that may affect the accuracy of both footprint products.

In order to find the logical relationship between the elevation, aspect, slope and the reference points with observed error, there was need to generate a slope map and the aspect map from the DEM and then add the values of elevation, slope, and aspect of each point. The aspect factor can only have influence on the radar data (UFC), because the radar data can be affected by the sensor viewing angle.

Figure 22 (left) was the slope map generated with the value range from 0 to 83.2 degrees; the slope map shows several areas with high slope values, this could be attributed to the hilly topographic nature of Kampala. The value between 29.69~83.2 degrees was considered as relatively high slope (a slope of 45 degrees equals 100 percent slope) that could influence the accuracy of the urban footprint products. The aspect map was quite complex and difficult to recognize; since the important issue was to generate the value, the map was not dispalyed. The range of the values of the aspect map are shown in figure 22 (right).

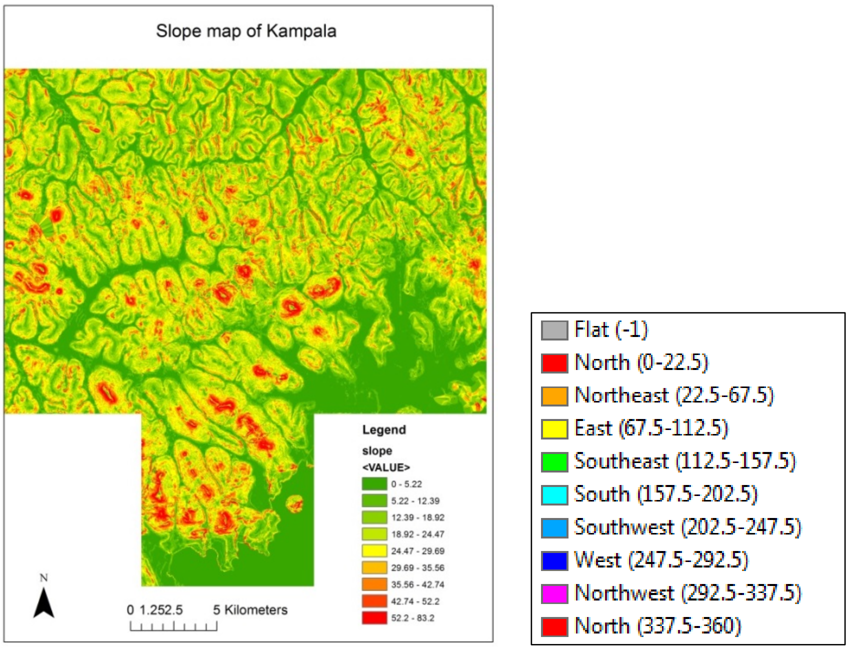


Figure 22 Slope map of Kampala (left) and value range of aspect map (right)

The other points which the values of slope, elevation and aspect had no problems need to be explained by other factors (table 10) that may cause errors (e.g. the surface characteristic of road can lead to some difference in built-up area detecting). The factors are identified based on the position of each point.

3.7.2. Structuring possible factors of quality variations by comparing with topographic data

The main purpose of this stage was to compare the two products with topographic reference data to extract cluster and to have concentration differences. Two methods were applied as follows:

(i) Hotspot analysis: hotspot analysis was conducted to identify where the clusters in the data were statistically significant; this was done using vector data. When doing hotspot analysis in ArcGIS, a high Z score for a feature indicates a significant hot spot (Grubesic & Murray, 2001). In this research, the GHSL is a continuous map with values ranging from 0~255 (changed to 0~100 for comparison), it was difficult therefore to accurately identify the wrongly classified areas with "difference map" analysis. Thus, generating a hotspot analysis to find the significant mismatching areas was a direct and useful method.

(ii) Difference maps: the "difference maps" were systematically calculated for the scenes under analysis for the purpose of identification and understanding of the agreement or disagreement of spatial patterns between the two information layers (Pesaresi et al. 2013). Based on some error spots in the difference maps and the analysis of the thematic differences between two layers, the main factors contributing to the difference could be identified.

The reference data used for GHSL and UFC was obtained from the statistical comparison results in section 3.6, the most suitable results were chosen as the reference data.

For GHSL:

A "difference map" was first made by subtracting the reference layer from the GHSL. The next step was to perform a hotspot analysis to check whether there was any spatial distribution of certain clusters in some areas (significant hotspots). Thus, factors influencing those areas could be identified based on the location of the hot spot.

For UFC:

Based on the process in section 3.5, the first step was in order to acquire the difference map showing the mismatched areas there was a need to convert the vector reference data into raster type using the cutting point (which was set using t-test in section 3.5)

The next step was to make a difference layer; which was done by subtracting reference layer (raster type) from the UFC data. Based on the difference map, the wrongly classified areas could be identified because the UFC had only two layer types. However, conclusions on factors influencing the mismatch of the image characteristics could not be drawn.

To analyse factors that may cause errors in describing the urban footprints, using slope and aspect factors, 1000 random points were generated in SPSS; with 500 showing wrongly classified areas and 500 representing areas with no errors. This was done to qualitatively calculate the relationship between the factors and the areas. Other factors also needed to be checked with the image mosaic in 2010.

3.8. Step 5: Reflection on the suitability of urban footprint products for urban planning

This phase primarily answered the research question in objective 3, regarding which urban planning applications would be sufficed by these products. Section 2.5 in the literature review mentioned several urban planning applications that would benefit from remote sensing data sets (urban footprint products). The term 'urban footprint' refers to a physical based definition; the urban footprint map would allow analysis for instance, of the percentile coverage of urbanized areas, their location and spatial configuration on a global, continental, national or regional level (Fritz et al., 2011). However, because of data limitation for both urban footprint products and the reference data; only a few examples of urban planning applications (land use and land cover mapping and urban densification analysis) were selected as shown below.

Comparing the two products with the urban area derived from land use map

The comparison of the two products was done with the land use map which was dissolved with one class representing urban land and the remaining part representing non-urban land. The corresponding maps are shown in figures 23, 24 and table 12, 13. The GHSL and the UFC are all set to the same processing extent as with the Land use map. The comparison was done using "raster calculator" in ArcGIS, in order to see which of the two (GHSL and UFC) was better for describing built-up and non-built-up area based on the urban area map data. However, there was only one reference land use map, but the GHSL and the UFC both had their unique definition of built-up area. Therefore, based on the existing land pattern shown by image mosaic (2010), the most suitable product for describing land cover or for describing land use functions can be determined.

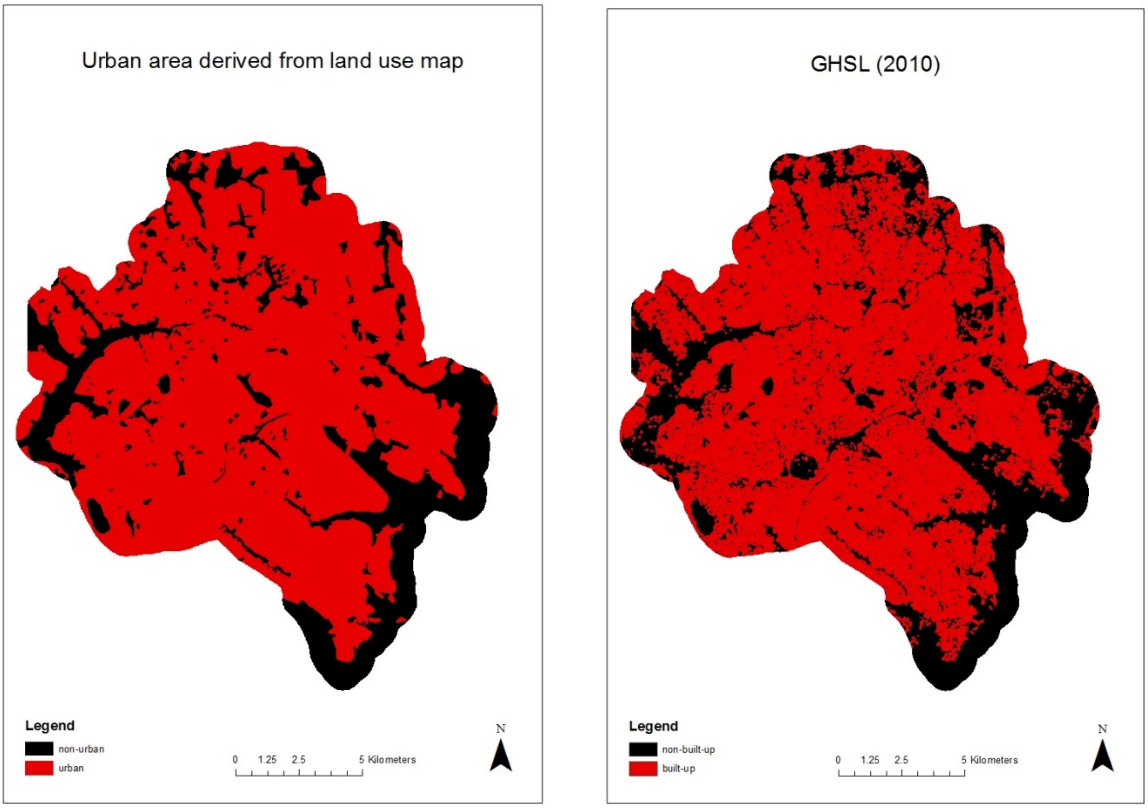


Figure 23 Comparison between urban area derived from land use map (left) and GHSL (right): both 10 m cell size

Table 12 Statically comparison between GHSL and urban area map

	GHSL (10 m resolution)	*LU map (10 m resolution)*
Built-up /urban area	179.3597 km² (74%)	188.5096 km² (77%)
Non-built-up/non-urban area	63.9566 km² (26%)	54.8067 km² (23%)
Total =243.3163		

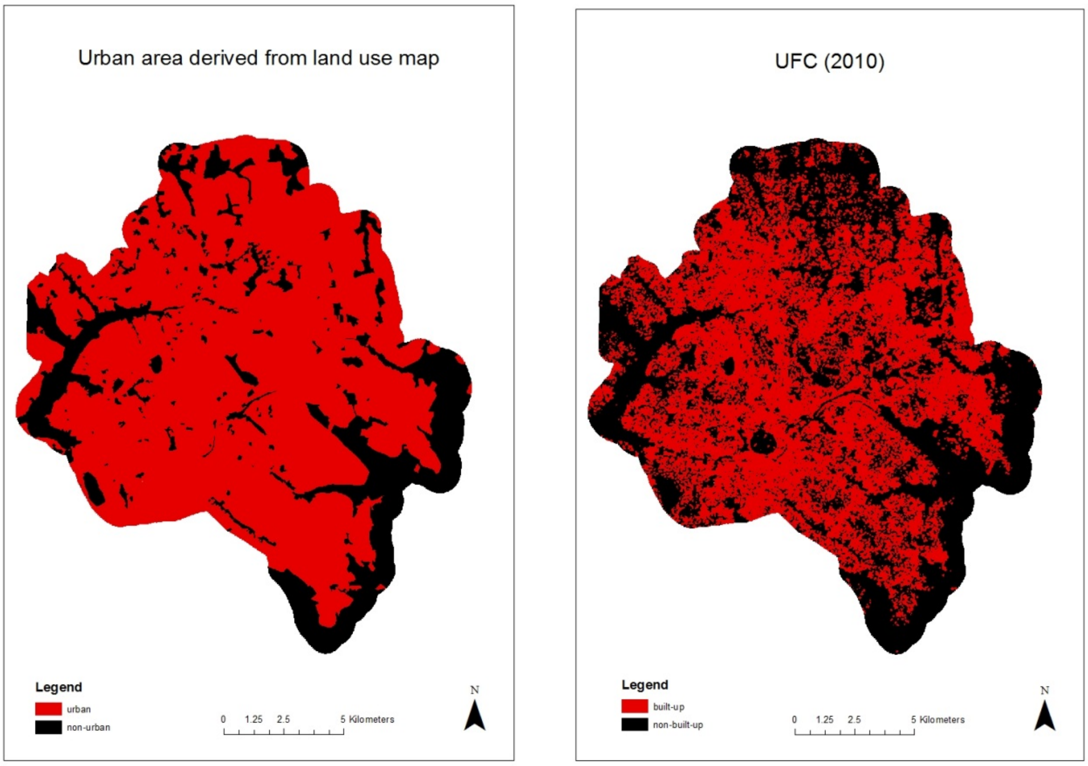


Figure 24 Comparison between urban area derived from land use map (left) and UFC (right): both 20 m cell size

Table 13 Statically comparison between UFC and urban area map

	UFC (20 m resolution)	*LU map (20 m resolution)*
Built-up /urban area	133.1728 km² (55%)	188.5268 km² (77%)
Non-built-up/non-urban area	110.1435 km² (45%)	54.7895 km² (23%)
Total =243.3163		

Urban densification analysis:

Figure 25 (left) shows the land use map for residential areas with three levels of densification, it was used to analyse urban densification pattern based on the same areas as on the GHSL and the UFC layer. Since each of the densification level had quite a number of polygons on the residential map, three polygons in each density class were selected randomly for further analysis with the GHSL and the UFC. These polygons are shown in figure 25 (right). In order to match with the three classes of densification on the reference map, three scopes based on shape area for GHSL were set (by converting the value range from 0~255 to 0~100). If the average pixel value for each polygon ranged between 0~33, it was classified as low density, 34~66 as middle density, and 67~100 as high density. On the other hand, the UFC only had two values; therefore the pixel range of the UFC was redefined based on the percentile pixel coverage of the built-up areas as follows; if built-up pixel area ranged between 0% to 33% it was classified as low density, 34%~66% as middle density, and 67%~100% as high density. The next step was to compare with the 9 polygons to see the percentage covered by individual buildings. Thus, by comparing both products with the residential map, conclusions were drawn on which layer was better to use for urban (building) densification applications.

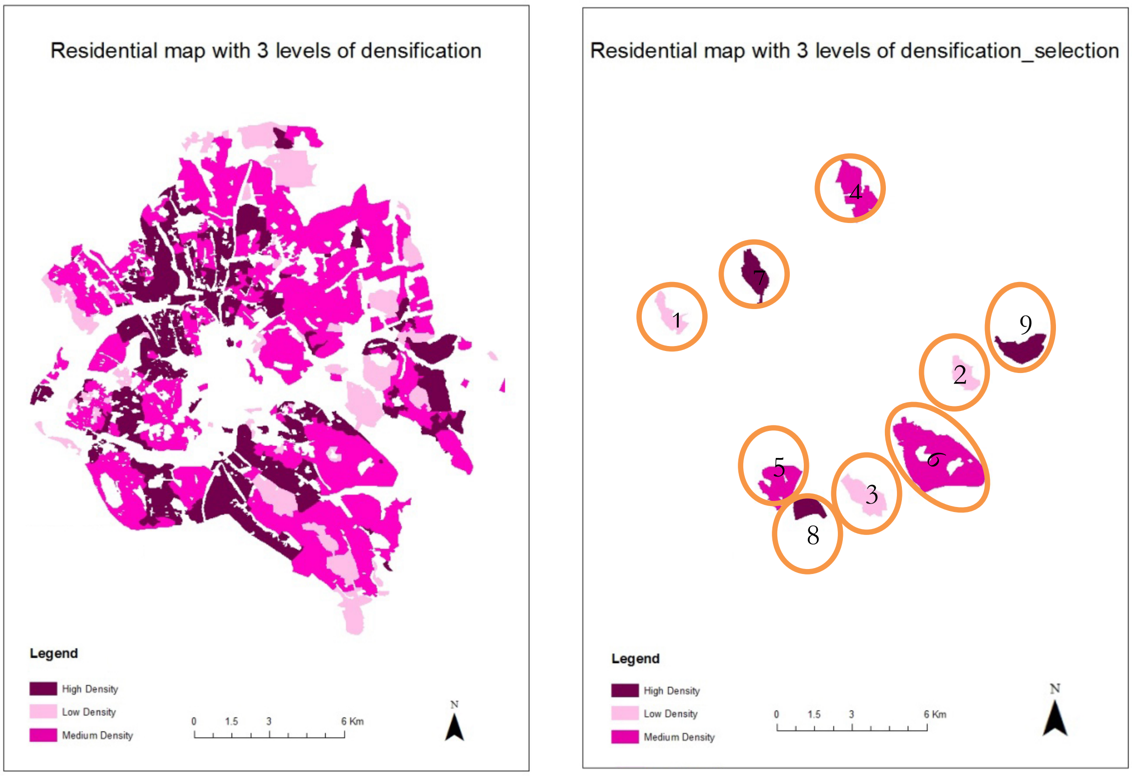


Figure 25 Residential map with 3 classes of densification (left) (generated from the land use map in 2012) and the 9 test areas selected from the residential map (right)

4. RESULTS AND DISCUSSIONS

4.1. Introduction

In this chapter the outcomes of this research are presented and discussed in detail sequentially. First, the accuracy results of GHSL and UFC that were checked against ground truth reference points are presented and discussed and conclusions drawn on the factors that may have caused errors. The second stage is presentation and discussion of results of the comparison between topographic reference data and the urban footprint products; the key factors responsible for the accuracy assessment are presented and discussed as well. Finally, based on information from both urban footprint products urban planning applications that would benefit from this study are discussed.

4.2. Results of accuracy assessment with ground truth points

The main objective of the accuracy assessment in this research was to derive a quantitative description of the accuracy of the urban land cover and to deduce possible reasons that would cause errors. The results of error matrix table based on the comparison with the GCP products are as follows:

Table 14 Error matrix comparing the GHSL with GCP

Class Name	*Reference totals*	*Classified totals*	*Correct numbers*	*Producers accuracy*	*Users accuracy*
Non-built-up area	40	42	28	70.00%	66.67%
Built-up area	106	104	92	86.79%	88.46%
Totals	146	146	120		
Overall Classification Accuracy =82.19%					

Table 15 Kappa Statistics comparing the GHSL with GCP

Overall Kappa Statistics=0.5592	
Conditional kappa for each category	
Non-built-up area	0.5409
Built-up area	0.5788

Table 16 Error matrix comparing the UFC with GCP

Class Name	*Reference totals*	*Classified totals*	*Correct numbers*	*Producers accuracy*	*Users accuracy*
Non-built-up area	40	57	37	92.50%	64.91%
Built-up area	106	89	86	81.13%	96.63%
Totals	146	146	123		
Overall Classification Accuracy =84.25%					

Table 17 Kappa Statistics comparing the UFC with GCP

Overall Kappa Statistics=0.6503	
Conditional kappa for each category	
Non-built-up area	0.5167
Built-up area	0.8770

The error matrix compared the reference points to the classified points. Although the GHSL has a higher overall accuracy than the UFC, they both have a relatively high accuracy of more than 80% (table 14 and table 16 respectively).

Also, as shown table 14 above by the error matrix of GHSL, both the producer's accuracy and user's accuracy are higher for built up areas than non-built areas. It is not however consistence for the error matrix of UFC; the producers accuracy for non-built-up areas is higher than the built areas; while the user's accuracy for built-up areas is higher than the non-built up areas.

The kappa coefficient expressed the proportionate reduction in error generated by the classification process compared with the error of a completely random classification (section 2.3). It is also a measure of map accuracy derived from the error matrix. It was used to test whether the classification results had different levels of accuracy. Based on table 15 and 17, a kappa of 0.5592 is in the "moderate" agreement and 0.6503 is in the "substantial" agreement.

In conclusion, the overall accuracy of the UFC is slightly better than that of the GHSL, and the kappa statistics of the UFC also has a higher value than the GHSL.

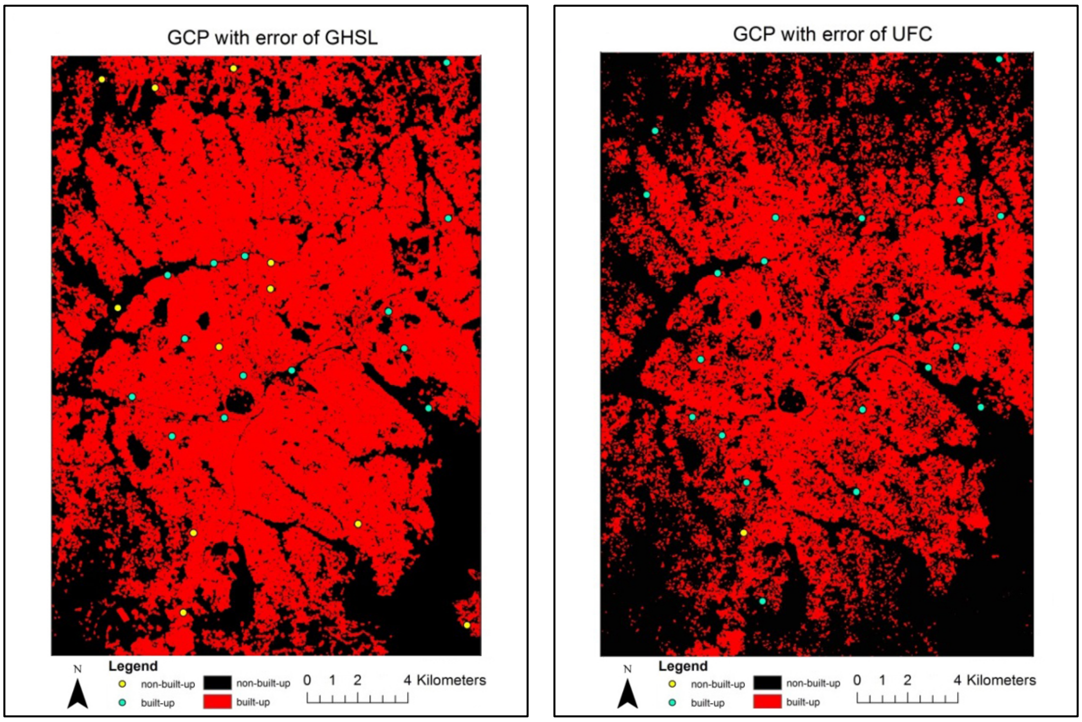


Figure 26 Reference points with error located on the GHSL (right) and the UFC (left)

Figure 26 shows the reference points that did not match with the urban footprint products. There were 27 points that did not match after comparison with the GHSL; 12 of them represented non-built-up area while 15 of them represented built-up area. Likewise, there were 24 points that did not match after comparison with the UFC; with only one of them representing the non-built-up area and 23 of them representing the built-up area. This means that the radar performed better at distinguishing built-up and non-built-up than optical data. This process was used to measure the attribute accuracy (classification accuracy).

Discussions of Results:

(1) The urban footprint products and the ground control points were collected from different years (2010 and 2012); this may imply that some areas which were classified as non-built-up in 2010 may change to built-up in 2012. The assessment was further complicated by the fact that some of the different sources of reference data did not match.

(2) The reclassification process for GHSL from continuous value to binary value could cause uncertainty by simply setting "equal interval" as classification method (figure 27), and the new two classes layer of GHSL were not accurate based on the original value distribution (see figure 28).

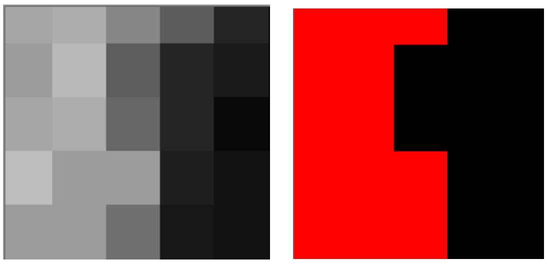


Figure 27 Same part of the GHSL for continuous (left) and binary (right) map

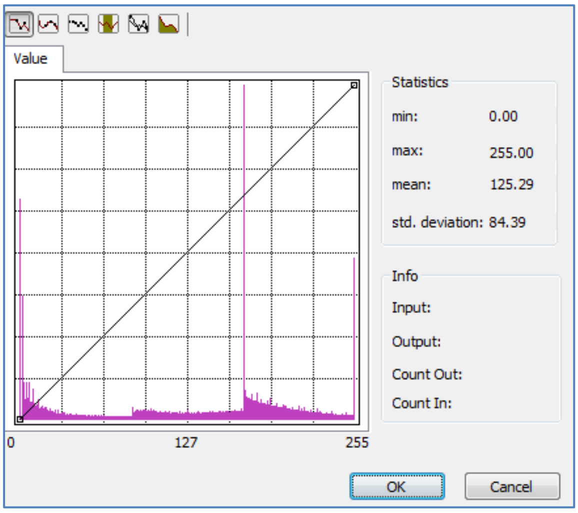


Figure 28 The value distribution of the original GHSL

(3) Both JRC and DLR data had different definition of built-up area and non-built-up area (section 1.1). Also, the GCP were already defined by previous field work and were done based on their understanding. Abebe (2013) mentioned that the built-up area in his study did not only consist of apparent non-vegetative, artificial land cover such as buildings or roads, but also all other manifestations related to residential, commercial, industrial or transportation land use, while the non-built-up area included agriculture land, parks, grasslands, forests, wetlands, green space and so on.

4.3. Factors influencing the quality of the images by comparing with ground truth points

As shown by figure 27, there was a series of points which were wrongly classified on both of the two products. In an attempt to establish the factors that influence the quality by comparison with these points the only information that could be gathered was the location of the points but not land use patterns.

Table 18 Reference points with error (GHSL) (nBU shows that the point was representing non-built-up area but wrongly classified as built-up area, BU shows a contrary situation)

Reference points with error (GHSL) and factors	Elevation	Slope	Built environment factors	Natural environment factors
0 nBU	1130.60	1.11	*No data*	Wetlands
1 BU	1154.31	29.52	*No data*	*No data*
2 BU	1194.68	17.30	*No data*	*No data*
3 BU	1157.96	4.78	*No data*	Wetlands
4 nBU	1150.06	1.15	*No data*	Wetlands
5 BU	1142.70	14.01	Centrelines	*No data*
6 BU	1142.70	17.54	Buildings	*No data*
7 BU	1159.07	2.35	Roads	*No data*
8 BU	1142.50	32.74 (high)	*No data*	Wetlands
9 BU	1159.64	15.33	Roads	*No data*
10 nBU	1230.67	47.48 (high)	*No data*	*No data*
11 BU	1144.18	11.38	Railways	*No data*
12 BU	1149.23	3.01	Centrelines	*No data*
13 BU	1158.80	10.33	Roads	*No data*
14 BU	1165.29	19.75	Buildings	*No data*
15 nBU	*No data*	*No data*	*No data*	Vegetation
16 BU	1155.24	3.57	Centrelines	Wetlands
17 BU	1155.99	1.38	Roads	*No data*
18 nBU	1206.13	33.32	*No data*	Vegetation
19 nBU	1238.51	30.52 (high)	Centrelines	*No data*
20 nBU	1146.5	8.77	*No data*	*No data*
21 nBU	1177.43	29.87 (high)	*No data*	*No data*
22 nBU	1161.45	10.26	*No data*	Wetlands
23 nBU	1198.74	42.24 (high)	Buildings	*No data*
24 nBU	*No data*	*No data*	*No data*	Vegetation
25 nBU	1250.25	51.71 (high)	Roads	*No data*
26 BU	1128.28	25.81	Railways	*No data*

From table 18, the elevations of all these points with errors did not show significant differences, thus the elevation factor can be overlooked. Some of the points that showed that they represented built-up areas, while in fact they represented non-built-up areas on the GHSL were mostly showing high slope value; the reason could be that the optical systems detected cliffs or steep slopes as small buildings.

Buildings and the different types of roads were the main factors influencing the accuracy of the GHSL; the building size, orientation and surface (reflective material and non-reflective material (wood, plastic)) could be the elements that affect the buildings for further research. As for the roads, since the GHSL did not include roads as built-up areas in its definition, it was reasonable that some reference points representing built-up areas were displayed as non-built-up areas in GHSL. There were also some other points displayed as non-built areas in GHSL while in actual sense they represented built up areas; these points were mostly affected by the vegetation and wetlands. Tall and dense vegetation on the other hand was detected and presented as buildings; while wetlands were so variable that their appearance and boundaries fluctuated over time, they are at the same time flowing objects and have strong reflection from the sun which could cause errors.

Table 19 Factors of reference points with error (UFC) (nBU shows the point was representing non-built-up area but wrongly classified as built-up area, BU shows a contrary situation)

Reference points with error (UFC) and factors	**Elevation**	**Slope**	**Aspect**	**Built environment factors**	**Natural environment factors**
0 BU	1173.31	26.26	Northwest	Buildings	*No data*
1 BU	1209.38	26.38	West	Buildings	*No data*
2 BU	1146.41	5.83	Southwest	*No data*	Vegetation
3 BU	1161.78	36.77 (high)	Northeast	Buildings	Wetlands
4 BU	1142.70	17.74	South	*No data*	Vegetation
5 BU	1189.74	13.53	Southwest	Roads	*No data*
6 BU	1168.81	29.26	North	Buildings	Wetlands
7 BU	1165.29	18.94	East	Buildings	*No data*
8 BU	1165.20	26.12	South	*No data*	Vegetation
9 BU	1153.27	28.93	Southwest	Centrelines	*No data*
10 nBU	1206.12	34.05 (high)	East	*No data*	Vegetation
11 BU	1288.64	5.04	South	*No data*	Vegetation
12 BU	1188.50	18.75	South	Roads	*No data*
13 BU	1128.38	25.85	Southwest	Railways	*No data*
14 BU	1130.43	17.22	Southwest	Roads	*No data*
15 BU	1155.18	3.6	Northeast	Roads	*No data*
16 BU	1171.70	8.32	East	*No data*	Vegetation
17 BU	1194.39	17.31	North	Buildings	*No data*
18 BU	1165.53	26.08	West	Buildings	*No data*
19 BU	1168.93	20.14	Northwest	Buildings	*No data*
20 BU	1154.28	29.5	West	*No data*	Wetlands
21 BU	1195.23	38.84 (high)	Northwest	Buildings	*No data*
22 BU	1142.50	32.74 (high)	Northeast	Buildings	*No data*
23 BU	1155.99	1.17	Southwest	Centrelines	*No data*

Table 19 shows the factors that may have influenced the accuracy of the radar data; contrary to GHSL, the high slope areas tended to wrongly classify the built-up areas as non-built-up areas. This was because the steep slopes resulted in equally high backscatter of radar sensor, or where an unfavourable viewing geometry prevented the representation of the built-up structures in the resulting radar image. The southwest direction occupied the largest amount in all these points; the aspect may show a loss of response associated with viewing geometry, for example, with building aspect in respect to the sensor direction, which can be associated with orbit direction. The buildings and natural environment factors were as earlier discussed; the roads possess some aspects that may have caused errors, for instance geometric aspects (shape and orientation), topological aspects between roads (disjoint, touch, overlap, contains/contained by, covers/covered by, equal), and differences in surface texture.

All these factors represented by the wrongly classified points implied that they may have an influence on the accuracy of the urban footprint products. However, specific reasons need to be elicited by a further analysis of certain clusters of land patterns.

4.4. Results of accuracy assessment with topographic data

The following tables show the results of error matrixes and kappa statistics produced by comparing the two footprint products and their corresponding reference data (both groups of 400 reference points were converted from topographic reference data).

Table 20 Error matrix table comparing the GHSL with the topographic data converts to points

Class Name	*Reference totals*	*Classified totals*	*Correct numbers*	*Producers accuracy*	*Users accuracy*
Non-built-up area	200	114	112	56.00%	98.25%
Built-up area	200	286	198	99.00%	69.23%
Totals	400	400	310		
Overall Classification Accuracy =77.50%					

Table 21 Kappa Statistics of comparing the GHSL with the topographic data converts to points

Overall Kappa Statistics=0.5500	
Conditional kappa for each category	
Non-built-up area	0.9649
Built-up area	0.3846

Table 22 Error matrix comparing the UFC with the topographic data converts to points

Class Name	*Reference totals*	*Classified totals*	*Correct numbers*	*Producers accuracy*	*Users accuracy*
Non-built-up area	200	173	140	70.00%	80.92%
Built-up area	200	227	167	83.50%	73.57%
Totals	400	400	307		
Overall Classification Accuracy =76.75%					

Table 23 Kappa Statistics of comparing the UFC with the topographic data converts to points

Overall Kappa Statistics=0.5350	
Conditional kappa for each category	
Non-built-up area	0.6185
Built-up area	0.4714

For this assessment, both the user’s and producer’s accuracies were important because to be certain that the GHSL and the UFC were neither missing built-up areas (omission errors) nor mislabelling non-built-up areas as built-up area (commission errors). The overall accuracies of both products and their corresponding reference data sets proved relatively high and similar results (77.50% and 76.75%).

Compared with accuracy assessment with GCP, the accuracies show a slight decrease for both urban footprints. This is due to the fact that a set of reference points were randomly selected from a high-detailed reference data (created by digital building footprints and road networks). The GHSL was thereafter reclassified into binary 'built-up/non-built-up' map, but the 'cutting point' could not be defined appropriately. On the other hand, the reference data for UFC which was created by buildings and roads did not match the definition of UFC (the built environment incorporates all non-vegetated, human-constructed elements).

Therefore, the error matrix of the GHSL and that of UFC could not be compared because different data were used. The rationale for using different reference data was the assumption that the GHSL majorly captures buildings, while the UFC has the potential of capturing buildings and roads which may have an elevation.

4.5. Results of comparison between the two products with topographic data

4.5.1. Quantitative analysis of GHSL

As discussed in previous chapter (under section 3.6), the main purpose of this stage was to understand and statistically quantify the relationship between the two products and the topographic reference data.

The scatter plot analysis used to test the relationshsip between the GHSL and the building footprint reference data (and also the building plus roads footprint reference data) could not be done for all the available data sets (it was difficult to see the relationship for such a large number of data sets). Therefore only a random 5% of the data values (i.e. 143,864 cells) were used to check the relationship between both of them.

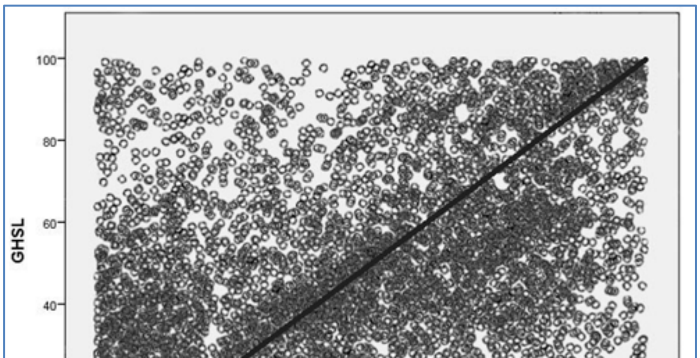


Figure 29 Correlations between the GHSL and the (building footprints) reference data

The scatter plot shown in figure 29 indicates that there are quite a number of overlapping points close to the diagonal but also many points located far from the line. These residuals reason could be due to: 1) the study area near the boundary may include some cells with no building polygons; 2) some remaining errors in the building polygons (e.g. courtyards counted as built-up); 3) the conversion process of the GHSL from value range between 0~255 to 0~100 was assumed to be linear.

Table 24 Correlations between the GHSL and the building footprints reference data

		GHSL	Reference
GHSL	Pearson Correlation	1	.749**
	Sig. (2-tailed)		.000
	N	143864	143864
Reference	Pearson Correlation	.749**	1
	Sig. (2-tailed)	.000	
	N	143864	143864

** Correction is significant at the 0.01 level (2-tailed).

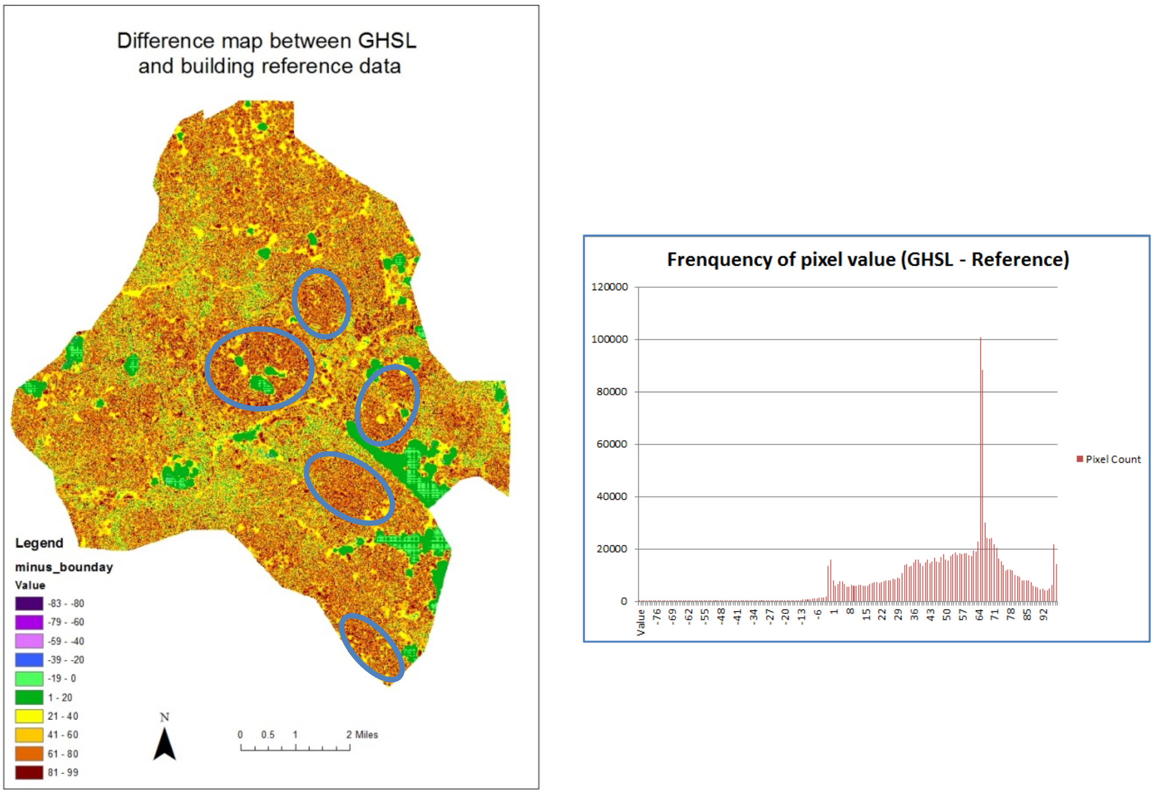


Figure 30 Difference map calculated by the GHSL minus the building reference data (left) (blue circle shows concentration of big differences) and the frequency of pixel value generated by the GHSL minus building reference data (right)

After computing the shape area in each grid for the building footprints map and convert the GHSL from 0~255 to 0~100, the data were plotted (figure 29). The data distribution in the scatter plots shows a relatively positive correlation between the GHSL and the building footprints reference data with an R^2 of .749** (table 24). Figure 30 (left) shows the difference map which was calculated by subtracting the building reference data (with value ranging from 0~100) from the GHSL (with values also ranging from 0~100). The negative value shows that if for instance the GHSL indicates an area is non-built-up, the reference data would mostly show that the same area is built-up area and vice versa. From figure 30 (right) it is obvious that the positive values are larger than the negative values. This means that the GHSL shows an overestimation of built-up area by comparing with the building footprints. In that case, there is a need to check if the reference data that includes both buildings and roads could have better results.

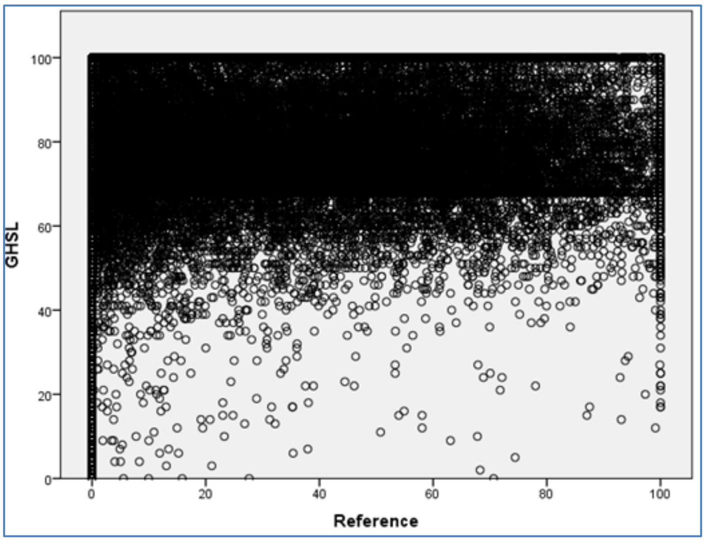


Figure 31 Correlations between the GHSL and the (building plus roads footprints) reference data

Table 25 Correlations between the GHSL and the building plus roads reference data

		GHSL	Reference
GHSL	Pearson Correlation	1	.307**
	Sig. (2-tailed)		.000
	N	143864	143864
Reference	Pearson Correlation	.307**	1
	Sig. (2-tailed)	.000	
	N	143864	143864

After comparing the GHSL with the buildings plus roads reference data as shown in figure 31 and table 25 (the R^2 equals .307**), it is obvious that they shows a very weak relationship between each other. So the building footprint data was deemed better for representing the GHSL as reference data, than buildings plus roads. Therefore, when generating the hotspot areas for structuring possible influencing factors, the building footprints reference data was used.

4.5.2. Quantitative analysis of UFC

After converting the topographic reference data into the same resolution and the same type with the UFC, the statistic differences between the two layers were shown as follows:

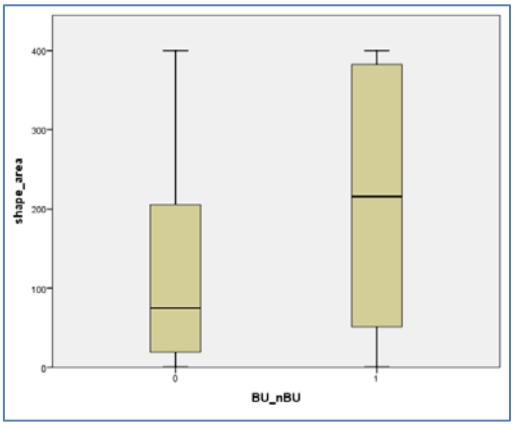


Figure 32 Boxplot showing the range of shape area for the built-up area"1" and non-built-up area "0" of the UFC

The boxplot shown in figure 32 for the reference data with binary categories demostrated the range of shape areas of each type; with 0 representing non-built-up area and 1 representing built-up area. The middle line shows the median of the shape area in each category and as it can be observed in the boxplot, the median for built-up area is higher than that for non-built-up areas. By comparing 0 and 1 values, it can be observed that they both had similar low scores.

Based on table 26 below, the mean shape area for non-built-up area (gridcode=0) and built-up area (gridcode=1) in each grid are 120.7 m^2 and 210.09 m^2 respectively. However the appropriate cutting point for delineating built-up and non-built-up area for the reference data (which used to compare with the UFC) could not be simply set based on the mean value of both groups. There is therefore the need to check the data (shape areas) distribution which is shown by figure 33; this figure shows the two groups of frequency distrubution, and as observed, the two lines roughly met at 110 m^2. Based on this figure therefore, the reference data representing the non-built up was set at less than 110 m^2, while built up was set at more than 110 m^2. This method was applied here because the shape area of built-up areas was more than non-built-up area for this study and the cutting point needed to be set based on the shape area distribution of the reference data.

Table 26 T-test for the shape area of the built-up "1" and non-built-up area "0"

Case Processing Summary

	Cases					
	Included		Excluded		Total	
	N	Percent	N	Percent	N	Percent
shape_area * BU_nBU	934096	100.0%	0	0.0%	934096	100.0%

Report

shape_area

BU_nBU	Mean	N	Std. Deviation
0	120.70	650558	119.116
1	210.09	283538	152.025
Total	147.83	934096	136.332

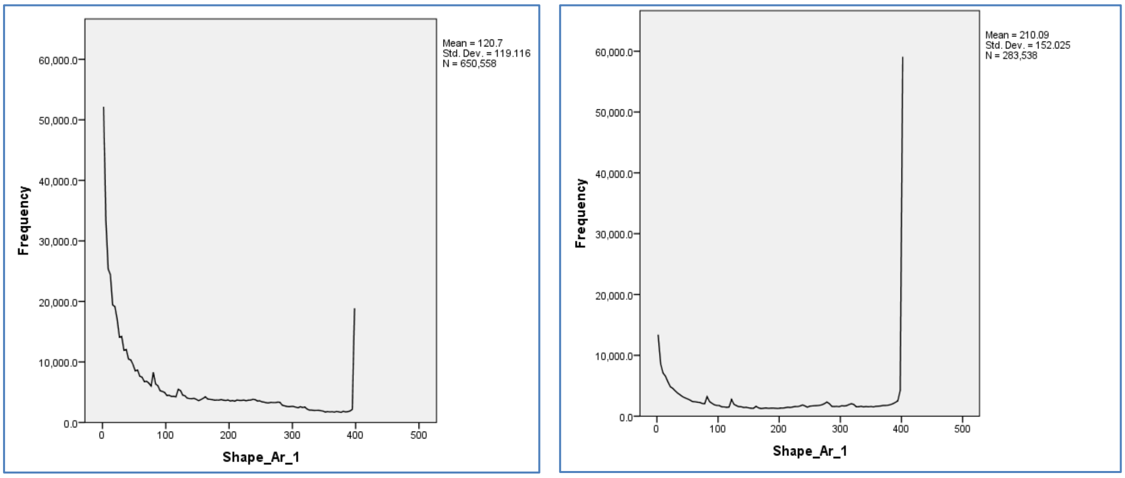


Figure 33 Distribution of shape area for the built-up area and non-built-up area

Table 27 Chi-square test between the UFC and the reference (buildings plus roads) data

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
reference * UFC	1199530	100.0%	0	0.0%	1199530	100.0%

reference * UFC Crosstabulation

Count

		UFC		
		0	1	Total
reference	0	248554	22898	271452
	1	186296	741782	928078
Total		434850	764680	1199530

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	464489.544[a]	1	.000		
Continuity Correction[b]	464486.451	1	.000		
Likelihood Ratio	483273.318	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	464489.157	1	.000		
N of Valid Cases	1199530				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 98405.96.

b. Computed only for a 2x2 table

Table 28 Chi-square test between the UFC and the reference (buildings) data

Case Processing Summary

	Cases					
	Valid		Missing		Total	
	N	Percent	N	Percent	N	Percent
reference * UFC	1199530	100.0%	0	0.0%	1199530	100.0%

reference * UFC Crosstabulation

Count

		UFC		Total
		0	1	
reference	0	276695	296086	572781
	1	158155	468594	626749
Total		434850	764680	1199530

Chi-Square Tests

	Value	df	Asymp. Sig. (2-sided)	Exact Sig. (2-sided)	Exact Sig. (1-sided)
Pearson Chi-Square	68942.400[a]	1	.000		
Continuity Correction[b]	68941.402	1	.000		
Likelihood Ratio	69551.643	1	.000		
Fisher's Exact Test				.000	.000
Linear-by-Linear Association	68942.343	1	.000		
N of Valid Cases	1199530				

a. 0 cells (0.0%) have expected count less than 5. The minimum expected count is 207642.84.

b. Computed only for a 2x2 table

The UFC data and the corresponding reference data are categorical data sets which could not be distributed normally because they aren't continuous. However, the Pearson's chi-square tested whether there was any association between the two categorical variables. As seen from table 27, the value of the chi-square statistic is 464489.544, which is within rounding error (464489.54). This value is also significant ($p<.001$), showing that the reference data and the UFC had a relatively strong relationship between each other. Table 28 indicates the relationship between the UFC and the building reference data. The value of the chi-square statistic is 68942.400, which is lower than the rounding error (464489.54), the larger pearson Chi-square value in SPSS indicates greater association. Even from the cross tabulation table, the number of mismatched value is 454241, which is bigger than 209194 (buildings plus roads as reference data). Therefore, the UFC data matches better with the buildings plus roads than with only buildings.

4.6. Factors influencing the quality of the images compared with topographic data

The purpose of this stage was to find out and analyse if there were any factors that resulted to the wrongly classified areas after the quality assessment process.

4.6.1. Structuring of possible factors affecting the accuracy of GHSL

For the GHSL data, the values were already converted to a range of 0~100 from values ranging between 0~255, thus it was difficult to form a difference layer like the UFC which contained only two values. One part of the hotspot map of the GHSL which compared with the corresponding reference data is as shown by figure 34, since the whole map could not be shown clearly.

Based on section 3.7.2, a high Z score and small P value for a feature indicates a significant hot spot. The red area in figure 34 indicates that these are statistically hot spot areas (areas with a GiZ score higher than

2.58 standard deviation are described as hot spot areas). The red area can be used to generate the factors that may have influence the quality of the GHSL since it can be complex to find out all the wrongly classified areas based on just comparing the two continuous layers.

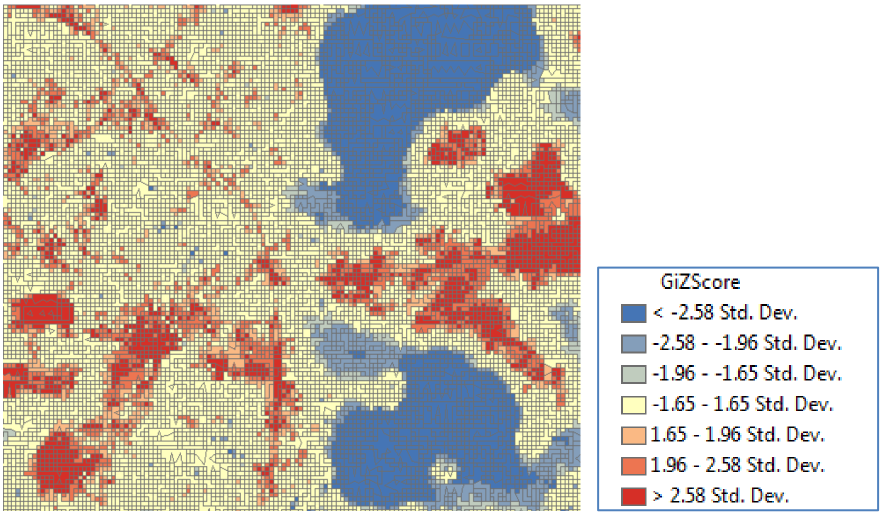


Figure 34 One part for hotspot analysis map of GHSL comparing with the reference data

All the hotspot areas were thereafter converted into one map showing the highly mismatched areas (figure 35). These hotspot areas were grouped into 5 error concentration areas to facilitate analysis of the influencing factors separately; group one had the most concentration clusters among all the groups. These groups are discussed in detail in the following section.

Figure 35 Hotspot map of GHSL

Figure 36 Hot spot area of group 1

(a)

(b)

(c)

Figure 37 Images for group 1

Figure 37 (a) shows the whole image of figure 36; as it can be observed; the hot spots are distributed based on numbers of buildings along the roads. There are also quite a number of tall trees that contributed to these hotspots. By zooming in the image (figure 37(b)), the shape area of the buildings are seen to be large and are not only simple polygons (figure 37(c)). These areas are mostly distributed on residential area and commercial areas (checked by LU map); however, areas are not densely built-up but are rather covered by large numbers of dense and tall vegetation. In summary, in hotspot group 1, the influencing factors were shape and size of buildings and large vegetation areas.

Figure 38 Hot spot area of group 2

Figure 39 Images for hotspot group 2 ((a) left (b) right)

Group 2 hotspot areas (as shown by figure 38) are located on relatively low density residential areas characterized by small numbers of low height and small size buildings, and also with a complex multidirectional roads structure. To some extent, these complicated and crowed places affected the accuracy of the optical image.

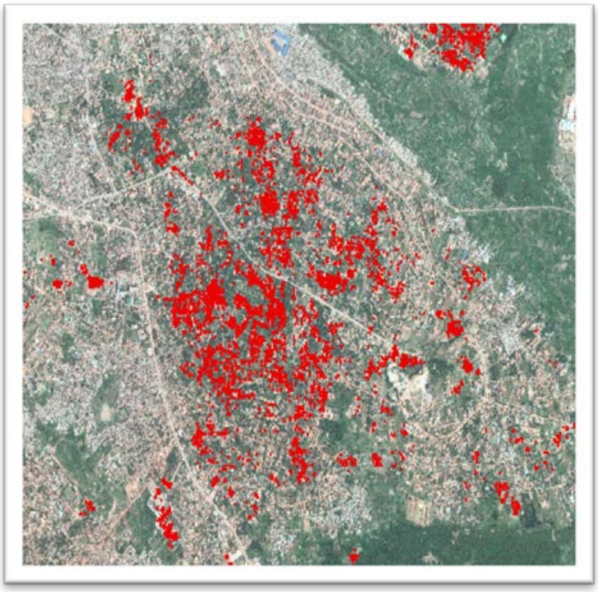


Figure 40 Hot spot area of group 3

Figure 41 Images for hotspot group 3 ((a) left (b) right) (the orange circle shows the same areas on both images)

The hotspot areas of group 3 were also mostly distributed in the residential areas with some small parts in commerical areas and utility areas. These areas are surrounded by wetlands, and also area characterized by low density houses that are sparsely distributed and large vegetated areas. Figure 41 (b) shows 5 round buildings (of utility land use); these buildings have a relatively strong effect on the quality of the GHSL, because of the shape and material of the buildings.

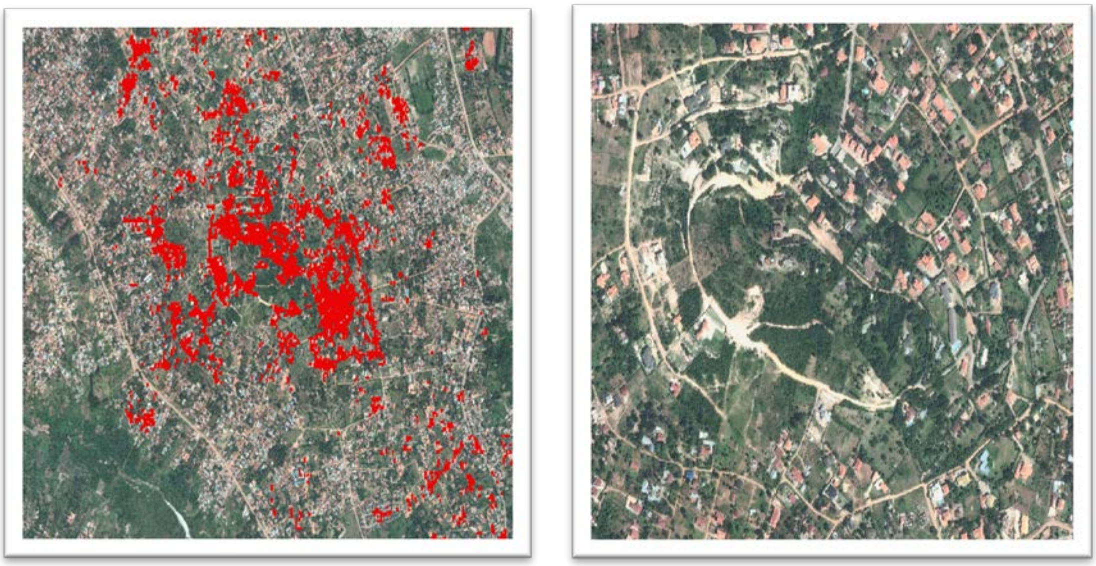


Figure 42 Hot spot area of group 4 (left) and image of group 4 (right)

The fourth group of hotspot concentration areas were mostly located on residential and commercial area; characterized by scattered buildings surrounded by large areas of vegetation buffers. What bought about errors and difficulty in remote sensing for this group was probably due to the large numbers of tall trees which ended up blocking lower buildings and roads.

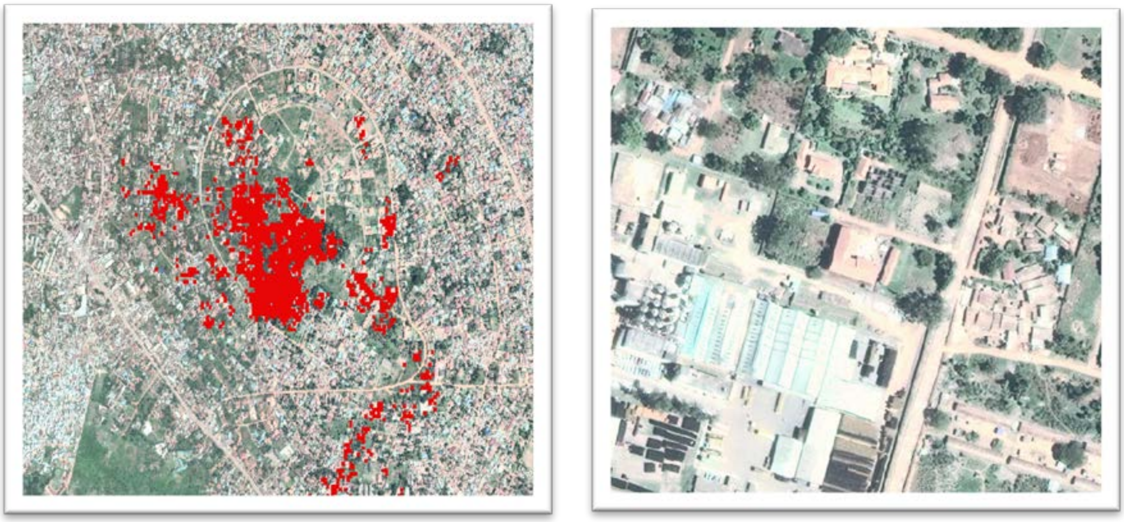


Figure 43 Hot spot area of group 5 (left) and image of group 5 (right)

The areas of hotspot group 5 were mostly concentrated on industrial land use; as shown by figure 43 (right), the construction material had relatively stronger reflection of the light, compared with the other parts of the image. This could be the significant factor influencing the quality of the image in this group.

As seen from the preceding discussion on the five groups of the hotspot areas, in can be concluded that GHSL cannot work very well in low density areas, buildings built with reflective materials, in dense and tall vegetation and in areas with low and oversized buildings. GHSL however performs better in high density areas, such as in slums. Ground truth would be necessary for in a future study to accurately establish the land exact land patterns.

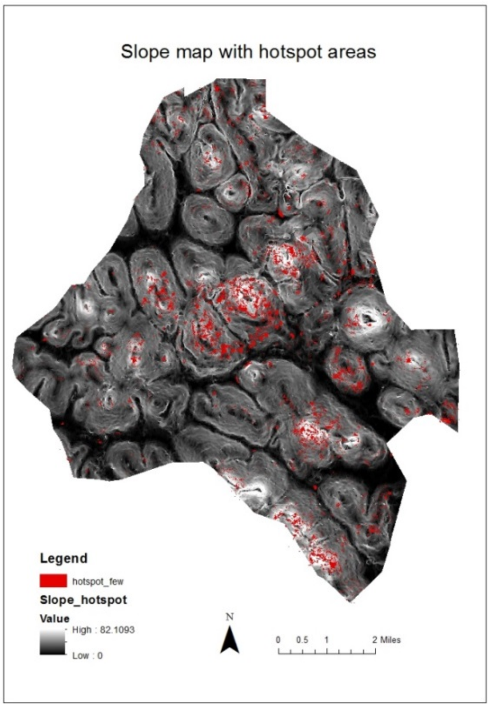


Figure 44 Hotspot map of GHSL overlaid with slope map

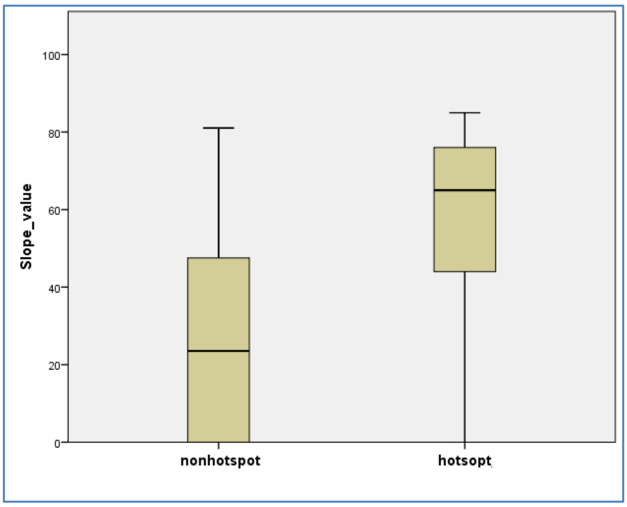


Figure 45 Boxplot of the relationship between the hotspot and non-hotspot areas with slope value

Just to extend the discussion on hotspot areas; as shown by figure 44 and 45, most of the hot spot areas are located on relatively high slope areas, with value 0 showing the slope value of non-hotspot areas, and value 1 showing the slope value of hotspot areas, which means that high slopes could be a strong factor causing the misclassification for GHSL.

4.6.2. Structuring of possible factors affecting the accuracy of UFC

Based on figure 46, the total shape area for the study area was 139.688 km²; out of this area, 56.772 km² showed a mismatched area obtained from UFC and the corresponding reference (buildings plus roads) raster layer. The yellow and black pixels represented areas where the UFC and the reference raster layer were wrongly classified as built-up area and wrongly classified as non-built-up area, respectively. On the other hand, the blue pixels show the correctly classified areas. As it can be observed from the map, the area wrongly classified as built-up area occupies a larger percentage. Based on the results displayed on table 29, it can be deduced that the UFC is relatively better at describing non-built-up areas than built-up area.

Table 29 Shape area of UFC based on comparison

nBU/BU	Original shape area of the UFC	Wrongly classified shape area	Residues
BU	110.216 km²	40.216 km²	70 km²
nBU	83.472 km²	16.556 km²	66.919 km²

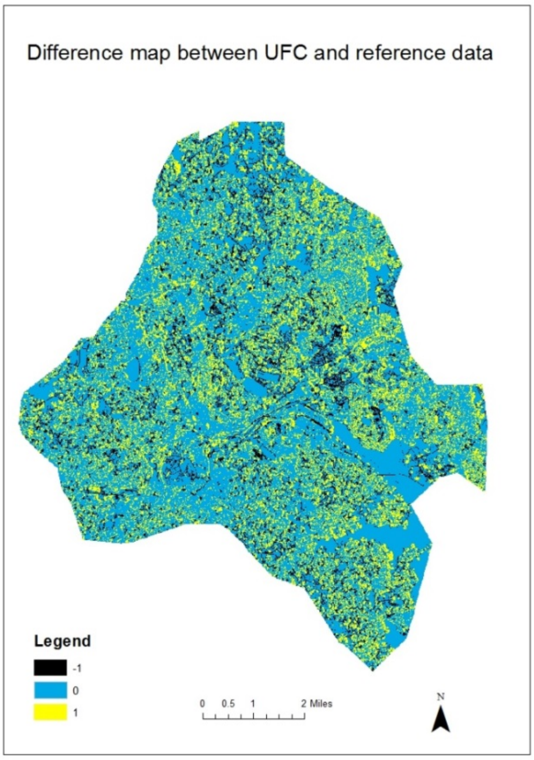
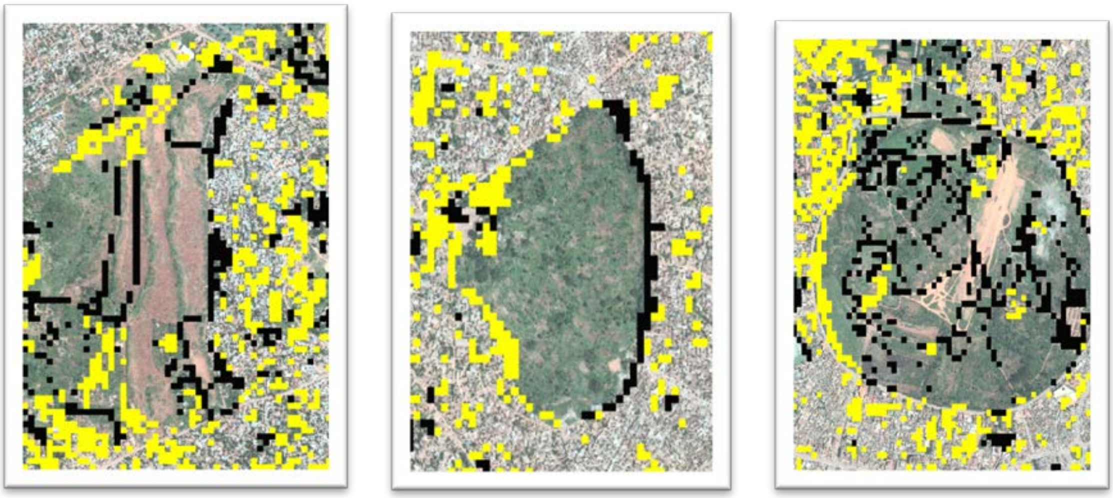


Figure 46 Raster overlay map for UFC and reference layer

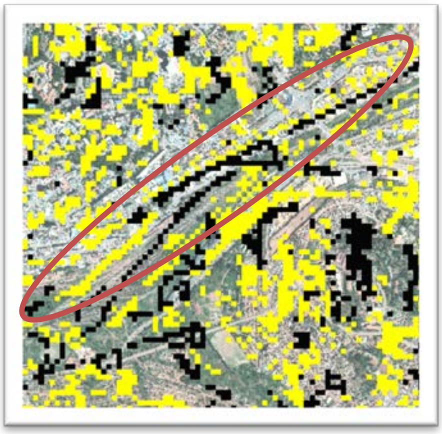
The wrongly classified areas (as shown in figure 46) obtained by comparing UFC with reference data are distributed all over the map. By a simple visual check, it is difficult to identify any special patterns of the errors on the map. However, some information can be acquired if some sample areas are taken for a detailed analysis.



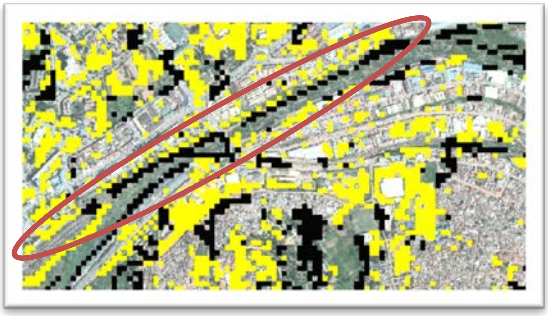
(a) (b) (c)

Figure 47 Examples of wrongly classified areas on the image mosaic

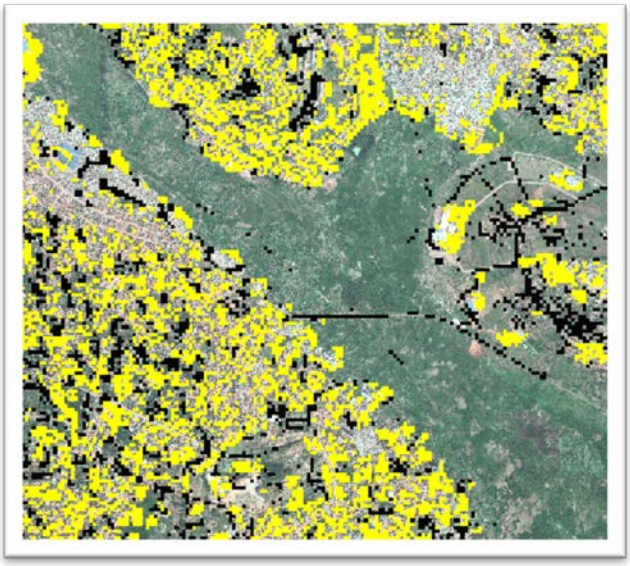
The three images shown in figure 47 show that the wrongly classified areas are mostly located on the bounday of two land cover types; this phenomenon can be brought about by the boundary vagueness, for instance, between vegetated areas and the buildings; and between the vegetated areas and bare soil. These boundaries could not therefore be detected clearly based on the remote sensing system. Most of the wrongly classified pixels located along the bounday are shown by the black colour (non-built-up for the UFC but built-up for the reference data).



(a)



(b)



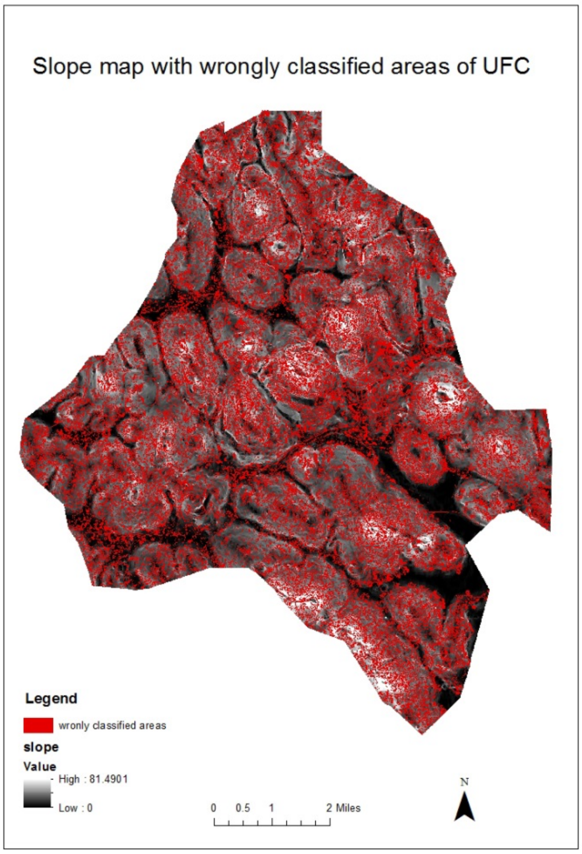
(c)

Figure 48 Examples of wrongly classified areas on the image

In figure 48 (a) and (b) above, the areas with errors shown by the black colour are mostly distributed along the big roads (roads were detected as non-built-up areas on UFC), both black pixels and yellow pixels are distributed in areas with high building density and in vegetated areas. According to figure 48 (c) the wrongly classified areas are mostly located on the high building density areas (yellow pixels occupy most part).

In summary, the big roads and high building density areas were the main factors affecting the accuracy of the UFC data; some areas with vague boundary between two land cover types were also easily wrongly detected. Therefore it can be said that UFC performs better in low density areas.

After analysis of the factors discussed above, it can be concluded that the natural environmental factors shown on the image mosaic, do not have strong effect on the accuracy of footprint products. The next factor to be analyzed was slope. Figure 49 (left) shows the slope map of wrongly classified areas of the UFC, most of these areas are scattered on the hilly areas. As shown by figure 49 (right), the value 0 shows the areas with no errors and value 1 show the areas with errors. As observed in the figure, it can be concluded that the areas with errors are more likely to be located on the higher slope lands than areas without errors. However, the boxplot shows that the wrongly classified areas were also located on the low slope lands. Therefore, compared with the GHSL, the slope does not affect the data quality of UFC significantly.



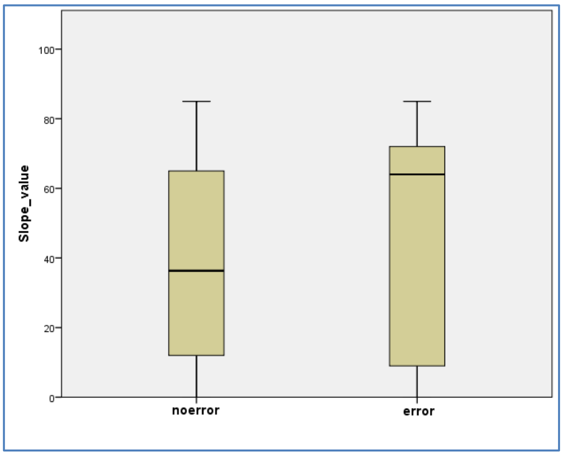


Figure 49 Slope map of wrongly classified areas of the UFC (left) and boxplot showing the relationship between the slope value and the areas with error and areas without error (right)

Occasionally, individual buildings or even entire neighbourhoods were not represented in the image. In addition to those factors discussed above, these omissions could be explained by factors related to viewing geometry (from aspect map generated from the elevation map); there was however no information about the data source. Table 30 shows the percentage of areas with errors and those without errors in each aspect type; as shown by the table, there is no significant difference between them. So the aspect factor (at least based on the 1000 random selection points) was not a significant issue.

Table 30 Relationship between aspect and the areas with error and without error

	Flat	North	NE	East	SE	South	SW	West	NE	North
Areas with error (points)	4 %	14 %	15 %	6 %	11 %	9 %	10 %	10 %	11 %	10%
Areas without error(points)	9 %	9 %	11 %	13 %	12 %	6 %	14 %	9 %	9 %	8 %

4.7. Reflecting the suitability of urban footprint products for urban planning applications

Based on the original data information (figure 1 (left) and figure 2), the two data sets have quite a number of differences. First, they were generated from two types of systems (optical and radar sensor); secondly, they were explained by different semantics definition of "built-up area" and "non-built-up area"; and third, they have different layer format and resolution. On one hand, GHSL is a continuous map (0~255), which means it is free from categorical definition sets; built-up area in GHSL definition include the 'influence' zones of the buildings, i.e. the buffer around a building. A higher value shows that there is a higher possibility that buildings exist. At the same time, GHSL has a finer image structure (resolution=10 m), which can analyse densification issues (such as estimation of building density) and peri-urbanization issues (transformation from natural and rural areas to urban areas). On the other hand, UFC is a binary map (resolution=20 m), with built-up area (all structures with a vertical components) and non-built-up area. UFC covered a larger part of Kampala (shape area=59 km^2,) compared to GHSL (shape area=26 km^2). Both products could contribute to research and analysis of urbanization patterns (city regions, urban corridors), population assessment and the spatiotemporal dynamics of urban development (growth rates), and to predict future urbanization processes.

There are certain urban planning applications that both products require to be checked through accuracy assessment and statically comparison as follows:

4.7.1. Comparing the two products with the urban area derived from map

As shown in table 31 there is a difference of 12 % (yellow and blue colours) between the GHSL and the urban area map, and 27 % difference (table 32) between the UFC and the urban area map. UFC classifies a large portion as non-built area-25 % (which is urban area in the land use map). There would be therefore need to check the distribution of both maps to explain the differences in a future study.

Table 31 Statistic difference between the GHSL and the urban area map

Built-up area for GHSL but non-urban area for urban area derived from LU map (10m resolution)	19.8261 km^2 (8%) (red)
Non-built-up area for GHSL but urban area for urban area derived from LU map (10m resolution)	10.6762 km^2 (4%) (yellow)
Same area	212.814 km^2 (88%)(black)
Total =243.3163	

Table 32 Statistic difference between the UFC and the urban area map

Built-up area for UFC but non-urban area for urban area derived from LU map (20m resolution)	5.0844 km^2 (2%) (red)
Non-built-up area for UFC but urban area for urban area derived from LU map (20m resolution)	60.4384 km^2 (25%)(yellow)
Same area	177.8064 km^2 (73%)(black)
Total =243.3163	

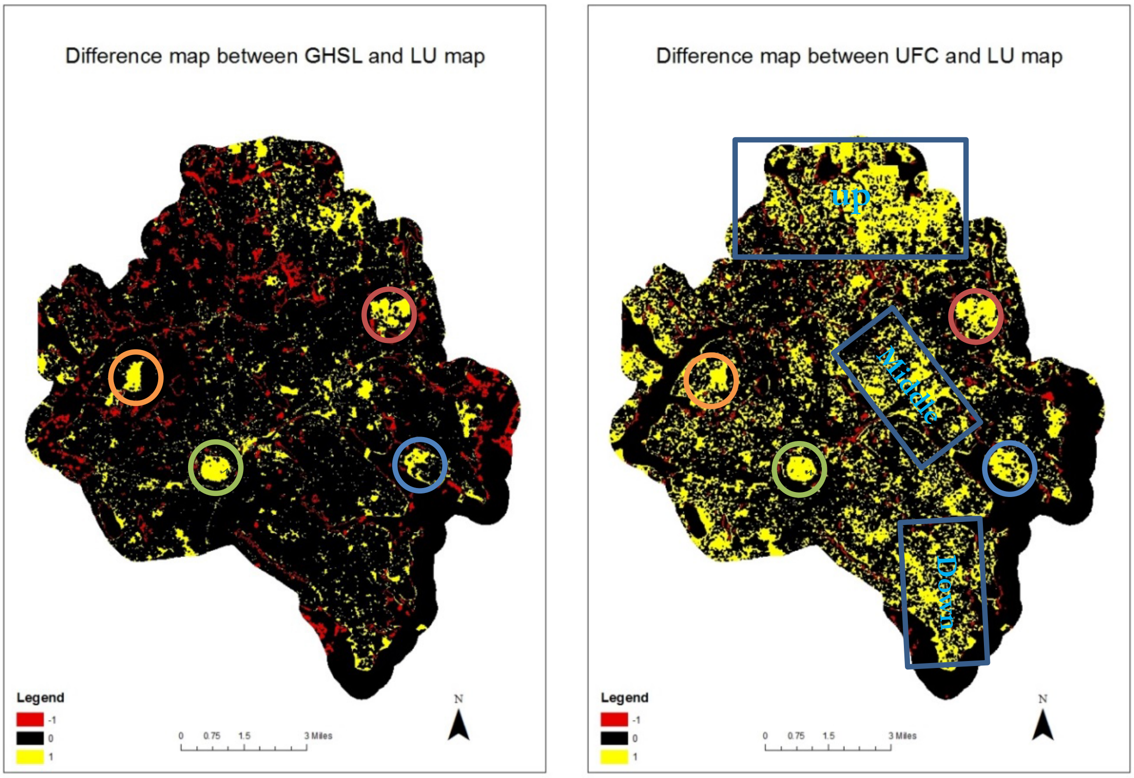


Figure 50 Difference maps between the land use map with the GHSL (10 m resolution) (left) and the UFC (right) (20 m resolution)

In figure 50 above, the yellow areas represent conflict areas; meaning that when the urban footprint products indicated the areas were non-built-up areas, the urban area map indicated that they were urban areas instead; the reverse was true for the areas in red colour; the black areas however indicated a perfect match during. This map was produced after raster layer calculation.

There were also four pairs of areas which were in the same position for both maps; first were the areas in the green circle representing cultural land use function-this was also defined as urban area under section 3.3.1. The cultural land consisted of palaces and royal tombs, however, both products detected this areas as non-built-up covered by vegetation and bare soils, therefore in this case, both products were a perfect match (figure 51 (a)). The second pair were the areas in the orange circle; the area on the land use map is used for agriculture, residential and construction functions; however the corresponding image as shown by figure 51 (b) contains vegetation, bare soil and scattered houses. The third pair were areas in the red circle; which represented residential function (low building density), and mixed uses (agriculture and residential), on the image shows that these areas contain roads and low density buildings surrounded by vegetation (figure 51 (c)). The fourth pair, represented by the blue circle show heavy industries and civic industries on the land use map, however, its corresponding image contains roads, low density buildings and some green spaces (figure 51 (d)).

Figure 50 (left) also shows three groups of concentration differences (up, middle and down); the corresponding areas on the image are shown in figure 52, these areas are largely characterized by large vegetation, bare soils and low density of buildings; even though the main land use functions in this areas based on the land use map are residential and transportation. This implies that UFC data is better at detecting thematic land cover classes such as buildings, streets, bare soil, grassland forest and water, rather than land use functions.

Therefore, as shown by the preceding discussion, both products can be used to detect vegetation and bare soil relatively well as compared to land use functions. Sparse building could not also be detected by both products, but were instead shown as vegetation cover or bare soil. At the same time, as shown by figure 50 (right), there are very few red areas and relatively many yellow areas; it can therefore be concluded that the UFC is better at describing environmental, open space and agricultural land use functions than other land use types. Based on comparison with the land use map and image mosaic, it can also be concluded that UFC is better at describing land cover than land use. GHSL on the other hand could be used to detect differences between urban and non-urban areas over the years for urban planning management.

(a) (b) (c) (d)

Figure 51 Images shown for the areas which the urban map and urban products are not matched

(a)

(b)

(c)

Figure 52 Images showing conflict areas between the urban map and the UFC (a-up, b-middle, and c-down)

4.7.2. Urban densification analysis

Table 33 below shows the results of urban densification analysis; that italic values mean that the products were beyond their specified range that had been set before. Only one value in the GHSL was outside the scope; however for the UFC there were four values beyond the limits. This situation could be due to three reasons: (1) the randomly selected areas may have perform better for the GHSL, while the others areas may have perform better for the UFC; (2) the GHSL had a ranging value from 0 to 255, while UFC contained only two values- therefore calculation for the two products may lead to different values; (3) the built-up area for the GHSL mainly contained buildings, while that of UFC contained all man-made structures with a vertical dimension. However, comparison of the densification levels of the residential areas, which was done through average building density in each polygon were a good match for the two products (shown in table 33 column 3).

Table 33 Density information of the GHSL (number of average values in each polygon) and the UFC (percentage of built-up pixels in each polygon), the building means the percentage of buildings in each polygon

	Reference (densification level)	Building (0~100%)	GHSL (0~100)	UFC (0~100%)
1	Low (polygon)	19	26	25
2	Low(polygon)	23	28	24
3	Low(polygon)	24	24	***43***
4	Middle(polygon)	58	67	***25***
5	Middle(polygon)	69	***88***	*81*
6	Middle(polygon)	70	62	60
7	High(polygon)	85	80	81
8	High(polygon)	89	90	93
9	High (polygon)	83	97	***55***

The residential land occupied a large area in the study area; as seen from the results where the densification levels compared with both products. The densification levels in the residential land were based on the building density (definition of the GHSL) rather than buildings plus other elevated structures (definition of the UFC), thus the GHSL is better for urban densification analysis.

5. CONCLUSIONS AND RECOMMENDATIONS

5.1. Introduction

Conclusions are structured as per the research objectives of this research. Specific conclusions are given per sub-objective so as to respond to the formulated research questions. This is followed by recommendations and indications of future research direction.

5.2. Conclusion

5.2.1. Specific conclusions and key findings

Sub-objective-1: To develop an assessment method to determine the quality of the urban footprint products.

In order to prepare for the accuracy assessment process, the quality of the reference data was checked. Firstly, the GCP showed a high accuracy, there were 270 points in total, only three of them were wrongly located on the image. Then the building polygons and the road networks were checked by RMSE calculation, and topographic checking in ArcGIS. Since the RMSE measured the positional accuracy, the building polygons (RMSE=0.0475332) performed better than the roads (RMSE=0.120294). Topographic checking of the buildings showed that more than ten thousand of the polygons had errors out of the 252,252 polygons indicating poor data quality. Therefore this study recommends that KCCA needs to better focus on the quality control of datasets.

The approach used to compare the reference data with the two products were not done directly. An error matrix table was generated to compare the two products with the GCP and the topographic data also converted to points to test the overall accuracy. Both GHSL and UFC showed similar results after comparing with both groups of reference data; even though, the comparison with topographic data showed poor results for both products. This may be due to the fact that the definitions of built up area for both products differed; for GHSL, only buildings represented the built-up area, whereas for UFC, buildings and other man-made structures with an elevation represented the built-up areas, some of the roads located near the building concentration areas and with moving cars on them are more likely to be detected as built-up areas for UFC.

A statistically comparison was also made for both products with the topographic data (buildings and buildings plus roads as reference data) in order to check which type of reference data performed better for the two products. The results shown by the scatter plots and the chi-square tables indicated that the GHSL was better described by the digital building polygons and the UFC was better described by the buildings plus roads together. This can be explained by the definition of both products, the built-up area described by the GHSL is any given area or geographical space where buildings can be found. For the UFC the built-up area is described by buildings and other structures that have an elevation. Roads could be elevated structures but not all types of roads in Kampala had an elevation; this could explain why there were some wrongly classified areas.

It cannot be simply said which products showed a better accuracy, it can only be concluded that comparing with different types of reference data showed different accuracy.

Sub-objective-2: To identify possible factors affecting the quality of the two products and assess the extent to which the quality of the two products are affected by such factors.

Several factors were tested to check whether they affected the quality of the products; this included buildings, roads, vegetation, wetlands, slopes and aspect (only for radar data (UFC)). A series of wrongly classified points were identified by comparing the two products with the GCP, and this may have a big influence on the quality of these products. Checking the exact features of such factors is recommended for a future study.

By generating some certain clusters of areas that were wrongly classified, it was found that for GHSL, areas covered by low buildings density and were surrounded by tall vegetation were easily wrongly classified, as well as buildings with irregular sizes and shapes. UFC, on the other hand was not good at detecting high buildings density areas, big roads and shared boundaries-most areas next to a shared boundary were wrongly classified. High slope influenced the quality of GHSL more than UFC; this was depicted by qualitatively calculation. Aspect on the other hand did not affect the accuracy of the UFC. In conclusion, it was found that all these wrongly classified data affects the quality of the two products. Both products performed relatively well in highly vegetated areas and extremely high built-up density.

Sub-objective-3: To reflect on the suitability of urban footprint products for urban planning applications.

Suitability of urban footprints products for urban planning applications was tested by comparison with Kampala urban area map (2012) and urban densification analysis. Comparison with urban area map was to show how good the two products can be used to describe a land use map. From this study, conversion of the land use map into a binary map with urban and non-urban areas using raster calculator, was done better using GHSL than UFC. A further analysis could identify the various types of land uses such as high density residential and commercial areas, open spaces, environment, and agriculture land; which both products defined well. However, for lower density residential areas UFC performed better at describing land covers, than the land use functions.

For urban densification analysis, three levels (based on buildings density) of residential areas, and the building polygons were used to test with the two products; this was done by calculating the percentage of buildings that matched well in each density level. Thus the residential density level can be described by the building density level. By calculating the average value of built-up and the percentage of built-up area in each density level, GHSL performed better than UFC. This could be due to the fact that GHSL represents the 'influence' zones of buildings as well. Even though this was tested with residential buildings densities, it would be difficult to say for other land use types.

5.2.2. General conclusions

This study was successfully in assessing the quality of urban footprint products by comparing them with the available reference data sets, as well as structuring of possible factors that may affect the accuracy of the urban footprint products. Based on the data information and available data source, it is possible to apply in urban planning applications such as urban densification analysis and mapping land use and land cover analysis.

- Based on the accuracy assessment with the ground truth reference points obtained from Abebe (2013) and Vermeireren et al. (2012), a high overall accuracy for both products was obtained: 82.19% (GHSL) and 84.25% (UFC). With the location of the wrongly classified reference points, the factors affecting data quality could be identified, except for the data features.
- Secondly, based on the accuracy assessment with the topographic reference data, by converting the topographic data into a series of random selection points, the overall accuracies are 77.50 % (GHSL) and 76.75 % (UFC). The decreased accuracy could have resulted from possible data processing problems and mistakes that could have emerged from random selection. Most importantly, the definition of the GHSL and the UFC and their relative reference did not completely match.
- By comparing with GCP, only a small portion of points was used to structure possible factors that resulted to the wrongly classified areas. However, for the purpose of identifying specific areas with errors, there is need to compare the target layers and the reference data sets on pixel by pixel basis. For the GHSL which is a continuous data with ranging values, the analysis of areas with errors was generated by the hotspot areas (concentration of largest differences), while for the UFC it was directly acquired by a raster calculation process. The accuracy of both footprint products strongly depends on the urban pattern.
- The result of this study is an added value for reinforcing the accuracy of urban footprints products in the future and for detecting what type of areas brings about errors.
- Based on the available data and spatial analysis of both urban footprint products, the GHSL is better for analysing urban densification, while UFC functions better at indicating the physical land type (land cover).

5.3. Future research directions

For future improvement of the findings of this study, some of the recommendations are listed below:

- To this end, this study assessed the quality of the GHSL and the UFC on the basis of comparing these products with various sources of reference data for Kampala city, and structuring possible factors that may affect their accuracy. However, due to the limitation of reference data sets and some missing values occurring for the urban footprint products, only a portion of Kampala was represented in this study. Therefore, a further research could incorporate the remaining areas of the city.
- The factors influencing the quality of the wrongly classified areas mainly depended on image mosaic and the value of slope and aspect, there were however some errors that could not be explained. Future studies could attempt to find more factors that may have influence on the accuracy of radar data and optical data to further boost the quality of these products.
- Owing to the limitation of data information and lacing of enough reference data, description of land use maps and urban densification analysis were the only urban planning applications considered in this research. It is known that remote sensing data can also be used in other aspects of urban planning applications such as monitoring urban growth, urban infrastructure and utility mapping, traffic management among others. It would be useful to consider more urban planning applications in future studies.

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