SPATIO-TEMPORAL SLUM MAPPING AT CITYWIDE SCALE USING HIGH-RESOLUTION IMAGES

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ABSTRACT

Rapid urbanisation in low-and middle-income countries has led to the proliferation of slums, with over 60% of the urban population living in deprived areas. Whiles remote sensing promise a sustainable source of information on slums, methods for citywide slum maps remains uncertain, and only few studies have focused on the spatio-temporal dynamics of slums. Moreover, the remote sensing community does not sufficiently understand the spatial information required of end-users. This study presents a processing chain for spatio-temporal slum mapping at a citywide scale using low-cost SPOT 6 image using Accra, Ghana as a case study. The processing chain relies on free and open software for geospatial (FOSS4G) solutions. Our research comprises of three parts: understanding the spatial information requirements of end-users, understanding ethical concerns of slum maps, citywide land-use mapping at street-block level, with the focus on slums, and change detection and analysis of uncertainties. We found out that the required spatial information and its level of details vary depending on the purpose of the institution. Interviewed experts agreed to make slum information publicly available. However, they raised geo-ethical issues that map producers need to address. Using the random forest (RF) classifier, land-use maps achieved high overall accuracy of over 80%. We applied class probability membership obtained from RF to identity uncertain street-blocks and further investigated the causes of uncertainties on grounds. The study identified three main causes including similar morphological characteristics of slums and old towns, areas with slum-like appearance due to unplanned and uncontrolled extension and slum areas which have been regularised. Post-classification change detection was applied to analyse spatio-temporal dynamics between 2013 and 2017 at the street-block level. we revealed that land-use change is stable is Accra with over 90% of the area remaining unchanged. Slums appeared on vacant lands or in kiosk estates whereas slums in floodable zones disappeared. Finally, we exploited the trajectory error metrics to assess the accuracy of change detection. Change detection accuracy using trajectory error metrics improve from 53% to 67% when uncertain street-blocks were removed. The proposed framework offers a way to map slums at a citywide scale with high accuracy to support pro-poor initiatives and produced the needed information required by end-users.

Keywords: slum, change detection, geo-ethics, spatial information requirement, street-blocks

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"Believe you can and you're half way there"-Theodore Roosevelt

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LIST OF ABBREVIATIONS

CNN	Convolutional neural networks
DOP	Department of Planning
EO	Earth Observation
ERP	Equivalent reference probability
ESA	European Space Agency
FCN	Fully convolutional network
LUSPA	Land use and Spatial Planning Authority
NADMO	National Disaster Management Organisation
NDVI	Normalised Difference Vegetation Index
NGO	Non-Governmental Organisation
NIR	Near-infrared
OBIA	Object-based image analysis
PD	People's Dialogue
PPD	Physical Planning Department
PWD	Public Work Department
RF	Random forest
RS	Remote sensing
SMAP	Sequential Maximum a Posteriori
SVM	Support vector machine
TDC	Tema Development Company
UAV	Unmanned aerial vehicle
USPO	Unsupervised segmentation parameter optimisation
VHR	Very high resolution
VSURF	Variable selection using random forest

1. INTRODUCTION

1.1. Background and justification

Most low-and middle-income countries are experiencing rapid urban transition and are facing an unprecedented growth of slum-like communities (UN-Habitat, 2015). These are seen in areas of poor housing condition, poor environmental quality, lack of social services and infrastructure (UN-Habitat, 2016). UN-Habitat (2003) defines a slum as any specific place where half or more of all households lack better-quality water, improved sanitation, sufficient living area, durable housing, and secure tenure. Unfortunately, credible and up-to-date spatial information about their existence and dynamics required to support decision making is not readily available (Mahabir, Crooks, Croitoru, & Agouris, 2016).

Slum mapping is essential for a wide range of user groups including policymakers, planners, slum dwellers and international organisation such as UN-Habitat and Slum Dweller International (SDI). These information helps identify and monitor slum growth to know where to intervene (Duque, Patino, & Betancourt, 2017). It is also vital for United Nations agencies seeking to alleviate poverty under the Sustainable Development Goals (SDGs) as well as monitor the progress of implementing these development goals (UN-Habitat, 2016). Furthermore, it is useful for local governments seeking to improve slum conditions. However, slum mapping is a difficult task. Mapping slums from grounds is time and resource-intensive and when mapped from space requires expert knowledge and its computational costly (Leonita, Kuffer, Sliuzas, & Persello, 2018). The problem is even more complicated as there is no agreed area-level definition of slum (Lilford et al., 2019), no agreement on methods (Kuffer et al., 2020) and end-user requirements are not well understood by map producers (Kuffer et al., 2018). These conceptual ambiguity and complexities contribute to 'why' most slums are not mapped.

Lilford et al. (2019) identified three broad sources of data to study and map slum, namely, household survey, ground surveys of features in an area, and remote sensing (RS) imagery. Traditionally, information on slum conditions is derived mainly from socioeconomic indicators using census data. These sources of data are expensive, time-consuming, low temporal coverage, often published at a very aggregated level and omit areas with no physical accessibility (Duque, Patino, Ruiz, & Pardo-Pascual, 2015). They provide a partial view of slums, such as ignoring the spatial intra-urban variability of the slums (Ajami, Kuffer, Persello, & Pfeffer, 2019). They are further affected by issues including ecological fallacy (Martínez, Pfeffer, & Baud, 2016), aggregation bias (Paelinck, 2000) and modifiable area unit problem (Vogel, 2016). Recent studies show that RS offers several advantages over other methods, including objectiveness, low cost and global coverage (Leonita et al., 2018). It can capture different physical characteristics and high temporal resolution (Mahabir et al., 2016; Kuffer et al., 2016). It is faster and offers the opportunity to measure the spatial heterogeneity of urban poverty at any scale. However, they usually ignore the socioeconomic aspect of slum characteristics (Lilford et al., 2019).

Slum mapping using RS focus on the location of slum, characteristics of slum and temporal changes of slum (Kuffer, Pfeffer, & Sliuzas, 2016). Despite the importance of spatio-temporal slum mapping including monitoring of upgrading projects and assessing the performance of urban management policies (e.g. climate change risk, natural hazards, and health), only a few studies have focused on them. One of the main reasons is the limited availability of temporal images and the difficulty in producing high accuracy change detection results (Pratomo, Kuffer, Kohli, & Martinez, 2018). If temporal analysis is applied, it is done on a very small area due to the complex spatial pattern of slums or high cost of Very High Resolution (VHR) images (around 25 euros/km² of image from Digital Globe). Another issue relates to the transferability of temporal mapping methods. In this context, transferability means the capability of a method to provide generic functionality for spatiotemporal slum mapping with limited adaptation (Kohli, Warwadekar, Kerle, Sliuzas, & Stein, 2013).

With the availability of VHR images and advancement in earth observation (EO) methods such as object-based image analysis (OBIA), support vector machines (SVM), random forest (RF), and convolutional neural networks (CNN), it is now possible to use cost-effective solutions to map the growth of slums at a fine level of spatial details (Kuffer et al., 2020; Leonita et al., 2018). However, there is no conclusion in literature about the best method for spatio-temporal slum mapping (Kuffer et al., 2020). Rule-based OBIA and Fully Convolutional Networks (FCN) showed limitations in mapping change trajectories due to the uncertainty of slum boundaries (Liu & Kuffer, 2019; Pratomo et al., 2018). These limitations will increase when applied at a citywide scale. Therefore, this study proposed a semi-automated approach to map slums at a citywide scale, which is sparsely researched. Consequently, it uses the results for change detection to analyse slum dynamics and spatial patterns. This provides useful information for policymakers and urban planners.

1.2. Research problem

Contemporarily, there has been an increase in EO-based methods for slum mapping (Mahabir, Croitoru, Crooks, Agouris, & Stefanidis, 2018). However, several challenges still exist. These challenges include scalability (most studies focus on small areas but not citywide scale), transferability, integration of context knowledge, aggregation scale, geo-ethics, temporal analysis and uncertainties of mapping results (Kuffer et al., 2020). Moreover, RS community does not sufficiently understand the spatial data required by potential users and the geo-ethical concerns in making slum information publicly available (Gevaert, Kohli, & Kuffer, 2019; Leonita et al., 2018).

Most often, researchers limit their study to slum areas only or very small area (Duque et al., 2017; Kohli, Stein, & Sliuzas, 2016). Citywide slum mapping is needed for effective planning and management. Slums are connected to their surroundings and should be seen as a component of the general mapping process (Sliuzas, Kuffer, Gevaert, & Pfeffer, 2017). Most studies have focused on proof-of-concept rather than providing usable data for different stakeholders (Duque et al., 2017; Liu & Kuffer, 2019). Methods for large scale applications remain uncertain due to several factors such as the complexities of urban environment (Ma et al., 2017). For instance, Grippa, Georganos, Vanhuysse, Lennert, & Wolff, (2017) demonstrated that using the same optimised segmentation parameter on a small area underperforms when applied on a large area due to heterogenous of urban environment. Therefore, there is the need for a general, scalable, and efficient state-of-the-art method to better analyse the growth of slums at a citywide scale. This will also help identify slums dynamics or slum-like conditions that exist but have not been documented.

Most slum mapping studies use VHR or unmanned aerial vehicle (UAV) images (Kuffer, Pfeffer, & Sliuzas, 2016; Kuffer et al., 2020). Although these images have the capability to map detailed spatial information, they are costly (price ranging from 15 to 40 euros/km²) and computational-intensive, especially for large scale mapping. Therefore, many cities in developing countries cannot afford such images. Additionally, Wang, Kuffer, & Pfeffer (2019) showed that VHR might not be required when mapping settlement boundaries as they can reduce classification accuracy due to the excessive object-level complexities. Thus, high data cost, high complexity and high computational costs prevent optimal usability of VHR data at city scale. However, low-cost images such as SPOT 6 (1.5m resolution) or the freely available Sentinel-2 (10m resolution) images which can be an alternative are under-researched. These images are cost and computationally efficient as compared to VHR images. Furthermore, one scene covers large areas making it suitable for large-scale application than VHR images.

This research focuses on spatio-temporal slum mapping at a citywide scale using Accra, the capital of Ghana, as a case study. The official slum dataset is highly fragmented, outdated and inconsistent due to the participatory mapping approached used to collect it (AMA, 2011). This approach is costly, time and effort-intensive and has limitations for large area mapping and monitoring (Leonita et al., 2018). Furthermore, no data is available outside the inner city of Accra. Therefore, this study proposes the utilisation of low-cost SPOT 6 images to analyse slum dynamics at a citywide scale. In this context, low-cost is defined as the relatively inexpensive (SPOT 6 cost 3.60 euros/km^2 and Pleides (0.5m resolution) cost 12.50 euros/km^2 (Airbus, 2019)) and less computational cost (processing power) of SPOT 6 images compared to very high-resolution images. Comparatively, SPOT platform has more historical data (data archive has image since 1986) than sentinel-2, which was recently launched in 2015. Also, the opportunity to apply for SPOT 6 images through the European Space Agency (ESA) third party grant (providing images for research purposes free of charge) contributed to the decision of using SPOT 6 images. In addition, Wang et al. (2019) study concluded that the optimal resolution for separating slum from non-slum is around 2 meters. Similarly, Engstrom et al. (2015) used 2.4m spatial resolution image to successfully map slums in Accra. This study proposes a semi-automated method for spatio-temporal slum mapping using Free and Open Source Software for Geospatial (FOSS4G) solutions. These solutions are relevant for developing countries which have limited funds, and their rapid pace of urbanisation requires frequent slum map updating. The developed processing chain may be reused, adapted or improved in other areas. The outcome will serve as the basis for long term pro-poor development plans, allocation of social service, and disaster response.

1.3. Research objectives

The main objective is to develop a processing chain for spatio-temporal slum mapping at a citywide scale using low-cost SPOT 6 image and free & open-source software. In this context, processing chain means the compilation of methods with generic functionality for many domain application and requires limited adaptation for different case studies. This objective allows analysing slum dynamics at a citywide scale. Specifically, the study aims to achieve the following objectives;

To identify slum information required by end-users and geo-ethical concerns in making such data publicly available

1. What is the spatial information required by different user groups?

2. What are the ethical issues concerning making slum data publicly available?

To develop a semi-automated method for slum mapping at a citywide scale

1. What are the morphological characteristics of slums and non-slums in Accra?

2. Which strategy is best for classification at a citywide scale?

3. Which aggregation scale is appropriate for citywide slum mapping?

4. Which image features can be generalised for spatio-temporal slum mapping?

5. What are the causes of uncertainties in the proposed method?

To analyse the spatio-temporal dynamics of slums at a citywide scale

1. Which method is appropriate for slum change detection at a citywide scale?
2. How to assess the accuracy of change detection?
3. What are the differences when uncertainties are integrated into change detection?
4. What kind of spatial change patterns can be extracted from slum maps?

1.4. Thesis structure

This thesis consists of seven chapters. Chapter one presents a brief research background, justification, research problem, objectives and outline of the thesis. Chapter two provides a review of spatio-temporal slum mapping at a citywide scale. It discusses current challenges for citywide slum mapping, including scalability and level of aggregation. It further provides an overview of change detection methods and how to assess land change accuracy. Chapter three briefly describes the profile of the study area, including characteristics of slums and residential densities in Accra. It also describes data and software used for this research. Chapter four describes the methodology of the research. It demonstrates the methodological workflows used for the study from fieldwork to change detection and spatio-temporal analysis. The results of the study are presented in chapter five. It describes the main findings to each research objectives and questions. Chapter six deal with the discussion of the main findings. In chapter seven, we conclude and outline recommendations and future directions to improve spatio-temporal slum mapping further using RS.

2. LITERATURE REVIEW

This chapter gives a review of spatio-temporal slum mapping at a citywide scale. It provides a review of the concept of EO-based methods for slum mapping. It further describes the main opportunities and limitations for citywide slum mapping. Lastly, it provides a concise review of change detection methods and how to assess land change accuracies.

2.1. Conceptualising slums from remote sensing

The problem with slum mapping begins with the fuzziness on the definition of a slum. In general, the term "slum" is often used for marginalised groups usually in deprived areas. For example, Favela in Rio de Janeiro, Kachi Abadi in Karachi, Zongo in Ghana. UN-habitat definition of slum households is widely accepted. According to this definition, any household which lacks any one of the following indicators as considered as slum household: better-quality water, improved sanitation, sufficient living area, durable housing, and secure tenure (UN-Habitat, 2003). However, this definition fails to capture important area-based risk associated with living in deprived areas. For example, flood zones, crime, and lack of infrastructure such as roads, schools, health facilities. Also, the UN-habitat definition can overestimate deprived areas in some cities. For example, almost the entire city of Accra was classified as slum (Weeks, Hill, Stow, Getis, & Fugate, 2007).

Area-based slum definitions have received much attention in recent years (Lilford et al., 2019). The definition used morphological features such as building density, size, height, organic settlement pattern, and lack of infrastructure to define and identify slums (Kuffer, Barros, & Sliuzas, 2014; Taubenböck & Kraff, 2014). However, there is no universally accepted area-based definition. Several efforts have been made to define slums including expert meetings (Sliuzas, Mboup, & Sherbinin, 2008), operational definitions and developing frameworks (Lilford et al., 2019; Mahabir et al., 2018). This conceptual ambiguity is due to high diversity and dynamics of slums characteristics (e.g. building materials) within the same city or across the world. Despite these diversities, slum areas have some common characteristics such as high population densities, and usually organic settlement patterns (Kohli, Sliuzas, Kerle, & Stein, 2012).

Weeks et al. (2007) showed that the concept of slum links with multiple deprivations associated with a neighbourhood. In the same way, Kohli, Sliuzas, & Stein (2016) defined slum as areas of sub-standard housing conditions and poor environmental conditions. In EO-based methods, it has been believed that "if you see a slum, you will know it". This notion expresses the idea that slum has unique morphological characteristics such as building size, and building density from non-slum areas. Based on this notion, Kohli et al. (2012) developed a generic slum ontological (GSO) framework to conceptualised slums from VHR images. GSO consist of environ, settlement and object-level to map the morphology of slums. However, a recent study shows that slum characteristics are context-dependent (Duque et al., 2017). Therefore, its operational definition of mapping should be clear.

Unfortunately, most studies failed to provide an operational definition of slum (Kuffer, Pfeffer, & Sliuzas, 2016). In this study, the purpose is to develop a method that is consistent over time and fits local context so that slum growth can be monitored. Hence, slums are operationalised using the ontology proposed by

Kohli et al., (2012) and integrated with local context knowledge, including typology and stage of slum growth. Slums are defined as a concept of place with slum characteristics such as high building densities, irregular settlement patterns, and no or small roads.

2.2. Scalability of methods

Recent studies have employed landscape metrics (Liu, Huang, Wen, & Li, 2017), texture and OBIA (Hofmann & Bekkarnayeva, 2017), machine learning coupled with contextual features (Duque et al., 2017; Engstrom et al., 2015), and deep learning to map slums (Liu et al., 2019; Mboga, Persello, Bergado, & Stein, 2017). Other studies have combined OBIA and machine learning (Grippa et al., 2018). Despite these numerous studies, there is no conclusion or general agreement on the best method suitable for detecting and delineating slums (Kuffer et al., 2020; Thomson et al., 2020). For example, Mboga et al., (2019) applied FCN method for detecting slums. Leonita et al., (2018) implemented RF and SVM learning classifiers for detecting slums in Bandung, Indonesia. Grippa, Lennert, Georganos, & Mboga, (2019) combined OBIA and machine learning for land-use mapping and estimating population. Although they achieved high classification accuracy, most of these studies relied on very high-resolution images (0.3-0.5m resolution). Additionally, most machine learning studies have been proof-of-concept, usually covering a small area within the city. The urban environment is highly heterogeneous, which may affect existing methods. For example, Leonita et al., (2018) approach achieved high accuracy on a small scene but underperformed when applied on a larger area. Also, Ajami et al., (2019) have shown that slums have large intra-urban variation within a single city which can affect citywide slum mapping. Further problem for mapping slums refer to distinguishing characteristics of slums and inadequate reference data covering all the different appearance of slums affects existing methods (Pratomo, Kuffer, Martinez, & Kohli, 2017). Therefore, there is the need for a scalable and efficient methodological framework (Kuffer et al., 2020).

One major concern when mapping at a citywide scale is the choice of the sensors. Most slum mapping studies use VHR or UAV images. UAV images with a resolution of 3-5cm allow mapping at object-level (e.g. building outlines) and accurate estimation of roof areas (Sliuzas et al., 2017). Similarly, VHR images with resolution up to 0.3m can provide detailed characteristics of slums. However, such images are expensive and difficult to acquire at a citywide scale. Little attention has been paid to free of charge Sentinel (Wurm, Weigand, Schmitt, Gei, & Taubenbock, 2017) or low-cost SPOT 6 images when mapping slums. Such data can be suitable for slum mapping at a settlement scale. Comparatively, they are computational more efficient than VHR or UAV images.

2.3. Level of aggregation

In an urban environment, slums can be mapped at different scales, ranging from pixels to administrative boundary depending on the purpose of the study. Moreover, the differences in spatial resolution potentially affect EO-based methods (Sliuzas et al., 2017). According to the existing literature, pixel scale, segment (object level), administrative boundary, grid and street-blocks are the commonly used mapping units (Figure 2.1) (Engstrom, Ofiesh, Rain, Jewell, & Weeks, 2013; Kuffer, Pfeffer, Sliuzas, & Baud, 2016; Stow, Lippitt, & Weeks, 2013).

The pixel is a popular mapping unit. However, studies have shown that it is not the appropriate mapping unit when using VHR images (Blaschke, 2010; Blaschke et al., 2014). It is affected by noise known as salt and pepper effects (Wang et al., 2019). Also, policy and decision-making are usually performed at the wards, block, or neighbourhood level making them not useful for policy-relevant information. Furthermore, object-level segments have the ability to create homogenous neighbourhood which could be suitable for aggregation (Kuffer, Pfeffer, Sliuzas, et al., 2016). However, aside from it been challenging to obtain good segments, they have in particular limitation for change detection studies. They produce a lot of false object changes because of uncertainties or differences in segment boundaries for different years. Administrative boundaries are often large aggregated mapping unit that is likely to contain a mix of slum and non-slums area. This means that pockets of slums are likely to be omitted or not captured, and it hides the spatial differences within units (Kuffer et al., 2018). The grid-scale could be an appropriate mapping unit. It is easy to create and provides sufficient spatial details. In terms of temporal analysis, the grid-scale promises a fixed boundary and prevent noise (Thomson et al., 2020; Thomson, Stevens, Ruktanonchai, Tatem, & Castro, 2017). However, they do not follow the general urban structure or morphology. Street-blocks or city-blocks is said to be the most appropriate mapping unit (Bochow, Taubenbock, Segl, & Kaufmann, 2010). It provides adequate spatial details and follows the urban structure (Grippa et al., 2018). However, official street-blocks data from city authorities are not readily available, especially in data-scares regions. Even if available, they suffer from inconsistency and incompleteness, especially at the peri-urban areas. The availability of OpenStreetMap (OSM) data can be used to create street-blocks.

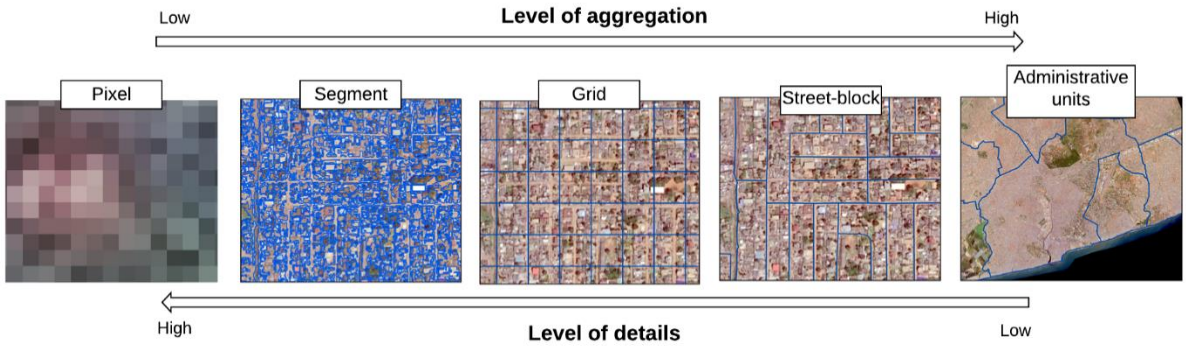


Figure 2.1 Different levels of aggregation.

2.4. Change detection

Spatial dynamics and patterns of slums can be understood through change detection methods. Change detection is the process of identifying changes in spatial patterns using two or more images of the same area but different times (Hussain, Chen, Cheng, Wei, & Stanley, 2013). This helps to measure changes over time quantitatively. Over the years, several change detection techniques have been developed. Tewkesbury, Comber, Tate, Lamb, & Fisher, (2015) identified six types of change detection, namely: layer arithmetic, post-classification change, direct classification, transformation, change vector analysis, and hybrid change detection. From literature, post-classification change detection is seen as the best technique for this study (Hofmann & Bekkarnayeva, 2017; Li & Zhou, 2009; Macleod & Congalton, 1998). Furthermore, post-classification change detection is commonly used in slum mapping studies (Kit & Lüdeke, 2013; Badmos, Rienow, Callo-Concha, Greve, & Jürgens, 2018; Pratomo et al., 2018) and its less sensitive to radiometric variation in different images.

Post classification is a quantitative change detection technique that provides detailed change matrix (from-to change) information. It compares two or more individual classified images for detailed change analysis (map to map change detection) (Tewkesbury et al., 2015). It has the advantage of knowing the change transition explicitly. Post-classification change detection allows identifying specific changes at the object level (e.g. buildings) or area level (e.g. Slums) changes (Pratomo et al., 2018; Teo & Shih, 2013). This indicates that post-classification change detection allows answering specific change question in context. However, the accuracy of post-classification change detection depends on the quality of the classified maps. It has the disadvantage of compounding error from the individual classified maps (Teo & Shih, 2013). Therefore, the input classified maps should be of high quality to reduce the effect of this problem.

Several frameworks for analysis of change detection have been developed. These have been categorised into pixel-based and object-based unit of analysis (Chen, Hay, Carvalho, & Wulder, 2012; Hussain et al., 2013). The classical pixels-based approaches use pixels as the fundamental unit of analysis without considering the spatial context, whereas object-based approaches create image objects and use for analysis.

2.4.1. Pixel-based and object-based change detection

The pixel-based is the traditional approach where spectral characteristics are used to detect changes. It compares pixel to pixel to detection changes. However, it is not suitable for VHR images due to issues of high within-class and low-between-class variance in such images (Volpi, Tuia, Bovolo, Kanevski, & Bruzzone, 2012). The large variability results in too many changes being detected known as "salt and pepper" therefore decreasing the overall accuracy of pixel-based change detection approaches (Hussain et al., 2013). It also does not consider the spatial context that is the spatial arrangement of real-world objects, and their relationships are not modelled and analysed (Tewkesbury et al., 2015).

Object-based change detection creates image objects and uses them for change detection. It considers the spatial context (e.g. shape and size) of objects which is similar to the human analyst who focuses on objects in images rather than pixels (Blaschke et al., 2014; Hussain et al., 2013). This approach is suitable for VHR images (Hofmann & Bekkarnayeva, 2017). However, object-based change detection is affected by high uncertainties of object boundaries. A study has shown that the level of uncertainty increase towards the boundary (Kinkeldey, 2014). This problem will worsen as slum boundary plays an important role. For example, Liu & Kuffer, (2019) and Pratomo et al., (2018) raised the issues of uncertain boundaries that affected the change detection accuracy.

One challenge with change detection is how to define change. Object-based change detection inevitably generates sliver polygons when objects are individually mapped and compared (post-classification change detection). They may arise as a result of image misregistration or inconsistent segmentation due to variation in weather, sun angle, cloud coverage (Chen et al., 2012).

2.4.2. Change detection accuracy assessment

Methods to validate the changes are often lacking. The commonly used methods for change detection accuracy is the traditional error-matrix and kappa coefficient (Macleod & Congalton, 1998). However, they are developed for thematic single-date classification and not suitable for temporal change detection task. Yuan, Elvidage, & Lunetta (1999) proposed the multiplication aggregation method using accuracy from individual classification. However, it ignores the correlation between individual classification layers.

The change detection matrix was proposed by Macleod & Congalton, (1998). It is a modification of the single-date classification accuracy for change detection. Other methods, including area-based accuracy assessment (Lowell, 2001), trajectory error matrix (Li & Zhou, 2009) and rule-based rationality evaluation

(Liu & Zhou, 2004) have been proposed. Up-to-date, there are no agreed-upon methods for assessing the accuracy of change detection models.

Furthermore, obtaining reference data for accuracy assessment remains a challenge. Most studies used point-based reference data for checking change accuracy (Liu & Kuffer, 2019; Pratomo et al., 2018). Although it is easy to generate point reference data, it underestimates object-based map accuracy and does not consider contextual information (Chen et al., 2012). Also, point-based methods require an excessive number of points to provide good estimates. However, area-based reference data considers spatial and contextual information when generating the reference (Lowell, 2001).

2.5. Conceptual framework

The growth of slums is one of the challenges most of the low-and middle-income countries face today (UN-HABITAT, 2011). Unfortunately, there is little information about their existence and dynamics. Although RS promises a sustainable source of information on slums and their dynamics, they face different challenges, including scalability and transferability. This affects spatio-temporal analysis to understand slum dynamics and spatial patterns. However, advancement in EO methods can be used to address these challenges. Figure 2.2 shows the conceptual framework of the study. Figure 2.1 shows that the challenges of slum mapping at a citywide scale includes uncertainties, transferability, scalable methods, and local context knowledge. Other challenges, such as data and user requirements relate to spatial data and level of details required by end-users. This helps to provide data required by end-users. When these challenges are overcome, change detection can be performed. Consequently, slum dynamics and patterns can be analysed.

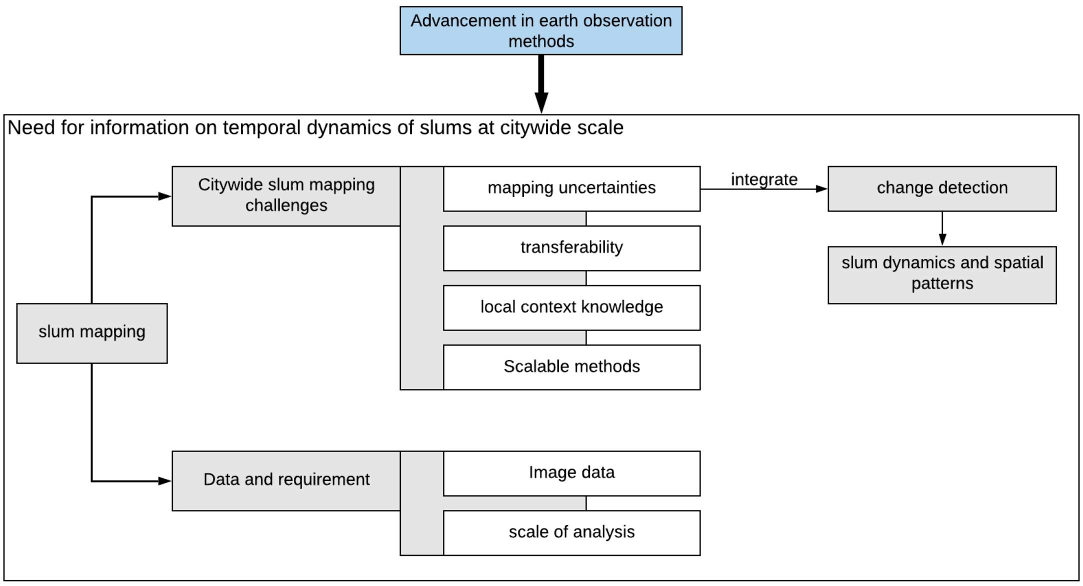


Figure 2.2 Conceptual framework.

3. STUDY AREA AND DATA DESCRIPTION

This chapter presents the profile of the study area. It further describes the raw data and software used in this study. Lastly, it describes the characteristics of slums and residential densities in Accra.

3.1. Study area, data and software

The study area is Accra, the capital city of Ghana situated along the Gulf of Guinea of West Africa. Figure 3.1 shows the study area. According to the 2010 census, it is a highly dynamic coastal city with more than 4 million inhabitants (Ghana Statistical Service, 2010). About 18% of the total population of Ghana live in Accra. The historical effects, including race-based town planning, military cantonments, and migrant communities of the city has contributed to high inequality (Agyei-Mensah & Owusu, 2010). Also, rapid urbanisation in the city has resulted in increasing housing deficit and inadequate socioeconomic facilities such as education, health, sanitation, and utilities leading to the proliferation of slums (AMA, 2011). The city has diverse population groups. For example, in-migrant neighbourhoods. In 2010, 34% of residents in Accra lived in slums. The core city has a total land size of 173.2 km^2, with slum dwellers occupying 15.7% of the total land area. In 2016, 265 slums were identified within the 10 sub-metros of Accra Metropolitan Assembly (AMA) using participatory rapid appraisal tool (People's Dialogue, 2016). Additionally, the 2014 cholera outbreak casualties occurred mostly in deprived neighbourhoods such as Old Fadama, Usher town and Mpoase (Arku, 2015).

Accra was selected because to the best of our knowledge, no slum mapping beyond AMA administrative boundary has been done. The largest area of interest (AOI) on slum mapping was 243 km^2 (see figure 3.1 blue boundary), which covers only AMA catchment area (Engstrom et al., 2015). However, Accra has sprawled to cover Kasoa, in the central region and some part of Eastern region (Nasawan, Berekuso and Aburi). Therefore, to capture the diversity of economic activities and urban sprawl, we selected an AOI that covers both the core city and peri-urban areas. Therefore, the AOI was selected using the boundary of urban centres provided in the global human settlement layer (GHSL) and not restricted to administrative boundaries. This includes some part of the Greater Accra region and some part of the Central region, allowing us to assess the intra-urban dynamics of slums. The AOI covers 764.3km^2. Additionally, the availability of cloud-free SPOT images of 2013 and 2017 from the ESA allows capturing the temporal dynamics of the city. Accra suffers from cloud cover and experiences dust storms occasionally (Weeks et al., 2007). These dates were the best cloud-free images the covers the area of interest. Table 3.1 present the data available and its sources.

The study relies on FOSS4G solutions. FOSS4G solutions are crucial for low-and middle-income countries characterised by limited funds and allow anyone to review and adapt them to their needs (Rico & Maseda, 2012). They form the bases for spatial data infrastructure (SDI), where resources for system development and maintenance are scarce (Brovelli, Minghini, Moreno-Sanchez, & Oliveira, 2017). Thanks to the FOSS4G active community, they have robust and reliable software for geospatial application such as GRASS GIS and QGIS for raster and vector processing and analysis. They are efficient for raster and vector-based applications (Grippa et al., 2017). PostGIS was used for storing, managing and processing large vector datasets.

Additionally, Python and R coding software was used for advanced statistical methods, mainly machine learning. The codes were implemented in Jupyter notebook to allow sharing of codes for reproducibility. The Jupyter notebook format integrates GRASS GIS functions with python and R programming languages creating a semi-automated processing chain from input of initial dataset to final change detection analysis.

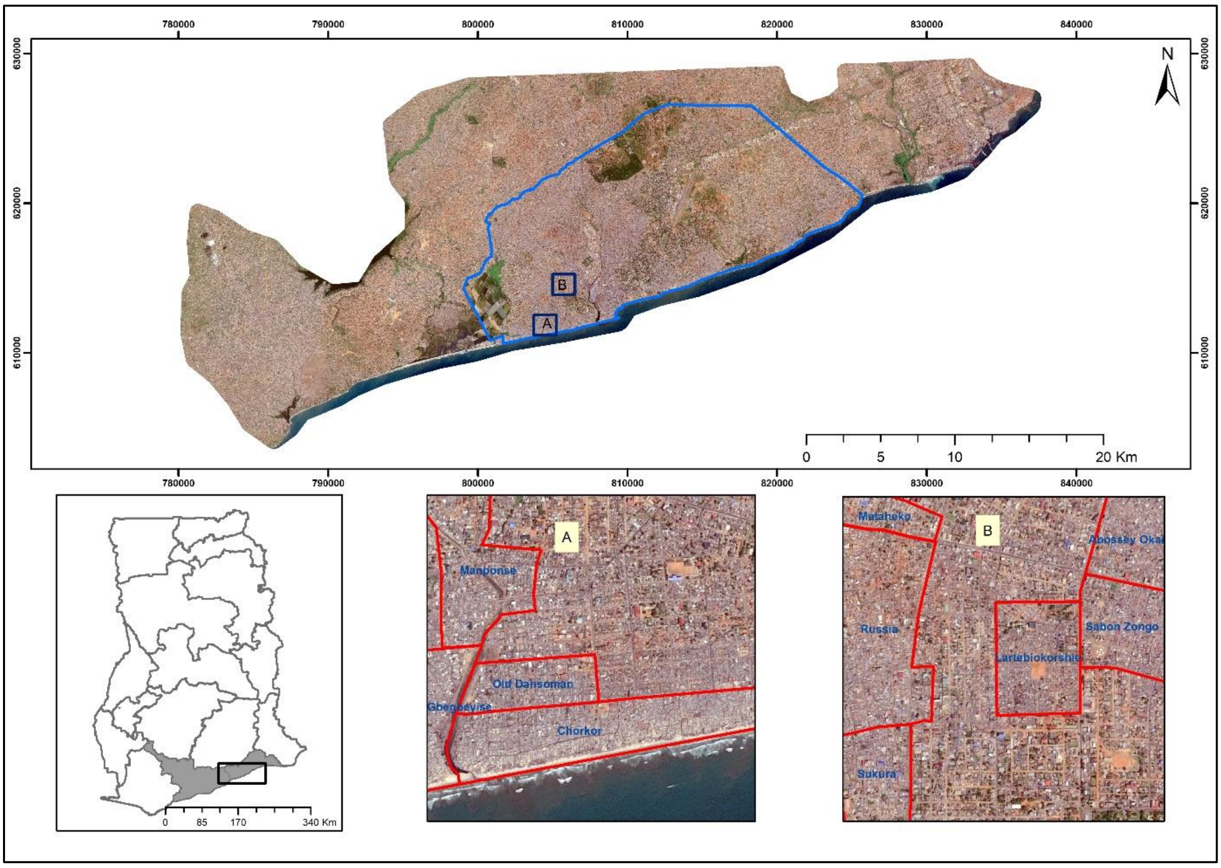


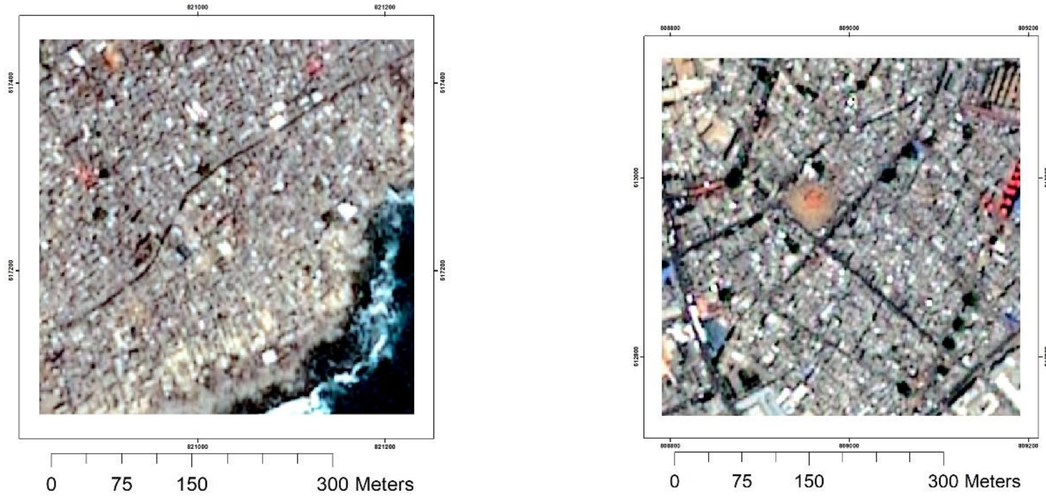
Figure 3.1 Location of study area, Accra, Ghana. A) and B) shows typical examples of slum (Images used to vizualise the slums: SPOT 6, 2017).

Table 3.1 Data sources used in this study.

Data	Resolution (m)	Type	Date	Source
SPOT 6	1.5	Panchromatic	17/12/2013	ESA
SPOT 6	1.5	Panchromatic	01/04/2017	ESA
SPOT 6	6	Multispectral	17/12/2013	ESA
SPOT 6	6	Multispectral	01/04/2017	ESA
54 location of slums	-	Shapefile	01/01/2011 to 01/08/2016	Accra Metropolitan Assembly
Buildings	-	Shapefile	-	Accra Metropolitan Assembly
Communities	-	Shapefile	-	Accra Metropolitan Assembly
OpenStreetMap data	-	Shapefiles	2020	OpenStreetMap

3.2. Characteristics of slums and residential densities in Accra

Slums in Accra vary in size, nature, typology and deprivation. The physical characteristics of slums are similar to "old towns" in Accra (see Figure 3.2). Old towns are neighbourhoods that existed before settlement planning became part of the government system of Accra (People's Dialogue, 2016). They are usually fishing communities that have grown over time. These neighbourhoods are usually deprived areas predominantly housed by low-income groups. Additionally, there are different types of slums in Accra. The typology includes: indigenous (e.g. Okponglo), migrants (e.g. Sabon Zongo), and cosmopolitan (e.g. Kwashieman) (Agyei-Mensah & Owusu, 2010). Indigenous slums are the old towns, migrant slums consist of foreigners, and cosmopolitan is a mixed of indigenes and migrants.

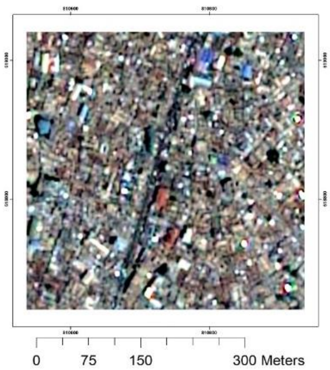
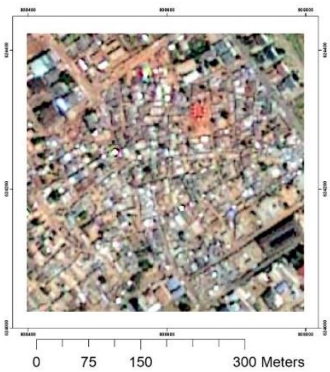


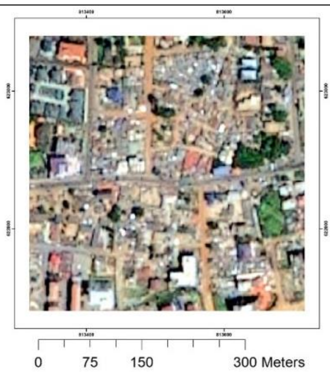
a) Teshie old township b) Nima slum

Figure 3.2 Physical appearance of Oldtown and typical slum: (a) old township (b) Typical slum (source of the images used to visualise the slums: SPOT 6 image, 2017).

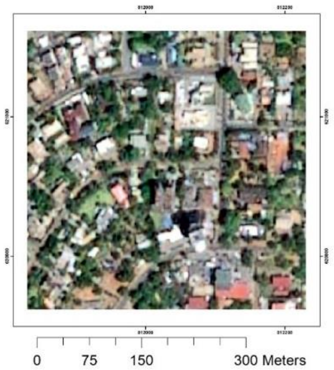
Slums in Accra can be grouped into three development stages as proposed by Sliuzas et al., (2008). They are infant, consolidated and matured slums. According to Sliuzas et al. (2008), few houses are found during the infant stage. They become consolidated when they grow in numbers with the introduction of some services such as water and improved living conditions. The matured stage is when the growth leads to high densification, and the settlement boundary already has a shape. Residential densities are broadly categorized into low and high-density residential. Low-density residential consist of mainly large single-family house on large plot size (villa type), and small self-contained units. They are usually located at the periphery of the city. High-density residential consist of single storey traditional compound house, multi-storey compound house, apartments, and terrace housing. They are usually located within the city. Table 3.2 and 3.3 describes slum and residential densities characteristics in Accra adopting the general slum ontology approach proposed by Kohli, Sliuzas, Kerle, & Stein, (2012) to ensure consistency.

Table 3.2 Characteristics of slums.

Slum types	level	Indicators
A: Matured 	Environs	**Location:** They are usually located along water bodies and major drains such as the sea and rivers. Other slums are located on state land close to the central business district (CBD) or flood zones. **Neighbourhood characteristics:** They may be old traditional neighbourhoods (old towns), old migrant towns or cosmopolitan neighbourhoods.
	Settlement	**Shape:** They usually tend to follow elongated shape features such as sea, rivers, drains, and roads (e.g. Odaw river). **Density:** High roof coverage with no or little vegetation. More than 90% of roof coverage.
	Object	**Buildings**: Permanent building materials with iron roofing sheet. They are usually compound family housing and detached building type. **Access network:** They have inadequate roads. The roads are usually not connected.
B: Consolidated 	Environs	**Location:** They are usually located close to high income group. **Neighbourhood characteristics:** close of high-income neighbourhoods
	Settlement	**Shape:** They have irregular shape **Density** High roof coverage with no or little vegetation. More than 80% of roof coverage
	Object	**Buildings:** mix of permanent and temporal building materials. Small building size **Access network:** irregular and unconnected roads
C: Infant	Environs	**Location:** In small pockets within the city. They often develop on open paces or state lands. **Neighbourhood characteristics:** usually close to neighbourhood of high income, extension areas and industrial site.

		
	Settlement	**Shape:** small pocket within the city with irregular shape
		Density: High roof coverage with no or little vegetation. More than 80% of roof coverage
	Object	**Buildings:** Mix of permanent and temporal building materials. Small building size.
		Access network: No road within the area
Kiosk Estate	Environs	**Location:** close to industrial site
		Neighbourhood characteristics: Predominantly found in industrial areas.
		
	Settlement	**Shape:** occupies less than 0.5ha of land with no clear shape
		Density: high roof coverage
	Object	**Buildings:** movable structure with wooden materials. Very small building size
		Access network: no road within the area

Tale 3.3 Characteristics of residential densities.

Residential type	Level	Indicators
High density residential 	Environs	**Location:** Located in the inner city or close to the CBD **Neighbourhood characteristics:** usually single/compound family housing residents**.** Housing type includes single storey traditional compound house, apartments and terrace housing
	Settlement	**Shape:** usually elongated street-blocks **Density:** large roof with low vegetation (less than 15%). Vegetation is usually trees.
	Object	**Buildings:** permanent building materials with aluminium roofing sheet **Access network:** well-defined street pattern
Low density residential 	Environs	**Location:** usually located at the periphery **Neighbourhood characteristics:** Usually single family housing residents. Housing types are predominantly, large single family house and small self-contain units.
	Settlement	**Shape:** large street-blocks **Density:** low roof coverage with high vegetation (more than 15%). vegetation is usually trees, lawns and shrubs.
	Object	**Buildings:** permanent building materials with aluminium roofing sheet, or coated roofing sheet/stones. **Access network:** well-defined street pattern

4. RESEARCH METHODOLOGY

This chapter describes the methodology of the research. It begins with the fieldwork to understand the local context, spatial information and geo-ethical related to making slum information available. It is followed by image processing to change detection and analysis. Figure 4.1 illustrates the main steps of the methodology. It starts with expert interviews and field observation to understand user requirement and ground-based causes of uncertainty. Afterwards, land-cover and land-use map were processed from the two images. The results of land-use were used for change detection and analysis of slum dynamics.

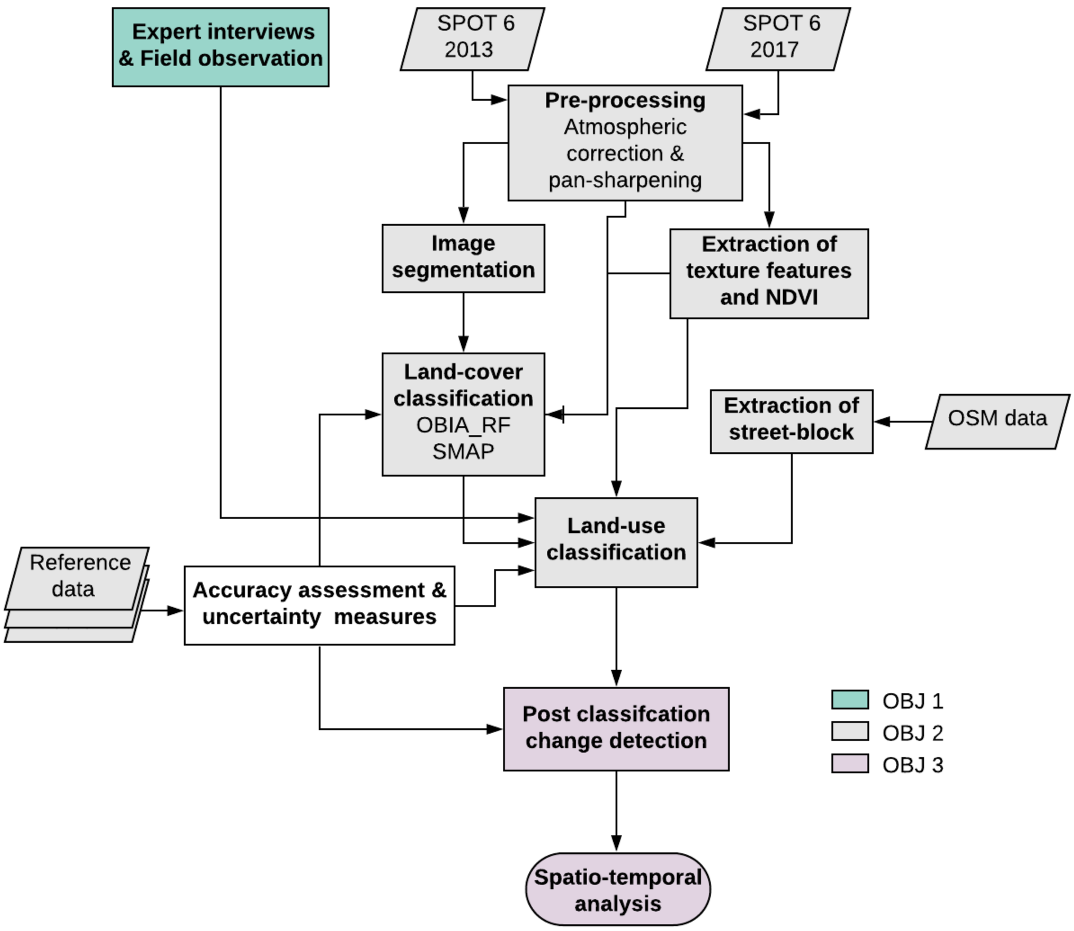


Figure 4.1 Flow chart of research methodology implemented in this study.

4.1. Fieldwork

Land-use maps were initially created without local context knowledge. Using the GSO approach introduced some uncertainties, such as the confusion between old towns and typical slums. For example, most areas of the core city were classified as slums (Figure 4.2). Moreover, the RS community does not sufficiently understand the data required by users and their concerns in making such data publicly available (Gevaert et al., 2019; Leonita et al., 2018). This communication gap raises issues of acceptance and usage of EO-based data. Therefore, fieldwork was carried out to assess the usability of the final mapping products and geo-ethics concerns in making RS-based data publicly available. It also investigated the causes of uncertainties in the initial model.

Firstly, topic-focused interviews were conducted with local experts working on slums to understand local context-knowledge, spatial data requirement, geo-data privacy and causes of uncertainty. Topic-focused interviews are flexible and can fully explore the topic (Groenendijk & Dopheide, 2003). From literature, the following institutions were identified as they relate to slum issues in the study area (AMA, 2011; People's Dialogue, 2016). They include Land Use and Spatial Planning Authority (LUSPA), Physical Planning Department (PPD), Public Work Department (PWD), National Disaster Management Organisation (NADMO), Non-Governmental Organisation (NGO's) mainly Peoples Dialogue on Human Settlement (PD), Tema Development Company (TDC), Department of Planning (DOP) of Kwame Nkrumah University of Science and Technology (KNUST). Table 4.1 presents an overview of institutions related to slum issues and their roles. Based on their roles, they were purposively selected as they relate to slums issues in the study area. To have diverse views on the subject matter, four planners from four different districts (Accra Metropolitan Assembly, Tema Metropolitan Assembly, Ablekuma Municipal Assembly and Ledzokuku municipal assembly), two experts from PWD (Tema Metropolitan Assembly and La-Dade Kotopon municipal assembly) and one each from the other institutions were interviewed.

Table 4.1 Local experts related to slum and their roles. LUSPA: Land Use and Spatial Planning Authority; NADMO: National Disaster Management Organisation; PPD: Physical Planning Department; PWD: Public Works Department; PD: People's Dialogue; DOP: Department of Planning; TDC: Tema Development Company.

Level	Institution	Roles
National	LUSPA	Preparing policies and planning standards
	NADMO	Ensuring disaster prevention and management
District	PPD	Human settlement planning and management
	PWD	Responsible for ensuring development control
NGO	PD	Responsible for slum profiling and communication participation
Research	DOP	Slum related research
Company	TDC	Managing all land and slum regularisation within the Tema catchment area

To identify the causes of uncertainties, ground observation and inventory were conducted. Fourteen location points were sampled using specific criteria based on visual assessment of the initial classification and uncertainty results (see figure 4.2). Afterwards, a buffer of 1000 meters was created for each point. Field observation was then carried out within the 1000 meters buffer. Quickscan approach was used. Pictures of the visited areas were taken with GPS camera. The selection criteria used includes;

- Areas classified as slum (more than 70% certainty) but not slums in the reference data available
- Areas classified as uncertain (less than 70% certainty) but are slums in the reference data
- Areas classified as high-density residential but are slums in reference data
- Areas classified as non-residential but are slums in reference data

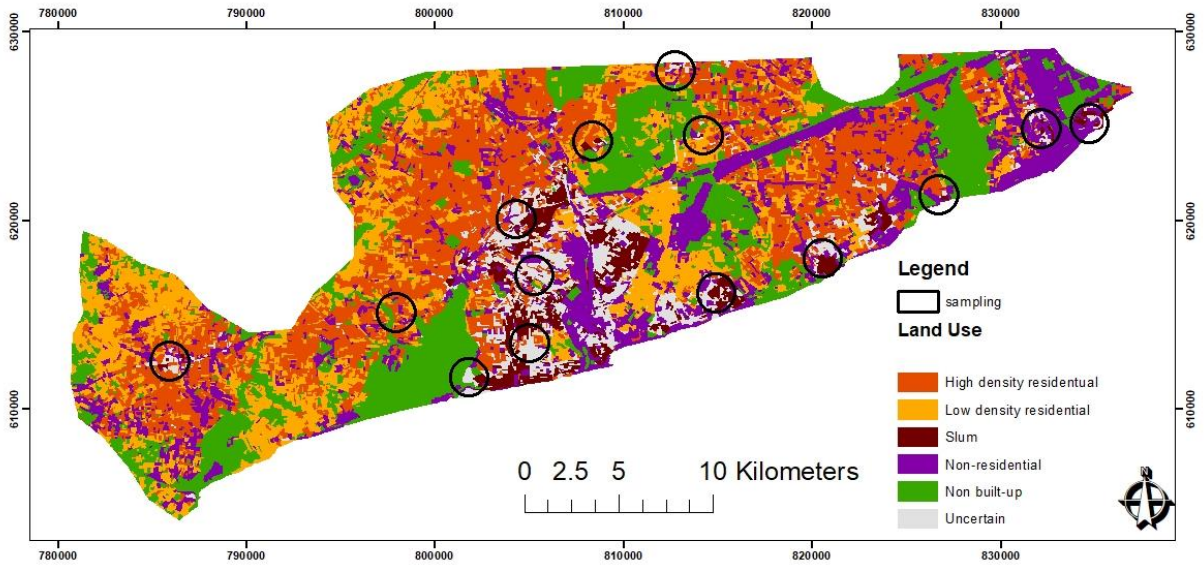


Figure 4.2 Sampling location for field observation.

4.2. Pre-processing

Both atmospheric correction and pan-sharpening tasks were carried out in the pre-processing phase. Firstly, an atmospheric correction using i.atcorr in GRASS GIS was performed to reduce the impact of radiometric and atmospheric variation in the two images. These errors can affect the overall accuracy and produce false change detection (Hussain et al., 2013). Lastly, pan-sharpening was performed in Erdas Imagine Software using modified intensity hue saturation (IHS) resolution merge algorithm with nearest neighbour resampling.

4.3. Image segmentation

The classical procedure for selecting parameters for segmentation is based on trial and error that relies on visual assessment of segments and gradual modification until best-fit results are obtained (Hay, Castilla, Wulder, & Ruiz, 2005). Although it allows flexibility in adding expert knowledge, it is time-consuming and hardly reproducible (Drăguţ, Csillik, Eisank, & Tiede, 2014). To overcome this problem, recent studies have proposed unsupervised methods for segmentation. It uses images statistics to determine the optimal parameters for segmentation. Belgiu & Drăguţ, (2014) compared one supervised (segmentation accuracy assessment) and two unsupervised (estimation of scale parameter and segmentation optimization procedure) approach. They found out that both approaches achieved similar classification accuracy. Additionally, unsupervised segmentation parameter optimisation (USPO) in GRASS GIS has achieved remarkable results in recent studies (Grippa, Georganos, Vanhuysse, Lennert, & Wolff, 2017; Grippa, Wolff, et al., 2017). USPO combines intra-object variance and inter-object spatial autocorrelation measures to create homogenous objects (Lennert, 2015).

In this study, segmentation was performed using i.segment module in GRASS GIS. The method uses a region-growing and merging algorithm (Momsen & Metz, Markus, 2015). Initially, all four multi-spectral information were used as input for segmentation. However, it was computational intensive as it took 13 hours to completely segment the AOI using HP workstation Z620 with two Intel Xoen E5-2680.

Therefore, the panchromatic image (1.5m resolution) was used for segmentation. The computational time was four hours. Using visual assessment, it produced meaningful segments compared to using the four multi-spectral bands.

Prior to the optimisation of segmentation parameter, over-segmentation and under-segmentation were empirically tested using i.segment to obtain threshold range to be used for USPO. i.segment uses two main parameters, namely the "threshold" for controlling the tolerance for merging homogenous objects and "minsize" for controlling the minimum size of a segment. Afterwards, the new GRASS GIS extension for USPO named i.segment.uspo was used to select the optimum parameter automatically.

Georganos et al. (2018) have shown that using a single parameter for the whole scene produces poor results due to the high spatial heterogeneity within the image, especially for large-area mapping. Therefore, the study was partitioned into several subsets and applied USPO procedure locally in each subset. This is good for large scale mapping to reduce segmentation errors and overcome spatial variation problems. Through trial and error (testing different window size), the whole image was subdivided into regular tiles using a grid size of 500 meters. 500m grid size was used because visually, it created more homogenous zones than other sizes and reduced the computational time.

4.4. Extracting texture features

Studies have shown that using spectral information and geometrical features from segmentation are insufficient to map land-use and land-cover in the urban environment due to the complexity of the area (Kuffer, Pfeffer, Sliuzas, et al., 2016; Wurm et al., 2017). Texture features are effective to quantify the spatial and structural patterns which can serve as supplementary features to improve feature space differences (Engstrom et al., 2015; Kuffer et al., 2020). In this study, the land use classification methodology, on the one hand, relies heavily on the use of only contextual image information. On the other hand, it combines contextual features and land-cover information for land-use mapping.

Grey-Level Co-Occurrence Matrix (GLCM) were extracted to characterised the spatial patterns observed in VHR resolution images (Kuffer, Pfeffer, Sliuzas, Baud, & van Maarseveen, 2017). These features have proven to show good performance for slum extraction (Kohli, Sliuzas, et al., 2016; Kuffer, Pfeffer, Sliuzas, et al., 2016). However, selecting good texture features as input for classification have always been a challenge when using VHR images (Georganos, Grippa, Vanhuysse, et al., 2018). These features can add up to several hundred and sometimes leads to information redundancy. This will not only increase computational cost and data storage but also can negatively affect the performance of the classifier. This is described as the curse of dimensionality or Hughes phenomenon (Hughes, 1968). Therefore, selecting appropriate textural features was an important task in this study.

A recent study comparing four different feature selection techniques (correlation-based feature selection, RF mean decrease in accuracy, RF recurvise feature elimination, and variable selection using RF) have shown that near-infrared (NIR) band performed well in all the techniques (Georganos, Grippa, Vanhuysse, et al., 2018). Therefore, the NIR band is used as input for extracting texture features. Firstly, GLCM was computed with varying size ranging from 5x5 to 27x27 with an increasing factor of two to identify the best kernel size. Variable selection using RF (VSURF) algorithm was used to select good kernel size (Díaz-Uriarte & Alvarez de Andrés, 2006). The VSURF algorithm identifies most important features by removing smallest variable importance while retaining the accuracy through a stepwise search. The selected features are the ones with the small out of bag (OOB) error. VSURF is said to be suitable for tree-based classifiers and has achieved good results in a recent study (Georganos, Grippa, Vanhuysse, et al., 2018). Based on the test, a moving size of 5x5 was used for land-cover mapping. A kernel size of 21x21 and 27x27 was used for land-use mapping. These kernel sizes were included to account for the varying contextual properties. Textual statistics extracted includes angular second moment (ASM), measures of correlation (MOC), variance, entropy and contrast. These features promise good results in slum mapping. They can measure local variation (e.g. contrast), and orderliness or disorderliness in pixel values (e.g. entropy). For example, slums often have organic morphology and could have high entropy compared to formal areas (Kuffer, Pfeffer, Sliuzas, et al., 2016).

For all the texture features, object statistics were computed using GRASS GIS addon called i.segment.stats. It also computes the spectral and morphological statistics of objects (area, perimeter and compactness). For this study, statistics computed include minimum, maximum, standard deviation, coefficient variance, sum, mean, median, first quartile and third quartile for original bands, texture features and normalised difference vegetation index (NDVI). Table 4.2 presents an overview of the features used for land use and land cover mapping. In total, 154 features were extracted for classification. In order to speed up the processing time, the pool object in multiprocessing package in python was employed. Also, r.object.geometry addon was used to skip the need to vectorise the segments when computing the morphological statistics resulting in a significant gain in time.

Table 4.2 Image features used for classification.

Group	Variables
Spectral features	Red
	Green
	Blue
	Near infra-red (NIR)
Texture feature	Angular second moment (ASM)
	Measures of correlation (MOC)
	Variance
	Entropy
	Contrast
Vegetation index	Normalised difference vegetation index (NDVI)
Land-cover	Proportion of built-up
	Proportion of vegetation
	Proportion of bareland
	Proportion of water

4.5. Land-cover classification

Supervised classification using both OBIA and pixel approaches were implemented for land-cover classification. Training and testing sampling were created using random and stratified random sampling with data from OSM. An intensive visual interpretation was used for the final labelling of every point from OSM data by two experts to avoid wrong mislabelled samples. All disagreements between experts were removed from the samples. The visual assessment was an important step because of seasonal and temporal changes for the two images and OSM data. In addition, bareland was manually sampled since they are not included in OSM. In total 4031 and 3996 samples were used for 2013 and 2017, respectively. Table 4.1 shows the landcover classification scheme for both years. For classification, samples were randomly split into 67% for training and 33% for validation. Initially, subclasses of vegetation (trees, dry and wet vegetation) and bareland (untarred road and baresoil) were classified. Afterwards, they were reclassified into the four main land-cover types (built-up, bareland, vegetation and water).

Table 4.1 Sampling scheme for land-cover classification.

Land cover	Subclass	Number of sample for 2013	Number of sample for 2017
Built-up	Buildings	960	901
	Asphalt	100	100
Vegetation	Tree	533	517
	Wet vegetation	875	470
	Dry vegetation	243	487
Bareland	Bare soil	408	672
	Untarred road	812	749
Water	Rivers, drains, and streams	100	100
Total		**4031**	**3996**

The land cover framework combines OBIA and machine learning. RF classifier was used for OBIA classification (Breiman, 2001). It requires the definition of the number of trees (ntree) and number of input features (mtry) to be considered at each node split. It is popular in RS studies as RF is relatively user-friendly and has a high prediction accuracy. It can handle high data dimensionality and not affected by overfitting (Belgiu & Drăguţ, 2016). It is also efficient in parameter selection and computationally fast. Input features include multi-spectral band, geometric statistics (area, perimeter and compactness), Normalised Difference Vegetation Index (NDVI) as well as all texture features. The two main parameters in RF were optimised through cross-validation of the OOB error. This provided optimised hyperparameters for land-cover classification.

Moreover, pixel-based classification using sequential maximum a posteriori (SMAP) was performed. The SMAP performs contextual image classification using a spectral class model called Gaussian mixture distribution. Image segmentation is done in region rather than segmenting each pixel separately like conventional maximum likelihood. (McCluaey,1995). In this study, we combine multi-spectral, NDVI and all texture features for land-cover classification. The method is implemented in GRASS GIS using i.smap. Firstly, a square buffer of 3 meters was created using the sampled points. Afterwards, a visual assessment was carried out to check if samples are overlapping for every class type. Lastly, i.gensigset module was used to generate signatures and classification was carried out.

4.6. Street-block extraction

Urban landscape composes of hierarchical patterns which can be analysed at different scale such as street-block and grid (Wang et al., 2019). For this study, street-blocks are used for the land use classification. The street-block is the most fundamental and appropriate unit to map urban structure types (USTs) because most boundaries in cities are made by road network (Bochow et al., 2010). These boundaries usually show homogenous structures types. Also, it provides sufficient spatial details relevant to urban planning.

However, reference street-block data are not easily accessible or outdated, especially in data-poor regions like Accra. This study relies on OSM data to overcome this limitation. The quality of OSM in terms of completeness and thematic accuracy has been improving in recent years. As shown in the work of Fonte et al., (2017), OSM has the potential to increase thematic level of land use and land cover mapping in data-poor regions. It also gives a good approximation of results obtained from conventional methods. Visual assessment of data from OSM in Accra shows high level of completeness making it useful for the study. Also, authoritative data for Accra are often not available, especially for the peri-urban areas, so taking advantage of OSM data is an ideal solution.

Street-blocks were extracted, adapting the framework of Grippa et al., (2018). The semi-automated workflow used OSM data to create street-block geometries to be used as urban landscape units to land use map. It takes advantage of PostGIS, open-source software for storing, managing and processing large vector datasets. Python was used, and codes were implemented in Jupyter notebook to make it easily reproducible.

In reality, it is difficult to obtain homogeneous land use within street-block, especially in the peri-urban areas with fewer data. Therefore, supplementary map features such as waterbodies, drains, railways and residential areas were added to the model to reduce the creation of large parcels. This was done to ensure high intra-homogeneity of urban structure types.

Firstly, a bounding box of AOI was created and subdivided into tiles to be used for downloading OSM data. OSM data was automatically downloaded using OSM extended API or Xapi (OpenStreetMap Wiki contributors, 2018). OSM data was then imported in PostgreSQL database using osm2pgsql command-line. Afterwards, the interested map features were extracted using their "key=value" pairs in the OSM tagging scheme (Davidovic, Mooney, Stoimenov, & Minghini, 2016). These map features (Lines and polygons) features that intersected with AOI are converted into linear features.

The topology function in PostGIS was used to snap nodes into fully connected lines (merging neighbouring nodes) using a user-defined distance threshold (tolerance of 7). Similar to Grippa et al. (2018), urban blocks and sliver polygon (undesirable polygon) were generated after snapping. This is due to redundant linear feature geometries in OSM such as multilane roads, interchange and highway ramps. Therefore, the sliver polygon was removed using shape (compactness measure) and size criteria since they are thin and small. The best criteria were defined to select sliver polygon using a trial and error approach. Sliver polygons were then merged to their neighbouring non-sliver polygon which shares the larger border. The latest step iterates in the code until there is no sliver polygon. Friesen, Taubenböck, Wurm, & Pelz, (2018) shows in their work that the average morphological size of small slum unit is 1.6 hectares. For this study, the minimum street-block was set to 0.5 hectares to capture pocket of slums.

4.7. Land-use classification

By visually interpreting different urban structure types, a land-use scheme was prepared *(see section 3.2)*. The city of Accra is characterised by several types of land-use, including residential, commercial, industrial, administrative zones. For the purpose of this study, a clear focus is made on having better thematic precision of slums than for other class. Therefore, the land-use scheme is infant slums, matured slum, high-density residential, low-density residential, non-residential (commercial, industrial, and administrative) and non-built-up (vegetation and open space). Consolidated slums were added to matured slums due to difficulty in obtaining samples. They have a similar physical appearance as matured slums making it challenging to generate sampling using visual interpretation. Also, urban land use is often a mixture of activities within street-block. However, this study aimed to map dominant activities in the block.

Initially, 500 street-blocks were randomly sampled for training and validation. Each sampled street-block was assigned a label by an expert using a computer-assisted photo-interpretation (CAPI) according to the dominate land-use class. The labels were based on the urban structure characteristics described in section 3.2. There was imbalance sampling for infant slum, matured and high–density residential class. For this reason, an extra 210 street-block for 2013 and 235 street-block for 2017 were manually sampled for infant, matured and high-density residential. This explains why sample distributions were not uniform. Table 4.2 shows the land-use sampling strategy. Samples were randomly split into 67% for training and 33% for validation. Features generated for land use classification includes NDVI, RGB and NIR, texture features and/or land cover. R.zonal.class was used to compute the proportion of land cover in every street block.

Table 4.2 Land-use mapping sampling scheme.

Land use	Number of sample for 2013	Number of sample for 2017
Infant slum	45	38
Matured slum	114	121
High density residential	145	152
Low density residential	119	121
Non-residential	140	142
Non-built-up	147	161
Total	**710**	**735**

Again, RF was selected among other machine learning classifiers for land use classification. Two main parameters, namely, the number of trees and number of randomly selected features in RF were optimised through cross-validation of the OOB error. This provided optimised hyperparameters for land-use classification. We selected 1000 trees and square root of number of features (default) at each split.

4.8. Accuracy assessment and uncertainty measures

The reliability of the final mapping output depends on its accuracy and level of confidence. Classification rate was obtained from a confusion matrix by comparing the predicted classes with a reference set. Overall accuracy, precision or producer accuracy (PA) and recall or user accuracy (UA) were computed. The overall accuracy reveals the rate of correctly classified street-blocks. Precision and recall were included to reveal the misclassification per each class Precision is the error of failing to assign a correct street-block to a particular class. Recall refers to the wrong label of a particular class. Recall measures the reliability of the classification and precision measures the ability to classify a particular class (Foody, 2002). Visual assessment was also carried out.

The occurrence of uncertainties in EO-based applications is inevitable. Such uncertainties affect the credibility of the mapping product. A recent study has shown that due to the subject definition of slums, reference data used for training and validation have low agreement in complex areas (Pratomo et al., 2017). This adds to the uncertainties in the mapping results. Moreover, the high temporal dynamics of urban environment raises the issue of uncertainty. For example, the gradual transition between slums and non-slums, including densification process, upgrading and self-help improvement would affect the overall classification. Therefore, assessing uncertainties was necessary since the land-use maps were used for change detection.

In this study, uncertainty is defined as the probability that a street-block is correctly classified. The uncertainty investigation focused on slum street-blocks only. These uncertainties could arise from the definition of slum affecting the generation of training samples, local contexts such as old towns and transition zones of the urban environment (Wang et al., 2019). For example, the similar physical morphology of slum and old towns can introduce uncertainties in the model.

Analysing uncertainties can be expressed as existential and extensional uncertainties (Molenaar, 2000). In this study, existential uncertainty refers to the possibility that a street-block is classified as a slum but does not correspond to a slum on the ground or the possibility that a slum street-street-block is not detected. Extensional uncertainty refers to the level of confidence a street-block is classified as a slum. It occurs when the certainty of the prediction (spatial variation accuracy) is low thus less than 70% based on commonly reported overall accuracy on RS-based slum mapping studies (Kuffer, Pfeffer, & Sliuzas, 2016). This usually happens when street-block contains heterogeneous land-cover types.

To showcase the implication of these uncertainties and integrate into change detection model, field observations and interviews were conducted to assess existential uncertainty. Also, the class probabilities obtained from RF was used to analyse extensional uncertainties. This study used the equivalent reference probability measure (ERP) proposed by Bogaert & Waldner (2016). It is built on the concept of information-based criteria that has the advance of taking maximum probability values into accounts while committing for the full set of probabilities. ERP can be derived from any classifier that provides soft outputs (probabilistic or probabilities membership proxies such as number of trees, activation level, etc.). Moreover, the confusion matrix does not provide a distribution of uncertainty in space or street-block. Therefore, confidence maps were computed from the ERP to assess per street-block areas with high and low certainties.

4.9. Change Detection

Post-classification change detection was applied after independent land-use classification. Change trajectories were mapped at the street-block level. The focus of the study is to identify slum growth. Therefore, land use maps were reclassified into binary classes, namely, slum and non-slum (see table 4.3). Slum includes infant and matured slums. They were combined because of sampling (not enough number of samples) and unique morphological characteristics of infant slums, which affected the land-use classification. The Non-slum class includes high-density residential, low-density residential, non-residential and non-built-up. Slums were given a label of 1 and 10 for 2013 and 2017 respectively. Non-slums were given the label of 2 and 20 for 2013 and 2017 respectively. These labels were used to identity change trajectory using the plus operation.

Table 4.3 Old and new labels for change detection.

Class labels		Years	
Old class	**New class**	**2013**	**2017**
Infant and matured slum	slum	1	10
high-density residential, low-density residential, non-residential and non-built-up	Non-slum	2	20

For change-detection analysis, the binary classification results of 2013 and 2017 were overlaid to obtain the change detection map. Four change trajectories were identified since the study used two images and two classes. They are 11,12,21,and 22. The description of the change trajectory is presented in table 4.4.

Table 4.4 Description of change trajectory.

Change/no change class	Trajectory value	Description
Slum remained slum	11	No change in both year
Non-slum remained non-slum	22	No change from non-slum to non-slum
Slum to non-slum	21	Changed from slum to non-slum
Non-slum to slum	12	Changed from non-slum to slum

4.10. Land-use change detection accuracy assessment

Accuracy assessment was performed to assess the credibility of the change detection map. In RS, the most common methods for assessing accuracy is the traditional error matrix and kappa coefficient (Olofsson, Foody, Stehman, & Woodcock, 2013). However, these methods are designed for single date thematic mapping (Macleod & Congalton, 1998). Li & Zhou, (2009) proposed the trajectory error matrix (TEM) for change detection accuracy assessment. TEM employs a rule-based method that divides all possible trajectory into confusion sub-groups. Accuracy measures are then derived from the subgroups to avoid listing all trajectory types. TEM produces six confusion sub-groups used to reduce the complexity of the change confusion matrix. Moreover, the method has been applied in recent temporal slum analysis studies (R. Liu et al., 2019; Pratomo et al., 2018).

Firstly, reference data was created using the stratified random sampling design. From land-use change analysis, there was a small proportion of changes trajectory, thus from non-slum to slum or vice versa. Therefore, the stratified random sampling design was used to identify and allocate enough samples to produce small standard error for the change user's accuracy estimate (Olofsson et al., 2014). In this study, no change/change trajectories in table 4.4 were used to identify strata. Consequently, 30 street-blocks were randomly selected per strata and labelled them through visual image photo-interpretation.

Secondly, similar to Li & Zhou, (2009), six confusion sub-groups were used for classifying trajectory combination (see table 4.5). In S1, "no change" trajectories are correctly detected with correct land use classification, i.e., both reference and classification agreed that there was no change. In S2, "change" trajectories are correctly detected with correct land use classification, i.e., both reference and image classification agreed that there was a change. In S3, "no change" trajectories (both reference and classification indicate no changes) are correctly detected with incorrect land use classification. In S4, "no change" trajectories are incorrectly detected as "change". In S5, "change" trajectories are incorrectly detected as "no change". Lastly, in S6, "change" trajectory (both reference and classification indicate changes) are correctly detected with incorrect land use classification.

Table 4.5 Confusion sub-group of TEM Green is correct classification with correct change trajectory, yellow is incorrect classification with correct change trajectory, and red is incorrect classification with incorrect change trajectory.

Group	Classification outcome	Description
S1	Correct	"No change" with correct classification
S2		"Change" with correct classification
S3	Not correct	Correctly detected as "no change" but with incorrect classification
S4		Incorrect detection "no change" trajectory as "change"
S5		Incorrect detection "change" trajectory as "no change"
S6		Correctly detected as "change" but with incorrect classification

After defining the sub-groups, accuracy indices according to the six sub-groups were computed. As proposed by Li & Zhou (2009), overall accuracy (A_T) and change/no change accuracy($A_{C/N}$) were used to measure overall accuracy. A_T is the sum of correctly detected no change and change(only correct classification) over the total sample (Eq. 1). $A_{C/N}$ is the sum of all correctly detected as no change or change (with or without correct classification) over the total sample (Eq.2). Also, accuracy difference indices were computed to measure the extent $A_{C/N}$ can represent the accuracy of individual trajectory. Three indices, namely, Overall accuracy difference (OAD), accuracy different of no change trajectory ($ADIC_N$), and accuracy different of change trajectory ($ADIC_C$). OAD measures the difference between "$A_{C/N}$" and "A_T". $ADIC_N$ and $ADIC_C$ measure the accuracy of each no change and change trajectory, respectively (see Eq. 4 and 5).

$$A_T = \frac{S1+S2}{\sum_i^6 S_i} X\ 100 \quad \text{(Eq. 1)}$$

$$A_{C/N} = \frac{S1+S2+S3+S6}{\sum_i^6 S_i} x\ 100 \quad \text{(Eq.2)}$$

$$OAD = A_{C/N} - A_T \quad \text{(Eq.3)}$$

$$ADIC_N = \frac{S1}{S1+S3} x\ 100 \quad \text{(Eq.4)}$$

$$ADIC_C = \frac{S2}{S2+S6} x\ 100 \quad \text{(Eq.5)}$$

5. RESULTS

In the chapter, the results of the study and their interpretations are discussed. This covers slum information needed by end-users and geo-ethics issues related to making slum information publicly available, results of land-cover and land-use classification, and change detection outcome including accuracies as well as spatial dynamics of slums.

5.1. Spatial information requirement and Geo-ethnics

In general, the RS community does not sufficiently understand the spatial data needed by different user groups (Leonita et al., 2018). They need to produce maps that can be used by different user groups as well as developing techniques suitable for local policy-making to support pro-poor projects. Through topic-focused interview, this study investigated user data requirements. Local experts were asked about their presently available spatial information on slums. It was followed by the spatial information that was missing and needed to support the slum related activities. Moreover, the study investigated the geo-ethical considerations needed to make slum data publicly available.

5.1.1. Spatial information presently available on slums

Table 5.1 presents an overview of the spatial information presently available on slums in Accra. Most of the institutions have socioeconomic data at the community scale (enumeration area used by Ghana Statistical Service). These data are collected through household surveys during census, or preparation of medium-term development plans. However, the household surveys approach suffers from low coverage. In this context, low coverage means that not all slum areas and slum householders are included. The extent of slum information is available at the District, Municipal or Metropolitan level of the institutions. District, Municipal or Metropolitan is the small second-level administrative unit smaller than the city. The data are inconsistent because the indicators used are not comparable across institutions. For instance, TDC used land tenure indicator whereas NGO's combined social, economic and environmental indicators. Although all institution reported 100% completeness, they do not have a mechanism to validate the slums maps similar to Leonita et al., (2018) findings in Bandung, Indonesia.

Table 5.1 Spatial information presently available on slums LUSPA: Land Use and Spatial Planning Authority; NADMO: National Disaster Management Organisation; PPD: Physical Planning Department; PWD: Public Works Department; PD: People's Dialogue; DOP: Department of Planning; TDC: Tema Development Company.

	National		**District**		**NGO**	**Research institution**	**Company**
	LUSPA	**NADMO**	**PPD**	**PWD**	**PD**	**DOP**	**TDC**
Information type	-	Socioeconomic data	Location and Socioeconomic data	location	Socioeconomic data	Socioeconomic data	Location and land tenure
Coverage (%)	-	60	40	40	70	5	40
Completeness (%)	-	100	100	100	100	100	100
Accuracy	-	-	-	-	-	-	-
Aggregation level	-	Community	District and community	Community	Community	-	Community
Update interval	-	Every four months	10 to 4 years	10 to 4 years	-	-	-
Method of collection	-	Household survey	Household survey	Household survey	Household survey	Household Survey	Household survey

5.1.2. Spatial information required by Users

By asking local expert of spatial information lacking, the study was able to identify the spatial information required by different user group. The missing information includes slum dynamics, boundary, population, stage of slum growth and level of deprivation (Table 5.2). Additionally, the study investigated how data should be provided to end-users. The results of the expert interviews showed that while some experts (NGO and NADMO) wanted the final out in slum and non-slum, other experts (PPD, PWD, DOP and TDC) opted for land-use map. Experts from NGO and NADMO mentioned that the final output should include the degree of slum (showing good to worst slums) and non-slum with a combination of social, economic and environmental indicators. Experts from PPD, PWD, DOP and TDC mentioned that the final output should be a land-use map. They said that providing such information will help monitor land-uses changing into slum and vice versa. Moreover, experts from PPD, PWD, NADMO, NGO and TDC wanted quarterly information on slums. This temporal granularity was selected because it is in line with the quarterly report. The expert from LUSPA mentioned yearly updates to formulate policies and plans.

Table 5.2 Spatial information required by interviewed users. LUSPA: Land Use and Spatial Planning Authority; NADMO: National Disaster Management Organisation; PPD: Physical Planning Department; PWD: Public Works Department; PD: People's Dialogue; DOP: Department of Planning; TDC: Tema Development Company.

	National		District		NGO	Research institution	Company
Institution	LUSPA	NADMO	PPD	PWD	PD	DOP	TDC
Slum dynamics		√	√		√	√	√
Slum boundary		√	√	√	√	√	√
Stage of slum		√	√	√	√	√	√
Slum population	√	√	√		√	√	√
Level of deprivation		√	√		√	√	
Users Activities	Formulating policy and planning standards	Planning and management	Planning and management	Management	Inventory	Research	Planning and management

5.1.3. Level of aggregation needed by users

One purpose of the study was to investigate the mapping scale needed by end-users. The results of the expert interviews show the local diversity of information needed by the various institutions (Table 5.3). The experts from LUSPA working at the national level opted for administrative boundary, whereas other experts (NADMO, PPD, PWD and TDC) chose street-block or grid. They mentioned that working at this scale can provide detailed information to achieve their goal. For example, the expert from PWD wanted highly disaggregated map at 100m grid size to identify kiosks slums (temporal slums).

Moreover, different user groups have different needs in terms of the level of details and aggregation (Figure 5.1). For example, PPD needs more detailed information (e.g. stage of slum) to take the initiative to relocate, redesign or upgrade. Detailed information on the level of deprivation also helps in deciding where and when to intervene. PWD requires disaggregated data with less detail. PWD purpose is to ensure development control. Therefore, identifying slum location and undocumented slum areas, i.e. slum areas that have not been identified and mapped, is essential. Similar to PWD, TDC expects disaggregated data to prevent the development of slums in the catchment area.

Table 5.3 Level of aggregation. LUSPA: Land Use and Spatial Planning Authority; NADMO: National Disaster Management Organisation; PPD: Physical Planning Department; PWD: Public Works Department; PD: People's Dialogue; DOP: Department of Planning; TDC: Tema Development Company.

	National		District		NGO	Research Institution	Company
Aggregation level	LUSPA	NADMO	PPD	PWD	PD	DOP	TDC
Administrative unit	√					√	
Street-block		√	√		√	√	
Segments				√		√	
Grid		√	√	√	√	√	√

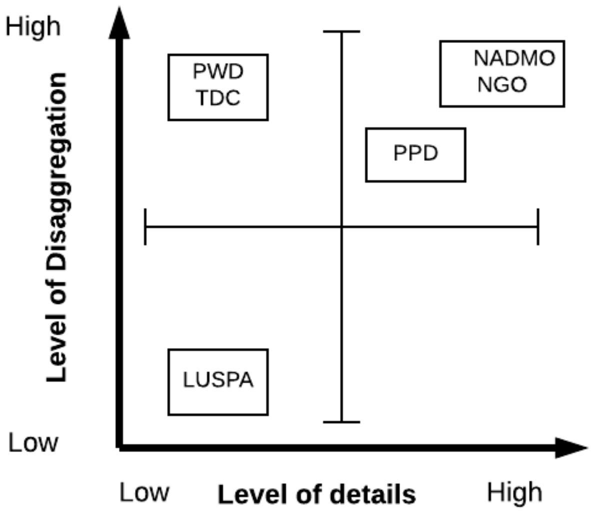


Figure 5.1 Level of details and aggregation. LUSPA: Land Use and Spatial Planning Authority; NADMO: National Disaster Management Organisation; PPD: Physical Planning Department; PWD: Public Works Department; PD: People's Dialogue; DOP: Department of Planning; TDC: Tema Development Company.

5.1.4. Geo-ethics

Regarding ethics, the study focused on issues and challenges of making EO-based slum information publicly available. Local experts were asked questions related to their foreseen problems and concerns in making slum information publicly available. The results from the interviews showed no objection in making slum information publicly available by all parties. The expert from PD mentioned that "*slum housing means more to the slum dweller than the stereotypical picture of deprivation and poverty*." This means that slum dwellers prioritised having a place to sleep than their poor living conditions. For this reason, slum dwellers fear the risk of eviction and stigmatisation than making them visible. Therefore, any effort to make slum visible should ensure adequate privacy. To ensure adequate privacy and produce satisfactory slum information for all users, PD hinted that matured slums are no/less threat to eviction than kiosk and infant slums.

In addition, experts raised geo-ethical concerns that should be considered before making slum information publicly available. After showing experts samples of RS-based data on slums, one major concern was how the maps were prepared. Most experts attested that they have little knowledge of EO-based methods, mainly machine learning classification approaches and cannot comprehend the mapping processes. Experts mentioned that such information would be used if the conceptual and operation definition fit into their local context. They also mentioned that detailed metadata should accompany such data.

Experts criticised the use of only physical characteristics to map slums. Experts (PPD, PWD and research institution) mentioned that the housing strategies (e.g. incremental housing development) and uncontrolled extension would present most part of Accra as slums. This may happen because most of the new extensions are developed without settlement layout (Adarkwa, 2012). Furthermore, old towns have similar characteristics of typical slums. These local context knowledge introduce uncertainties in the training data and final map product.

Moreover, experts were asked about the problems they foresee in using RS-based information since their accuracy usually ranges from 80 to 90% (Kuffer, Pfeffer, & Sliuzas, 2016). Experts were willing to use spatial information with accuracy over 70%. However, they raised concerns on how the final product is validated. They mentioned that map producers should clearly describe how the accuracy measures were performed and make the metrics available to support the interpretation of the maps. For example, areas with field validation should be reported. They indicated that map producers should report on the uncertainties related to the final product and elaborate on the potential implications of using such information.

Experts raised concerns regarding the potential and limitation of RS-based information. They expect map producers to provide a guideline on how the data should be interpreted through training and workshops. The main conclusion on major deliverables is presented in Figure 5.2. Lastly, experts agreed that everyone, including communities, should have access to slum information.

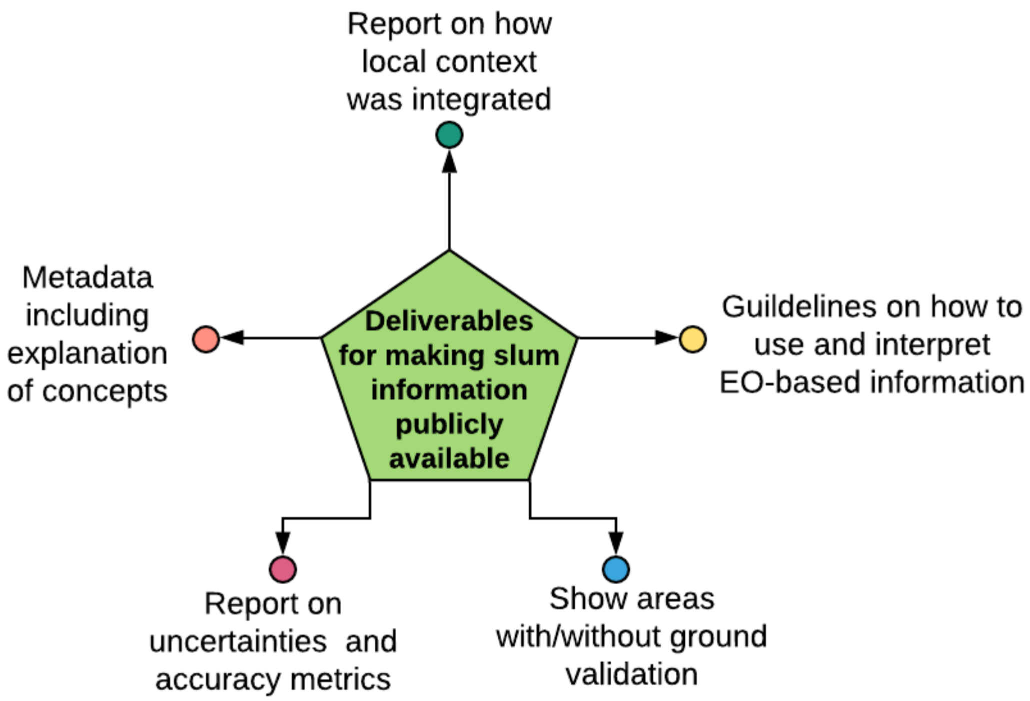


Figure 5.2 Expected outcomes that should accompany earth observation-based slum information

5.2. Image segmentation

The proposed local USPO showed varied optimised threshold value per grid (Figure 5.3). Low values of the optimised threshold were observed in non-built-up areas whiles high optimised threshold values were observed in built-up areas. Similar results were obtained by Georganos, Grippa, Lennert, et al., (2018). Non-built-up (mix of different crop types, trees, and bareland) zones have low optimised threshold values because of the unique spectral properties, i.e. high local variance in objects. Higher optimised threshold values were observed in built-up areas, which resulted in under-segmentation of objects. Thus, the use of the local USPO did not achieve satisfactory results. Although quantitative assessment of segmentation quality was not the scope of this study, visual assessment reveals that under-segmentation occurred. Most of the under-segmented areas were related to merging of buildings and asphalt within the innercity. Therefore, they were used for land-cover classification because they were classified as built-up.

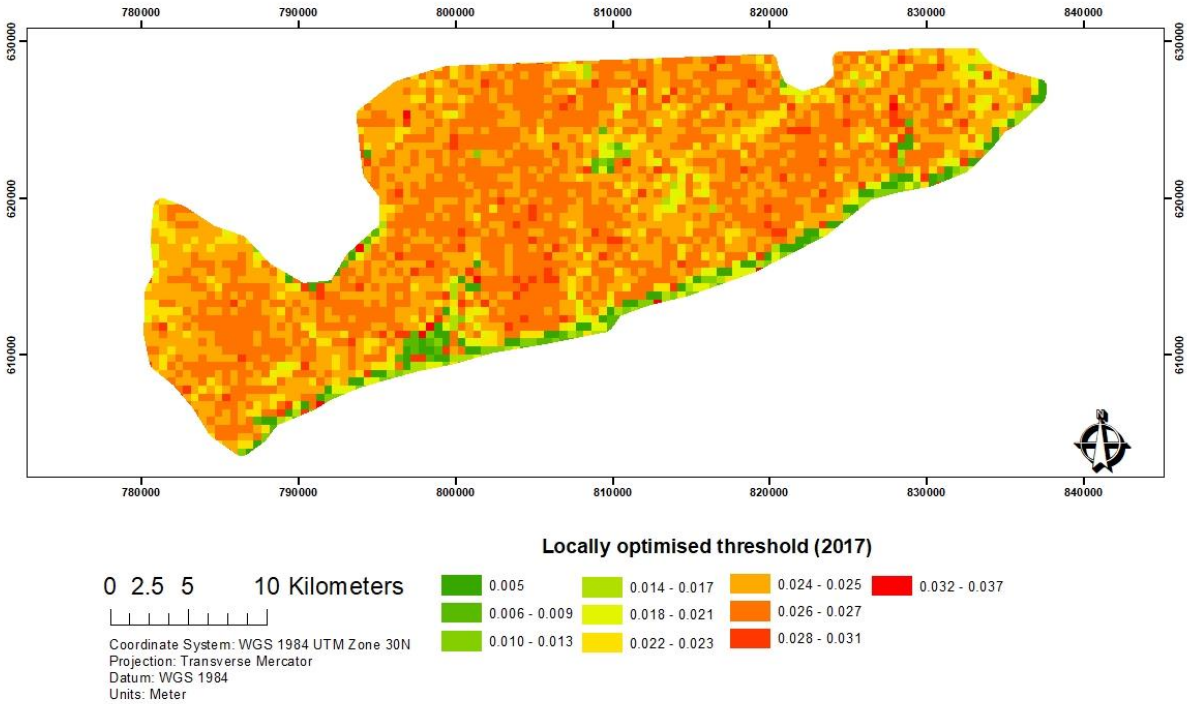


Figure 5.3 Spatial distribution of local USPO thresholds.

5.3. Land-cover classification

The study compared the performance of pixel-based classification using SMAP and OBIA combined with RF (OBIA_RF). Using stratified random points, both methods achieved an overall accuracy of over 88% (Table 5.4). OBIA_RF achieved higher accuracy than SMAP in 2017. However, both methods obtained similar results in 2013. Nonetheless, Cohen's kappa was low in OBIA_RF compared to SMAP. The low kappa coefficient of OBIA_RF can be attributed to the overestimation of built-up, which have the largest spatial coverage (Foody, 2002).

Table 5.4 OBIA_RF and SMAP accuracy assessment results.

Year	Classifiers	Time (minutes)	OA (%)	Kappa
		2013		
	OBIA_RF	30	88.9	0.83
	SMAP	7	88.6	0.86
		2017		
	OBIA_RF	30	90.1	0.84
	SMAP	7	89	0.85

Figure 5.4 presents subregion of the land-cover classification results. In general, the SMAP result is noisier than OBIA_RF. Visual assessment of OBIA_RF confirms an over-estimation of the built-up areas (Figure 5.4b). Visually, there was a high confusion between built-up and bareland as well as bareland and vegetation. The over-estimation of built-up can be associated with the under-segmentation. On the other hand, SMAP over-estimated vegetation areas (Figure 5.4c). This can be related to the acquisition date. The 2013 image was acquired in the wet season, whereas the 2017 image was acquired in the dry season. Furthermore, there was less confusion between built-up and bareland. To reduce the confusion between vegetation, bareland and built-up, subclasses of vegetation (tree, dry vegetation and wet vegetation) and bareland (untarred road and baresoil) were experimented. However, the experiment did not show an improvement. Hence, SMAP was used as input for the land-use classification.

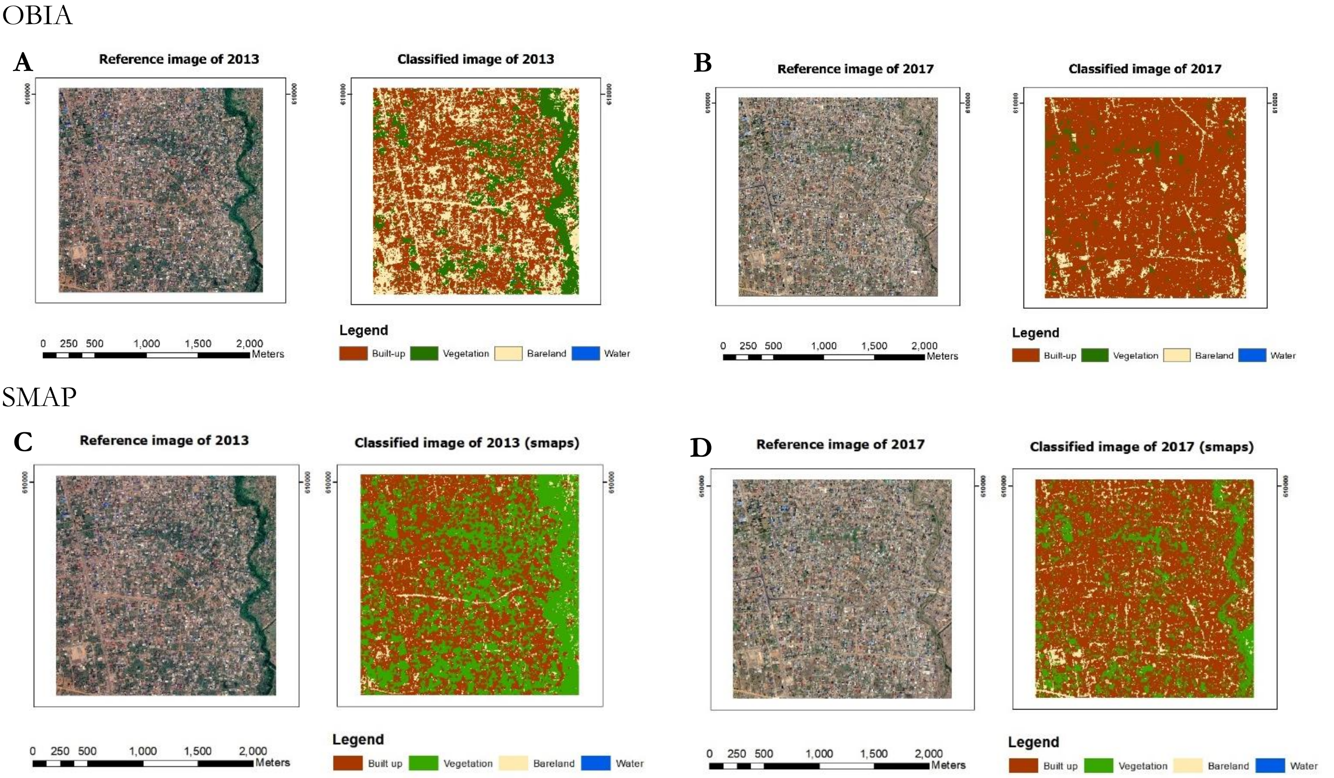
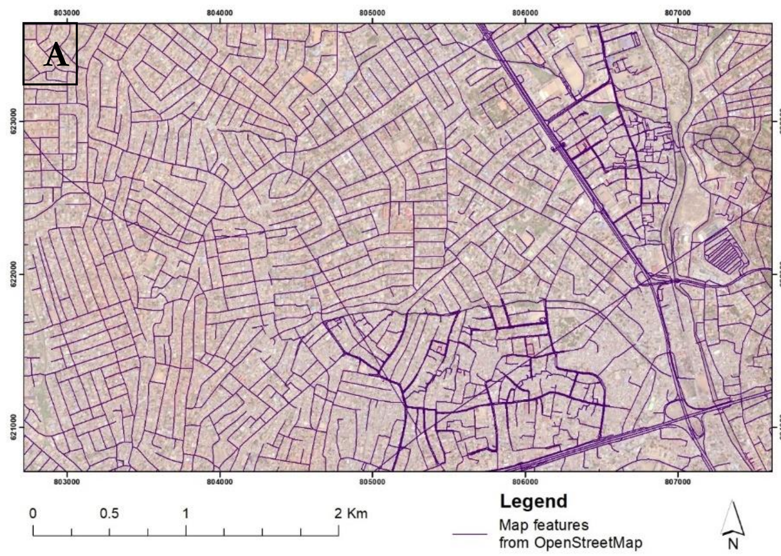


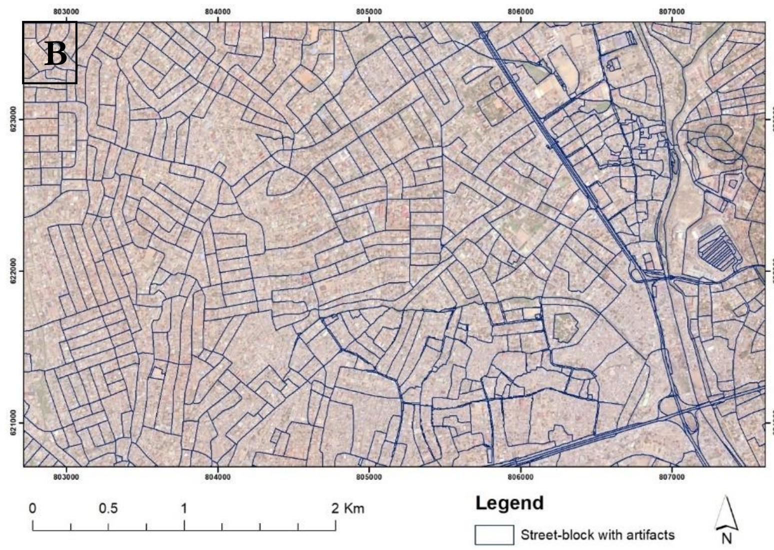
Figure 5.4 A subregion showing classification maps of OBIA Random Forest (RF) and SMAP A) OBIA_RF 2013 B) OBIA_RF 2017 C) SMAP 2013 D) SMAP 2017.

5.4. Extraction of street-block geometries

The proposed processing chain was able to create street-blocks geometries at a citywide scale. The workflow relies on the capability of PostGIS for managing large amount of data (more than 190,000 line segments) and the integration with QGIS for visual assessment. In total, 26,316 blocks with sliver polygons were extracted using a tolerance of 7. The sliver polygons accounted for 26.9% of the initially extracted blocks. Sliver polygons were removed using a trial and error rule approach based on the compactness, and size of blocks. The final layer contains 19,213 block geometries for Accra.

Figure 5.4 shows the results of different stages of street-block extraction. Imported line segments from OSM had many spatial and topological problems (Figure 5.3a). The snapping of line segments cleaned initial errors to some extent with the presents of sliver polygon (Figure 5.3b). The final street-blocks are presented in Figure 5.3c.





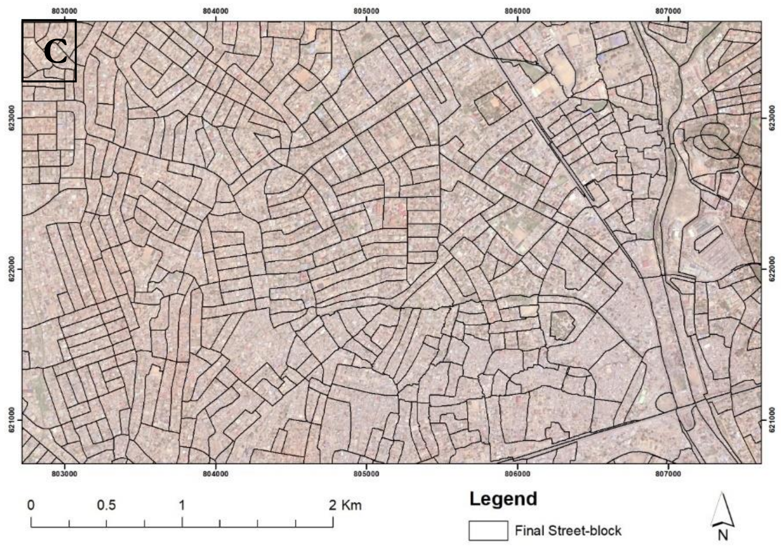


Figure 5.5 A subregion showing extraction of street blocks from OSM data. A) vector layers from OSM B) street-block with artefacts (sliver polygon) C) final street-block.

5.5. Land-use classification

A comparison between using only contextual features and land-cover combined with contextual features (from now on called LCLU) was performed to identify the best strategy for citywide slum mapping. Both approaches achieved high overall accuracy and F1-score of over 80% (Table 5.5). F1-score was used to assess the disparities between classes (Sokolova & Lapalme, 2019). The accuracy results are not significantly different. Also, an experiment of having one slum class for both approaches achieved a very high overall accuracy of over 90%. Therefore, the errors in the first level propagate into the subclasses. In addition, 2017 achieved lower accuracies in both approaches than in 2013. This could be associated with the difficulty in identifying infant slums in 2017 images (Table 5.6).

Table 5.5 A comparison of contextual and LCLU overall accuracy and F1-scores for 2013 and 2017.

	2013		**2017**	
	Contextual features	**LCLU**	**Contextual features**	**LCLU**
Overall Accuracy	0.866	0.868	0.834	0.839
F1-score	0.90	0.91	0.84	0.84

Assessment of the per-class accuracy reveals that the precision and recall for all subclasses achieved high score of over 80% except for infant slums (Table 5.6). Infant slums achieved a lower recall of less than 40% in all cases, and precision of infant slums ranges from 60 to 75%. Moreover, the F1 score, which defines the harmonic mean of precision and recall is lower than 52%. This means the prediction under-perform on classifying infant slums.

The assessment of the confusion matrix shows misclassifications (confusion) between infant slum, matured slum and high-density residential in all cases as expected (Appendix 1). These subclasses have similar morphological characteristics. Visual assessment of both contextual features and LCLU approach reveals no large difference (see Figure 5.6, 5.7, 5.8, and 5.9).

Table 5.6 Precision, recall and F1 score of contextual features and LCLU HDR: high-density residential, LDR: low-density residential, NON-RST: non-residential, NON-BLT: non-built-up, LCLU: Land-cover confined with contextual features. Green colour: High accuracy, yellow: medium accuracy and red: low accuracy.

Class	Precision	Recall	F1-Score	Support	Precision	Recall	F1-Score	Support
	Contextual features				LCLU			
				2013				
HDR	0.81	0.91	0.86	47	0.81	0.94	0.87	47
LDR	0.96	0.98	0.97	48	0.98	0.96	0.97	48
Infant	**0.6**	**0.4**	**0.48**	**15**	**0.75**	**0.4**	**0.52**	**15**
Matured	0.82	0.87	0.85	38	0.85	0.92	0.89	38
Non-RST	0.96	0.88	0.92	58	0.96	0.91	0.94	58
Non-BLT	0.96	0.97	0.97	71	0.96	0.97	0.97	71
				2017				
HDR	0.87	0.88	0.88	52	0.88	0.87	0.87	52
LDR	0.9	0.88	0.89	40	0.89	0.85	0.87	40
Infant	**0.6**	**0.25**	**0.35**	**12**	**0.6**	**0.25**	**0.35**	**12**
Matured	0.79	0.91	0.85	46	0.76	0.96	0.86	46
Non-RST	0.84	0.82	0.83	45	0.84	0.82	0.83	45
Non-BLT	0.86	0.88	0.87	48	0.86	0.88	0.87	48

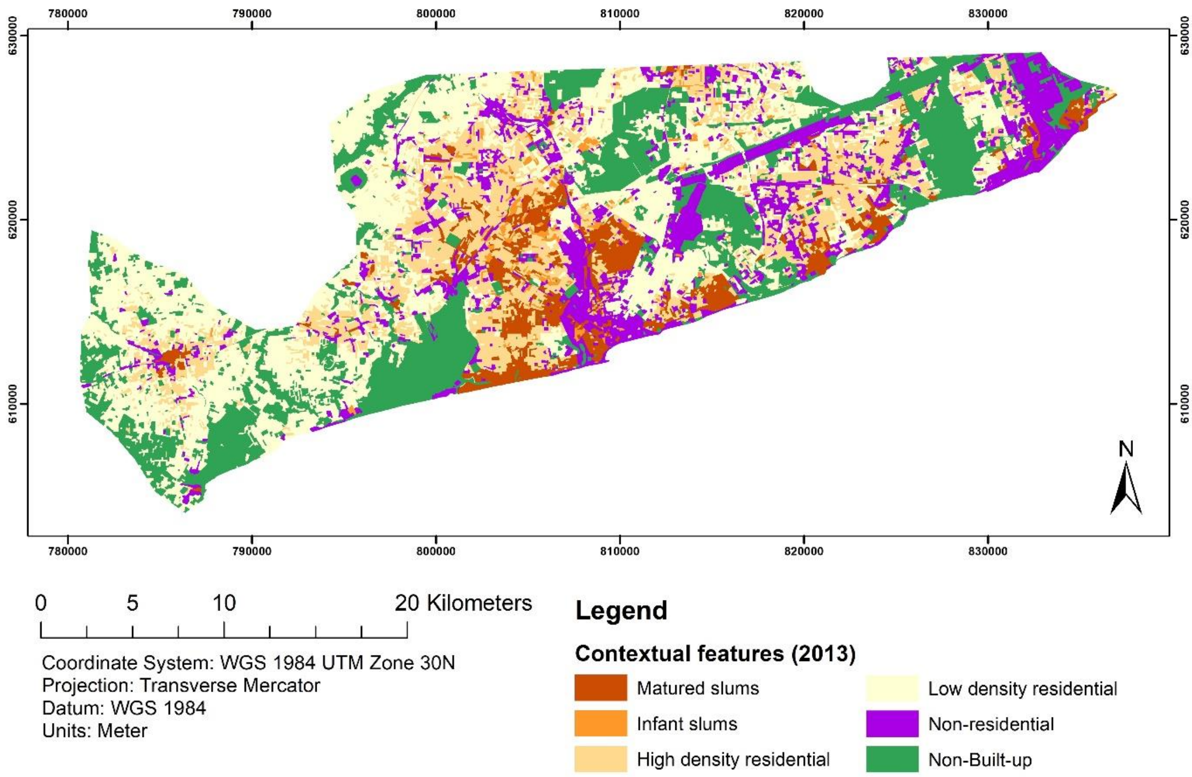


Figure 5.6 Land-use map of 2013 using contextual features.

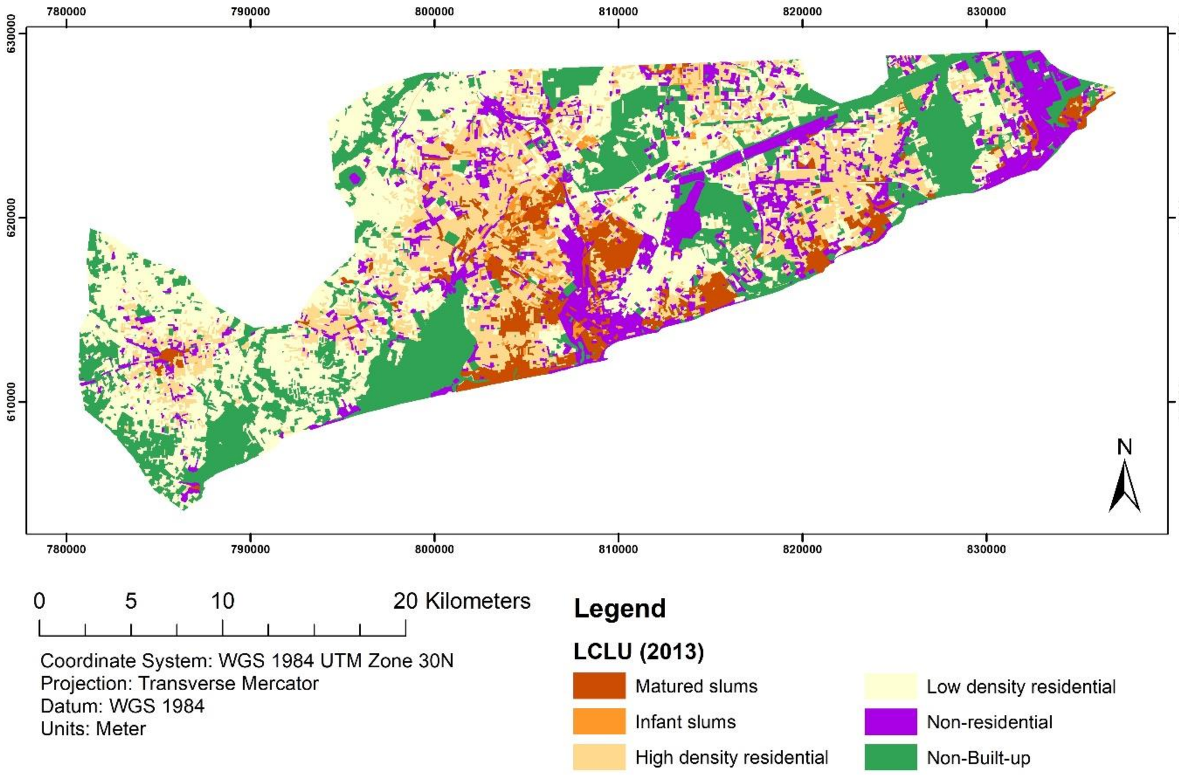


Figure 5.7 Land-use map of 2013 using LCLU. LULU: land-cover combined with contextual features.

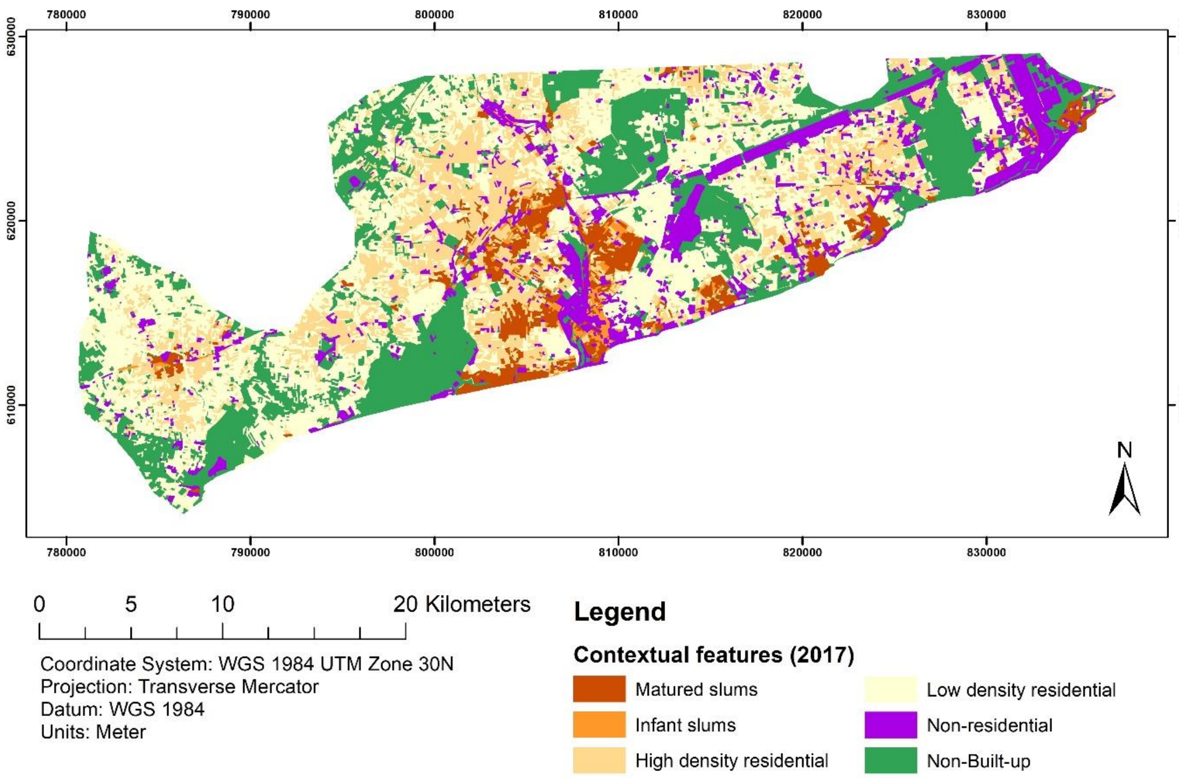


Figure 5.8 Land-use map of 2017 using contextual features

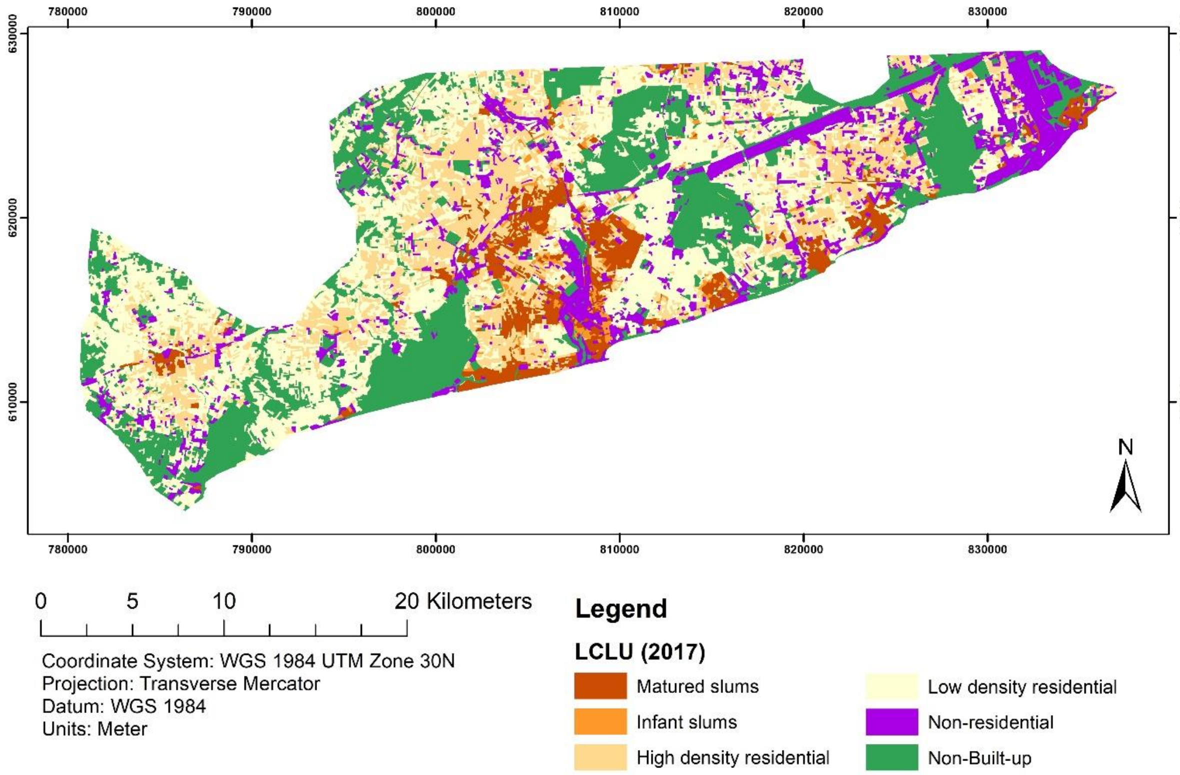


Figure 5.9 Land-use map of 2017 using LCLU. LULU: land-cover combined with contextual features.

5.5.1. Random forest feature importance

One purpose of the study was to investigate which image features are most suitable for slum extraction. Table 5.7 presents the top five image features from the RF. The most important features are related to the vegetation in all cases. The best feature for classification was the NDVI similar to the results of Sandborn & Engstrom, (2016) and Grippa et al., (2018). For LCLU approach, the proportion of built-up and vegetation features were the best features for distinguishing classes. This confirms other studies (e.g., Kohli et al., 2012) that concluded slums have low vegetation cover hence making it a useful feature for separating classes.

Table 5.7 Top five random forest image feature of importance (mean decrease in accuracy) Ndvi: Normalised different vegetation index, Prop_1: Proportion of built-up, Prop_2: Proportion of vegetation, img_red: red band, img_4: near-infrared band.

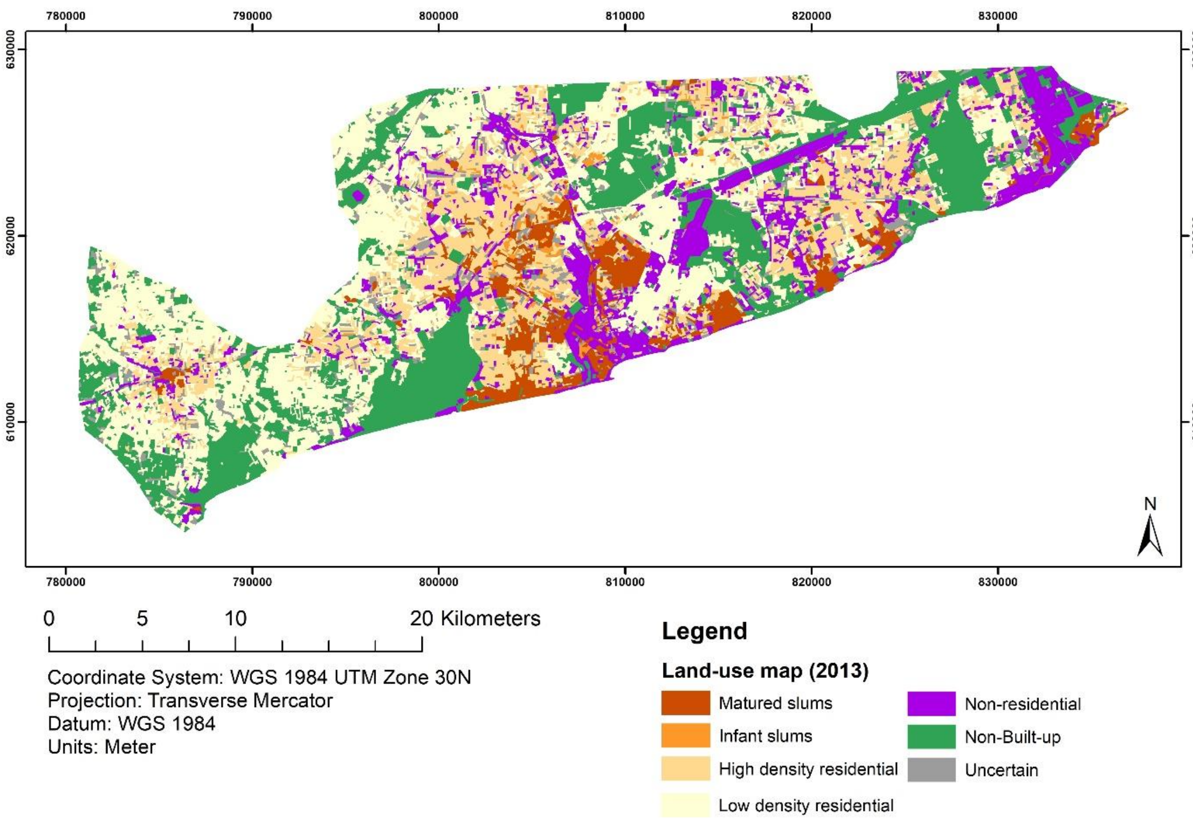
Contextual features		LCLU	
	2013		
Features	**importance**	**features**	**importance**
Ndvi13_third_quart	0.033883	Prop_1	0.045596
Ndvi13_median	0.030225	Ndvi13_third_quart	0.026201
Ndvi13_mean	0.029685	Ndvi13_meadian	0.023191
Ndvi13_first_quart	0.021100	Ndvi13_mean	0.022494
Img_red_third_quart	0.020089	Prop_2	0.021942
	2017		
Ndvi17_mean	0.030243	Prop_1	0.045059
Ndvi17_median	0.029523	Prop_2	0.034018
Img17_4_median	0.023478	Ndvi17_median	0.024421
Ndvi17_third_quart	0.022240	Ndvi17_mean	0.022790
Img17_4_mean	0.021432	Ndvi17_third_quart	0.022260

5.6. Uncertainty analysis and thematic improvement of maps for change detection

Reliable land-use classification results are crucial for post-classification change detection (Singh, 1989). Apart from the use of the confusion matrix, spatial variation of accuracy was analysed using class membership probability of every street-block provided by RF. The confidence map shows the uncertainty associated with every street-block and demonstrates which street-blocks are more likely to be the true classes. Identifying the extensional uncertainties allow to investigate ground-based causes of uncertainties (existential uncertainties) (Kohli, Stein, et al., 2016). Confidence maps are presented in appendix 2. Darker regions represent street-blocks with high certainty. From ERP results, heterogeneous street-blocks experience high uncertainty with values between 0.2 and 0.4.

Most RS-based slum mapping studies usually report overall accuracy from 70 to 90% (Kuffer, Pfeffer, & Sliuzas, 2016). Therefore, street-blocks were labelled uncertain if the ERP is less than 70%. Overall, 7.6% and 7.4% street-blocks were labelled uncertain for contextual feature and LCLU for 2017 respectively. Whiles 6.4% street-blocks were labelled as uncertain in both cases for 2013. Based on the low uncertainties in LCLU, they were used for change detection. Final land-use mapping is presented in Figure 5.10

A



B

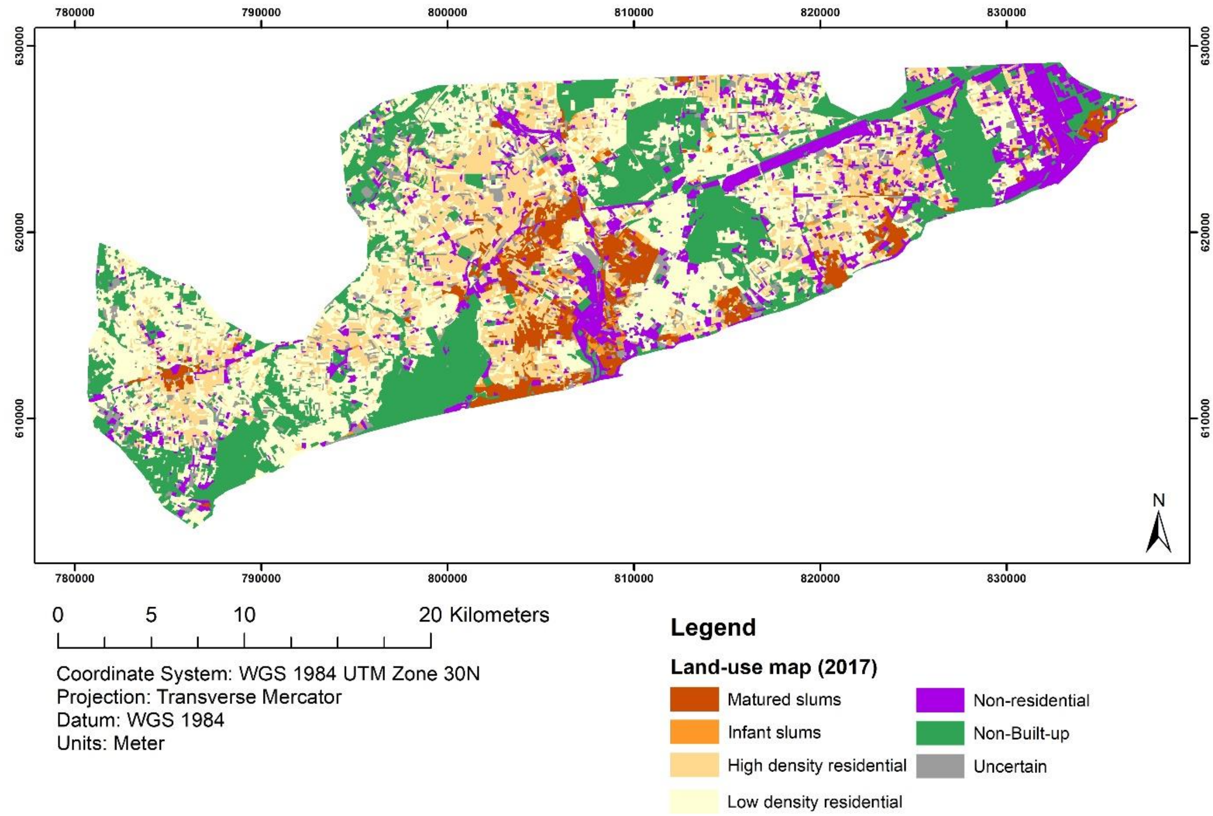


Figure 5.10 Final land-use map of Accra for the years a) 2013 b) 2017.

With the initial land-use classification results (before fieldwork), fieldwork was carried out to investigate the existential uncertainties (ground-based uncertainties only) associated with slum street-blocks. From field observation, three main causes of uncertainties were identified. They include morphological similarities of typical slum and old towns, presence of areas with slum-like appearance due to unplanned and uncontrolled extension, and presence of slum neighbourhoods which have been regularised or upgraded.

Morphological similarities of typical slums and old towns make them difficult to be distinguished without local-context knowledge (Figure 5.11). These old towns have high building density and irregular settlement patterns similar to typical slums (Weeks et al., 2007). It also introduces uncertainties in generating reference data (Pratomo et al., 2017).

Figure 5.11 Morphological similarities between old towns and typical slum a) Kasoa old town b) Sukura.

Additionally, areas with slum-like appearance introduce uncertainties. Due to unplanned and uncontrolled extension, some areas (e.g. Tema community 1 (see Figure 5.12)) appear as slum when only the physical characteristics are used to detect slum. These areas are predominantly housed by both low and middle-income group. They have access to social services and infrastructure, such as electricity and potable water.

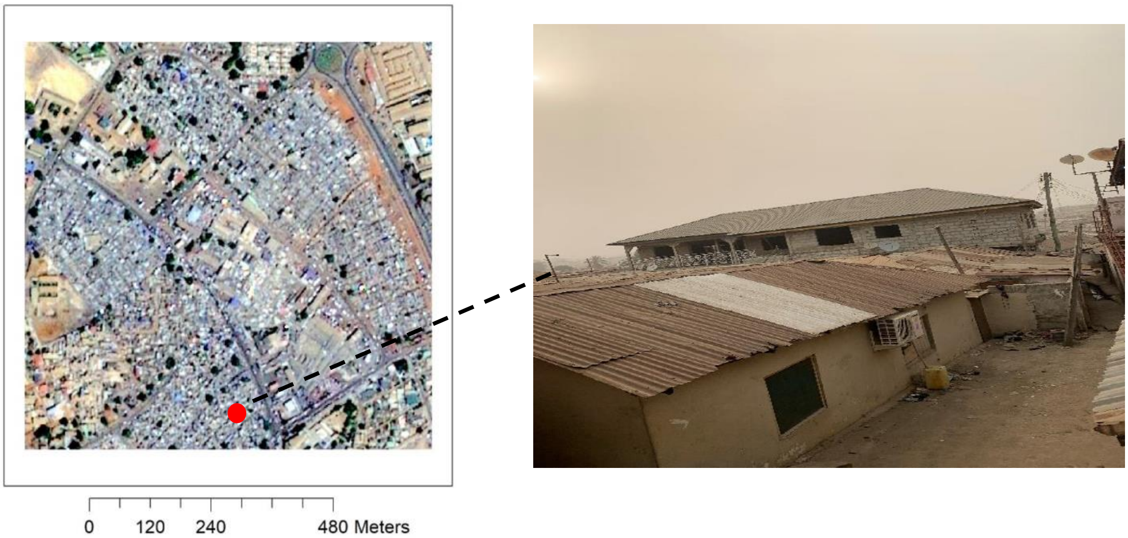


Figure 5.12 Slum-like appearance (Tema community 1)

Lastly, slum communities which have been regularised or upgraded introduced some uncertainties. In the upgrading, it was not possible to follow the strict planning standards of planned areas but rather adapted to the existing situation. For example, they result in the creation of alleys or small size of the road. Also, they may be upgraded with the provision infrastructure such as electricity, water and sanitation but not spatial redesign of the neighbourhood, thus they are still seen as slum from images. This could be one of the reasons why end-users do not agree with using only the physical properties of slums.

5.7. Change detection

The accuracy of change detection was assessed using TEM. Table 5.8 presents the accuracy of change detection. For A_T assessment, only 53.3% of the samples have correct change trajectory. $A_{C/N}$ obtained an accuracy of 59.2, which is high than A_T. $A_{C/N}$ is higher than A_T because it does not consider the correctness of the classification and change trajectory. The assessment shows low overall accuracy. In addition to the overall accuracy, individual trajectories were assessed. The study obtained an OAD of 5.8% signifying higher accuracy in change/no change trajectory than correct classification and change trajectory. This means that despite being detected correctly as change/no change, some change trajectories do not match the reference data. $ADIC_C$ is higher than $ADIC_N$, indicating that most change classes were correctly detected than no-change changes. Furthermore, $ADIC_C$ achieved 100% accuracy, indicating that all change trajectory were correctly detected whiles 88.1% of no-change were correctly detected from the sample.

Table 5.8 Accuracy of change detection.

Indices	**Value (%)**
Overall accuracy (A_T)	53.3
Change/no change accuracy ($A_{C/N}$)	59.2
Overall accuracy difference (OAD)	5.8
Accuracy difference of no change trajectory ($ADIC_N$)	88.1
Accuracy difference of change trajectory ($ADIC_C$)	100

Uncertain street-blocks obtained from uncertainty analysis was integrated into the final change detection maps to show areas with uncertain change/no change trajectory. After integrating uncertainties in the change detection, TEM method proposed in section 4.10 was performed to check if the map would improve. The only modification was the exclusion of uncertainties street-blocks from sample selection. The overall accuracy increased from 53.3% to 66.7%. and the change/no change accuracy increased from 59.2% to 70.8% (Table 5.9). This showed a large improvement in the model when uncertain street-blocks were excluded.

Table 5.9 Accuracy of change detection after integrating uncertainty analysis.

Indices	**Value (%)**
Overall accuracy (A_T)	66.7
Change/no change accuracy ($A_{C/N}$)	70.8
Overall accuracy difference (OAD)	4.1
Accuracy difference of no change trajectory ($ADIC_N$)	91.5
Accuracy difference of change trajectory ($ADIC_C$)	100

5.8. Analysis of the dynamics of slums

Figure 5.13 presents a map showing the change trajectory of land-use from 2013 to 2017. In general, 90.3% of the study area remained unchanged, and 3.2% of land changed (Table 5.10). While 1.8% changed from slum to non-slum, 1.4% changed from non-slum to slum. 6.4% of the study area was classified as uncertain. In Accra, slums disappeared in areas close to river. An example of this dynamic is slums along the Kole Lagoon disappeared in 2017 (Figure 5.14). This is the results of large eviction at Old Fadama by the AMA in 2015 (Oppong, Asomani-Boateng, & Fricano, 2020). These slums are characterised by kiosk or temporal structures, making them a high threat to eviction (appendix 3). Moreover, slums appeared on vacant land usually owned by the state or areas locally called "Kiosk estate". Kiosk estate is where landowners provide land for poor people to put up temporal structures without services (e.g. water and sanitation) at a cheap cost (monthly rent of 20 -30 cedis).

Even though the results from change shows 1.4% change from non-slum to slum, visually assessment shows that most of the change trajectory from non-slums to slums were not correct (Figure 5.15). This can be associated with the confusion between slums and high-density residential. However, there were changes within street-blocks that were not captured due to the level of aggregation.

Table 5.10 Change trajectory between 2013 and 2017.

Change trajectory	**Area (km^2)**	**Percentage**
Slum remained slum	35.95	5.6
Non-slum remained non-slum	541.1	84.7
Slum to non-slum	11.8	1.8
Non-slum to slum	9.2	1.4
Uncertain	41.1	6.4
Total	639.2	100

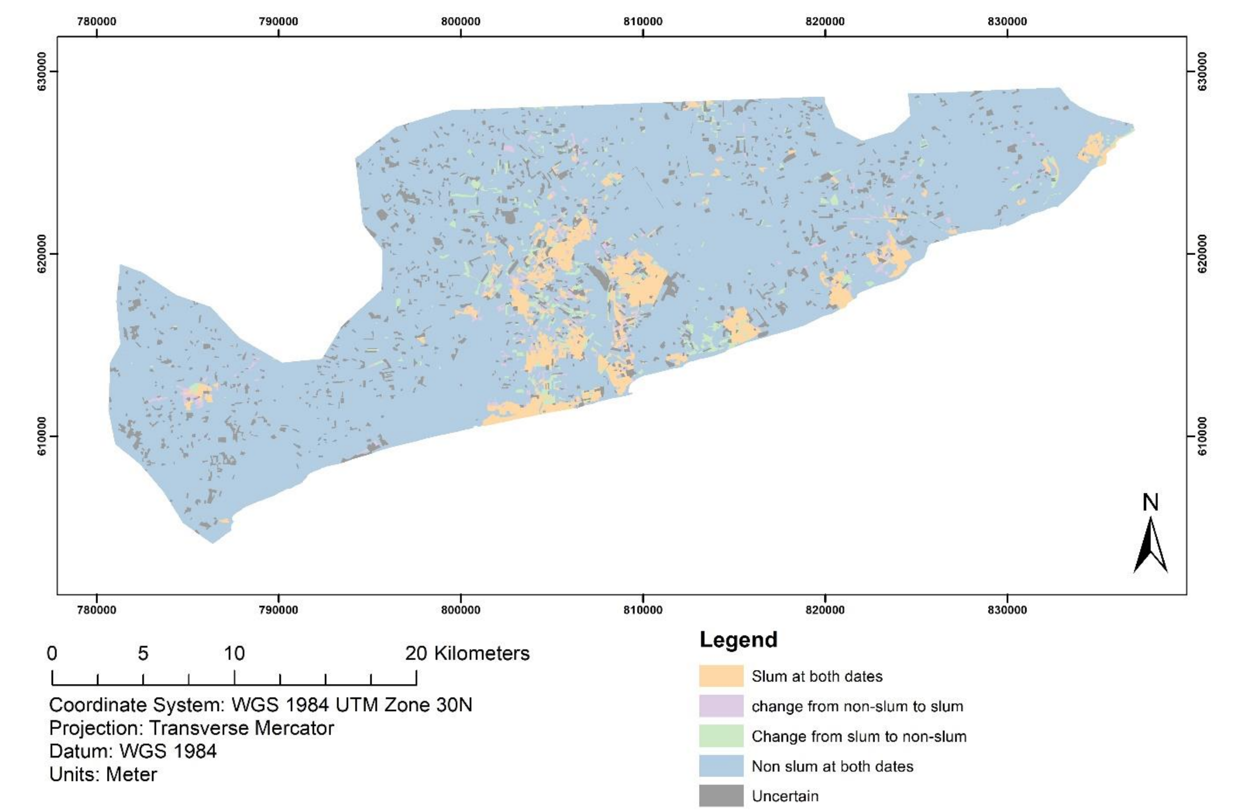


Figure 5.13 Change trajectory map of slums and non-slums between the years 2013 and 2017.

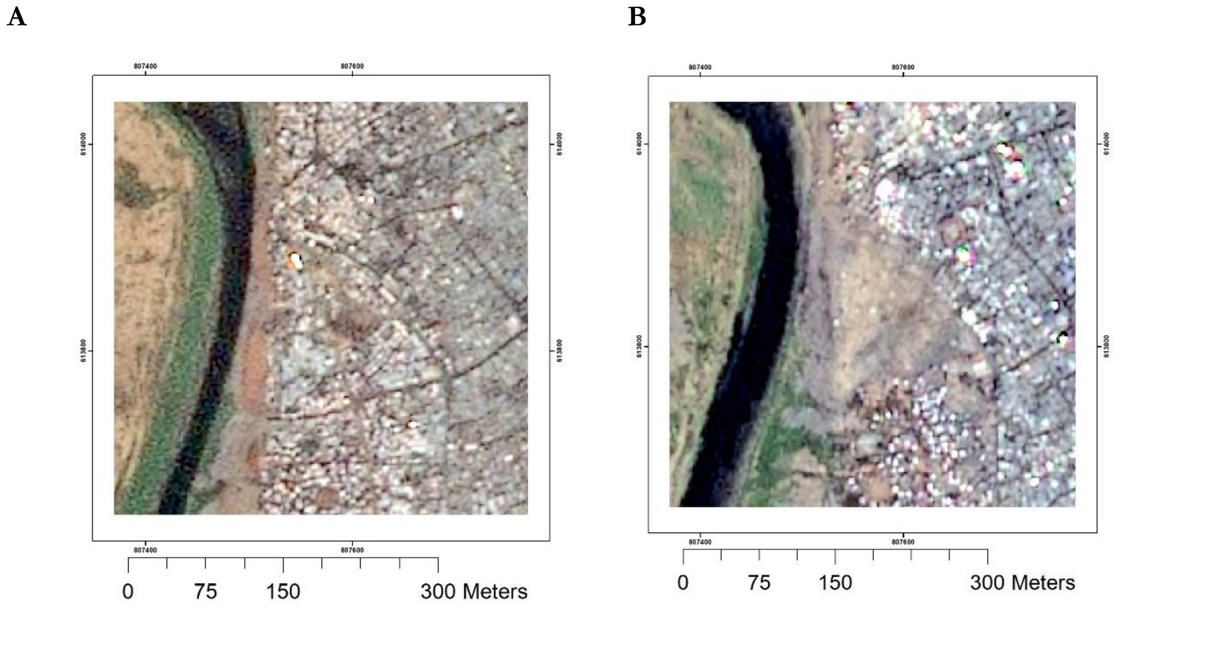


Figure 5.14 Example of slum disappearing (Old Fadama). A)2013 B)2017 (source of the images used to visualise the slums: SPOT 6 image of 2013 and 2017).

A **B**

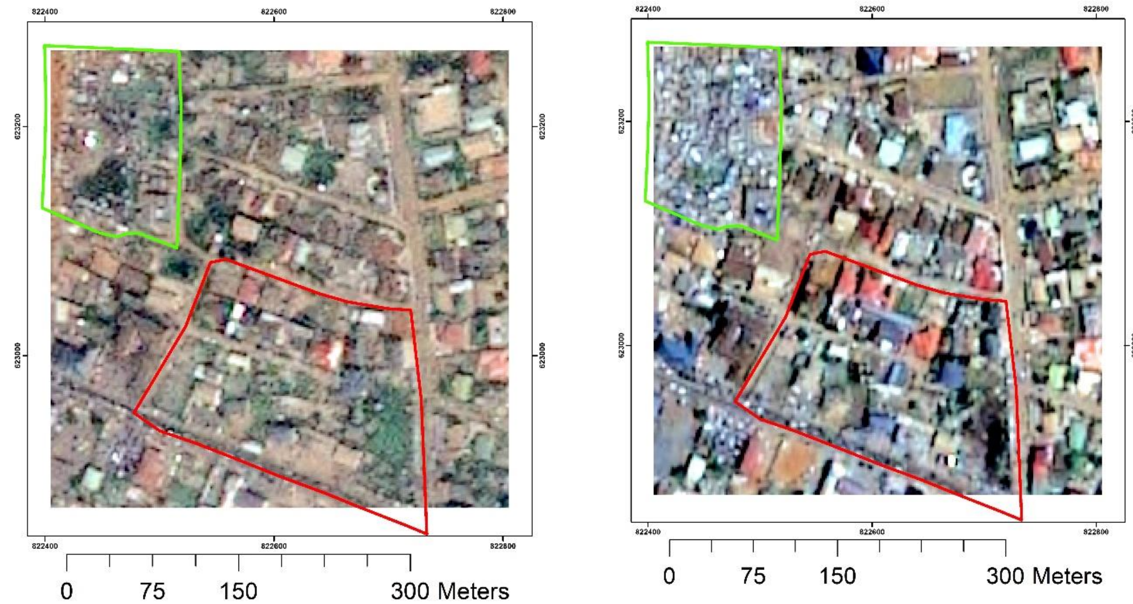


Figure 5.15 Examples of change non-slum to slum in green and wrong change trajectory from non-slum to slum in red. A)2013 B)2017 (source of the images used to visualise the slums and non-slums: SPOT 6 image of 2013 and 2017).

6. DISCUSSION

EO-based methods have the potential to map slums dynamics. The results of this study reveal that land-use change between slums and non-slums in Accra is more stable between 2013 and 2017. Over 90% of the area remained unchanged. However, there were changes which occurred within street-blocks that could not be captured due to the level of aggregation. Most slums disappeared in areas susceptible to flooding (Figure 5.14) and slum appeared on vacant land usually owned by the state or "kiosk estate". According to the PD experts, infant or kiosk slums have a high threat of eviction and do not want to be visible. Therefore, this study produced maps at the street-block level, which could not capture kiosk slums. Producing high level disaggregated map means putting the most vulnerable people in danger. As researchers, we aim to provide data to support and improve slum dwellers living conditions rather than contributing to their stigmatisation and risk of eviction. Therefore, the level of aggregation proves to be ideal for the problem.

Additionally, the proposed processing chain of using low-cost Spot 6 with a spatial resolution of 1.5m, covering 764.3 km^2 proves to be operational for large area mapping. The advantage of the proposed method is the integration of local context knowledge, and it relies on FOSS4G solutions from initial pre-processing to change detection analysis. Even though the proposed method achieved interesting results, perspectives for further development are discussed below.

6.1. Spatial information requirements

In general end-users requirements are not well understood by the RS community, and most EO studies never ask these questions (Kuffer et al., 2020; Thomson et al., 2020). This study has shown that the spatial information required by different user groups varies depending on the goal of the institution. For example, NGO's need data on slum location and growth. Having access to such information, they can support them in developing pro-poor programs including provision of social amenities such as water and sanitation to improve their livelihood as well as assisting slum dwellers facing eviction. Additionally, different user groups require a distinct level of details and aggregation. Map producers should make a distinction between the level of details and aggregation needed by different user groups. In this study, we produced land-use map, which includes different stages of slum at street-block level. This level of details and aggregation meet the requirement of most interviewed users except for TDC. TDC are more interested in highly disaggregated slum information to prevent slum growth. Further works should provide a more disaggregated map (e.g. grid-scale or segments) to identify kiosks or temporal structure in slums. Such information is needed by PWD and TDC to ensure development control. Also, a slum index could be developed to depict the differences between the good to worst slums to help NAMDO, PPD and PD to prioritised pro-poor initiatives (Engstrom, Pavelesku, Tanaka, & Wambile, 2017).

Although all institutions have different purposes, they all raise similar concerns (such as report on level of accuracy and uncertainties, and guidelines on how to use and interpret the maps) in making slum data publicly available. This indicates the importance of including end-users in the mapping process. In general, end-users prefer a more bottom-up approach, as discussed by Lilford et al. (2019). This was also confirmed by the expert interviews done in Accra. Further research should investigate the data required by health institution, environmental institutions and slum dwellers themselves.

6.2. Land-cover and land-use classification

6.2.1. Segmentation and feature selection

The experiments showed that the local segmentation demonstrated different optimised threshold per grid depicting its ability to capture the very heterogeneous urban morphology. Surprisingly, high optimised threshold values were obtained for built-up and low optimised threshold values for non-built-up areas. Non-built-up areas achieved low optimised thresholds due to a high local variation in the panchromatic band. Also, there was a mix of different crop types, grass, trees and baresoil that increased the complexity of such zones. Local USPO achieved high optimised threshold values for built-up areas which were expected to have high intra-object variance leading to under-segmentation.

Correspondingly, the grid size used for local USPO may have affected the segmentation quality as discussed by Drăguţ, Belgiu, Popescu, & Bandura, (2019) and Georganos, Grippa, Lennert, et al., (2018). This could be one of the reasons why local segmentation did not achieve meaningful objects. Also, the use of regular grids introduced edge effect, such as the splitting of buildings. Further research could use street-blocks to make it adjustable to the urban landscape. Moreover, USPO requires a predefined range to obtain optimised parameters (threshold and “minsize”). Therefore, having a large range can lead to under segmentation, and a small range can lead to over-segmentation. The best segmentation can be achieved by testing different range parameters.

Regarding feature selection, as mentioned by Georganos, Grippa, Vanhuysse, et al. (2018), some useful texture features are likely to be excluded when using expert-based knowledge. As a solution, we computed several hundred features and used VSURF feature selection procedure to select the most discriminant features. However, studies have concluded that the feature selection technique used can impact the performance of the classification (Cánovas-García & Alonso-Sarría, 2015). Future works could compare different methods and select the one with the best classification results.

6.2.2. Sampling

For the land-cover classification, the study relied on OSM for the creation of training and validation dataset. This is an important experiment to support scalability as the generation of manual reference is very time-consuming. However, the study area suffers from data incompleteness. For example, there was no data on bareland. OSM data are also affected by seasonal variations of vegetation. Therefore, the training and validation dataset still relied on expert intervention. Additionally, the use of points for training and validation excluded contextual information, therefore, further research could explore the use of superpixels for creating training and validation dataset (Kanavath & Metz, 2017). Superpixels can be created and used to visually assign labels to include contextual information into the model, especially for SMAP.

For land-use classification, we faced difficulty in using visual interpretation to distinguish different slum stages. The similar appearance of consolidated and matured slums poses challenges. In this study, consolidated slums were combined with matured slums since they have similar morphological characteristics and was difficult in distinguishing them visually. Also, there was an inadequate number of samples for infant slums for both training and validation. This affected the infant class classification. Although RF is said to be robust for small sampling size (Belgiu & Drăguţ, 2016; Folleco, Khoshgoftaar, Van Hulse, & Bullard, 2008), however, it underperformed in this study. From the confusion matrix, it had the lowest accuracy for F1 score, precision and recall. Comparatively, it is better than CNN which cannot handle this small number of samples (Mboga et al., 2017).

Regarding generating reference samples for change detection, we even faced more problems using visual interpretation. It was difficult to determine changes if street-block did not change a lot. For example, only 5% changed from vegetation to buildings. Liu & Zhou, (2004) proposed accuracy analysis by rule-based rationality evaluation with post-classification comparison. Based on that, further research can define threshold rules to determine changes within street-blocks to be used to generate reference data.

6.2.3. Street-block extraction

The quality of street-blocks relies on the level of completeness of OSM data. Although the study did not evaluate the geometric and semantic quality of the street blocks, some aspect can still be reviewed. The addition of other linear features such as rivers and drains reduce the impact of large blocks, especially at the peri-urban. Still, some land-use classes such as the kiosks slums could not be captured due to large street-blocks, especially at the industrial zones (Figure 6.1). The typical size of Kiosk slums around 500m^2 (one plot). Further research can add large roof buildings, especially at the industrial areas to further sub-divide large street-blocks into small ones. Moreover, removing sliver polygons were done based on trial and error (rigorous parameter tuning) and expert knowledge. Further research should focus on developing a robust and effective way of removing sliver polygon.

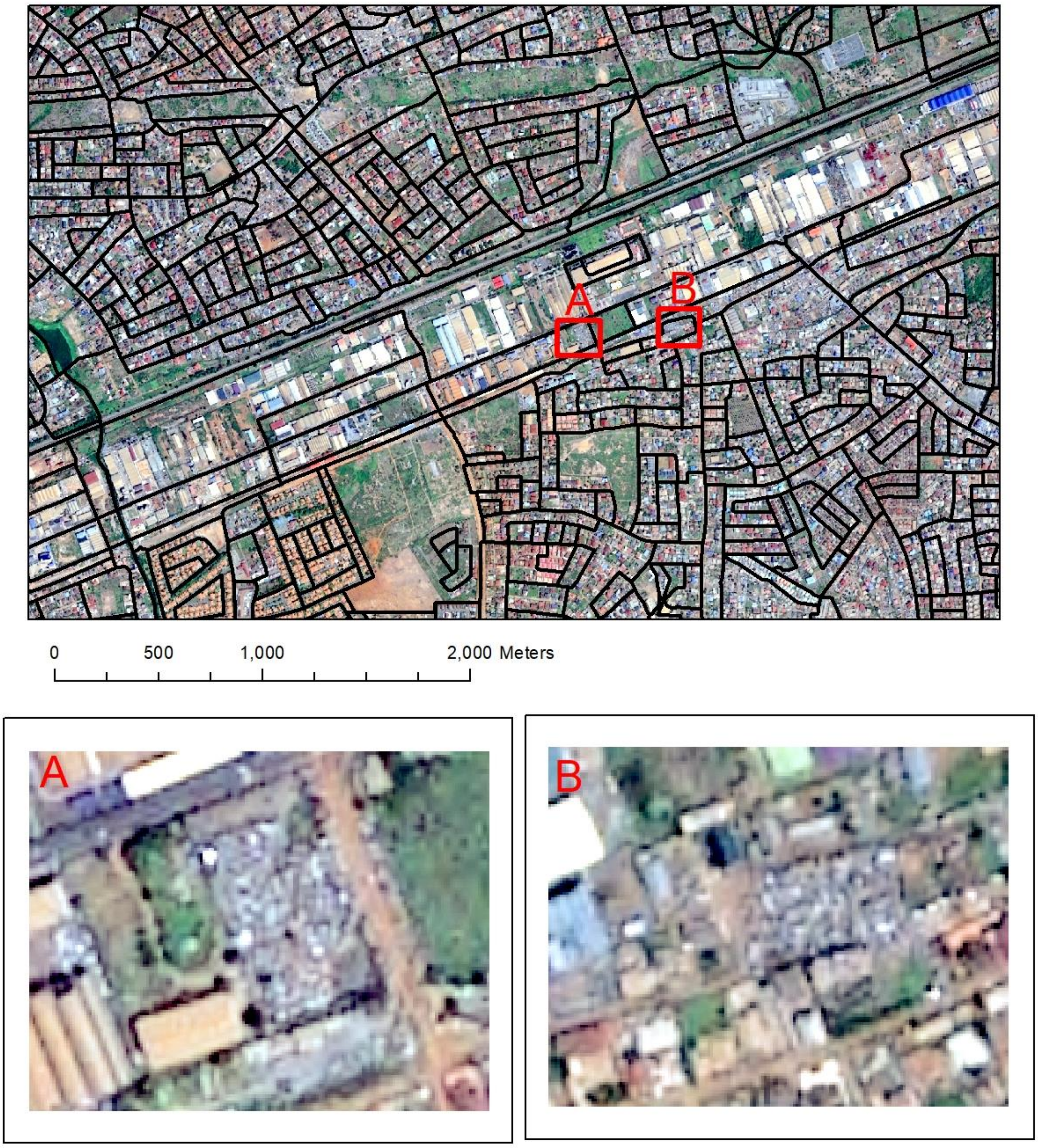


Figure 6.1 Large street-blocks omitting kiosk slums. (source of the images used to visualise Kiosk slum: SPOT 6 image, 2017).

6.2.4. Land-use classification

RF was the only classifier used for the land-use classification. Aside from its high prediction accuracy (Belgiu & Drăguţ, 2016), the study took advantage of the class membership probability to estimate spatial uncertainties. The classification results had an overall accuracy of over 80%, indicating the effectiveness of using this classifier. Similar results were obtained by Grippa et al. (2018) and Engstrom et al. (2015). The high accuracy shows that RF is robust for large scale mapping. The use of contextual features only and LCLU approaches achieved similar overall accuracy. Although high overall accuracy was obtained, classification errors were related to the different classes of slums. The precision of infant slums range from 60 to 75%, and recall was lower than 40% in all cases (both contextual and LCLU approach as well as the two years) (Table 5.6). The low score of infant slum can be associated with the difficulty in obtaining training and validation dataset for both years (45 and 38 street-blocks for 2013 and 2017respectively). They are usually found at few locations and experience rapid transition (Ranguelova et al., 2019). The low precision and recall of infant slums confirm that GLCM underperforms in identifying less prominent patterns in the urban environment (Kit, Lüdeke, & Reckien, 2012).

Contrarily to findings in other studies (Belgiu & Drăguţ, 2016; Folleco et al., 2008), RF underperformed on a small sample size class in this study. This could be associated with the complexity of the class. Also, the confusion between slums and high-density residential areas can be reduced by adding building height or terrain information (topography), thus digital elevation model (DEM). Comparatively, slums usually have low height making them distinguishable from high-density residential with height information (Kohli et al., 2012). With the continuous availability of google earth street views, scene information can be added to improve the classification (Ibrahim, Haworth, & Cheng, 2019). Moreover, other contextual information, such as risk maps and socio-economic data can be integrated.

One major advantage of the proposed method is the use of predefined boundaries for classification, because non-experts do like the noisy EO ouput. Furthermore, it produced map which meets the requirement of interviewed experts. One problem of slum mapping has been the uncertainties of slum boundaries (Pratomo et al., 2017). In general, studies suffer from the fiat boundary problem (Smith & Varzi, 2000) where there are high uncertainties on the boundary of slums (Liu & Kuffer, 2019; Pratomo et al., 2018). The high uncertainties of boundaries are not only machine learning problem, but also they happened when delineated by experts (Kohli, Stein, et al., 2016; Pratomo et al., 2017). In this study, we predefined the boundary of slums for land-use classification. This approached helped to overcome the fiat boundary problem by providing an operational boundary for citywide mapping. However, with the proposed aggregation level, kiosk slums were not captured. These slums are usually located at industrial areas covering less than 0.2 hectares. Further research can explore the use of grid to capture them.

6.2.5. Computational cost

One major bottleneck of slum mapping at a citywide scale is the involved high computational cost. Coupled with other problems such as image cost has hindered the development of citywide slum mapping. The use of street-blocks combined with low-cost SPOT 6 images has allowed producing a citywide scale slum map. The main advantage of the use of contextual features approach is that it is relatively quick to process compared to the LCLU approach. The contextual features approach skips the segmentation and landcover classification stage, reducing processing time. In general, the computational problem was still experienced in this study. An overview of the different processing cost is presented in table 6.1. Intensive processing relied on HP workstation Z620 with two Intel Xeon E5-2680 (2.7GHz) and eight cores and eleven threads. The processing was parallel with 11 threads. The computational intensiveness was one of the reasons why several parameter ranges (threshold and minsize) for USPO were not tested. Testing different parameter ranges could help to improve segmentation results.

Table 6.1 Computational cost. System description: HP workstation Z620 with two Intel Xeon E5-2680 (2.7GHz), and eight cores and eleven threads.

Step	**Time (hours)**
Image segmentation	13
Texture features extraction	69
Computation of features statistics	19
Extraction of street-block	43
Land cover classification	2
Land use classification	0.5

6.3. Change detection and slum dynamics

The proposed approach was tailored for identifying change trajectories at a citywide scale. Integrating uncertainty information from land-use classification with change detection improved the overall change detection accuracy (from 53% to 67%). This provides useful information for both map producers and end-users to understand the nature of errors better and improve the map quality (see Figure 5.13).

The use of TEM reveals moderate overall accuracy similar to other studies (R. Liu et al., 2019; Pratomo et al., 2018). The visual assessment shows most of the change trajectory were correctly detected except for changes from non-slum to slum. The false change detection was associated with the vegetation phenology between the two images causing confusion between slums and high-density residential. The seasonal variation in the images may have affected the change detection because vegetation was the most important feature for distinguishing classes. Similar issues were identified in Duque et al. (2017) study.

It is difficult to determine actual changes from false change using pixel or object-based methods (R. Liu et al., 2019; Pratomo et al., 2018). For example, in object-based change detection, a change in the shape of an object or a slight shift as a result of different viewing angle will be detected as changes. This approach of predefining boundaries helps to overcome such difficulties. However, the proposed approach could not capture within street-block dynamics. Visually, most changes in the study area occurred within street-blocks. This could explain why over 90% remained unchanged. Further studies can subdivide street-blocks to better capture changes. The study could have two hierarchy levels where change detection analysis can be performed at the object level or small grid-scale and final maps are shown at the street-block level. within detailed information at object level, landscape metrics can be used to assess the compactness or disperse within street-blocks. This details are needed for analysis and the level of details in the final product should be minimised to ensure mapping ethics.

7. CONCLUSION

The main objective of this study was to develop a processing chain for spatio-temporal slum mapping at a citywide scale using low-cost SPOT 6 image and Free & Open-Source Software. In this section, the conclusions of the research findings are presented for each objective

7.1. Sub-objective 1: To identify slum information required by end-users and geo-ethical concerns in making such data publicly available

In this study, we have identified the spatial information required by end-users through topic-focused interviews. The study has shown that end-users have varied spatial information. Depending on the purpose of the institution, they also have different requirement for the level of details and aggregation scale. The TDC and PWD mentioned that they need high disaggregated data to be able to monitor settlement growth and prevent slum growth. PD, PPD and NADMO would need a high level of detailed and disaggregated data to be able to plan and management pro-poor initiatives.

Additionally, they found out that interviewed experts do not oppose to making slum information publicly available. The PD experts mentioned that slum dwellers, especially those in Kiosk or infant slums have a high risk for eviction and do not want to expose their location. Therefore, providing a high level of detailed and disaggregated information would put slum households at risk and contributes to their stigmatisation. In general, all interviewed experts raised similar geo-ethical concerns to consider before making slum information publicly available. They mentioned concerns including how accuracy measures were estimated, a detailed report on how to map was produced, how the map should be interpreted and expect detailed metadata from map producers.

7.2. Sub-objective 2: To develop a semi-automated method for slum mapping at a citywide scale

In the second objective, we have proposed a semi-automated approach for citywide slum mapping using SPOT 6 of 1.5m resolution. Our proposed method takes advantage of FOSS4G solutions for slum mapping at a street-block level. Moreover, the implementation of codes in Jupyter notebooks allows sharing of codes for reproducibility. The entire processing chain codes are available on a dedicated Github repository (https://github.com/maxwellowusu/Accra_slum_map.git). The approach has proved to be efficient to handle large datasets since the study area, Accra covers 753km^2 in total.

In this study, we found out that slums have unique morphological characteristics, thus building density, texture pattern, and geometry which can be distinguished from space. Employing EO-based methods allows to mapping different stage of slums and other land-use types at the street-block level. By using classifier, we compared the use of contextual features only and the combination of land-cover and contextual features for land-use mapping at a street-block level. Both approaches achieved a high overall accuracy of over 80%. No conclusion has been made of the best approach, but the contextual features approach was less computationally intensive than LCLU.

The use of street-blocks provided a suitable aggregation level useful for citywide slum mapping. To some extent, it helped to overcome the uncertain boundary problem. It follows the urban morphology, and most of the interviewed experts selected it. Furthermore, the use of OSM data for generating reference data was efficient to support scalability since manually creating reference is time-consuming. Using the mean decrease in accuracy, the top most important features were associated with vegetation.

Consequently, we have assessed the spatial uncertainties associated with every street-block to explicitly understand the quality of the land-use maps. We used ERP to assess extensional uncertainties and field observation to understands the causes of uncertainties (existential uncertainties). Most of the extensional uncertainties were found in heterogenous street-blocks. Field observation showed that ground-based uncertainties were caused by a similar physical appearance of slum and old towns, areas with slum-like appearance due to unplanned and uncontrolled extension and slum areas which have been regularised or upgraded. We conclude that local context knowledge is key for any EO-based slum mapping.

7.3. Sub-objective 3: To analyse the spatio-temporal dynamics of slums at a citywide scale

The study used post-classification change detection to map change trajectories. We used a predefined boundary to map change trajectories to deal with the problem of the uncertain boundary (fiat boundary). In addition, we applied the trajectory error matrix (TEM) to assess the credibility of change detection. Initially, we achieved an overall accuracy of 53.3%. However, when uncertain street-blocks were excluded from the assessment, the overall accuracy increase to 67%. We conclude that the use of uncertainty analysis in change detection helps to improve the quality of the map. We also visually checked the change trajectory and observed that except for slum to non-slum changes, other change trajectories were mostly correctly detected.

In order to simplify the change trajectories, we reclassified the land-used maps into slums and non-slums. From the results, it could be observed that over 90% of the Accra remained unchanged, 1.8% changed from slum to non-slum, and 1.4% changed from non-slum to slum. Moreover, 6.4% were classified as uncertain using the uncertainty analysis results of land-use mapping. By visual assessment, we identified that land changes occurred within street-blocks which were not captured. Most of the new slums appeared on vacant lands whereas slums close to rivers (flood zones) disappeared (usually eviction by AMA).

7.4. Recommendations

Having investigated the use of low cost SPOT 6 for spatio-temporal slum mapping, the following topics may be considered for future research:

- To have a holistic understanding of the spatial information required and geo-ethics in making slum information publicly available, further studies should investigate user requirements of health institutions, environmental institution, and slum communities.
- The use of a regular grid for local segmentation was affected by edge effects. Further research could explore the use of street-block for local unsupervised segmentation parameter optimisation to make it is adjustable to the urban landscape.
- The study area suffers from cloud covers and occasional dust storms, further studies can explore the use of radar images to identify slums. Radar images are able to produce quality images regardless of weather or time of the day. It is not affected by clouds.
- Due to the computation demanding of the proposed method, future research should consider the use of medium resolution and free of charge Sentinel-2 images.

LIST OF REFERENCES

Adarkwa, K. K. (2012). The changing face of Ghanaian towns. *African Review of Economics and Finance*, *4*(1), 1–29. Retrieved from https://www.ajol.info/index.php/aref/article/view/87230

Agyei-Mensah, S., & Owusu, G. (2010). Segregated by neighbourhoods? A portrait of ethnic diversity in the neighbourhoods of the Accra Metropolitan Area, Ghana. *Population, Space and Place*, *16*(6), 499–516. https://doi.org/10.1002/psp.551

Airbus. (2019). *Price list*. Retrieved from https://www.intelligence-airbusds.com/files/pmedia/public/r48725_9_airbusds_intelligence_pricelist_1.1.19.pdf

Ajami, A., Kuffer, M., Persello, C., & Pfeffer, K. (2019). Identifying a slums' degree of deprivation from VHR images using convolutional neural networks. *Remote Sensing*, *11*(11), 1–24. https://doi.org/10.3390/rs11111282

AMA. (2011). *Participatory slum upgrading and prevention*. Accra.

Arku, J. (2015). Accra recorded 20,500 cholera cases between June 2014 and Feb 2015. Retrieved May 24, 2020, from Graphic Online website: https://www.graphic.com.gh/news/health/20-500-cholera-cases-recorded-as-of-february-2015.html

Badmos, O., Rienow, A., Callo-Concha, D., Greve, K., & Jürgens, C. (2018). Urban Development in West Africa—Monitoring and Intensity Analysis of Slum Growth in Lagos: Linking Pattern and Process. *Remote Sensing*, *10*(7), 1044–1066. https://doi.org/10.3390/rs10071044

Belgiu, M., & Drăguţ, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS Journal of Photogrammetry and Remote Sensing*, *114*, 24–31. https://doi.org/10.1016/j.isprsjprs.2016.01.011

Belgiu, M., & Drăguţ, L. (2014). Comparing supervised and unsupervised multiresolution segmentation approaches for extracting buildings from very high resolution imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *96*, 67–75. https://doi.org/10.1016/j.isprsjprs.2014.07.002

Blaschke, T. (2010). Object based image analysis for remote sensing. *ISPRS Journal of Photogrammetry and Remote Sensing*, *65*(1), 2–16. https://doi.org/10.1016/j.isprsjprs.2009.06.004

Blaschke, T., Hay, G. J., Kelly, M., Lang, S., Hofmann, P., Addink, E., … Tiede, D. (2014). Geographic Object-Based Image Analysis - Towards a new paradigm. *ISPRS Journal of Photogrammetry and Remote Sensing*, *87*, 180–191. https://doi.org/10.1016/j.isprsjprs.2013.09.014

Bochow, M., Taubenbock, H., Segl, K., & Kaufmann, H. (2010). An automated and adaptable approach for characterizing and partitioning cities into urban structure types. *2010 IEEE International Geoscience and Remote Sensing Symposium*, *7*, 1796–1799. https://doi.org/10.1109/IGARSS.2010.5652972

Bogaert, P., Waldner, F., & Defourny, P. (2017). An information-based criterion to measure pixel-level thematic uncertainty in land cover classifications. *Stochastic Environmental Research and Risk Assessment*, *31*(9), 2297–2312. https://doi.org/10.1007/s00477-016-1310-y

Breiman, L. (2001). Random forests. *Machine Learning*, *45*, 5–32. https://doi.org/10.1201/9780367816377-11

Brovelli, M. A., Minghini, M., Moreno-Sanchez, R., & Oliveira, R. (2017). Free and open source software for geospatial applications (FOSS4G) to support Future Earth. *International Journal of Digital Earth*, *10*(4), 386–404. https://doi.org/10.1080/17538947.2016.1196505

Cánovas-García, F., & Alonso-Sarría, F. (2015). Optimal combination of classification algorithms and feature ranking methods for object-based classification of submeter resolution Z/I-Imaging DMC imagery. *Remote Sensing*, *7*(4), 4651–4677. https://doi.org/10.3390/rs70404651

Chen, G., Hay, G. J., Carvalho, L. M. T., & Wulder, M. A. (2012). Object-based change detection. *International Journal of Remote Sensing*, *33*(14), 4434–4457. https://doi.org/10.1080/01431161.2011.648285

Davidovic, N., Mooney, P., Stoimenov, L., & Minghini, M. (2016). Tagging in Volunteered Geographic Information: An Analysis of Tagging Practices for Cities and Urban Regions in OpenStreetMap. *ISPRS International Journal of Geo-Information*, *5*(12), 232. https://doi.org/10.3390/ijgi5120232

Díaz-Uriarte, R., & Alvarez de Andrés, S. (2006). Gene selection and classification of microarray data using random forest. *BMC Bioinformatics*, *7*, 1–13. https://doi.org/10.1186/1471-2105-7-3

Drăguţ, L., Csillik, O., Eisank, C., & Tiede, D. (2014). Automated parameterisation for multi-scale image segmentation on multiple layers. *ISPRS Journal of Photogrammetry and Remote Sensing*, *88*, 119–127. https://doi.org/10.1016/j.isprsjprs.2013.11.018

Drăguţ, Lucian, Belgiu, M., Popescu, G., & Bandura, P. (2019). Sensitivity of multiresolution segmentation to spatial extent. *International Journal of Applied Earth Observation and Geoinformation*, *81*, 146–153. https://doi.org/10.1016/j.jag.2019.05.002

Duque, J. C., Patino, J. E., & Betancourt, A. (2017). Exploring the potential of machine learning for automatic slum identification from VHR imagery. *Remote Sensing*, *9*(9), 1–23. https://doi.org/10.3390/rs9090895

Duque, J. C., Patino, J. E., Ruiz, L. A., & Pardo-Pascual, J. E. (2015). Measuring intra-urban poverty using land cover and texture metrics derived from remote sensing data. *Landscape and Urban Planning*, *135*, 11–21. https://doi.org/10.1016/j.landurbplan.2014.11.009

Engstrom, R., Ofiesh, C., Rain, D., Jewell, H., & Weeks, J. (2013). Defining neighborhood boundaries for urban health research in developing countries: A case study of Accra, Ghana. *Journal of Maps*, *9*(1), 36–42. https://doi.org/10.1080/17445647.2013.765366

Engstrom, R., Pavelesku, D., Tanaka, T., & Wambile, A. (2017). Monetary and non-monetary poverty in urban slums in Accra : Combining geospatial data and machine learning to study urban poverty. *CSAE Conference*, 1–45. Retrieved from http://www.cirje.e.u-tokyo.ac.jp/research/workshops/emf/paper2017/emf0724_2.pdf

Engstrom, R., Sandborn, A., Qin Yu, Burgdorfer, J., Stow, D., Weeks, J., & Graesser, J. (2015). Mapping slums using spatial features in Accra, Ghana. *2015 Joint Urban Remote Sensing Event (JURSE)*, (March), 1–4. https://doi.org/10.1109/JURSE.2015.7120494

Folleco, A., Khoshgoftaar, T. M., Van Hulse, J., & Bullard, L. (2008). Identifying learners robust to low quality data. *2008 IEEE International Conference on Information Reuse and Integration*, *33*(3), 190–195. https://doi.org/10.1109/IRI.2008.4583028

Fonte, C., Minghini, M., Patriarca, J., Antoniou, V., See, L., & Skopeliti, A. (2017). Generating Up-to-Date and Detailed Land Use and Land Cover Maps Using OpenStreetMap and GlobeLand30. *ISPRS International Journal of Geo-Information*, *6*(4), 125. https://doi.org/10.3390/ijgi6040125

Foody, G. M. (2002). Status of land cover classification accuracy assessment. *Remote Sensing of Environment*, *80*(1), 185–201. https://doi.org/10.1016/S0034-4257(01)00295-4

Friesen, J., Taubenböck, H., Wurm, M., & Pelz, P. F. (2018). The similar size of slums. *Habitat International*, *73*, 79–88. https://doi.org/10.1016/j.habitatint.2018.02.002

Georganos, S., Grippa, T., Lennert, M., Vanhuysse, S., Johnson, B., & Wolff, E. (2018). Scale Matters: Spatially Partitioned Unsupervised Segmentation Parameter Optimization for Large and Heterogeneous Satellite Images. *Remote Sensing*, *10*(9), 1440–1463. https://doi.org/10.3390/rs10091440

Georganos, S., Grippa, T., Vanhuysse, S., Lennert, M., Kalogirou, S., Wolff, E., … Lennert, M. (2018). Less is more : optimizing classification performance through feature selection in a very- high-resolution remote sensing object-based urban application. *GIScience & Remote Sensing*, *55*(2), 221–242. https://doi.org/10.1080/15481603.2017.1408892

Gevaert, C. M., Kohli, D., & Kuffer, M. (2019). Challenges of mapping the missing spaces. *2019 Joint Urban Remote Sensing Event (JURSE)*, 1–4. https://doi.org/10.1109/JURSE.2019.8809004

Grippa, Tais, Georganos, S., Vanhuysse, S. G., Lennert, M., & Wolff, E. (2017). A local segmentation parameter optimization approach for mapping heterogeneous urban environments using VHR imagery. In W. Heldens, N. Chrysoulakis, T. Erbertseder, & Y. Zhang (Eds.), *Remote Sensing Technologies and Applications in Urban Environments II* (pp. 20–37). https://doi.org/10.1117/12.2278422

Grippa, Tais, Georganos, S., Vanhuysse, S., Lennert, M., Mboga, N., & Wolff, E. (2019). Mapping slums and model population density using earth observation data and open source solutions. *2019 Joint Urban Remote Sensing Event (JURSE)*, 1–4. https://doi.org/10.1109/JURSE.2019.8808934

Grippa, Taïs, Georganos, S., Zarougui, S., Bognounou, P., Diboulo, E., Forget, Y., … Wolff, E. (2018). Mapping Urban Land Use at Street Block Level Using OpenStreetMap, Remote Sensing Data, and Spatial Metrics. *ISPRS International Journal of Geo-Information*, *7*(7), 246–267. https://doi.org/10.3390/ijgi7070246

Grippa, Tais, Wolff, E., Vanhuysse, S., Beaumont, B., Lennert, M., & Stephenne, N. (2017). An Open-Source Semi-Automated Processing Chain for Urban Object-Based Classification. *Remote Sensing*, *9*(4), 358–364. https://doi.org/10.3390/rs9040358

Groenendijk, L., & Dopheide, E. (2003). Planning and Management Tools: A Reference Book. ITC Special Lecture Notes Series. In *The International Institute for Geo-Information Sciecena and Earth*

Observation (ITC). Retrieved from https://ieeexplore.ieee.org/document/8808934/
GSS. (2010). *"Ghana– population and housing census 2010,."* Retrieved from http://www2.statsghana.gov.gh/nada/index.php/catalog/51
Hay, G. J., Castilla, G., Wulder, M. A., & Ruiz, J. R. (2005). An automated object-based approach for the multiscale image segmentation of forest scenes. *International Journal of Applied Earth Observation and Geoinformation*, *7*(4), 339–359. https://doi.org/10.1016/j.jag.2005.06.005
Hofmann, P., & Bekkarnayeva, G. (2017). Object-based change detection of informal settlements. *2017 Joint Urban Remote Sensing Event, JURSE 2017*, 1–4. https://doi.org/10.1109/JURSE.2017.7924588
Hughes, G. F. (1968). On the Mean Accuracy of Statistical Pattern Recognizers. *IEEE Transactions on Information Theory*, *14*(1), 55–63. https://doi.org/10.1109/TIT.1968.1054102
Hussain, M., Chen, D., Cheng, A., Wei, H., & Stanley, D. (2013). Change detection from remotely sensed images: From pixel-based to object-based approaches. *ISPRS Journal of Photogrammetry and Remote Sensing*, *80*, 91–106. https://doi.org/10.1016/j.isprsjprs.2013.03.006
Ibrahim, M. R., Haworth, J., & Cheng, T. (2019). URBAN-i: From urban scenes to mapping slums, transport modes, and pedestrians in cities using deep learning and computer vision. *Environment and Planning B: Urban Analytics and City Science*. https://doi.org/10.1177/2399808319846517
Kanavath, R., & Metz, M. (2017). i.superpixels.slic - GRASS GIS manual. Retrieved January 26, 2020, from https://grass.osgeo.org/grass76/manuals/addons/i.superpixels.slic.html
Kinkeldey, C. (2014). A Concept for Uncertainty-Aware Analysis of Land Cover Change Using Geovisual Analytics. *ISPRS International Journal of Geo-Information*, *3*(3), 1122–1138. https://doi.org/10.3390/ijgi3031122
Kit, O., & Lüdeke, M. (2013). Automated detection of slum area change in Hyderabad, India using multitemporal satellite imagery. *ISPRS Journal of Photogrammetry and Remote Sensing*, *83*, 130–137. https://doi.org/10.1016/j.isprsjprs.2013.06.009
Kit, O., Lüdeke, M., & Reckien, D. (2012). Texture-based identification of urban slums in Hyderabad, India using remote sensing data. *Applied Geography*, *32*(2), 660–667. https://doi.org/10.1016/j.apgeog.2011.07.016
Kohli, D., Sliuzas, R., Kerle, N., & Stein, A. (2012). An ontology of slums for image-based classification. *Computers, Environment and Urban Systems*, *36*(2), 154–163. https://doi.org/10.1016/j.compenvurbsys.2011.11.001
Kohli, D., Sliuzas, R., & Stein, A. (2016). Urban slum detection using texture and spatial metrics derived from satellite imagery. *Journal of Spatial Science*, *61*(2), 405–426. https://doi.org/10.1080/14498596.2016.1138247
Kohli, D., Stein, A., & Sliuzas, R. (2016). Uncertainty analysis for image interpretations of urban slums. *Computers, Environment and Urban Systems*, *60*, 37–49. https://doi.org/10.1016/j.compenvurbsys.2016.07.010
Kohli, D., Warwadekar, P., Kerle, N., Sliuzas, R., & Stein, A. (2013). Transferability of object-oriented image analysis methods for slum identification. *Remote Sensing*, *5*(9), 4209–4228. https://doi.org/10.3390/rs5094209
Kuffer, M., Barros, J., & Sliuzas, R. V. (2014). The development of a morphological unplanned settlement index using very-high-resolution (VHR) imagery. *Computers, Environment and Urban Systems*, *48*, 138–152. https://doi.org/10.1016/j.compenvurbsys.2014.07.012
Kuffer, M., Pfeffer, K., & Sliuzas, R. (2016). Slums from space-15 years of slum mapping using remote sensing. *Remote Sensing*, *8*(6), 1–29. https://doi.org/10.3390/rs8060455
Kuffer, M., Pfeffer, K., Sliuzas, R., & Baud, I. (2016). Extraction of Slum Areas From VHR Imagery Using GLCM Variance. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(5), 1830–1840. https://doi.org/10.1109/JSTARS.2016.2538563
Kuffer, M., Pfeffer, K., Sliuzas, R., Baud, I., & van Maarseveen, M. (2017). Capturing the diversity of deprived areas with image-based features: The case of Mumbai. *Remote Sensing*, *9*(4), 384–407. https://doi.org/10.3390/rs9040384
Kuffer, M., Thomson, D. R., Boo, G., Mahabir, R., Grippa, T., Vanhuysse, S., … Kabaria, C. (2020). The Role of Earth Observation in an Integrated Deprived Area Mapping "System" for Low-to-Middle Income Countries. *Remote Sensing*, *12*(6), 982–1008. https://doi.org/10.3390/rs12060982
Kuffer, M., Wang, J., Nagenborg, M., Pfeffer, K., Kohli, D., Sliuzas, R., & Persello, C. (2018). The Scope of Earth-Observation to Improve the Consistency of the SDG Slum Indicator. *ISPRS International*

Journal of Geo-Information, *7*(11), 428–456. https://doi.org/10.3390/ijgi7110428
Lennert, M. (2015). i.segment.uspo - GRASS GIS manual. Retrieved May 31, 2020, from https://grass.osgeo.org/grass78/manuals/addons/i.segment.uspo.html
Leonita, G., Kuffer, M., Sliuzas, R., & Persello, C. (2018). Machine Learning-Based Slum Mapping in Support of Slum Upgrading Programs: The Case of Bandung City, Indonesia. *Remote Sensing*, *10*(10), 1522–1548. https://doi.org/10.3390/rs10101522
Li, B., & Zhou, Q. (2009). Accuracy assessment on multi-temporal land-cover change detection using a trajectory error matrix. *International Journal of Remote Sensing*, *30*(5), 1283–1296. https://doi.org/10.1080/01431160802474022
Lilford, R., Kyobutungi, C., Ndugwa, R., Sartori, J., Watson, S. I., Sliuzas, R., … Ezeh, A. (2019). Because space matters: conceptual framework to help distinguish slum from non-slum urban areas. *BMJ Global Health*, *4*(2), e001267. https://doi.org/10.1136/bmjgh-2018-001267
Liu, H., & Zhou, Q. (2004). Accuracy analysis of remote sensing change detection by rule-based rationality evaluation with post-classification comparison. *International Journal of Remote Sensing*, *25*(5), 1037–1050. https://doi.org/10.1080/0143116031000150004
Liu, Hui, Huang, X., Wen, D., & Li, J. (2017). The use of landscape metrics and transfer learning to explore urban villages in China. *Remote Sensing*, *9*(4), 1–23. https://doi.org/10.3390/rs9040365
Liu, R., Kuffer, M., & Persello, C. (2019). The Temporal Dynamics of Slums Employing a CNN-Based Change Detection Approach. *Remote Sensing*, *11*(23), 1–21. https://doi.org/10.3390/rs11232844
Lowell, K. (2001). An area-based accuracy assessment methodology for digital change maps. *International Journal of Remote Sensing*, *22*(17), 3571–3596. https://doi.org/10.1080/01431160010031270
Ma, L., Li, M., Ma, X., Cheng, L., Du, P., & Liu, Y. (2017). A review of supervised object-based land-cover image classification. *ISPRS Journal of Photogrammetry and Remote Sensing*, *130*, 277–293. https://doi.org/10.1016/j.isprsjprs.2017.06.001
Macleod, R. D., & Congalton, R. G. (1998). A Quantitative Comparison of Change-Detection Algorithms for Monitoring Eelgrass from Remotely Sensed Data. *Photogrammetric Engineering & Remote Sensing*, *64*(3), 207–216. Retrieved from https://www.asprs.org/wp-content/uploads/pers/1998journal/mar/1998_mar_207-216.pdf
Mahabir, R., Croitoru, A., Crooks, A., Agouris, P., & Stefanidis, A. (2018). A Critical Review of High and Very High-Resolution Remote Sensing Approaches for Detecting and Mapping Slums: Trends, Challenges and Emerging Opportunities. *Urban Science*, *2*(1), 1–38. https://doi.org/10.3390/urbansci2010008
Mahabir, R., Crooks, A., Croitoru, A., & Agouris, P. (2016). The study of slums as social and physical constructs: challenges and emerging research opportunities. *Regional Studies, Regional Science*, *3*(1), 399–419. https://doi.org/10.1080/21681376.2016.1229130
Martínez, J., Pfeffer, K., & Baud, I. (2016). Factors shaping cartographic representations of inequalities. Maps as products and processes. *Habitat International*, *51*, 90–102. https://doi.org/10.1016/j.habitatint.2015.10.010
Mboga, N., Georganos, S., Grippa, T., Lennert, M., Vanhuysse, S., & Wolff, E. (2019). Fully Convolutional Networks and Geographic Object-Based Image Analysis for the Classification of VHR Imagery. *Remote Sensing*, *11*(5), 597–614. https://doi.org/10.3390/rs11050597
Mboga, N., Persello, C., Bergado, J., & Stein, A. (2017). Detection of Informal Settlements from VHR Images Using Convolutional Neural Networks. *Remote Sensing*, *9*(11), 1106–1124. https://doi.org/10.3390/rs9111106
Molenaar, M. (2000). Three conceptual uncertainty levels for spatial objects. *International Archives of Photogrammetry and Remote Sensing*, *XXXIII*, 670–677. Retrieved from https://www.isprs.org/proceedings/XXXIII/congress/part4/670_XXXIII-part4.pdf
Momsen, E., & Metz, Markus. (2015). i.segment - GRASS GIS manual. Retrieved May 20, 2020, from https://grass.osgeo.org/grass78/manuals/i.segment.html
Olofsson, P., Foody, G. M., Herold, M., Stehman, S. V, Woodcock, C. E., & Wulder, M. A. (2014). Good practices for estimating area and assessing accuracy of land change. *Remote Sensing of Environment*, *148*, 42–57. https://doi.org/10.1016/j.rse.2014.02.015
Olofsson, P., Foody, G. M., Stehman, S. V., & Woodcock, C. E. (2013). Making better use of accuracy data in land change studies: Estimating accuracy and area and quantifying uncertainty using stratified estimation. *Remote Sensing of Environment*, *129*, 122–131. https://doi.org/10.1016/j.rse.2012.10.031

OpenStreetMap Wiki contributors. (2018). Xapi - OpenStreetMap Wiki. Retrieved December 14, 2019, from https://wiki.openstreetmap.org/wiki/Xapi

Oppong, B. E., Asomani-Boateng, R., & Fricano, R. J. (2020). Accra's Old Fadama/Agbogbloshie settlement. To what extent is this slum sustainable? *African Geographical Review*, *1*, 1–19. https://doi.org/10.1080/19376812.2020.1720753

Paelinck, J. H. P. (2000). On aggregation in spatial econometric modelling. *Journal of Geographical Systems*, *2*(2), 157–165. https://doi.org/10.1007/PL00011452

People's Dialogue. (2016). *Citywide informal settlement: Putting Accra Metropolitan Assembly's (AMA) Informal Settlement on the Map*. Retrieved from https://www.pdghana.org/completed-projects/

Pratomo, J., Kuffer, M., Kohli, D., & Martinez, J. (2018). Application of the trajectory error matrix for assessing the temporal transferability of OBIA for slum detection. *European Journal of Remote Sensing*, *51*(1), 838–849. https://doi.org/10.1080/22797254.2018.1496798

Pratomo, J., Kuffer, M., Martinez, J., & Kohli, D. (2017). Coupling Uncertainties with Accuracy Assessment in Object-Based Slum Detections, Case Study: Jakarta, Indonesia. *Remote Sensing*, *9*(11), 1164–1181. https://doi.org/10.3390/rs9111164

Ranguelova, E., Weel, B., Roy, D., Kuffer, M., Pfeffer, K., & Lees, M. (2019). Image based classification of slums, built-up and non-built-up areas in Kalyan and Bangalore, India. *European Journal of Remote Sensing*, *52*(1), 40–61. https://doi.org/10.1080/22797254.2018.1535838

Rico, E. C., & Maseda, R. C. (2012). An Object-Oriented Approach to Automate Classification of Panchromatic Aerial Photographs with GASS GIS and R. In E. Bocher & M. Neteler (Eds.), *Geospatial Free and Open Source Software in the 21st Century* (pp. 123–140). https://doi.org/10.1007/978-3-642-10595-1

Sandborn, A., & Engstrom, R. N. (2016). Determining the Relationship Between Census Data and Spatial Features Derived From High-Resolution Imagery in Accra , Ghana. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*, *9*(5), 1970–1977. https://doi.org/10.1109/JSTARS.2016.2519843

Singh, A. (1989). Review Articlel: Digital change detection techniques using remotely-sensed data. *International Journal of Remote Sensing*, *10*(6), 989–1003. https://doi.org/10.1080/01431168908903939

Sliuzas, R., Kuffer, M., Gevaert, C., & Pfeffer, K. (2017). Slum mapping From space to unmanned aerial vehicle based approaches. *Proceedings of Joint Urban Remote Sensing Event (JURSE) 2017*, 1–4. Dubai, United Arab Emirates.

Sliuzas, R., Mboup, G., & Sherbinin, A. de. (2008). Diversity of global slum conditions – is a universal spatial definition of slums feasible? In *Expert Group Meeting on Slum Mapping*. Retrieved from https://www.alnap.org/help-library/report-of-the-expert-group-meeting-on-slum-identification-and-mapping

Smith, B., & Varzi, A. C. (2000). Fiat and Bona Fide Boundaries. *Philosophy and Phenomenological Research*, *60*(2), 401–425. https://doi.org/10.2307/2653492

Sokolova, M., & Lapalme, G. (2019). A systematic analysis of performance measures for classification tasks. *Information Processing and Management*, *45*(4), 427–437. https://doi.org/10.1016/j.ipm.2009.03.002

Stow, D. A., Lippitt, C. D., & Weeks, J. R. (2013). Geographic Object-based Delineation of Neighborhoods of Accra, Ghana Using QuickBird Satellite Imagery. *Photogrammetric Engineering & Remote Sensing*, *110*, 907–914. https://doi.org/10.1007/978-94-007-6732-4

Taubenböck, H., & Kraff, N. J. (2014). The physical face of slums: A structural comparison of slums in Mumbai, India, based on remotely sensed data. *Journal of Housing and the Built Environment*, *29*(1), 15–38. https://doi.org/10.1007/s10901-013-9333-x

Teo, T.-A., & Shih, T.-Y. (2013). Lidar-based change detection and change-type determination in urban areas. *International Journal of Remote Sensing*, *34*(3), 968–981. https://doi.org/10.1080/01431161.2012.714504

Tewkesbury, A. P., Comber, A. J., Tate, N. J., Lamb, A., & Fisher, P. F. (2015). A critical synthesis of remotely sensed optical image change detection techniques. *Remote Sensing of Environment*, *160*, 1–14. https://doi.org/10.1016/j.rse.2015.01.006

Thomson, D. R., Kuffer, M., Boo, G., Hati, B., Grippa, T., Elsey, H., … Kabaria, C. (2020). Need for an Integrated Deprived Area "Slum" Mapping System (IDEAMAPS) in Low- and Middle-Income Countries (LMICs). *Social Sciences*, *9*(5), 80–97. https://doi.org/10.3390/socsci9050080

Thomson, D. R., Stevens, F. R., Ruktanonchai, N. W., Tatem, A. J., & Castro, M. C. (2017). GridSample: an R package to generate household survey primary sampling units (PSUs) from gridded population data. *International Journal of Health Geographics*, *16*(1), 1–19. https://doi.org/10.1186/s12942-017-0098-4

UN-Habitat. (2003). *Slums of the world : the face of urban poverty in the new millennium?* Retrieved from https://unhabitat.org/books/slums-of-the-world-the-face-of-urban-poverty-in-the-new-millennium/

UN-Habitat. (2015). *Tracking Improvement in the lives of Slum Dwellers*. Retrieved from www.unhabitat.org

UN-Habitat. (2016). *Urbanization and Development Emerging Futures:World Cities Report*. Retrieved from www.unhabitat.org

UN-HABITAT. (2011). *Cities for All: Bridging the Urban Divide – State of the World's Cities 2010/2011*. London, UK: Earthscan.

Vogel, M. (2016). The Modifiable Areal Unit Problem in Person–Context Research. *Journal of Research in Crime and Delinquency*, *53*(1), 112–135. https://doi.org/10.1177/0022427815597039

Volpi, M., Tuia, D., Bovolo, F., Kanevski, M., & Bruzzone, L. (2012). Supervised change detection in VHR images using contextual information and support vector machines. *International Journal of Applied Earth Observation and Geoinformation*, *20*(1), 77–85. https://doi.org/10.1016/j.jag.2011.10.013

Wang, J., Kuffer, M., & Pfeffer, K. (2019). The role of spatial heterogeneity in detecting urban slums. *Computers, Environment and Urban Systems*, *73*, 95–107. https://doi.org/10.1016/j.compenvurbsys.2018.08.007

Weeks, J. R., Hill, A., Stow, D., Getis, A., & Fugate, D. (2007). Can we spot a neighborhood from the air? Defining neighborhood structure in Accra, Ghana. *GeoJournal*, *69*(1–2), 9–22. https://doi.org/10.1007/s10708-007-9098-4

Wurm, M., Weigand, M., Schmitt, A., Gei, C., & Taubenbock, H. (2017). Exploitation of textural and morphological image features in Sentinel-2A data for slum mapping. *2017 Joint Urban Remote Sensing Event, JURSE 2017*, 1–4. https://doi.org/10.1109/JURSE.2017.7924586

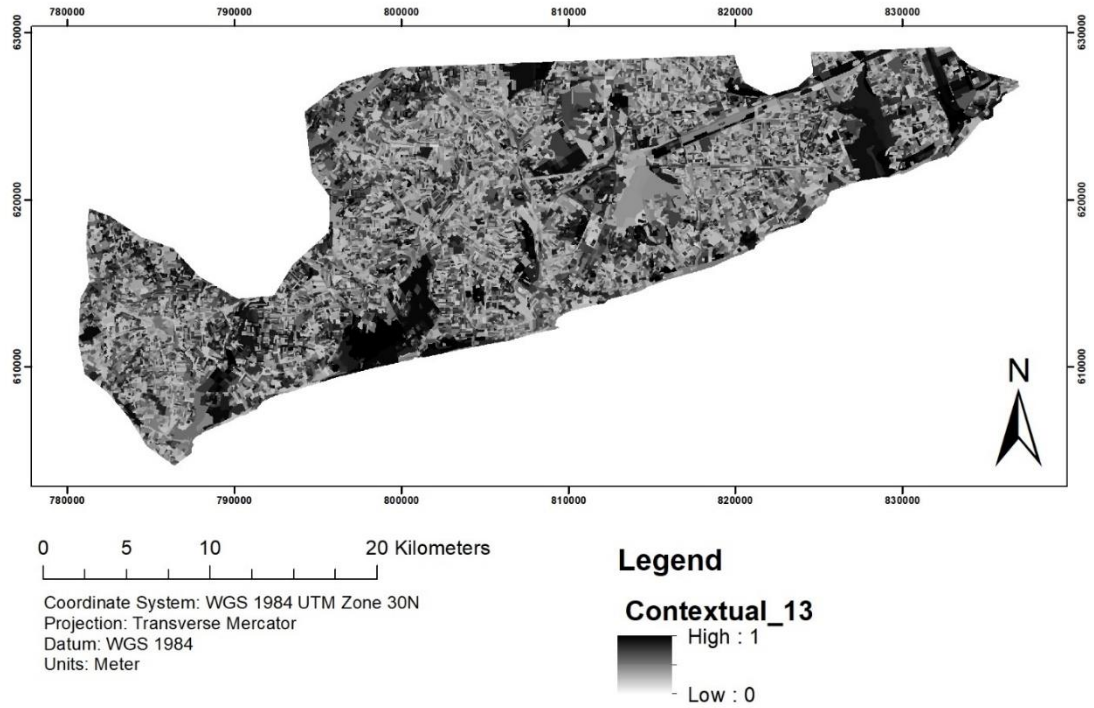
Yuan, D., Elvidage, C. ., & Lunetta, R. . (1999). Survey of multispectral methods for land cover change analysis. In R. . Lunetta & C. . Elvidge (Eds.), *Remote sensing change detection: Environmental Monitoring Methods and Application* (pp. 21–39). London: Taylor & Francis.

Appendix 1: Confusion matrix of land-use classification for contextual features and LCLU. HDR: high-density residential, LDR: low-density residential, NON-RST: non-residential, NON-BLT: non-built-up

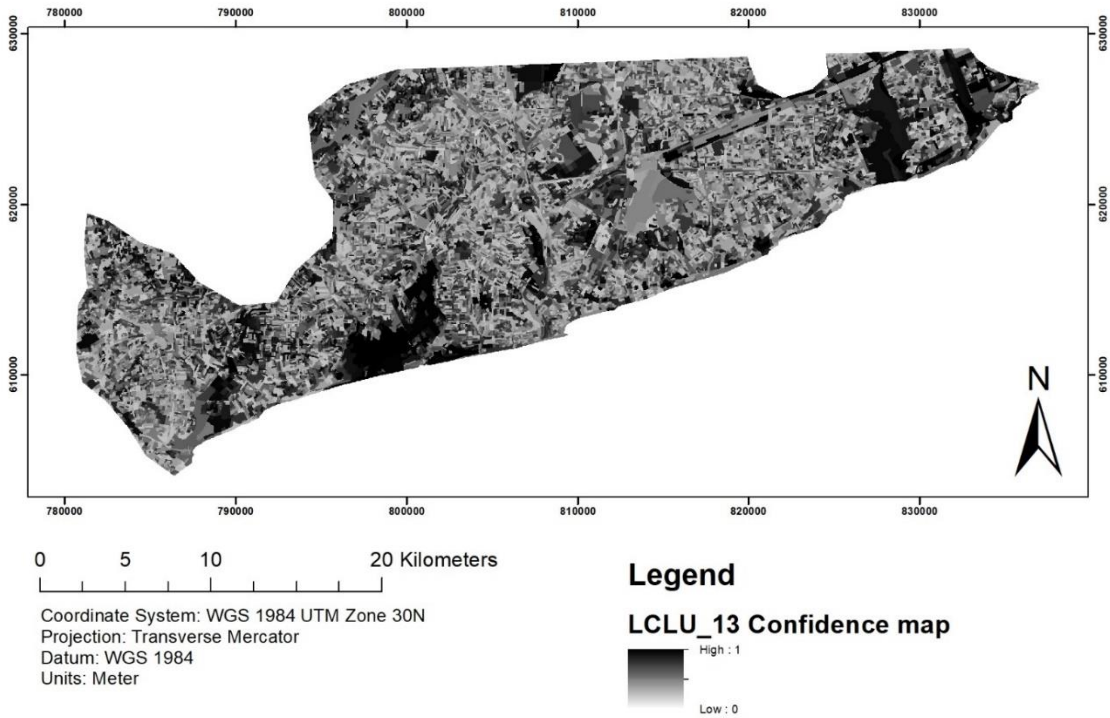
	Reference 2013 (contextual)						
	Classes	HDR	LDR	Infant	Matured	Non-RST	Non-BLT
Prediction	HDR	43	0	2	2	0	0
	LDR	1	47	0	0	0	0
	Infant	3	0	6	5	1	0
	Matured	4	0	1	33	0	0
	Non-RST	2	1	1	0	51	3
	Non-BLT	0	1	0	0	1	69
	Reference 2013 (LCLU)						
	Classes	HDR	LDR	Infant	Matured	Non-RST	Non-BLT
Prediction	HDR	44	0	2	1	0	0
	LDR	1	46	0	0	0	1
	Infant	3	0	6	5	1	0
	Matured	3	0	0	35	0	0
	Non-RST	3	0	0	0	53	2
	Non-BLT	0	1	0	0	1	69
	Reference 2017 (contextual)						
	Classes	HDR	LDR	Infant	Matured	Non-RST	Non-BLT
Prediction	HDR	46	0	1	5	0	0
	LDR	1	35	0	0	3	1
	Infant	3	0	3	5	0	1
	Matured	3	0	1	42	0	0
	Non-RST	0	3	0	0	37	5
	Non-BLT	0	1	0	1	4	42
	Reference 2017 (LCLU)						
	Classes	HDR	LDR	Infant	Matured	Non-RST	Non-BLT
Prediction	HDR	45	0	1	6	0	0
	LDR	1	34	0	0	4	1
	Infant	3	0	3	5	0	1
	Matured	2	0	0	44	0	0
	Non-RST	0	3	0	0	37	5
	Non-BLT	0	1	1	1	3	42

Appendix 2: Uncertainty map of land-use. A) contextual feature 2013 B) LCLU 2013 C)contextual features 2017 D) LCLU 2017. LCLU: land-cover combined with contextual features

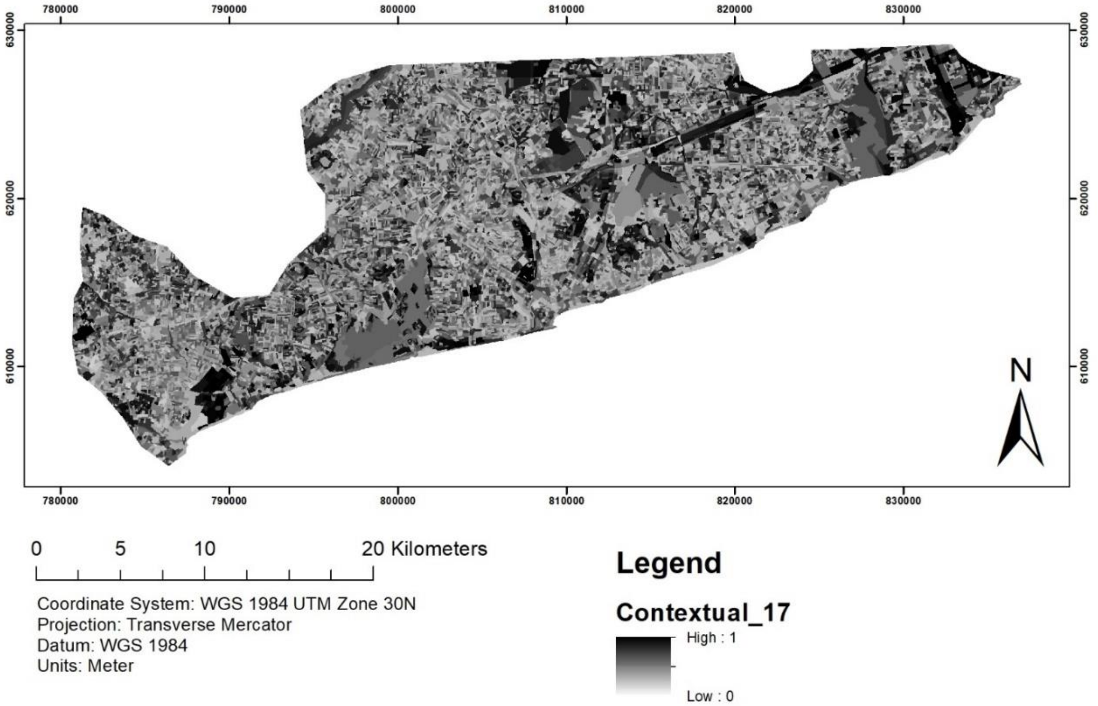
A



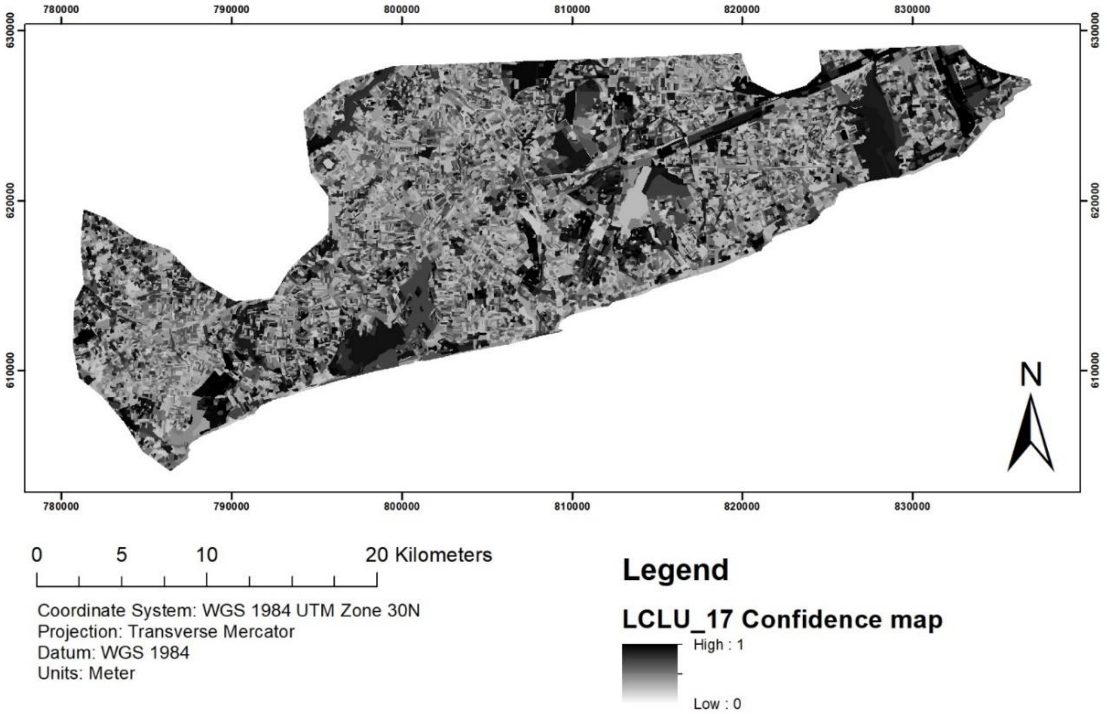
B



C


780000
790000
800000
810000
820000
830000
630000
620000
610000
N
0 5 10 20 Kilometers
Coordinate System: WGS 1984 UTM Zone 30N
Projection: Transverse Mercator
Datum: WGS 1984
Units: Meter
Legend
Contextual_17
High : 1
Low : 0

D


780000
790000
800000
810000
820000
830000
630000
620000
610000
N
0 5 10 20 Kilometers
Coordinate System: WGS 1984 UTM Zone 30N
Projection: Transverse Mercator
Datum: WGS 1984
Units: Meter
Legend
LCLU_17 Confidence map
High : 1
Low : 0

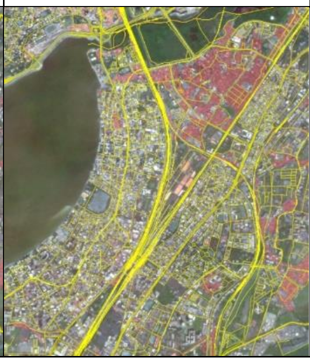
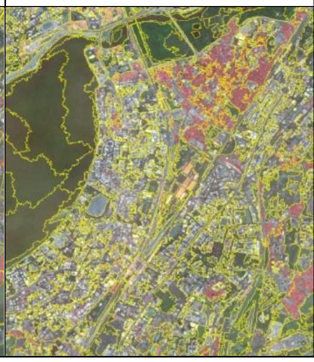
Appendix 3: Examples of Kiosk slum, Sprintex Road, Accra. (Source: field work, 2020)

Annex

Expert interview

Slum information

1. What is your role in slum planning, management or interventions?
2. Which criteria do you use to define a slum?
3. What spatial information do you have about slums (year, coverage area, completeness, accuracy)?
4. How do you use slum information?
5. What information do you lack about slums/deprived areas?
6. How often are information about slums (locations) updated?
7. How often would you require updated spatial information about slums?
8. What is the level of spatial detail on slums you would require to support your work?
9. Do you have land cover/ land use map? If yes, how was it prepared?
10. Will you consider slums as part of land use maps? If yes why? If no, why?

Administrative units (wards)	Blocks defined by the roads	Segments	Grids (100 x 100 m)
			

Geo-data Privacy

1. What would be your concerns if we upload slum information showing the boundaries to the public (international)?
   If yes, why?
   If no, why?
2. Slum maps from satellites have typically an accuracy of 80-90%, thus areas some slum areas might be omitted and non-slum areas wrongly mapped as slums. What problems would you foresee to make a slum map with such an accuracy publicly available?
3. What information will you consider sensitive?

Who should have access to slum information?