USING URBAN MORPHOLOGY AND CITIZEN SCIENCE METHODS FOR MAPPING SLUMS ACROSS DIFFERENT CITIES IN AFRICA

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July, 2024

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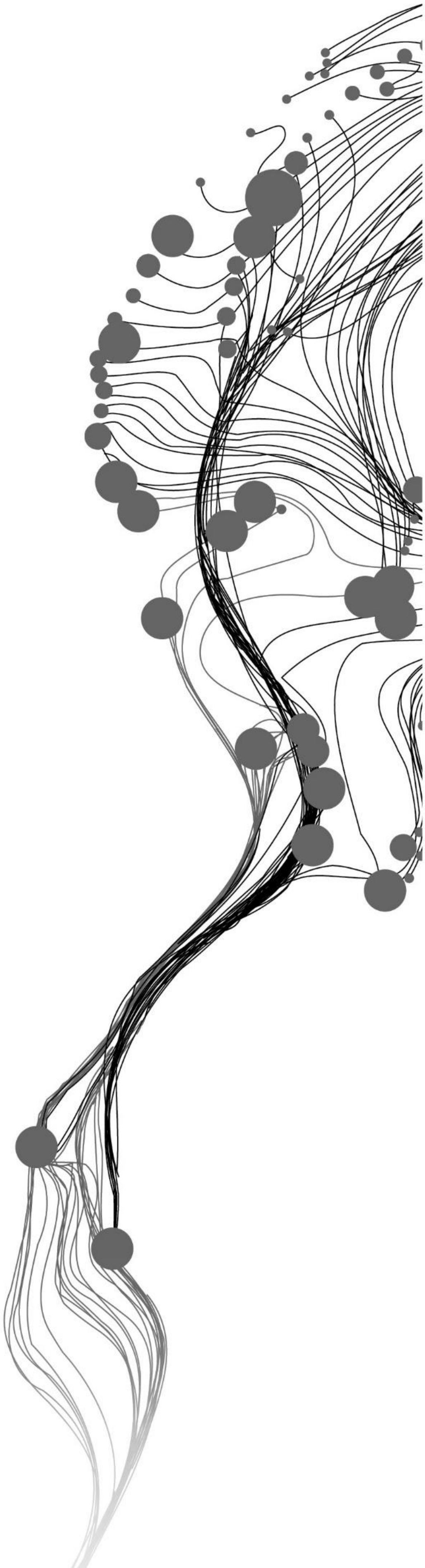

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UMAR ABDUL-RAHEEM
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Thesis submitted to the Faculty of Geo-Information Science and Earth Observation of the University of Twente in partial fulfilment of the requirements for the degree of Master of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

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ABSTRACT

The major challenge of rapid urbanisation is the proliferation of slums especially in Low- and Middle-Income Countries (LMICs). Previous studies have demonstrated the ability to map the location and extent of slums using Earth Observation (EO) data and Machine Learning (ML). However, these methods are still limited in spatial transferability partly due to the inter and intra-diverse characteristics of slums.

This thesis aims to improve the accuracy and spatial transferability of slum mapping models using an urban morphology-based framework and citizen science methods. Focusing on Nairobi, Kenya, and Accra, Ghana, the study leverages Random Forest (RF) models to distinguish slums and formal areas based on a comprehensive set of morphological features and open geospatial data. Results show that features such as building density, road conditions, and size of buildings are relevant parameters for the identification of slums. Validation through expert evaluation and quantitative analysis indicated high accuracy and precision, with accuracies exceeding 80% in transferring models trained in Nairobi to Accra. Key findings demonstrate that density-related metrics were significant indicators. However, over-reliance on density metrics can lead to misclassifications, especially in high-density formal areas. This limitation highlights the need for incorporating additional data, such as building heights, to improve model performance.

We conclude that our proposed methodology is effective for slum mapping and offers a cost-effective and scalable solution for urban planners and city authorities to map slums, contributing towards the achievement of Sustainable Development Goal 11 (SDG 11). This study recommends further testing of the approach in other cities, especially in Africa, with careful consideration of open dataset quality to ensure model reliability.

Keywords: Urban Morphology, Citizen Science, Slum mapping, Geospatial Data, Spatial Transferability, Random Forest

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LIST OF ABBREVIATIONS

3D	Three Dimension
ASF	Alaska Satellite Facility
ATMs	Automated Teller Machines
CBD	Central Business District
CNN	Convolution Neural Networks
CS	Citizen Science
DEM	Digital Elevation Model
EO	Earth Observation
ESA	European Space Agency
FCN	Fully Convolution Networks
FGDs	Focus Group Discussions
GCO	Generic Slum Ontology
GEE	Google Earth Engine
GIS	Geographic Information System
ISO/IEC	International Organisation for Standardisation/ International Electrotechnical Commission
LMICs	Low And Middle-Income Countries
ML	Machine Learning
MOMEPY	Morphometric Python
NDVI	Normalised Difference Vegetation Index
NIR	Near-Infrared
OSM	Open Street Map
R	Red
RF	Random Forest
SDG	Sustainable Development Goal
TSV	Tab-Separated Values
UMM	Urban Morphometrics
UN	United Nations
WCSS	Within-Cluster Sum of Squares
WSF3D	World Settlement Footprint Three Dimension
XFCN	Fully Convolution Xception Network

1. INTRODUCTION

1.1. Background

The 21st century is saddled by the enormous and entirely inevitable global challenges facing people and the environment. All nations worldwide face multi-faceted problems such as urbanization requiring urgent attention. Current trends show that the world is urbanizing at a rapid pace. More than half of the Earth's inhabitants reside in cities (Kraff et al., 2020), and this rate is expected to reach 68% by 2050. However, an increased level of urbanization is expected in low and middle-income countries (LMICs) in the global South and Asia (Khan, 2022), which often lack the resources to cope with such increasing numbers of people (Mahabir et al., 2018). The current trend of urbanization contributes to its accompanying challenges such as the increase in urban population leading city dwellers to live in unplanned areas commonly called "slums", with poor living standards due to inadequate housing, increasing the rates of poverty in LMICs (Mahabir et al., 2018).

The United Nations (UN) has recognised that to achieve Sustainable Development Goal 11(SDG 11): creating sustainable and inclusive cities, slum upgrading programs need to be prioritised. Target 1 of SDG 11 focuses on ensuring access for all to basic services, affordable housing, and slum upgrading. According to UN-Habitat (2023), approximately one billion individuals reside in slums, and if no effective measures are implemented, the number is projected to rise to around three billion by 2050.

Unfortunately, slums are frequently poorly represented or absent from maps and spatial datasets (Kuffer et al., 2016). The lack of detailed information about slums can be attributed to the limitations of current slum mapping methodologies such as survey-based (Leonita et al., 2018) and the varied slum characteristics across and within different contexts (Georganos et al., 2021). Kuffer et al. (2021) found a notable absence of a universally accepted methodological consensus for conceptualising slums.

Urban planners and policymakers must identify and understand poverty from a multidimensional perspective, including physical, social, and economic aspects, to effectively target and monitor policies that aim to alleviate poverty (UN-Habitat, 2022). The built environment can be an expression of urban poverty (Taubenböck et al., 2018), and slums serve as a physical manifestation of the living conditions of the people and, as such, serve as good proxies to inform human well-being (Kuffer et al., 2016). Earth Observation (EO) in combination with data collected on the ground, for example, via citizen science (CS) methodologies, allows one to monitor the urbanization process occurring in space, across large areas, and across time and can reveal the inherent living conditions in an area (Leonita et al., 2018). EO and CS have the potential to provide up-to-date data to map slums, their location, distribution, spatial coverage, and physical characteristics (Wang et al., 2019) and, thus, to further make evidence-based informed policies.

1.2. Research Problem

In sum, slums are on the rise in most urban areas especially in LMICs, as noted by Mahabir et al. (2016). Addressing this challenge is the key focus of SDG 11. The achievement of SDG 11 requires accurate and timely information about slums, emphasizing the need for an improved methodology that adequately provides accurate, up-to-date, and reliable information on slums, as noted by Kuffer et al. (2018).

Machine learning (ML) coupled with EO, and geospatial data collected via citizen science methodologies provide an accurate approach to slum mapping (Kuffer et al., 2016). However, a major research area that still needs improvement in the field of machine learning and deep learning is how to improve the transferability of such models (Kohli et al., 2013; Stark et al., 2020). As such, in the slum mapping domain, a research gap still exists concerning the transferability of slum detection models across different urban contexts (Kohli et al., 2013). This is partly due to the complexity and diversity of slums in different parts of the world and sometimes even variation in slums of the same city and the data used (Kuffer & Barros, 2011).

The existing research lacks sufficient integration of urban morphology and citizen science in the modelling process as recognised by Abascal et al. (2024) and Wang et al. (2023). According to Wang et al. (2023), the integration and quantification of relevant urban morphologies using geospatial data give a better understanding of the urban form. Urban morphology can effectively be related to socioeconomic conditions as compared to the use of abstract image features (Wang et al., 2023), which is the current approach utilised by most studies (e.g., Abascal et al., 2024; Persello & Stein, 2017; Stark et al., 2020). Additionally, image analysis-based approaches may require very high-resolution (VHR) images which are very costly to acquire especially for large areas (Abascal et al., 2024).

Given the recent increase in openly available global geospatial datasets such as Google Open buildings (Sirko et al., 2021) and the rise of urban data analytics techniques (Fleischmann et al., 2022), provide a reasonable substitute to explore. These cost-free datasets and technologies can be used to quantify the urban form, helping to identify slums (Stark et al., 2020; Wang et al., 2023). The morphological components capture the spatial aspects of slums, and it is important to understand the spatial characteristics of such areas as they differ from formal areas (Kuffer & Barros, 2011). By computing meaningful spatial metrics based on the morphology and incorporating this valuable information into machine learning models, this research strives to capture the diversity in slum morphologies and consequently, develop a standard and automated workflow that can enhance the transferability of these models, resulting in improved accuracy in mapping and analysing slums. The hypothesis is that common morphological characteristics (size, density, and pattern) exist in slums (Kuffer & Barros, 2011), and by leveraging this, the developed models can detect slums across areas of similar characteristics.

Given the complex, dynamic, and sociotechnical nature of slums (Owusu et al., 2021), there is a need for sufficient integration of local context knowledge to help capture the slum morphologies rather than just using the technical ideas from the experts' perspective (Kuffer et al., 2016). Current approaches often overlook the social dimension (Thomson et al., 2020). Considering a social perspective is important in slum mapping as slums are not just a technical phenomenon but a sociotechnical one (Owusu et al., 2023). CS is important in slum mapping and can help to provide up-to-date information that captures the slum realities effectively and helps improve the accuracy and effectiveness of the models to be developed (Colombo, 2018). The developed models and/or methodologies should represent the realities of the local context they are to be implemented in. The involvement of citizens in the process also helps to empower them, giving them the skills such as negotiation needed to be heard, which in the long run, can help toward the achievement of the overall goal of SDG 11 (Elias et al., 2023).

In sum, this study proposes an integration of urban morphology and citizen science methods in slum mapping to improve the accuracy of generating slum maps and the spatial transferability of such models. To achieve the study objective, the potential of citizen science will be leveraged to capture local knowledge to help understand well the slum context. This will lead to the identification of comprehensive morphological features. Additionally, we will use open data such as Google Open Buildings[1] (Sirko et al., 2021) and Python tools to calculate morphological metrics that will reflect the true condition of slum areas, thereby helping to improve slum mapping models. The study will contribute to improving the accuracy and spatial transferability of slum detection models using urban morphology and by highlighting the individual contribution of morphological features. The study will focus on two African cities, Nairobi in Kenya, and Accra in Ghana, which both have similar morphological characteristics to address the challenge of transferability in slum detection models.

1.3. Main Research Objective

To improve the accuracy and the spatial transferability of slum mapping models using an urban morphometric-based framework and citizen science approach.

1.3.1. Specific Objectives and Related Research Questions

The following specific objectives are needed to achieve the main objective.

1. To identify relevant urban morphological features that can distinguish slum and formal areas.
    a. What are the relevant urban morphological features that can be used to characterise slums from the literature review?
    b. What are the relevant urban morphological features that can be used to characterise slums from the field survey?
2. To assess the accuracy of the ML model trained using the identified morphological elements and features.
    a. What is the performance of the ML model developed using morphological features for slum detection?
    b. Which morphological features are important to detect slums?
3. To assess the spatial transferability of the ML model developed for slum mapping.
    a. To what extent do the urban morphological features improve the spatial transferability of the model?
4. To compare the most important morphological characteristics that can distinguish slum and formal areas from a citizen science and model perspective.
    a. What are the most important morphological characteristics to distinguish slums and formal areas?

[1] https://sites.research.google/open-buildings/

1.4. Thesis Structure

This thesis is composed of six chapters. Chapter 1 presents the introduction, providing an overview of the background and articulating the research problem to be addressed. Chapter 2 reviews the literature on slum mapping, with a focus on the application of EO data and machine learning within the slum mapping domain. Chapter 3 details the methodology employed, divided into technical approaches and citizen science-specific methods. Chapter 4 presents the results derived from the study. Chapter 5 engages in a discussion of the findings, and finally, Chapter 6 presents the conclusions and offers recommendations based on the study's outcomes.

2. LITERATURE REVIEW

This chapter presents a detailed review of scientific literature relevant to this study. It starts by reviewing the literature on the definition of key concepts utilised in this research. The second part provides an overview of the state of the art on slum mapping, the methodologies used, and the issues at hand. Lastly, an analysis of slum characteristics is presented, with an emphasis on the morphology of slums, encompassing the physical and spatial attributes.

2.1. Definition of Key Concepts

2.1.1. Slums

A high number of research have been conducted in the field of slum mapping, yet up to date, there is no universally agreed definition of the concept of slum. This is partly due to the inter and intra-diversity of slum morphologies in different parts of the world (Kuffer et al., 2016), and the absence of common criteria among experts for defining slums (Mahabir et al., 2018). While there is no consensus on the definition of slums, the term "informal settlements" is often used interchangeably with slums in the literature, which adds to the confusion surrounding the term (Kuffer et al., 2016) and making it hard to define (Bird et al., 2017).

The most widely known definition of a slum is given by the UN which focuses on the absence of five main indicators. A slum is defined as a household with one or more of the following conditions missing: quality water, improved sanitation, sufficient living space, durable housing, or secure tenure (UN-Habitat, 2022). This definition of slums is household-level based and does not reveal the area-level characteristics of a slum (Mahabir et al., 2016). Meanwhile, recent approaches are using remote sensing data to identify and map slums which require an area-level definition, but, with this definition, such methods may not be effective as only one indicator (durable housing) can potentially be extracted from a satellite image (Kohli et al., 2017). Other characteristics such as slum morphologies (e.g., shape, density, pattern, size, and street intersection) (Kuffer et al., 2016) are key for the detection of slums from EO and geospatial data.

The limitations of the household-level definition call for an area-level definition that includes other characteristics beyond the household level. As part of the efforts, Kohli et al. (2012) developed a systematic framework for identifying and classifying slums called the Generic Slum Ontology (GSO). The framework recognised the differences in slum definition and the heterogeneity of slum characteristics in different urban contexts. The ontology framework proposes three conceptual levels of slums at different spatial levels based on their morphological characteristics to form the foundation for image-based slum mapping (Figure 1). Kohli et al. (2012) stressed that the framework should be adopted in the local context combining various attributes that are relevant in that context.

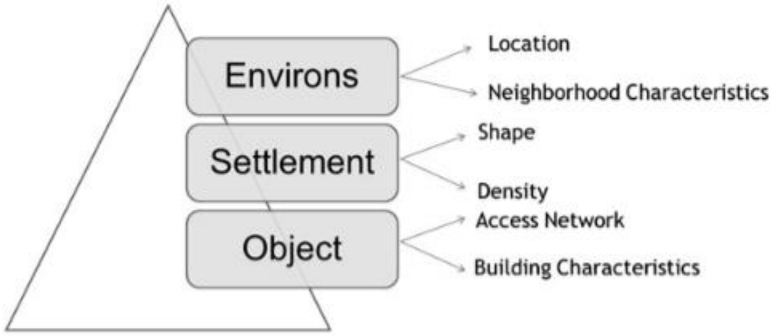


Figure 1: The framework of GSO at three spatial levels (Kohli et al., 2012).

Additionally, Abascal et al., (2022) developed a framework called the "Domain of Deprivation Framework". This framework aims to provide a globally applicable area-level definition of deprivation. It conceptualises deprivation into three spatial levels and nine domains: the household level, the within-area level, and the area connect level. The household level consists of socio-economic status and housing conditions. The within-area level consists of social hazards and assets, unplanned urbanization, physical hazards and assets, and environmental contamination. Lastly, the area connect level consists of infrastructure, access to facilities and services, and governance (Figure 2).

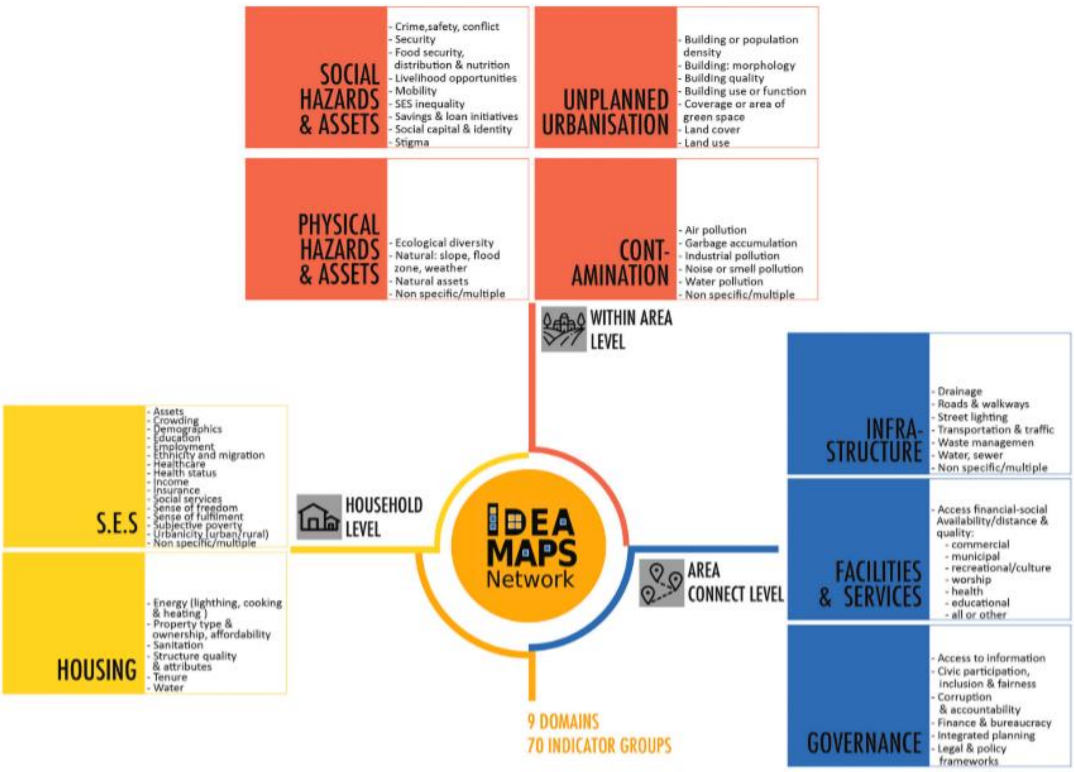


Figure 2: Domains of Deprivation Framework (Abascal et al., 2022).

For this thesis, we adopt an area-level definition of a slum because it aligns more effectively with the use of geospatial datasets to analyse slums. This captures the diverse slum morphologies within a set context referred to in the "domains of deprivation framework" as "within area level" and "area connect level". This study will focus on three domains within the framework: physical hazards and unplanned urbanization from the within-area level, and access to facilities and services from the area connect level. These domains include indicators such as building density, building morphology, proximity to hazards, and distance to facilities, which are indicators of deprivation that can be well understood using available geospatial datasets. This serves as the motivation to adopt this conceptual aspect of the framework. The study will compute meaningful metrics at the area and object levels such as building density and building size respectively and at the environs level to leverage the potentials of the two frameworks discussed.

2.1.2. Spatial Transferability

In the field of machine learning, transferability refers to the ability of a model to generalize its performance beyond its training data with minimum changes (Pratomo et al., 2016). Transferability can be viewed in different aspects including spatial transferability, temporal transferability, model transferability, domain transferability, and data transferability (Tuanmu et al., 2011).

For the thesis, we will focus on spatial transferability, which describes the ability of a model to produce similar results such as accuracy when applied in different geographical areas with similar characteristics to the geographic area it was trained (Owusu et al., 2024). A spatially transferable model has the potential to be scalable and saves time and resources to develop separate models for similar problems in different locations (Pratomo et al., 2016).

2.1.3. Urban Morphology

Urban morphology is the field of urban studies that seeks to understand the physical characteristics and the processes that shape the layout of the built environment over time (Moudon, 1997). The basic elements of urban morphology are the buildings, streets, and plots (Fleischmann, 2019) and the different combinations of these elements give the urban space its layout and appearance referred to as urban form.
Fleischmann (2019) analysed urban form by quantifying the morphologies. He identified six categories of spatial metrics called urban morphometrics that can be employed to understand the complexity of urban form, including shape, spatial distribution, dimension, diversity, density/intensity, and connectivity based on the basic morphological elements.

With the recent increase in geographic data science and open geospatial data, there is an increasing demand and contribution in the field of urban morphology studies. A science that helps to understand the growth and complex nature of our urban areas in this era of rapid urbanization, providing the ability to deliver new evidence-based knowledge to guide action (Fleischmann et al., 2022).

2.1.4. Citizen Science

Public participation in scientific research is not new but evolving with new ideas and technology and adopting different terms. In recent times, the term CS has been commonly used to refer to various forms of citizen participation in scientific knowledge production, resulting in an overlap with a wide array of terms describing different participatory methods, such as participatory mapping and community engagement (Owusu et al., 2023). Also, CS is often confused with data collection from citizens (Haklay et al., 2021). According to Raviscioni et al. (2022) CS goes beyond just data collection to include the citizens through the research process. CS is a bottom-up process that allows local stakeholders to be involved in projects, from data collection to hypothesis development (Bonney et al., 2009). CS empowers local stakeholders through knowledge creation and transfer whilst, giving them a voice in providing localized context information that may be overlooked by conventional methods (Fritz et al., 2017).

2.2. State of the Art on Transferable Slum Mapping

Within the last two decades, much attention has been given to the poverty domain (Hall et al., 2022). Specifically, the mapping of slums from EO data, partly due to the increasing availability of EO data, open geospatial datasets, and advancement in the field of ML and deep learning which provides new methods and approaches to understanding poverty from space (Kuffer et al., 2016).

Several studies have mapped slums using EO data and ML techniques (Abascal et al., 2022; Fan et al., 2023; Khan, 2022). The most recent studies in this domain use deep learning models such as Dense-Net 121, Convolution Neural Networks (CNN), and Fully Convolution Networks (FCN) to detect and model slums (Abascal et al., 2024; Ajami et al., 2019; Persello & Stein, 2017; Stark et al., 2020). Some studies have focused on conducting a binary classification of slums and non-slums using satellite imagery and geospatial data (Kraff et al., 2022; Leonita et al., 2018), while others have employed machine learning algorithms for multi-class classification (Abascal et al., 2022). Other studies have used meaningful spatial metrics together with image features to detect slums (Fleischmann, 2019; Kuffer et al., 2014, 2021).

Other studies (Engstrom et al., 2015; Mahabir et al., 2020; Owusu et al., 2023) employed geospatial data to derive meaningful morphological, physical, and social characteristics such as buildings, access to public facilities, and population counts respectively to map slums. However, this is not fully researched. This is because of the diversity in slum morphologies and the limited knowledge by planners to utilise these datasets fully (Chakraborty et al., 2015). This requires the inclusion of slum communities to fully capture a comprehensive list of morphological variables relevant to distinguishing slums (Owusu et al., 2021).

Some studies have focused on testing and improving the transferability of slum mapping models using imagery and open geospatial data across different countries in Africa, Asia, and South America (Owusu et al., 2023; Stark et al., 2020). Owusu et al. (2023) developed a Random Forest (RF) model leveraging open geospatial data and tested the developed methodology in three African cities: Nairobi, Kenya, Accra, Ghana, and Lagos, Nigeria, and achieved an accuracy of over 80% in all cities. Additionally, Stark et al. (2020) developed a transfer learned fully convolution Xception network (XFCN), that was trained using PlanetScope imagery, Open Street Map (OSM) data, and large slum sample data from 10 different cities, achieving a mean F1 score of up to 80%. This demonstrates the potential that a model trained from these diverse slums can improve the transferability of the model with high accuracy.

One notable missing aspect in all these studies is the inability to include local knowledge in their slum mapping approach (Jochem et al., 2021). Much attention is focused on generating and improving ML and deep learning models through technical means such as model parameter tuning (Probst & Bischl, 2019). This technical focus has the potential to identify patterns within data to learn settlement types. However, as slums are a sociotechnical phenomenon that requires the effective integration of the social and technical dimensions, these models may face the challenge of not capturing the diversity in slums and their definitions across and within cities (Owusu et al., 2021). Hence, the need to include local stakeholders in the slum mapping process to capture local knowledge (Owusu et al., 2023).

2.3. Slum Morphology: Physical And Spatial Characteristics of Slums

The morphology of slums refers to the spatial surroundings that characterize the built environment of slums such as building density and sizes and are the distinguishing features of slums from formal areas (Kuffer & Barros, 2011; Taubenböck & Kraff, 2014). The slum morphology is complex due to the inter and intra-diversity of slums in different parts of the world (Kuffer et al., 2016). The form of slums can be well understood by directly capturing their physical representation. Throughout the literature, morphological features such as shape, size, density, and pattern (Fleischmann, 2019; Kuffer et al., 2014; Moudon, 1997) are used to describe and identify the spatial layout of slums from formal areas. A better knowledge of the urban form and the spatial characteristics that effectively manifest slums and formal areas is needed for the effective identification of such areas (Kuffer et al., 2014).

To fully understand the morphologies of slums and formal areas, several studies have established a relationship between slums and formal areas using three morphological features (size, density, and pattern) (Fleischmann, 2019; Kuffer et al., 2014; Kuffer, Grippa, et al., 2021; Kuffer & Barros, 2011; Wang et al., 2023). These are considered the relevant morphological features for identifying slums. According to the authors, slum areas are characterized by smaller building sizes, a high density of buildings, and irregular building patterns relative to the characteristics observed in formal built-up areas. These three features are the basic elements of urban morphology and are common across different contexts (Kuffer et al., 2014), making them relevant in EO approaches for slum detection. Table 1: Common morphological characteristics of slums and formal areas (adopted from (Kuffer et al., 2014, 2016; Kuffer & Barros, 2011)) compares the morphological characteristics of slums and formal areas.

Table 1: Common morphological characteristics of slums and formal areas (adopted from (Kuffer et al., 2014, 2016; Kuffer & Barros, 2011))

Morphological element	**Slums**	**Formal Areas**
Size	• Small (substandard) building sizes	• Generally larger building sizes
Density	• High densities • Roof coverage of densities at least 80% or more	• Low-moderate density areas
Pattern	• Organic layout structure • No orderly road arrangement • Non-compliance with set-back standards	• Regular layout pattern • Available planned regular road arrangement • Compliance with set-back standards
Location Characteristics	• Located in hazardous areas of high-risk • No basic infrastructure	• Located in a planned area suitable for residential purposes • Basic infrastructure is provided
Greenery	• Less/no green spaces	• Some amount of green space is available

3. METHODOLOGY

3.1. Study Areas

This study will be conducted in two African cities with similar morphological characteristics, Nairobi, Kenya, and Accra, Ghana. The proposed framework will be trained in Nairobi and tested in Accra to assess its transferability across space. The model is chosen to train in Nairobi because it has a good amount of data available relative to Accra.

The reasons for the selection of these study areas are data availability, especially for Nairobi, slum diversity, advisors case study areas, high population of slum dwellers, increasing slum dwellers population, authorities' inability to cope with development, and highly researched.

3.1.1. Nairobi

The city of Nairobi, commonly known as "the green city in the sun" is the capital and largest city of Kenya, East Africa. It lies in the southern part of the country at Latitude 1°16'59" S and Longitude 36°49'00" E and occupies 696 square kilometers. The city has an approximate total population of about 4.4 million people (Kenya National Bureau of Statistics, 2019), with about 60% of its inhabitants living in slums (Mukeku, 2018), making it the city with the largest slum population in Africa. Some of the known slums in Nairobi include Kibera, Mathare, and Mukuru, each with its unique characteristics and challenges. The selection of Nairobi for this study was driven by the city's rapid urbanization and the pressing urban challenges that require attention. Additionally, the availability of both training and validation data, which are essential for this research, played a crucial role in its choice. Figure 3 shows the location of Nairobi, highlighting some of its slums.

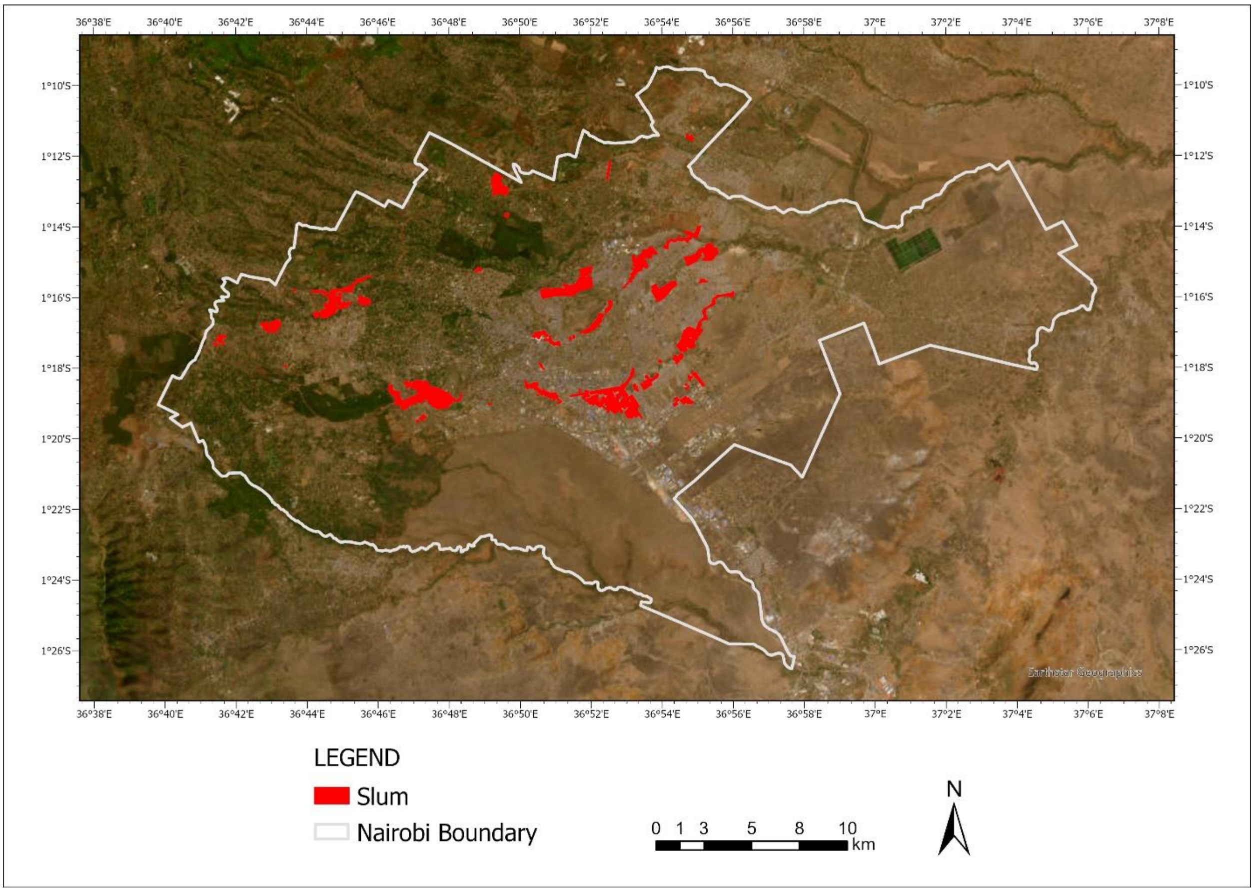


Figure 3: Study Area of Nairobi, Kenya with some slums. Basemap is sourced from Earth Geographics.

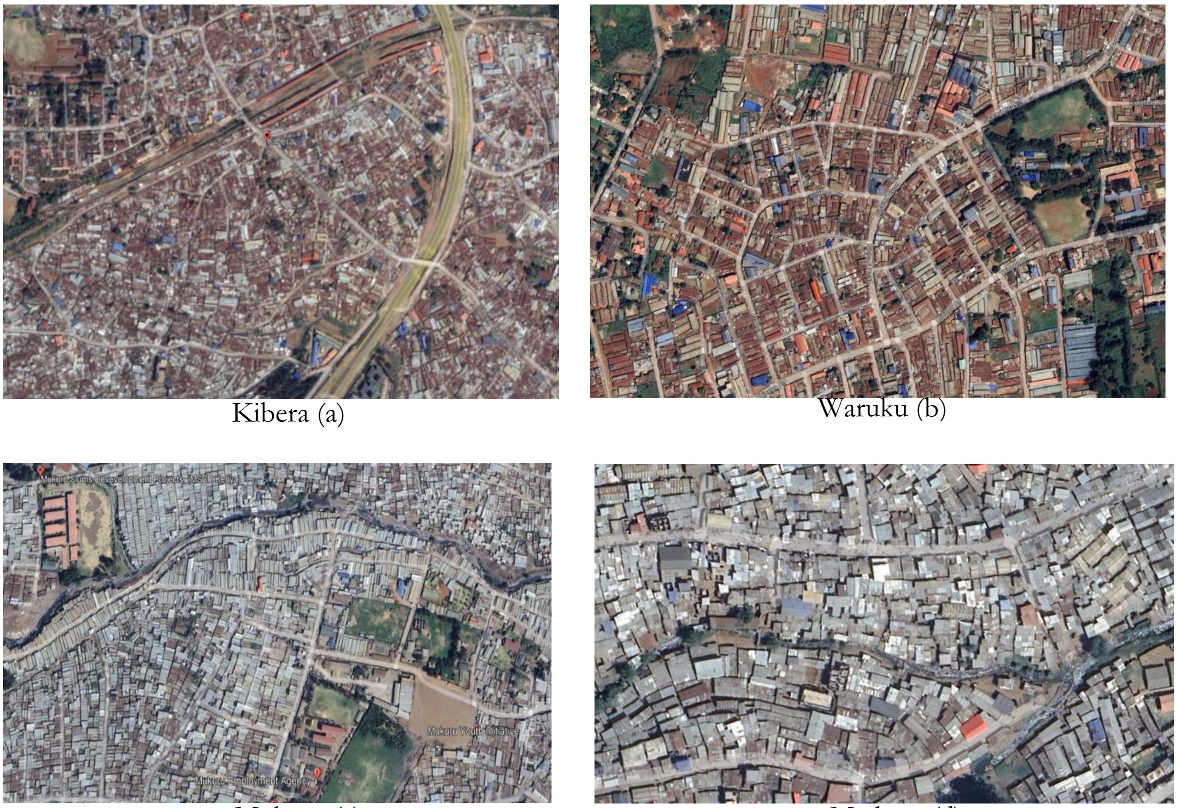
3.1.2. Slums In Nairobi

Slums in Nairobi, Kenya are characterised by high built-up and population densities, about 60% of the residents live in slums that cover about 5% of the city's total land area. This unequal distribution of land can be traced back to the colonial policies that promoted racial segregation (Mutisya & Yarime, 2011), where a minority occupies the majority of the urban space.

Most of the slums in Nairobi such as Kibera (Figure 4a) and Mathare (Figure 4b), which are the most populous and fast-growing are located close to the Central Business District (CBD), often near industrial areas (Ren et al., 2020). Many poor people live around these areas because of the expected benefits such as job opportunities and the low cost of living, reflecting a pattern driven by the proximity to economic opportunities. Furthermore, slums are commonly located along rivers, putting them at high risk of flooding (Mutisya & Yarime, 2011), near public dump sites, and along major infrastructure (e.g., railways, main roads). People live close to waste disposal sites to take advantage of recyclable materials such as empty cans and electronics, which are sold to generate income. While this practice provides a source of income, it poses severe health risks and environmental problems (Corburn et al., 2022).

Slums are characterised by temporary housing structures with elongated shapes and narrow paths that are difficult to navigate. Housing structures are made from iron sheets locally called "Mabatis," woods, and mud. Access to proper sanitation facilities, clean water, and electricity is a major problem in the slums, and residents rely on informal water vendors at high prices and illegal electricity connections (Mutisya & Yarime, 2011).

Moreover, slums in Nairobi are not homogenous, but exhibit inter and intra-variations (Figure 4). Areas are diverse in terms of functions and structure type, often combining residential, commercial, and self-helped services (Wang et al., 2023). For example, Kariobangi is a slum characterised by high-rise buildings compared to other slums like Kibera, typically constructed from cement and concrete. However, these areas still have limited sanitation facilities and access to clean water.



Kibera (a) Waruku (b)

Mukuru (c) Mathare (d)

Figure 4: Examples of slums and their diversities in Nairobi, Kenya. Images source: Google Earth Pro.

3.1.3. Accra

The city of Accra is found in the greater Accra region, it is the capital of Ghana and one of the largest and rapidly urbanizing cities in West Africa. It lies on latitude 5.55602 and longitude -0. 1969. The city has a total population of 2.6 million people and a land area of 8100 square kilometers (Ghana Statistical Service, 2021). It is the city that has the most slums in Ghana as in Figure 5 and some of the known slums include Old Fadama, James Town, Nima, and Old Dansoman (Owusu-Ansah et al., 2016). The sprawl of Accra is leading to the development of slums in other nearby regions such as Kasoa in the eastern region (Owusu & Kohli, 2020), this can be attributed to the increase in the population due to rural-urban migration as a result of the push and pull factors and the high cost of living in the city, which these migrants cannot afford (Sandborn & Engstrom, 2016).

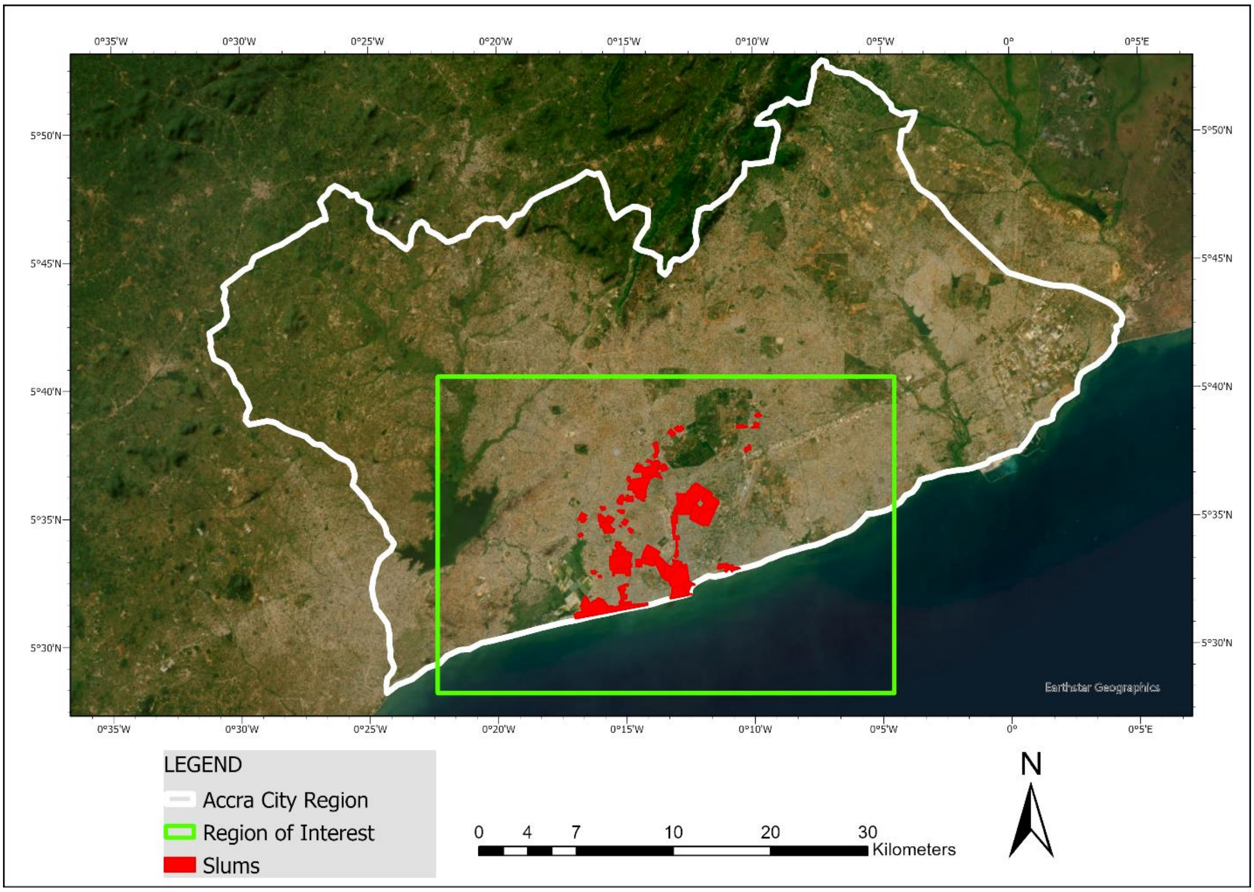


Figure 5: Study Area of Accra City Region, Ghana with some slums. Basemap is sourced from Earth Geographics.

3.1.4. Slums In Accra

Slums in Accra, Ghana are located close to city centers and major transportation routes. Slums such as Old Fadama, Nima, and Jamestown, have emerged because of the influx of migrants seeking economic opportunities, the majority of the migrants are from the northern parts of Ghana (Owusu-Ansah et al., 2016). The slums are characterised by irregular and narrow street layouts, coupled with high population, and building densities (Owusu et al., 2021). Housing structures are constructed with impermanent materials such as iron sheets, wood, and plastic, and often fail to meet building standards, contributing to poor living conditions (Emmanuel & Joseph, 2019). Like other slums, access to clean water is a significant problem, as residents typically depend on a few communal water points, leading to long queues and potential conflicts. Waste management is another critical issue, with inadequate services leading to heaps of garbage scattered throughout the slums (Raymond, 2019).

Additionally, slums such as Jamestown (Figure 6d) and Agbogbloshie (Figure 6c) are typically situated along the shores and near the Korle Lagoon, which makes them more susceptible to flooding but also strategically placed near the central business district and major markets (Emmanuel & Joseph, 2019). Despite these challenges, the slum communities in Accra demonstrate resilience, with strong social networks and informal systems of support (Owusu-Ansah et al., 2016). Figure 6 shows some visual examples of slums in Accra, Ghana.

Dansoman (a)

Old Fadama (b)

Agbogbolshie (c)

James Town (d)

Figure 6: Examples of slums and their diversities in Accra, Ghana. Images source: Google Earth Pro

3.2. Overall Methodology

Figure 7 describes the overall workflow of the research. It starts with reviewing literature in the context of slum mapping, urban morphology, geospatial data, EO, and ML to guide the identification of relevant features of urban morphology, spatial features, and related geospatial data that can be used effectively to characterise slums.

The development of a transferable model requires a detailed understanding of the morphology of slums. To achieve this, we captured local knowledge in the slum mapping process. CS was used to identify and rank morphological features using pairwise ranking techniques (Karpińska-Krakowiak, 2018). Through a participatory approach, slum dwellers were involved through focus group discussions to identify morphological, spatial, and physical features that can be used to distinguish slums from formal areas. The identified features were quantified, and meaningful geospatial data identified to measure them and included them in the modelling process. Owusu et al. (2021) showed that capturing morphological diversity through local knowledge enhances model performance and spatial transferability. Through purposive and convenience sampling techniques communities and slum dwellers were selected for the topic-focused discussions (Cochran, 1977), ensuring efficiency in the process given the limited timeframe for the fieldwork.

The Urban Morphometric (UMM) approach was used to quantify urban morphological elements (buildings and streets) using a built-in Python library (morphometric python: momepy) that serves as a toolkit for measuring urban morphology (Fleischmann, 2019). All processes were done in a geospatial cloud computing platform (CRIB) (Girgin Serkan, 2021). Other datasets such as Normalised Difference Vegetation Index (NDVI) and slope were resampled to a size of 100m to ensure easy data integration and to create a standard dataset for the machine learning model training (Owusu et al., 2023).

Once the data was prepared, a random forest classifier (Breiman, 2001) was trained, followed by accuracy and feature importance assessment. The choice of Random Forest (RF) for this study was motivated by the algorithm's robustness to high dimensionality and ability to handle issues of over-fitting in the training dataset (Zakaria et al., 2017).

The model's ability to predict slums in other cities was tested. As such, the model was tested in Accra to assess spatial transferability, and the results were compared with the model results for detecting slums in Nairobi and validated. Validation was done through visual inspection, comparison with expert maps, and the use of local experts (Owusu et al., 2021).

The last step in the methodology was to compare the feature importance from the machine learning model to the feature ranking acquired from the citizen perspective. This was to provide an understanding of the variables utilised by the ML and what the local stakeholders deem as most important.

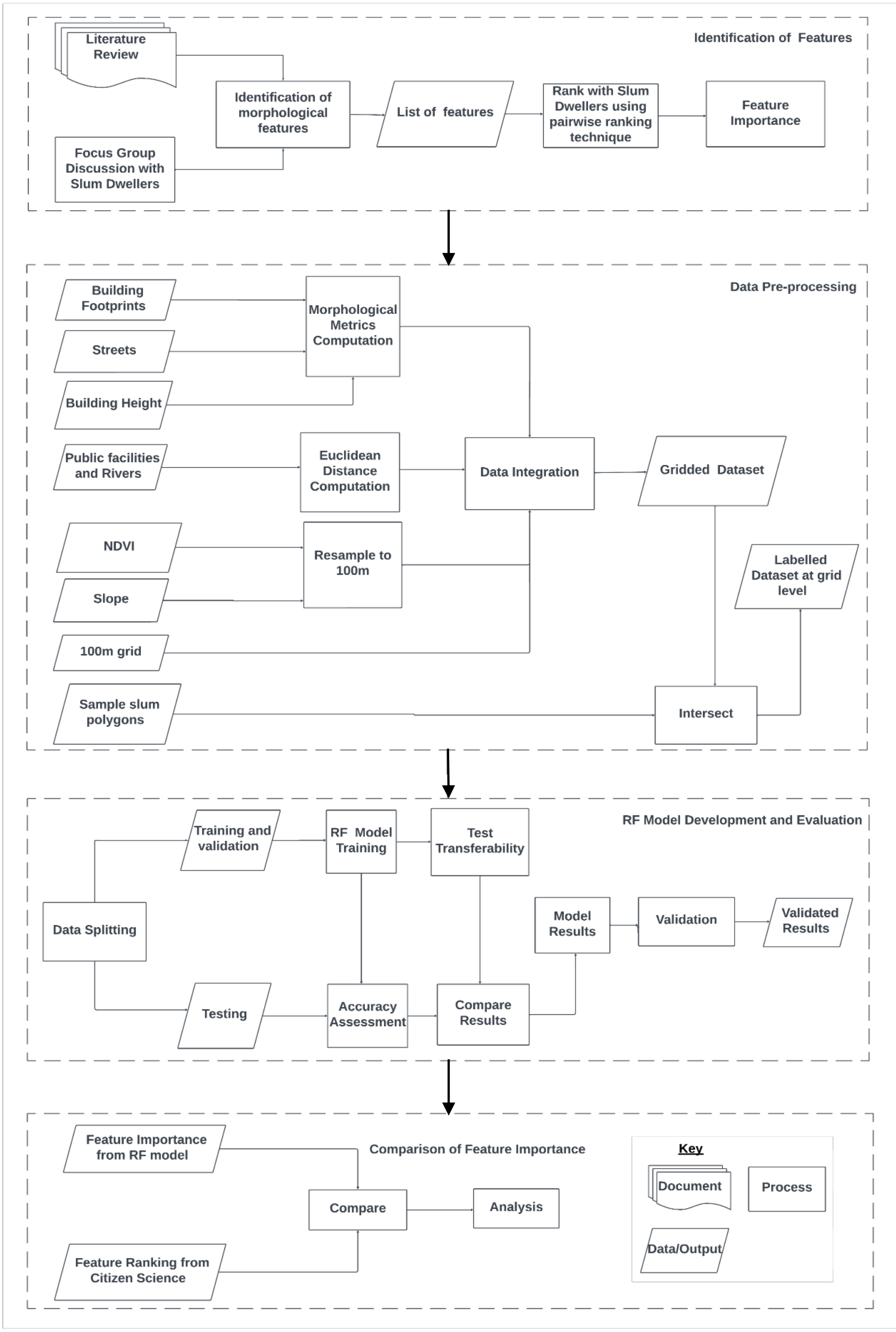


Figure 7: Methodology Flowchart

3.3. Tools: Momepy

Momepy which is the abbreviation for morphometric python is a state of the art regarding tools that provide advanced computing techniques for urban data analysis specifically urban form (Fleischmann et al., 2022). It is a tool that supports the shift toward quantitative geography. The tool is proposed as a shift in the field from traditional methodologies, tools, and graphical user interfaces such as Qgis and ArcMap, as an open tool that is available for use by all urban researchers. These tools have inherent restrictions on the transparency and reproducibility of research. The proposed method is fully replicable, reproducible, and expandable because it only requires open geospatial data from open sources such as OSM and relies on an entirely automated workflow (Fleischmann et al., 2022).

Momepy as proposed by Fleischmann (2019), provides a set of comprehensive and standardized morphometrics that can be used to quantify urban form at different scales. It is an open-source Python library that can be used by researchers to calculate relevant metrics to inform decision-making. The advantage of this tool is that it is scalable in that it can be applied at different scales, such as neighbourhood level or city-wide level, and enhances the detailed analysis of urban form (Fleischmann, 2019). This meets the basic requirement for the achievement of the main objective of this study, improving the accuracy and spatial transferability of slum detection models. Momepy has 6 modules representing 6 categories of urban morphometric characters that can describe the complexity of urban form: shape, dimension, spatial distribution, intensity, diversity, and connectivity.

3.4. Urban Morphometrics (UMM)

The metrics used in this research are adopted from Fleischmann (2019) as in Table 2, the author proposes detailed urban morphometric characters in six broad categories of urban form and formulas. In this research, all categories and related metrics are adopted.

Table 2: List of Morphometric Characters (adopted from (Fleischmann et al., 2022))

Category	Definition	Index	Element
Shape	The mathematical features of geometrical dimensions of individual objects	Form factor	Building
		Volume to Façade ratio	
		Circular compactness	
		Squareness	
		Corners	
		Equivalent rectangular index	
		Elongation	
		Centroid-corner distance deviation	
		Centroid - corner mean distance	
		Area	Tessellation Cell
		Circular compactness	
		Equivalent rectangular index	

Dimension	The basic geometrical dimensions of individual objects	Area	Building
		Height	
		Volume	
		Perimeter	
		Courtyard Area	
		Area covered	Neighbouring cells
		Reached area	Neighbouring segments
		Perimeter wall length	Adjacent buildings
		Longest axis length	Tessellation Cell
Intensity	The density of elements within a set context	Coverage Area Ratio	Tessellation Cell
		Floor area ratio	
		Mean inter-building distance	
		Block counts	
		Node density	Street network
		Proportion of four-way intersections	
Spatial Distribution	The spatial distribution of objects in space and their reciprocal positioning	Solar orientation	Building
		Cell alignment	
		Solar orientation	Tessellation Cell
		Shared walls ratio	Adjacent buildings
		Alignment	Neighbouring buildings
		Mean distance	
		Weighted neighbours	Tessellation cell
			Neighbouring buildings
		Building adjacency	
Diversity	The variety and richness of the elements in the study area	Tessellation area heterogeneity	Sanctuary area
		Tessellation area diversity	Accessibility radius
		Power law distribution of areas	Blocks
		Intersection type proportion	Street network
Connectivity	The spatial interconnection of the street network	Closeness centrality	Street network
		Page rank	

		Self-loop proportion	
		Node/edge connectivity	
		Node connectivity	

3.5. Auxiliary Variables

Table 3 presents the auxiliary variables that were combined with the morphological metrics computed from the building footprints and street elements.

Table 3: Auxiliary Variables

Indicator	Description	Reference
NDVI	The percentage of green vegetation in slum areas is less	(Kuffer et al., 2016)
Slope	Slums are in areas with a low slope of less than 10 degrees.	
Access to health	Slum dwellers lack adequate access to basic health facilities.	
Access to schools	Slum areas do not have adequate access to educational facilities.	

3.6. Spatial Unit of Analysis

The unit of analysis considered in this study is a square grid of 100m x 100 m resolution since it fits the context and allows for data integration. The choice of the grid size was informed by its common usage by most global datasets (World Pop datasets [2]) (Tatem, 2017), this will ensure easy integration of datasets from different sources (Jochem et al., 2021) as in the future, the work can make use of global datasets and ensure easy comparison with global demographic datasets. Also, all datasets were resampled to 100m resolution to allow for ethical and privacy reasons (Owusu et al., 2023) while maintaining analysis at a resolution that allows the capture of meaningful details like mean building size and distance between buildings. For vector datasets, values were assigned to the grids by aggregating all records that have their centroids within the grid and the average was calculated and assigned as the value for the grid. In the case of overlapping polygons in a grid, a simple proportion rule is used, where the value is assigned to the grid with a larger area of intersection. With raster datasets, the values are extracted to the grid centroids.

Later steps such as training data preparation and model training are done at this resolution. For the training data, sample slum polygons are intersected with the grid and those grids that intersect with the polygons are labelled and used for model development. This helps to prepare data in a standard format that is ready to use by any machine learning algorithm (Zakaria et al., 2017) and aid in the effective visualization of final outputs.

[2] https://www.worldpop.org/

3.7. Citizen Science Methodology

This section explains the materials, methods, and techniques employed during the fieldwork to achieve effective and successful citizen participation in the research. It includes the selection criteria for communities and participants, approaches used to ensure active participation, and the analytical methods applied to interpret the qualitative data accrued. Approval was acquired from the ethical committee of ITC (request form number, nr: 230669) to conduct the fieldwork activities.

3.7.1. Selection of Communities

For the focused group discussions (FGDs), five slum communities were purposively selected to identify and rank features that differentiate slums from formal residential areas. The communities selected were Kibera, Mukuru, Kariobangi, Waruku, and Pumwani as in Figure 8. These communities were chosen due to the pre-existing projects and established contacts by the Ideamaps team, facilitating the ease of organizing FGDs. Additionally, these communities were characterized by diverse physical attributes, providing a comprehensive range of perspectives and data for analysis (Georganos et al., 2021).

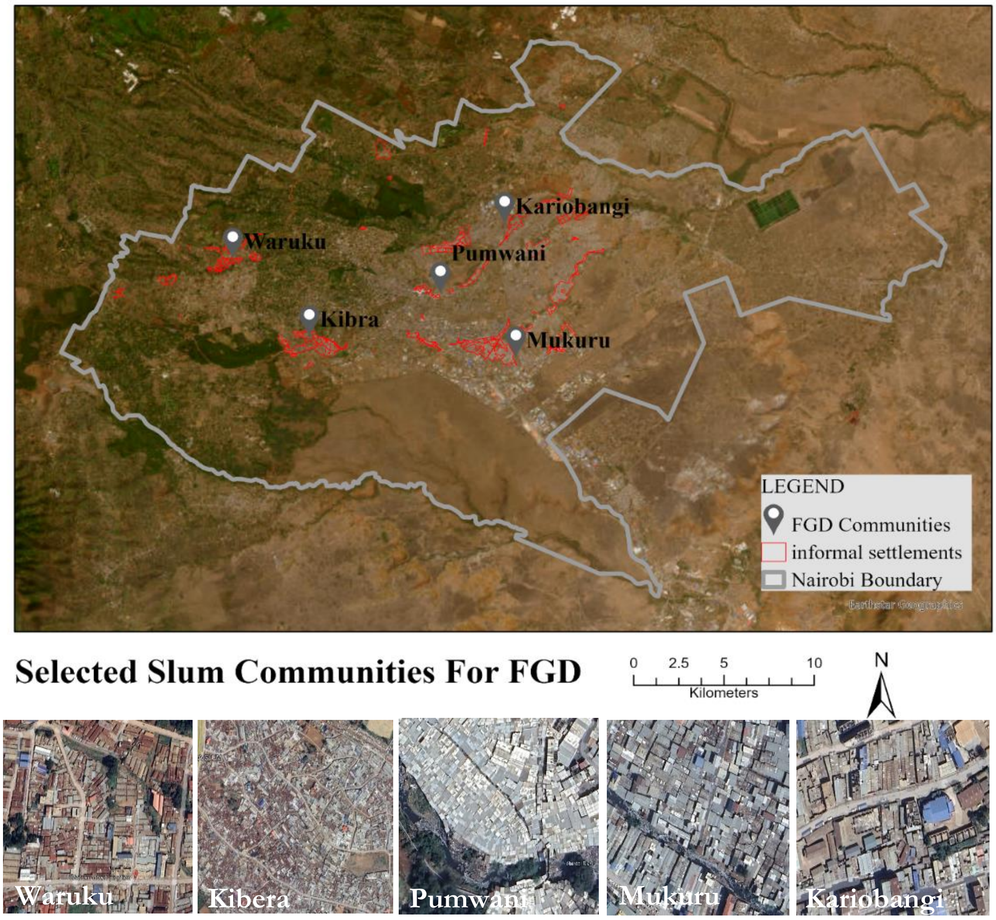


Figure 8: Selected communities for FGD. The Basemap of the main map is sourced from Earth Geogrphics and zoomed-in images are from Google Earth Pro.

3.7.2. Sample Population

A sample population of 50 individuals was strategically selected for the discussions. Representation from each community comprised 10 individuals, organized by the respective community leaders. These leaders were responsible for presenting participants from their community. Selection criteria were based on the availability and willingness of the participants, without consideration for demographic variables such as sex, age, and education level. Despite the technical nature of the discussions, which presupposed a high level of difficulty, no significant challenges related to participant diversity were observed during the process. Figure 9 shows the age and sex distribution of participants respectively.

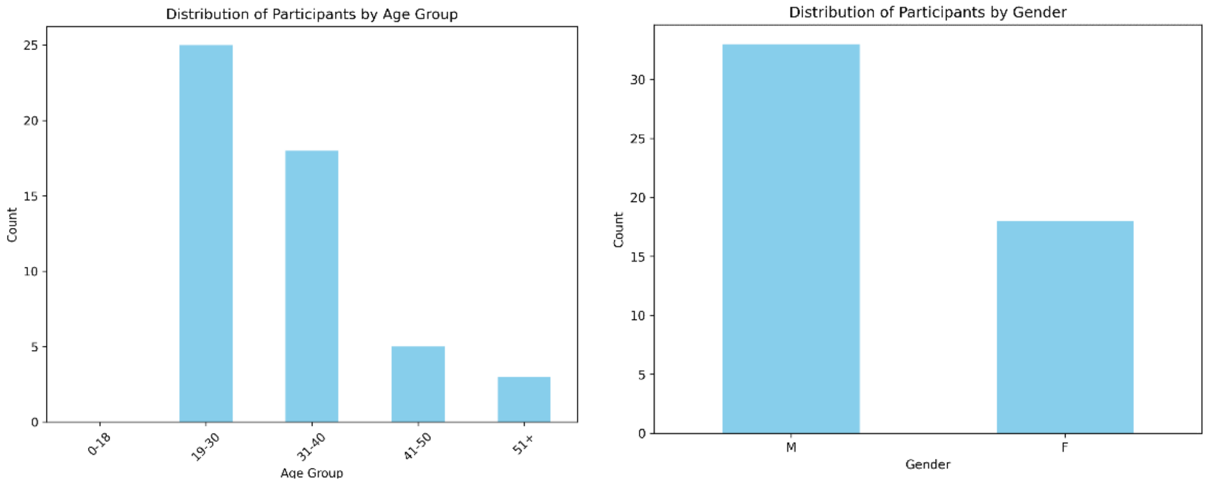


Figure 9: Age (left) and Sex (right) distribution of participants.

3.7.3. FGD Setting and Methodology.

Five FGDs were conducted, each with a duration of approximately three hours. The primary language of communication was English, supplemented by Swahili for clarification when necessary. Participants were engaged with the use of maps and figures[3] as in Appendix 7.8 to explain the tasks at hand. Each session was structured into two segments of approximately 90 minutes, with the first focusing on identifying variables that distinguish slums and formal areas and the second focusing on ranking the identified variables in order of importance. The whole process followed the methodology described by Abascal et al. (2024). Participants' time and effort were appreciated and as a thank you, a total amount of about 400 Euros was given for the entirety of the FGDs.

Before the commencement of each session, participants were provided with high-resolution A0-sized glossy maps, sourced from Google Maps as in Appendix 7.8.3. A reference point was established on the map to initiate the identification of known slum areas and formal areas, thereby setting the foundation for subsequent discussions. Typically, the reference point was the meeting location, as it was easily recognizable by participants. This initial task was estimated to take between 20 to 30 minutes.

The classified maps were displayed on the wall for all participants to view. The facilitator posed open-ended questions regarding the physical characteristics that indicate whether an area is a slum. Responses were documented by a note-taker. Further inquiries were made to understand the rationale behind the participants' classifications of areas as slums or non-slums, with a focus on specific attributes of buildings

[3] https://we.tl/t-LjweFWUgSE

and streets. The FGD guide provided in Appendix 7.8 was utilised throughout this process. Worth noting is that participants were made aware that the study is purely physical and morphological-based, and as such all discussion should be tailored in that direction. Factors such as social and economic factors were acknowledged when raised and efforts were made to relate them to the physical aspects of the urban environment. After extensive discussion, a multitude of variables were identified by all communities.

As the principal researcher and facilitator, and having conducted a literature review on related factors, a list of 74 morphological variables based on momepy was compiled. These variables were categorized into six major classes based on their similarities, as detailed in Table 2. This set of variables was not introduced initially to avoid biasing participants' perspectives with preconceived notions derived from the literature. Instead, these morphological variables were later presented to the stakeholders using illustrative figures and practical examples[4]. The variables were also related to what they have mentioned so far.

To achieve the objectives of the second session, which entailed ranking variables based on their perceived importance, a pairwise ranking technique was employed. This method involves comparing two variables or groups of variables at a time, based on the respondents' perceptions (Karpińska-Krakowiak, 2018). Due to the constraints of time, comparing all pairs of variables was not a feasible idea. To facilitate an efficient pairwise ranking session within the available time constraints, a grouping mechanism was employed, where variables were categorized into nine groups according to similarity as in Table 4. This categorization significantly reduced the time required for discussion and comparison.

Table 4: List of variables per group and respective codes used for FGDs.

SN	GROUP	CODE	EXPLANATION	Features
1	Dimension	a	This focuses on variables that describe the size of buildings and streets	Refer to Table 2
2	Connectivity	b		Refer to Table 2
3	Shape	c	This group of variables describes the general appearance of the buildings	Refer to Table 2
4	Intensity/Density	d	This describes how clustered or dispersed buildings and street networks are in a specified area.	Refer to Table 2
5	Spatial distribution	e	This includes variables that focus on the overall pattern of buildings and streets and how they are spread out in space	Refer to Table 2
6	Greenery	f	This focuses on the number of trees and the amount of vegetation present in each area	The amount of vegetation
7	Physical hazard	g	This focuses on the location characteristics in each area such as location close to dump sites	Distance to rivers Distance to legal and illegal waste dump sites

[4] https://we.tl/t-LjweFWUgSE

				Distance to industries Location in low-lying areas (slope in degrees)
8	Diversity	h	This set of variables focuses on the different characteristics of buildings and streets in each area	Refer to Table 2
9	Access to Facilities and services	i	These variables describe the distance from an area to a facility or service of interest	Distance to public schools Distance to colleges Distance to universities Distance to public hospitals Distance to clinics Distance to public parks Distance to banks Distance to Automated Teller Machines (ATMs) Distance to markets Distance to police stations Distance to restaurants

The pairwise ranking process entailed 36 comparisons among the nine groups, as dictated by the formula: N(N-1)/2, where N represents the number of variable groups. Each session lasted approximately one and a half hours, resulting in a ranking of variables from first to ninth within each community.

3.7.4. Addressing Tied votes

During the pairwise comparison process, instances may arise where variables receive an equal number of votes, necessitating a methodological approach to resolve these ties. In scenarios where only two variables are tied, the resolution is straightforward: we revisit the original votes cast during the pairwise comparisons. By examining the instances where the tied variables were directly compared, we can determine which variable was deemed more important by the majority and assign it a higher rank accordingly.

However, in more complex situations where more than two variables share the same ranking, the previous technique proves inadequate. To address this, we introduce an additional method utilising a Likert scale (Jebb et al., 2021), which ranges from 'most important' to 'least important.' The divisions on the Likert scale are based on the number of variable groups that are tied. For example, in the case of three tied variables, the scale would include 'most important,' 'important,' and 'least important' as distinct categories.

This Likert scale is then employed to conduct a voting process to resolve the tie. It is important to note that the focus of this exercise is qualitative rather than quantitative. Therefore, considerable emphasis is placed on documenting the rationale behind the initial tie and the subsequent decisions made to settle it. This ensures a comprehensive understanding of the variables' significance as perceived by the participants.

3.7.5. Communicating Results From FGD

To communicate the results derived from the FGDs, employing a pairwise comparison technique, necessitates a systematic approach. To facilitate this, a weighting system was introduced, inversely correlating with the ranks assigned during the pairwise comparison process, that is from one to nine. The highest weight of nine was allocated to the first-ranked variable group, while the ninth-ranked group received the lowest weight of one, as presented in Table 5.

Table 5: Weighting scheme utilised in variable ranking.

RANK	WEIGHT
1ST	9
2ND	8
3RD	7
4TH	6
5TH	5
6TH	4
7TH	3
8TH	2
9TH	1

To achieve an overall variable ranking encompassing the perspectives from the five communities and corresponding FGDs, the individual community rankings were aggregated for each variable group based on the defined weights. The weighted ranking approach facilitated the derivation of a comprehensive variable ranking, reflective of the collective insights acquired from all participating communities.

3.8. Overview of Datasets Utilised in This Study

This subsection presents the details of the datasets that were used in this study. It describes the attributes of the datasets such as the dataset name, original format, source, resolution, year of data acquisition, and the quality assessment of the data.

The Google Open Buildings dataset[5] was chosen for this research (Sirko et al., 2021). The dataset has wide coverage for Africa, is open access with no cost, and is globally available (Gonzales, 2023), making it highly useful for comparing the case study areas and helping towards the achievement of the overall objective of this study. The dataset consisted of polygon geometry information, their areas, and confidence level, excluding other information such as building type, building use, and height. The building footprint data was released in May 2023 as part of the effort of the open data community to fill the gap in data availability issues, especially in LMICs (Gonzales, 2023). The dataset is generated using deep learning algorithms including the U-Net model, trained to extract building footprint from high-resolution 50cm satellite imagery and further processed through geometry generation to produce building footprint polygons.

As the building footprints dataset from Google does not have height information, the world settlement footprint three-dimensional[6] (WSF3D) dataset at a 90m resolution was used to generate building height information (Esch et al., 2022). The dataset is generated from sentinel-1 and sentinel-2 satellite imagery in combination with a digital elevation model and radar imagery collected by the TanDEM-X mission. The dataset is the first globally available building height data with open access.

The street dataset was acquired from Microsoft through a GitHub repository[7]. The dataset was chosen because of its overall high precision (85.24%) and is near complete compared to OSM data, as it aims to fill the data gaps in OSM. The dataset was produced using a CNN to extract road networks from high-resolution 100cm satellite imagery in two main stages, semantic segmentation, and geometry generation.

The slum boundary datasets were acquired from IDEAtlas[8] and were used as samples to prepare the labelled dataset for the model training. The polygon shapefiles were intersected with gridded datasets to prepare the training data. The polygon datasets were generated by the IDEAMAPS and IDEAtlas groups, which are slum mapping groups working in the study areas to produce data for slum mapping.

The datasets for public facilities such as schools and hospitals were acquired from OpenStreetMap[9] (OSM), a collaborative, free, and globally accessible platform that provides geospatial data. River's shapefiles were also acquired from the same repository.

NDVI was derived from Sentinel-2 images. Sentinel-2 is a satellite mission provided by the European Space Agency (ESA) that provides very high-resolution 10m multispectral imagery with 16 spectral bands and 5 days revisit time. NDVI was derived using band 8, Near-Infrared (NIR), and band 4, Red (R). The NDVI

[5] https://sites.research.google/open-buildings/
[6] World Settlement Footprint (WSF) 3D - Building Area - Global, 90m - Data Europa EU
[7] GitHub - microsoft/RoadDetections: Road detections from Microsoft Maps aerial imagery
[8] https://ideatlas.eu/
[9] Export | OpenStreetMap

is calculated with the following formula: B8-B4/B8+B4. The data was accessed through the Google Earth Data Catalog[10].

Slope data was derived from a digital elevation model from ALOS PALSAR at a resolution of 12.5m. The inherent geometrics and radiometric distortion are corrected from the source and the dataset is distributed in GIS-compatible Geo TIFF format. The dataset was acquired through the Alaska Satellite Facility (ASF) official data portal[11].

Table 6: Overview of Datasets utilised in this study.

Data	**Source**	**Format**	**Resolution (Coordinate system)**	**Year**
Building footprints	Google open buildings	Geojson	50cm (EPSG:4326)	2023
Building Height	WSF	Raster		90m
streets	Microsoft	Geojson	100cm (EPSG:4326)	2022
Slum boundaries	Ideatlas	Shapefile		2021
Formal area boundaries	ESRI	Shapefile		2021
NDVI	Sentinel2	Raster	10m	2023
Slope	ALOS PALSAR	Raster	12.5m	2006 - 2011
Rivers	OSM	Shapefile		
Public Schools				
Public Hospitals				
Dump sites				
Open markets				
Police station				
Industrial areas				
Restaurants				
Public playgrounds				

[10] Harmonized Sentinel-2 MSI: MultiSpectral Instrument, Level-1C | Earth Engine Data Catalog | Google for Developers

[11] ALOS PALSAR - Radiometric Terrain Correction | Alaska Satellite Facility

3.8.1. Data Quality Check

This section presents a comprehensive assessment of the data quality for the open datasets employed in this study. The datasets include Google Open Buildings, OSM points of interest and rivers data, Microsoft Streets, WSF3D height dataset, ALOS PALSAR DEM, and reference slum and formal area polygons from IDEAtlas and Esri 3 Landcover Class datasets, respectively. The assessment follows the data quality elements defined by the International Organisation for Standardisation/ International Electrotechnical Commission (ISO/IEC) 25012:2008 data quality standard model.

ISO defines data quality as the degree to which data fulfils the requirements of its end-users. The organization has established standards for the evaluation of datasets, delineating data quality into fifteen distinct categories. These categories are divided into two principal perspectives: inherent data quality and system-dependent data quality. Inherent data quality suggests that data possesses intrinsic quality concerns, which are indicative of its capacity to meet user requirements, encompassing five specific attributes. Conversely, system-dependent data quality refers to the quality issues that arise from how data is stored or processed by a given computer system. This is shown in the data quality model delineated by ISO/IEC 25012, as depicted in Figure 10.

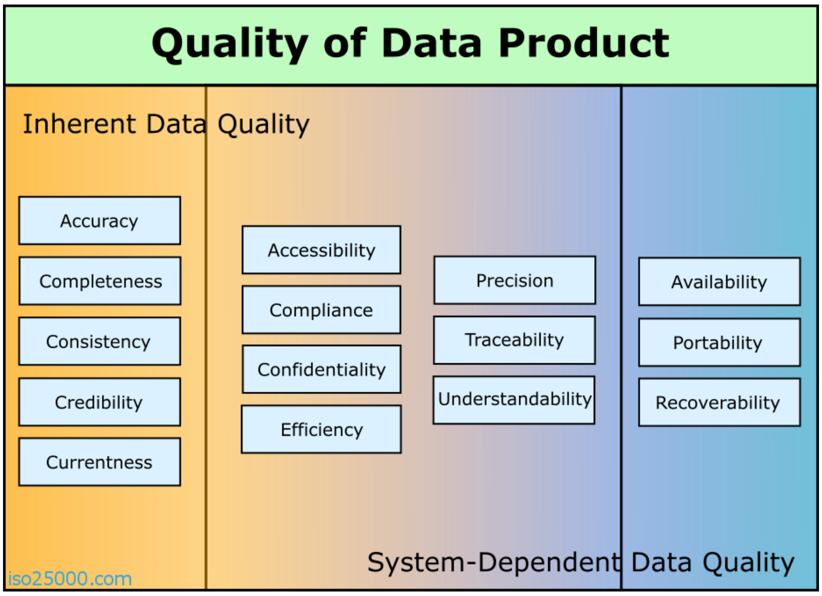


Figure 10: Data quality framework according to ISO/IEC 25012:2008

In the era of big and open data, it is essential to evaluate the quality of data employed in scholarly research to ascertain its potential influence on the study results. The framework established by ISO serves as a foundational guideline for the appraisal of data products. As indicated in Figure 10, this assessment will focus on six pivotal data quality attributes where five of these attributes (accuracy, completeness, consistency, credibility, and currentness), pertain to the inherent data quality. Additionally, precision, an attribute that intersects both the inherent and system-dependent data quality categories were examined.
In this study, the selected data quality attributes are defined as follows:

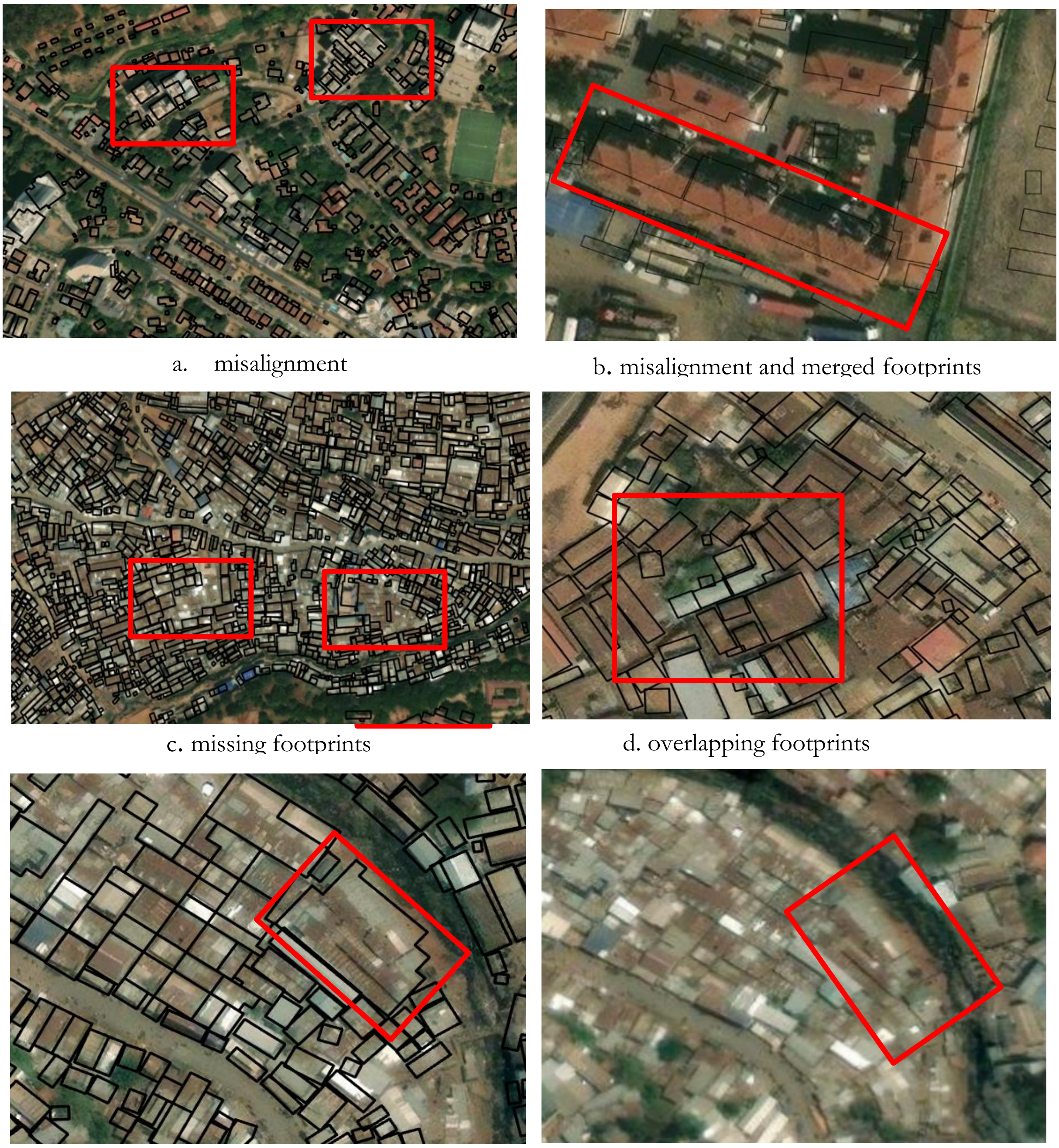
- Accuracy: describes the degree to which the dataset correctly represents the true value of the intended use context. In the context of slum mapping, for example, correctly delineated boundaries are essential for identifying slum areas accurately. However, this is difficult to quantify given the subjectivity in slum conceptualization.

- Completeness: describes the degree to which the dataset has all expected attributes and data points in the context of use.
- Consistency: the degree to which dataset records are coherent and without contradictions.
- Credibility: the degree to which the dataset is regarded as authentic in specific use cases. Credibility here refers to whether the community/ body that provides the slum boundary polygons has the sufficient ability to delineate slum boundaries accurately. This is important not only for the performance but also for the trustworthiness of the eventually developed model.
- Currentness: the degree to which data and data attributes are up to the right age in a specific context of use. Given the dynamic and rapid nature of slums, the slum datasets need to be up to date. For example, if a slum dataset was generated 5 years ago, the slums may have gone through several changes over time and the dataset will not be the true representation any longer.
- Precision: describes the degree to which datasets align with actual ground information in the use context. High precision ensures that the mapped features align closely with ground reality and influences the credibility of the model results.

3.8.2. DATASETS ASSESSMENT

3.8.2.1. Google Open Buildings

The Google Open Building dataset is the current and near complete dataset of building footprint available and is free to access by any user. The building footprint data faced several issues including alignment, overlapping, and merging several buildings into one building footprint, especially in the slums. The dataset has an added attribute that assigns every building a confidence level, which informs the probability that an extracted polygon is a building and not any other structure with the same shape as a building for example cars and mountains. The dataset only published building footprints with a confidence level above 0.65. Figure 11 provides some visual data quality issues identified and Table 7 summarizes the quality of the dataset per quality attribute. The quality of the data has been investigated through visual inspection with Earth Geographics base map.



a. misalignment

b. misalignment and merged footprints

c. missing footprints

d. overlapping footprints

e. merged footprints

f. merged footprints

Figure 11: Images showing some identified issues with the building footprint dataset. Building footprints is sourced from Google Open Buildings and base maps from Earth Geographics.

3.8.2.2. Microsoft Streets Dataset

The Microsoft Streets dataset is the most recent publicly available streets dataset made in 2023. The dataset is global and provides almost complete coverage for the study areas of this study. The major quality issues of this dataset are that some street segments are not connecting as in Figure 12, the data lack added attributes such as road type that can be used to filter roads if need be and the original file format that the dataset is stored is tab-separated values (TSV). This format is not a user ready format and requires added processing

Figure 12: Images showing some instances where street segments do not connect. The street data is sourced from Microsoft Streets and Base map from Earth Geographics.

steps before the data can be used in a GIS software.

3.8.2.3. OSM Data

OSM is a crowdsourced spatial data platform to create and distribute geospatial data free for the entire world. As OSM data is user-generated there is varied accuracy across different locations. The credibility of OSM data among researchers is a priority because of how the dataset is crowd-sourced and may have inherent errors (Quarati et al., 2021). Since crowdsourced geographic information suffers from a general lack of quality assurance because they may be provided by non-professionals, researchers have paid particular attention to the quality of OSM data (Borkowska & Pokonieczny, 2022). The river data from visual inspection is not complete for the entire study area and some river lines have sudden dead ends without them being connected as in Figure 13.

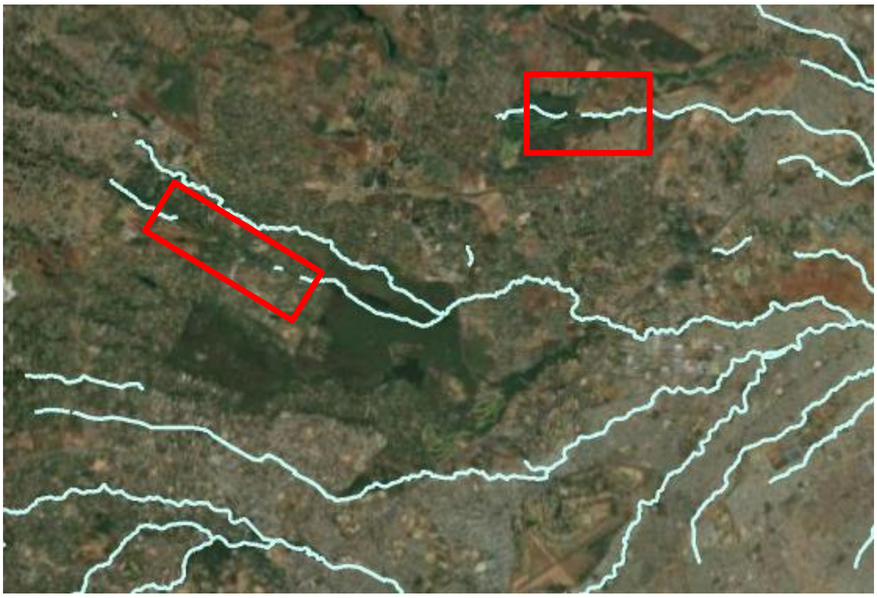


Figure 13: Image showing the issue of non-connecting OSM rivers. The base map is sourced from Earth Geographics.

3.8.2.4. WSF3D Dataset

The WSF3D height data is the only available global building height data. The dataset was made publicly available in 2015 and has not been updated since. In terms of completeness, the dataset may not capture all buildings in the study area given the that urban environment is not static but dynamic. The precision is low as the dataset is aggregated at 90m resolution, individual building height information extracted will have the same height. As a result of the lack of update, the data underrepresent the average height of buildings in the grid size used to create the data as it does not account for buildings constructed after the data creation period (2015) as illustrated in Figure 14.

a. Mean height = 3.3m

b. Ground photo of a section of the area within this grid

Figure 14: Selected grid showing the mean height assigned a grid based on WSF3D data and a ground photo of a section showing the underrepresentation of the data. The base map is sourced from Earth Geographics and the ground photo is from Google Earth Pro.

3.8.2.5. Reference Data

The reference data include the slum and formal area boundary polygons that were used. The slum polygons do not provide a complete representation of all the slums in the study areas as all slums are not delineated and have boundary uncertainties (Kohli et al., 2016). Also, some polygons do not cover any built-up area as in Figure 15 based on visual inspection with Earth Geographics base map. In terms of currentness, the reference data was last updated in 2021 and was co-created with slum dwellers which increases its credibility.

Figure 15: Images showing examples if slum boundaries with no building based on the base map used for visual inspection. The base map is sourced from Earth Geographics.

The formal reference data is created from an Esri Landcover 9 class dataset[12] of 2021. The built-up is masked out and intersected with the slum polygons to create the formal areas, and the remaining is labelled as formal and non-built-up. This dataset was only readily available for Nairobi and not for Accra, and we needed to take extra steps to complete the data for both study areas. The data is not very credible as there was no metadata available to provide information on who created the dataset and the definition of what makes the formal class. What is considered formal areas here is the built-up area minus the known slum areas. Also, the methodology of how the formal class was created is still unclear and the output included some non-built-up areas based on visual inspection with Earth Geographics base map.

Given the limitations and uncertainties of the ESRI dataset, we developed a technique to validate formal areas, especially in Accra. We divided the study area into sizable spatial blocks (2 kilometres x 1.5 kilometres) and identified the formal areas. With an expert and a local, we identified blocks that are formal areas and used that as the basis for our formal area reference data in Accra as in Figure 16. This systematic approach ensured a verifiable framework for identifying formal areas, enhancing the credibility of the spatial analysis conducted in our study.

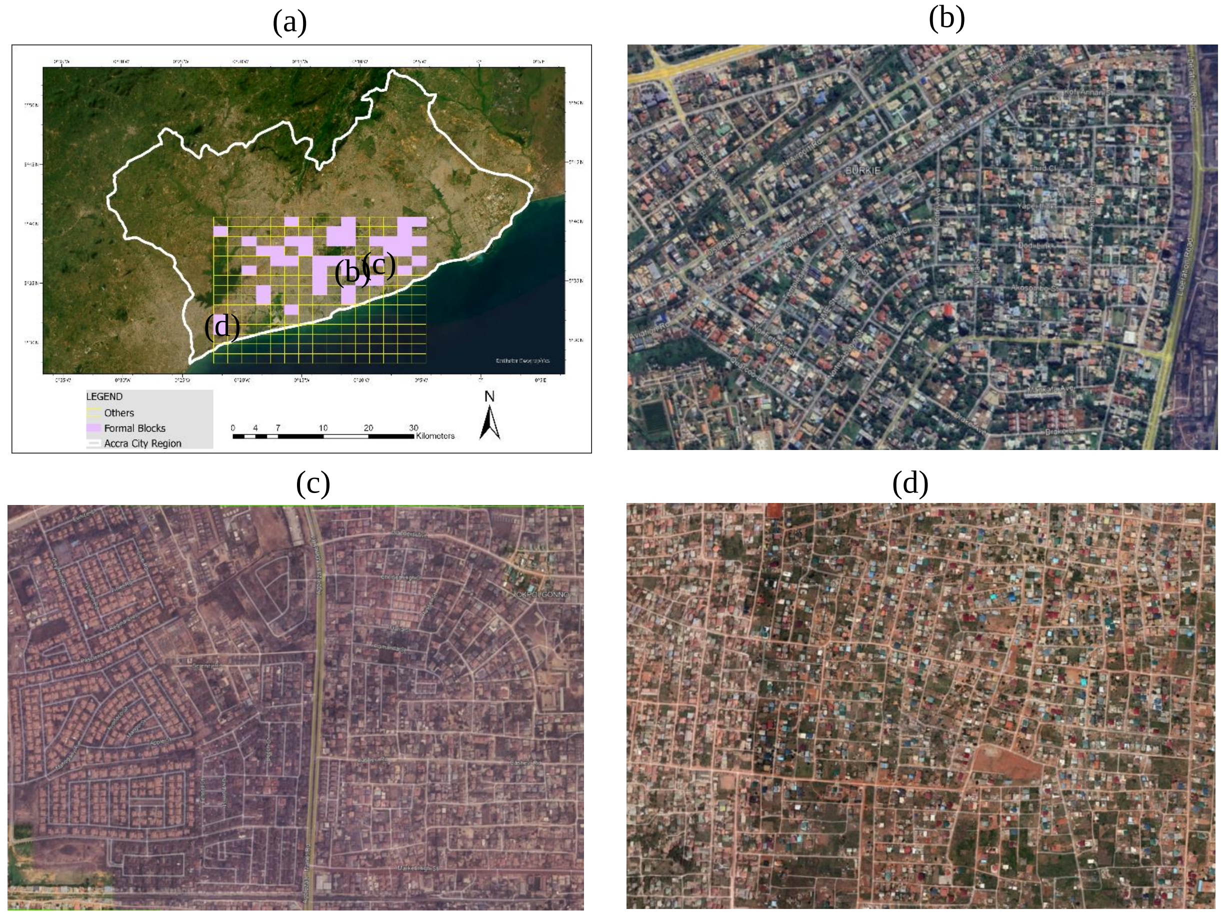


Figure 16: Blocks of formal regions and zoomed-in samples, Accra, Ghana

12 Esri | Sentinel-2 Land Cover Explorer (arcgis.com)

Table 7: Summary table of datasets per quality dimension assessed.

Data	Quality Dimension					
	Accuracy	**Completeness**	**Consistency**	**Credibility**	**Currentness**	**Precision**
Google Open Buildings	✓	✓		✓	✓	✓
Microsoft roads	✓	✓		✓	✓	
OSM	✓	✓		✓	✓	
WSF3D	✓	✓	✓		✓	✓
ALOS PALSAR DEM	✓				✓	
Slum Reference	✓	✓	✓	✓	✓	✓
Formal area Reference	✓			✓	✓	

The quality of the datasets has a direct impact on the accuracy and reliability of the slum mapping results such as what feature emerge as most important. The assessment revealed that while most datasets exhibit good data quality, certain areas require attention to mitigate potential impacts on the study. However, this assessment needs to be interpreted with caution as it was generated through visual inspection and not quantitative. Data cleaning and preprocessing strategies were employed to address the identified issues. By addressing the identified quality issues, the reliability of the slum mapping results can be enhanced, contributing to the overall success of the study.

3.9. Data Preprocessing and Aggregation

3.9.1. Preparing grids (spatial units of analysis)

A grid of 100m x 100m was created and used as the spatial unit of analysis (refer to section 3.6 for the rationale). An initial grid of 100m x 100m was created to serve as the analytical unit as in Figure 17. However, from visual inspection, discrepancies in alignment were observed when superimposing the newly created grids onto existing raster datasets. A new grid was created to mitigate this and ensure perfect alignment between the target raster and the reference grid. This was created by converting a raster layer at a 100m pixel to a vector dataset based on the unique values. This technique produced a grid of 100m x 100m that has perfect alignment and ensures that the extracted values in the subsequent steps represent the spatial location.

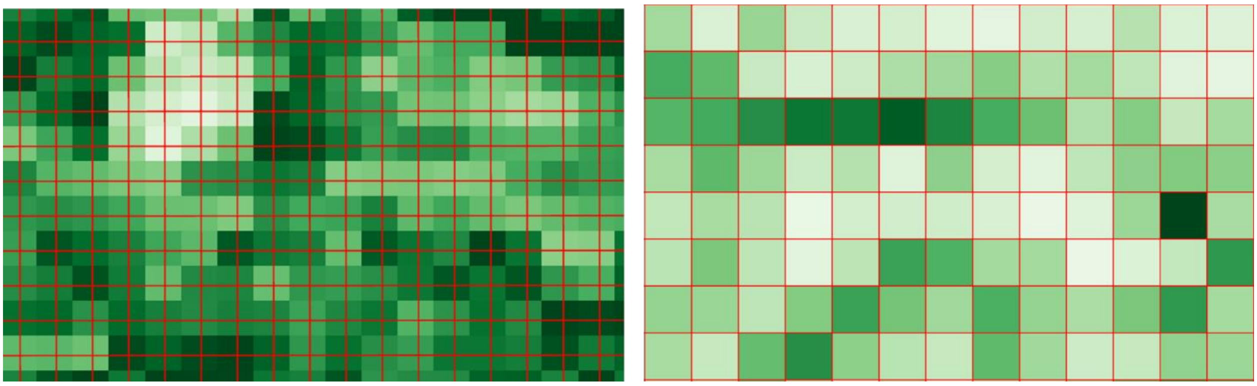


Figure 17: left: grids with alignment issues with raster and right: grid with well-aligned raster ready for data extraction

3.9.2. Preparing Predictor Variables

This subsection describes how the 113 predictor variables that describe urban form were generated.

3.9.2.1. Quantifying Urban Form

After cleaning and preprocessing the building footprint and street datasets, a total of 93 urban form metrics were computed, each reflecting the unique characteristics of individual buildings, streets, street blocks, and neighborhood-level characteristics informed by urban science studies (Fleischmann et al., 2022; Milojevic-Dupont et al., 2020; Wang et al., 2023). A tessellation was generated using the idea of a Voronoi spatial partitioning technique (Fleischmann et al., 2020). The tessellation, serving as a proxy for individual plots, facilitated the computation of neighborhood characteristics. This was achieved by establishing a spatial weight and defining the topological steps, which, in this instance, amounted to three topological steps. The measurements followed the original approach of (Fleischmann et al., 2022) and metrics were computed using momepy.

The street-level metrics encompassed the length of road segments, road density, node density, number of dead-ends, and cul-de-sacs, utilizing the capabilities of the momepy and graph module (Fleischmann, 2019). Furthermore, an association was established between streets and buildings based on proximity, ensuring that each building was linked to the nearest street segment. In addition, the concept of a 'street block' was introduced and street blocks were generated by turning lines into polygons, enabling the quantification of buildings per street block, thereby providing a comprehensive view of the urban form (Milojevic-Dupont et al., 2020). Refer to Table 2 for the urban form characters considered in this study and their broader groupings.

3.9.2.2. Auxiliary Variables

Point-of-interest data including schools and hospitals, were extracted from the OpenStreetMap (OSM) database, followed by the computation of Euclidean distances from these points to the periphery of the study area (Lloyd et al., 2019). The resultant output is a raster representation illustrating the straight-line distances from residential structures to the identified facilities of interest. This is used as a proxy to understand the degree of accessibility between slums and formal areas (Owusu et al., 2023). Employing a similar methodology, the Euclidean distances from water bodies, specifically rivers, were also calculated, thereby providing a spatial quantification of the straight-line distance of homes from these natural features and helping to understand their relationship to natural hazards such as floods.

To assess the vegetation coverage within slum and formal areas in the study area, an NDVI composite was generated. This composite represents an aggregation of data spanning a full calendar year and was derived from high-resolution Sentinel-2 satellite imagery (Lasaponara et al., 2022). The processing and analysis were conducted using the Google Earth Engine (GEE) platform. The NDVI composite was generated by selecting cloud-free images to ensure the highest quality and consistency. The index values were calculated using the standard NDVI formula: NDVI=(NIR+Red)/(NIR−Red), where *NIR* represents the near-infrared band, and *Red* denotes the red band of the electromagnetic spectrum captured by the Sentinel-2 sensors. The resulting NDVI values range from -1 to +1, with higher values indicating healthier and denser vegetation (Yang et al., 2022).

To generate a detailed slope analysis within the study area, a Digital Elevation Model (DEM) was acquired from the ALOS PALSAR dataset[13]. The individual GeoTIFF DEM files were mosaiced and masked to conform to the precise boundaries of the study region, ensuring that the subsequent analyses were spatially accurate and relevant. Utilising QGIS, the slope of the terrain was calculated in degrees from the DEM using the create slope from elevation layer algorithm from the raster terrain analysis tools group (Nizar et al., 2024). The slope calculation is a critical step in understanding the topography of the area, as it provides insights into the gradient and steepness of the land surface. This information is significant for understanding the locational attributes of slums and formal areas and how they are related to natural hazards such as floods (Kuffer & Barros, 2011).

3.9.3. Data Integration

Several steps were implemented before integrating and aggregating all datasets after cleaning and preprocessing into the designated spatial unit of analysis (100m x 100m grids). To facilitate this, centroids were generated from the central points of each grid cell and used to extract values from the raster datasets. During preprocessing, it was imperative to ensure that all raster datasets were resampled and properly aligned to match the 100m x 100m grid using the zonal statistics tool[14] as in Figure 18.

[13] ALOS PALSAR - Radiometric Terrain Correction | Alaska Satellite Facility
[14] https://pro.arcgis.com/en/pro-app/latest/tool-reference/spatial-analyst/zonal-statistics.htm

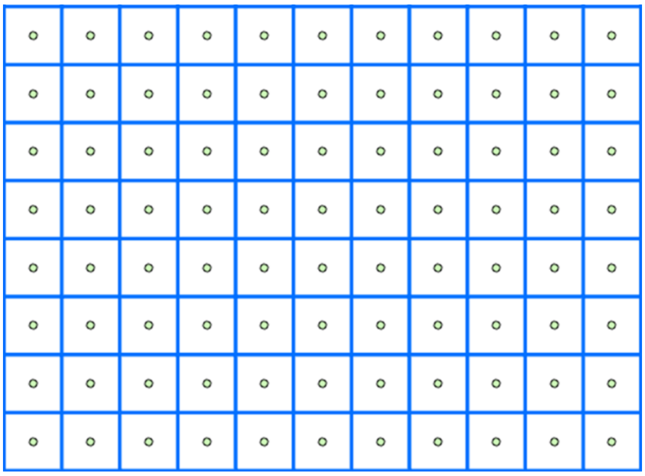


Figure 18: Example of spatial unit of analysis (100m x100m) and centroids used for data integration.

The subsequent step involved the extraction of raster values to the centroids of each grid cell. Once these values were extracted, the centroids were spatially joined to the grid, associating each attribute with a spatial unit. In parallel, urban form metrics computed at individual building levels were spatially joined to the reference grids based on the building centroids. The mean values of the respective buildings within the grids were calculated and assigned to the grid cells. This follows a similar workflow employed by Lloyd et al. (2019). This rigorous approach ensures that the spatial data retains its originality and relevance, providing ready data for modelling and analysis.

3.10. Training Data

The training data was prepared at the grid level and a binary classification scheme was employed (slums and formal areas) as in Figure 19. Reference data of slums and formal areas in polygon format were obtained and intersected with the grid dataset to create the training dataset.

First, we intersected all the grids in the study area with the slum and formal area polygons. During this intersection process, some grids were partially covered by either slums or formal areas polygon. To ensure the accuracy of our training data, we filtered out the grids using a threshold technique to retain only those that had more than 50% of their area covered by either slum or formal reference data.

This filtering step resulted in a set of grids where each grid had most of its area within a slum or formal region. At this stage, the training points for slum areas were completed and we had a total of 1280 and 2524 sample slum points for Nairobi and Accra respectively. However, for the formal areas, we encountered an issue of class imbalance because of the typical majority class problem (Kuffer et al., 2016), as the number of formal grids significantly exceeded the number of slum grids.

To address this imbalance, we undersampled the formal grids to match the number of slum grids. Specifically, with the number of slum sample grids as the basis, we undersampled the formal grids to the same number as the slum grids to have equal class representation to prevent the model from being biased towards the majority class (Buda et al., 2017). This step ensured that our training dataset had an equal number of samples for both slum and formal areas, thereby ensuring that our model is trained on a balanced dataset improving the robustness and accuracy of our model.

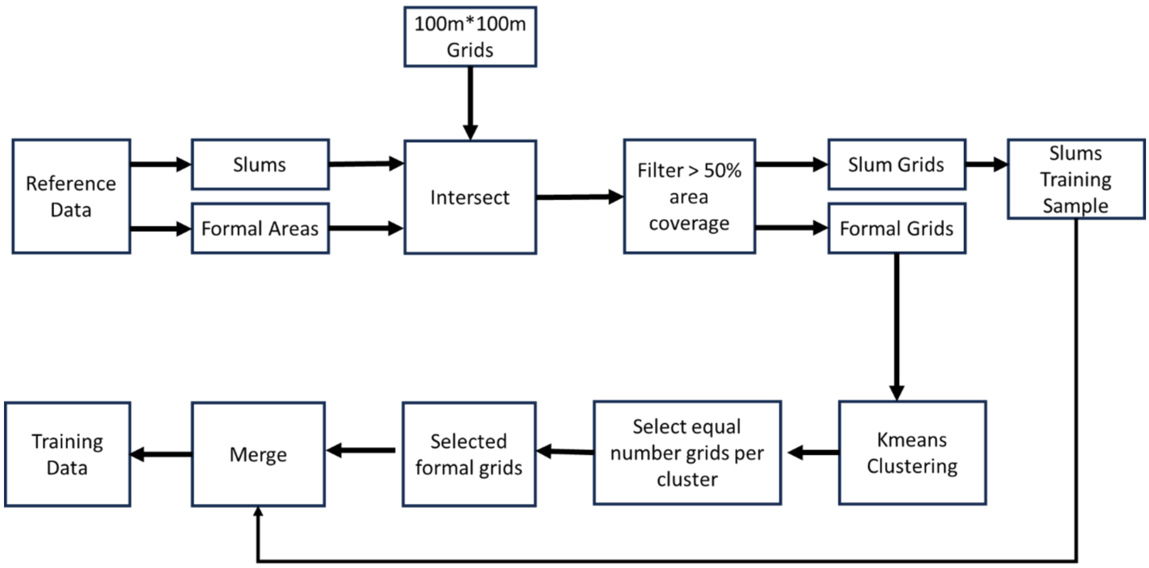


Figure 19: The workflow for preparing training data.

We followed a systematic approach to select an equal number of sample grids from the formal area. The process began by clustering the formal grids using the k-means clustering algorithm and 21 neighborhood-level urban form characters as followed by (Wang et al., 2023). This approach was only implemented in Nairobi. The input features were first standardized using the scikit learn standard scaler to have a mean of 0 and a standard deviation of 1. This is done because k-means and other clustering algorithms are sensitive to the scale of the input features since they are distance-based measures. We determined the optimal number of clusters by employing the elbow method as in Figure 20. The elbow method involves plotting the within-cluster sum of squares (WCSS) against the number of clusters (k) and identifying the point where the rate of decrease sharply changes, forming an "elbow" (Shi et al., 2021). Based on this method, we concluded that four clusters (k = 4) provided the most suitable and clean classification for our study purpose. Refer to appendix 7.2 for details of clustering results and formal area types identified.

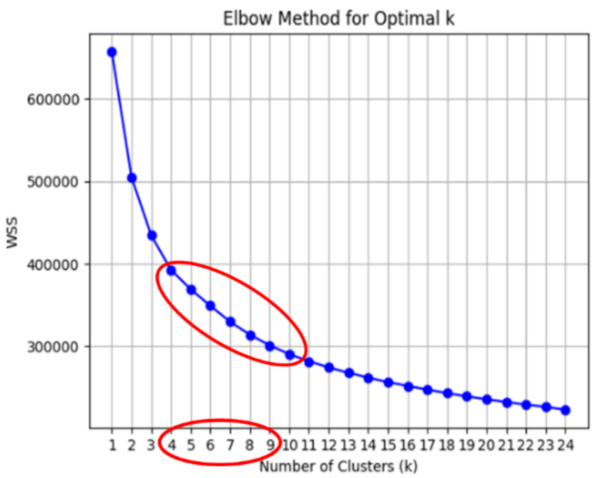


Figure 20: Elbow method used to determine optimal number of clusters.

After establishing that four clusters were optimal, we proceeded with the k-means clustering of the formal grids into these four distinct clusters. The next step involved dividing the total number of slum grids, which was 1,280, by the number of clusters (four). This calculation yielded 320, representing the number of formal grids to be selected from each cluster. We randomly sampled 320 formal grids from each of the four clusters. This stratified undersampling method ensured that our formal training set was representative of the diverse types of formal areas and helped preserve the heterogeneity within the formal class while balancing the overall number of training samples between slum and formal areas.

After the undersampling step, we merged the slum grids with the formal grids to create our complete set of training samples. We coded formal and slum classes as 0 and 1 respectively before the modelling. Table 8 shows the number of sampled points per class per city.

Table 8: Number of sampled points per class per city

Class	Label	Nairobi	Accra
Formal	0	1280	2524
Slum	1	1280	2524

To split our data into training and testing sets, we implemented additional steps to mitigate the effects of spatial autocorrelation which can lead to over-optimistic results as illustrated in Figure 21. Spatial autocorrelation is the concept that observations located in proximity to one another are likely to display similar characteristics. This phenomenon challenges the presumption that each observation is independent and identically distributed, potentially leading to an overestimation of a statistical model's accuracy (Getis, 2010). Instead of using a simple random split, we employed the technique of spatial blocks as implemented by Meyer et al. (2019). In this method, the study areas were divided into spatially distinct blocks (different block sizes were used in both countries: 8km x 5km for Nairobi and 2km x 1.5km for Accra), ensuring that training and testing data were separated by geographic space, thus reducing the risk of spatial autocorrelation.

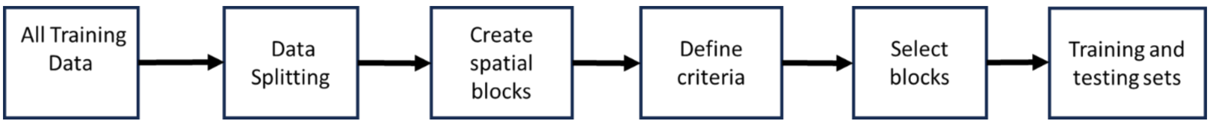
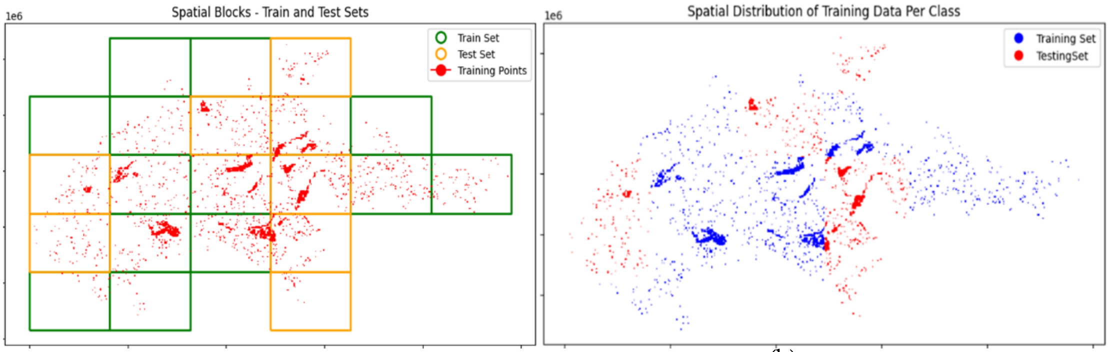


Figure 21: The workflow for data splitting.

Based on the distribution of our training samples, unfortunately, each block could not contain a mix of both classes, for this reason, we carefully implemented a checkerboard strategy that selected every third block as the testing set. This approach provided a more realistic assessment of the model's ability to generalize to new, unseen areas, as it simulates the real-world scenario where the model will be applied to different geographic regions. Figures 22 and 23 show all training data and data splitting into training and testing sets.



(a) (b)

Figure 22: spatial blocks used for data splitting (a) and training and testing sets (b) in Nairobi.

(a) (b)

Figure 23: spatial blocks used for data splitting (a) and training and testing sets (b) in Accra.

3.11. Random Forest Model Implementation

RF is an ensemble learning method that constructs multiple decision trees during training and outputs the mode of the classes (classification) or mean prediction (regression) of the individual trees (Breiman, 2001). It is particularly well-suited for handling large datasets with many features and can effectively manage overfitting for both classification and regression tasks (Ganjirad & Delavar, 2023). It has achieved good performance in classification tasks (Belgiu & Drăgu, 2016; Breiman, 2001). We utilized the Random Forest algorithm to classify urban built-up areas into slums and formal areas.

The prepared dataset was split into two, 70% for training and 30% for testing (Owusu et al., 2023). Data splitting was done using a technique that considers the spatial components inherent in the datasets and captures all diversity in the study areas. Hence, sample grids for training and testing sets were selected through a stratified random sampling technique with the end goal of avoiding the impact of spatial autocorrelation of the predictor variables (Cochran, 1977).

We utilized the Random Forest Classifier from the Scikit-learn library (Bala et al., 2019) in Python for our analysis. To fine-tune the hyperparameters, we used Grid-search with cross-validation (GridSearchCV) (Bergstra et al., 2012), with a five-fold cross-validation which is the default configuration across all models. Due to the random nature of RF, each experiment is repeated five times to mitigate the potential sampling effect, and we reported the mean accuracy (Milojevic-Dupont et al., 2020). The key parameters for setting up the models included (1) the number of trees in the forest (n_estimators), (2) the maximum depth of the trees (max_depth), (3) the number of features to consider when looking for the best split (max_features), (4) the minimum amount of data points in a leaf node before it can be split further (min_samples_split). And (5) the minimum number of data points required in a leaf node (min_samples_leaf).

We trained two RF models in Nairobi. we trained the first model using all 113 variables in the dataset. Based on the results of the first model, we selected the top 20 variables that had the most significant impact on the classification based on the feature importance. The feature importance is based on the Gini impurity - a measure of the degree of how well a potential split is separating the samples of the two classes in a particular node (Menze et al., 2009). We trained the second and simplified model using only the top 20 variables.

To evaluate the models' performance, we used the spatially distinct testing sets. The key metrics for quantitatively assessing the models' performance included accuracy, precision, recall, and F1-score (Kuhn & Johnson, 2016). Accuracy measures the proportion of correctly classified instances among the total instances (Naidu et al., 2023). Precision measures the proportion of true positive predictions among all positive predictions (Pratomo et al., 2016). Recall measures the proportion of true positive predictions among all actual positive instances (Hossin & Sulaimann, 2015). F1 Score measures the harmonic mean of precision and recall, providing a single metric that balances both (Vujović, 2021). The Confusion Matrix as in Table 9, a table showing the true positives, true negatives, false positives, and false negatives (Naidu et al., 2023), was also used to provide a detailed breakdown of the models' performance. Formula 1, 2, 3, and 4 show the calculation of the accuracy, precision, recall, and F1 score.

Table 9: Sample confusion matrix for binary classification

	Positive Prediction	Negative Prediction
Class A	True Positive (TP)	False Negative (FN)
Class B	False Positive (FP)	True Negative (TN)

$$(1)\ \ Accuracy = \frac{Number\ of\ correct\ prediction}{Total\ number\ of\ predictions\ made}$$

Where, the number of correct predictions equals (TP + TN), and the total number of predictions made equals (TP + TN + FP + FN).

$$(2)\ \ Precision = \frac{TP}{TP+FP}$$

$$(3)\ \ Recall = \frac{TP}{TP+FN}$$

$$(4)\ \ F1\ Score = \frac{Precision * Reacll}{Precision+Recall} * 2$$

3.12. Model Transferability

To evaluate the transferability of the RF models developed using data from Nairobi, we tested its performance in Accra. We created a dataset that included all the relevant predictors and the target variable (slum and formal areas) for Accra. This dataset was structured to match the format used in the Nairobi training data, ensuring compatibility with the trained model. we ensured that all variables in the Accra dataset had the same names as those used in the model training in Nairobi. This consistency in naming was crucial for the model to correctly identify the features.

We fed the Accra dataset into the two trained Random Forest models developed in Nairobi. Initially, we used the model trained on all variables (113 predictors) to classify the built-up area into slum and formal areas in Accra. We did the same for the model trained on the top twenty variables from the base model. To evaluate the model's performance, we compared its predictions to the actual reference data in Accra to determine the overall accuracy, precision, recall, and f1-score (Alam et al., 2024).

3.13. Validation Data

The model results were validated using slum reference boundary data from Spatial Collectives[15], a Nairobi-based organization focused on leveraging geospatial technology and community-driven data to support sustainable development and informed decision-making in Africa, to enhance our assessment. The polygons were overlaid and visually inspected with model results to assess the accuracy and reliability of the model output. Also, the model output was visually inspected by comparing it with Google Earth imagery. Additionally, an online interview was organized with local experts to validate the model output leveraging the power of local knowledge and experience.

[15] https://spatialcollective.com/category/spatial-collective/

4. RESULTS

This section presents the results of this study. The first subsection details the RF model performance for Nairobi, followed by the model transfer results in Accra. The next subsection presents a visual assessment of the model prediction for the entire Nairobi County and Accra city Region. The following subsection presents a validation of the model results in both cities by comparing them to existing slum boundary polygons and satellite imagery. The final subsection presents the results of the feature importance from the citizen perspective, model perspective, and a comparison of both.

4.1. Statistical Evaluation of Models

Table 10 summarizes the performance evaluation on the test set of the trained models, and the features used. It reports the overall accuracy and the macro averages of precision, recall, and F1-Score, given that all models were trained on a balanced dataset. The models, trained in Nairobi with either all features or the top 20 features achieved an accuracy above 80%, indicating that a complex model trained on all variables has no significant statistical difference from a model trained from only the top 20 informative features. Overall, with a small set of quality and informative features, a simple model can be trained, and that model may perform better.

Table 10: Evaluation of Model Performance

Model	City	Features	Accuracy	Precision	Recall	F1-Score
1	Nairobi	All	0.88	0.88	0.88	0.88
2	Nairobi	Top 20	0.88	0.89	0.88	0.88

4.2. Spatial Transferability Results.

We assessed the spatial transferability of the two models trained in Nairobi to detect slums in Accra. Table 11 summarises the spatial transferability results, both models achieved statistical accuracies above 80% with the all-features model achieving a higher test accuracy of 87% and the top 20 model, with an accuracy of 83%. This again explains that a few relevant input features can perform better, potentially reducing the complexity of ML models without compromising accuracy.

Table 11: Evaluation of Model Transferability

Model	Accuracy	Precision	Recall	F1-Score
All features	0.87	0.87	0.87	0.87
Top 20	0.83	0.85	0.83	0.82

4.3. Visual Evaluation of the Implemented ML Models

4.3.1. Nairobi

A comprehensive visual assessment was performed to evaluate the models' predictions against actual slum boundaries and satellite imagery, supplemented by validation from local experts.

The assessment revealed a consistent pattern: both models tended to over-predict the presence of slums. This overprediction was particularly noticeable in the western and northeastern parts, characterized by high-density formal residential zones that are not slums but predicted as slums. Notably, the model utilising all features exhibited a greater tendency to overpredict compared to the top-20 features model (Figure 24). This is supported by the overlay of slum reference data on the models' output, highlighting known slum locations.

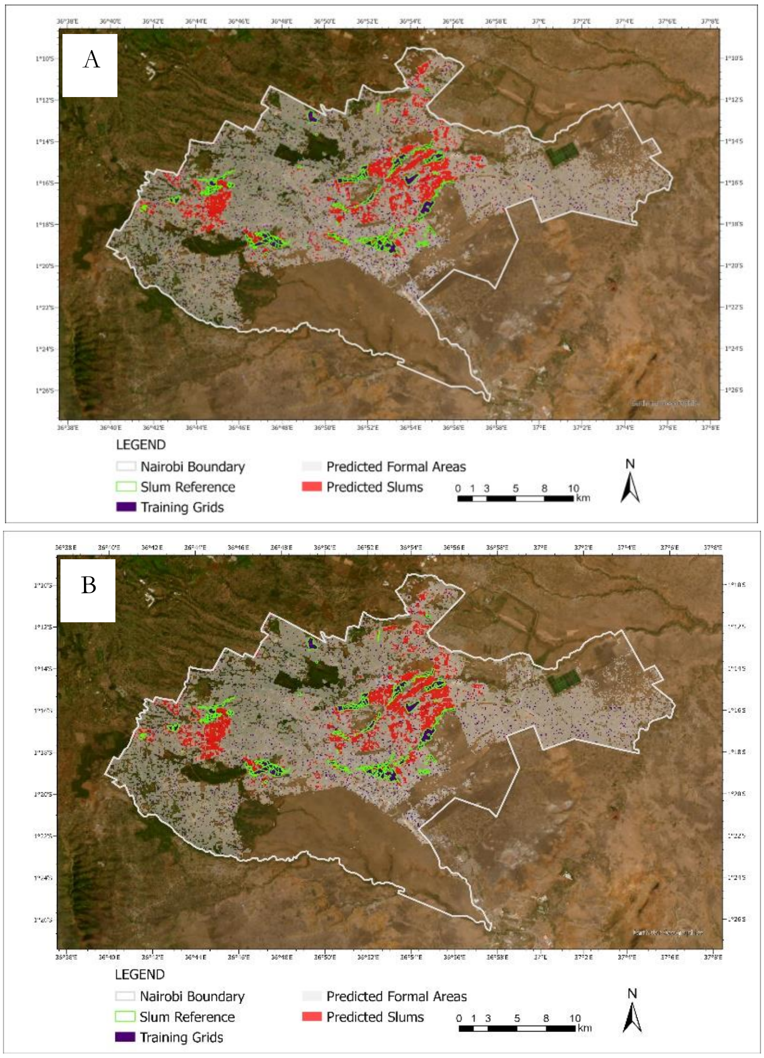


Figure 24: Model Predictions at city scale. All-features model (A) and Top-20 features model (B). Slum reference data is from IDEAtlas and Basemap is sourced from Earth Geographics.

Figure 25 presents the instances where the two models, the all-features model (model 1) and the top-20 features model (model 2) predicted the same class or a different class. Given that the models have similar patterns of predictions overall, yet there are instances where the two models predict different classes for the same grid.

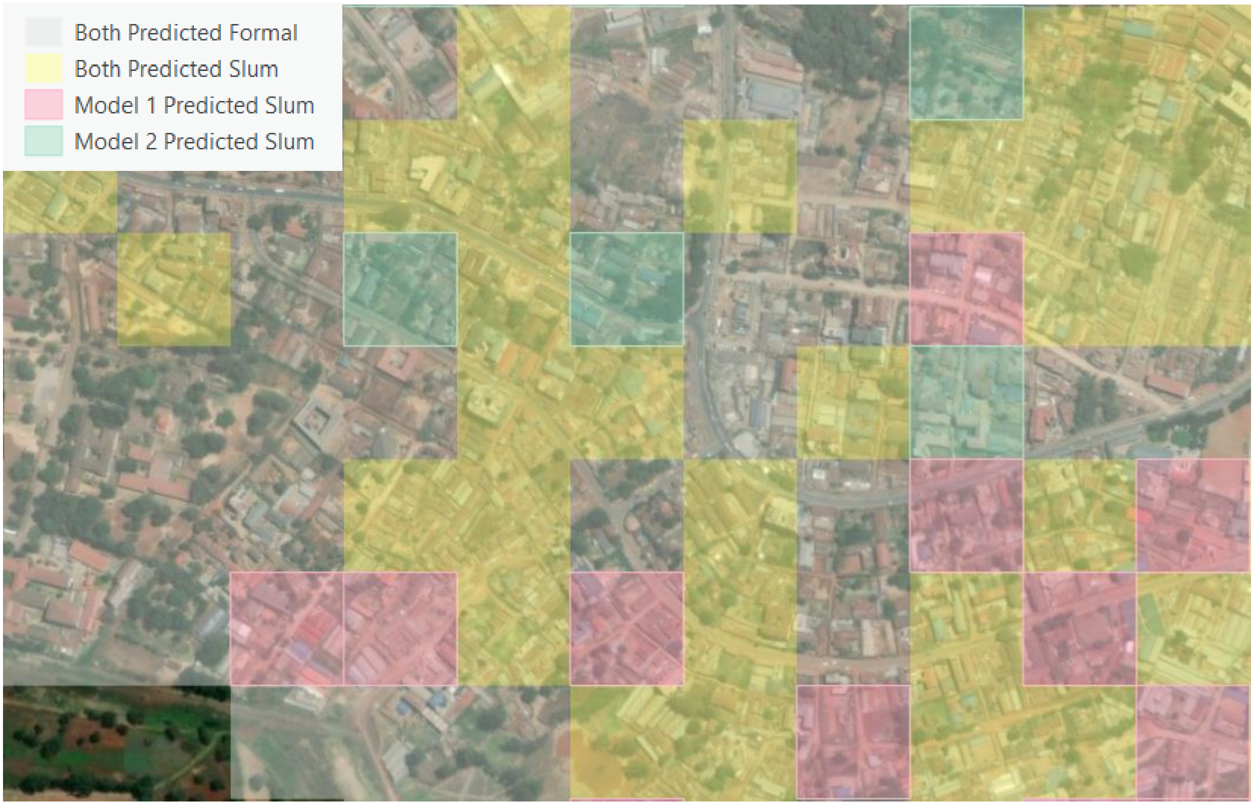


Figure 25: Visual Inspection showing differences and similarities in the models' predictions. Basemap is sourced from Earth Geographics. All-features model (model 1) and Top-20 features model (model 2).

Further visual assessment is presented, which focuses on the top-20 model's predictions with zoomed-in imagery (Figure 26) and established slum boundaries (Figure 27). Selected examples demonstrate instances of both accurate and inaccurate predictions. The imagery supporting this analysis was sourced from Google Earth Pro, offering high-resolution views for detailed examination. Additionally, we incorporated a slum boundary dataset provided by Spatial Collectives to enhance our assessment.

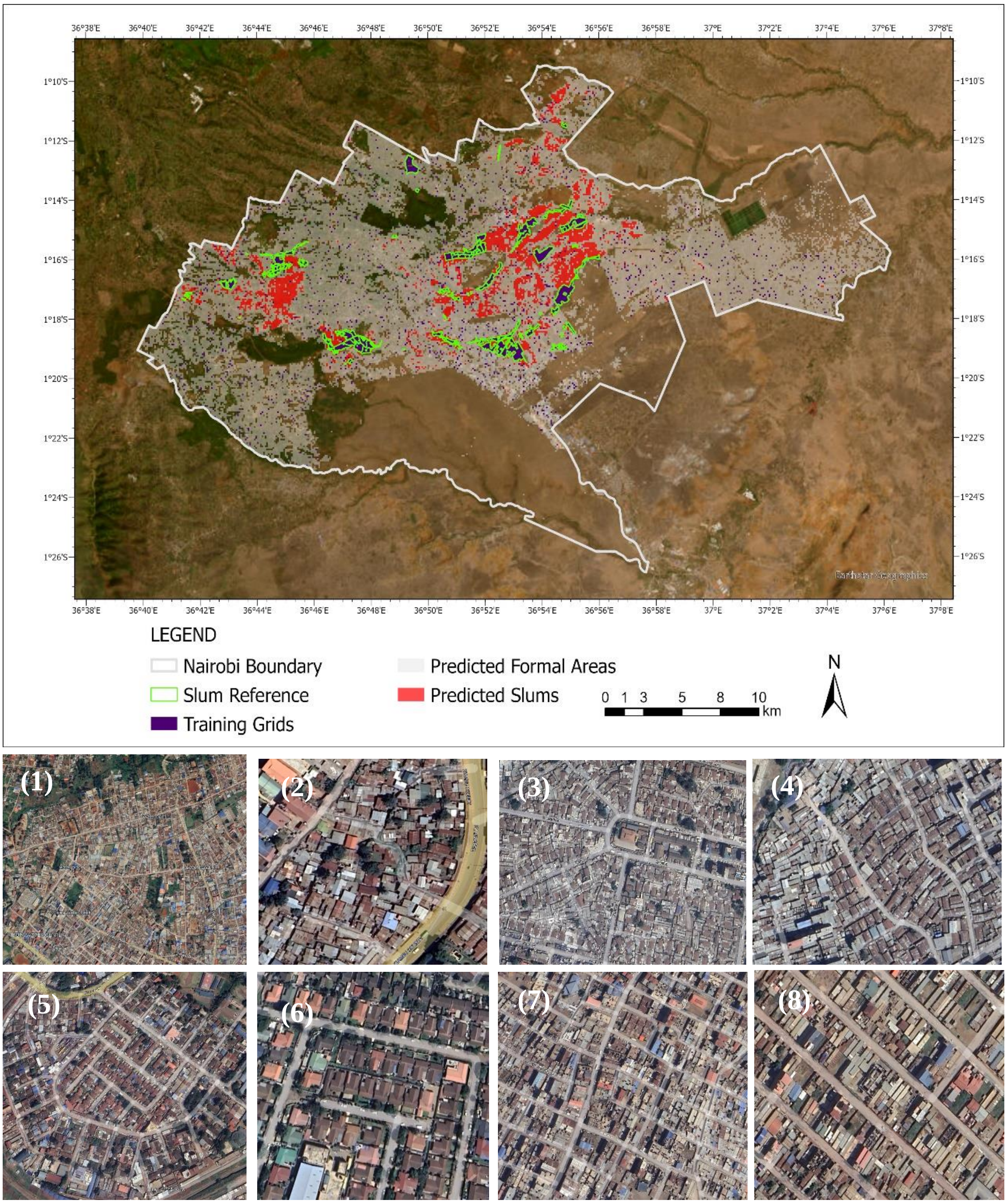


Figure 26: Examples of instances of accurate and inaccurate predictions from the top-20 model. Top four shows accurate predictions and bottom four shows inaccurate predictions. Slum reference is from IDEAtlas, Basemap is sourced from Earth Geographics and validation images are from Google Earth.

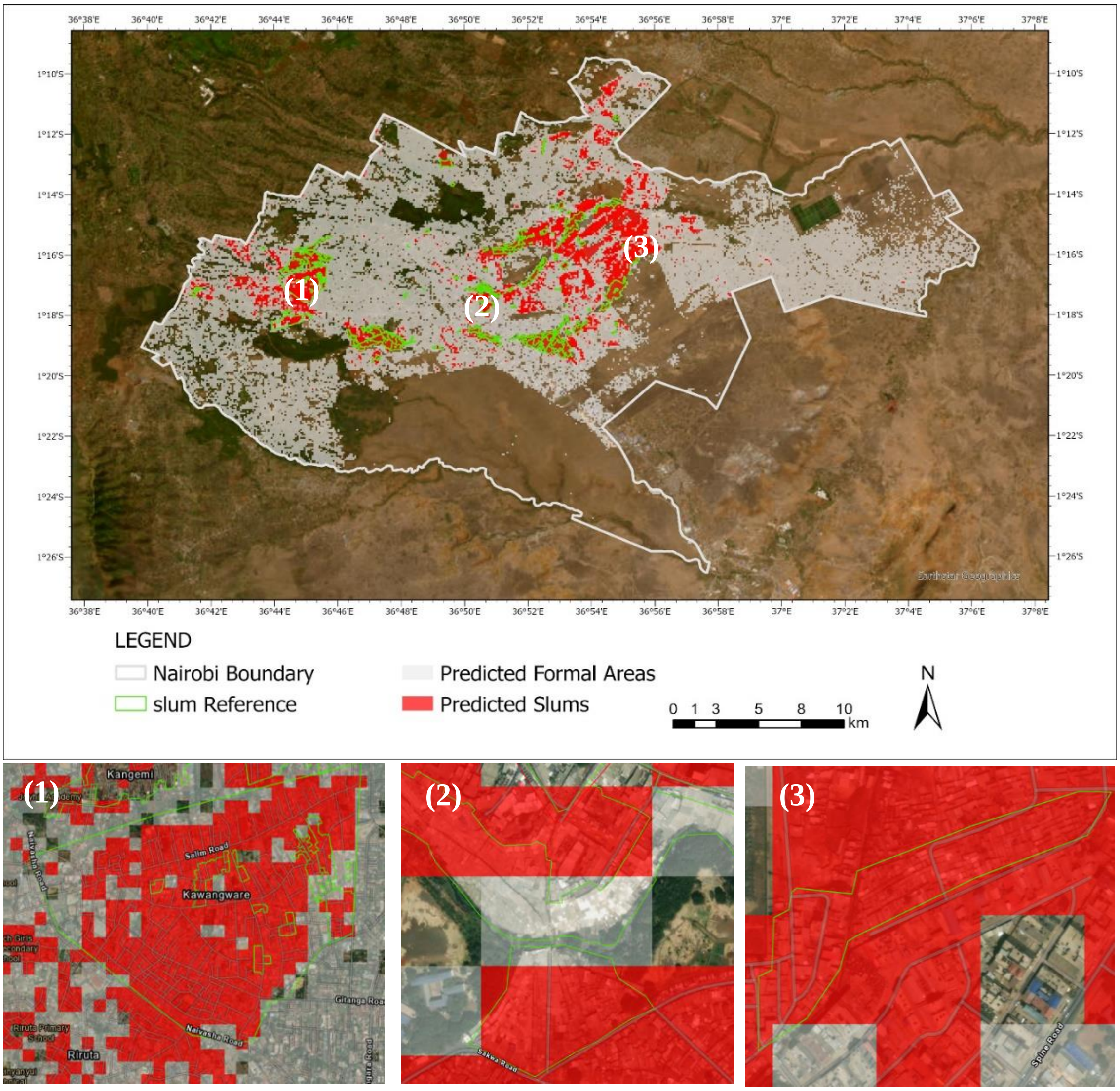


Figure 27: Validation of top-20 model prediction using slum reference data from spatial collectives with zoomed-in examples. Basemap is sourced from Earth Geographics.

4.3.2. Accra

The visual assessment of the two trained models in Accra revealed the models' ability in general to predict the slums with minimal errors as in Figure 28. This supports the high statistical accuracies achieved by the models. The all-features model (Figure 28a) performs very well at identifying known slums, primarily situated in the southern region of the study area. However, it should be noted that the models are over-predicting the slums especially the all-features model that predicts almost the entire city as slums. The reason is that high-density formal areas have a high probability of being predicted as slums because of the models' high dependence on density metrics.

The top 20 features model (figure 28b) has a good overall prediction as it has very few over-predictions. However, it should be noted that this model has a higher number of wrong predictions within the known slums compared to the all-features model, indicating that it lacks some of the critical features that are present in the all-features model, which may be necessary for a more accurate distinction between slum and formal areas in Accra.

We selected examples that demonstrate instances of accurate and inaccurate predictions within the study region from the top-20 model in the city of Accra (Figure 29). The model predicted high-density formal areas and old residential areas as slums, for example, Teshie Nungua.

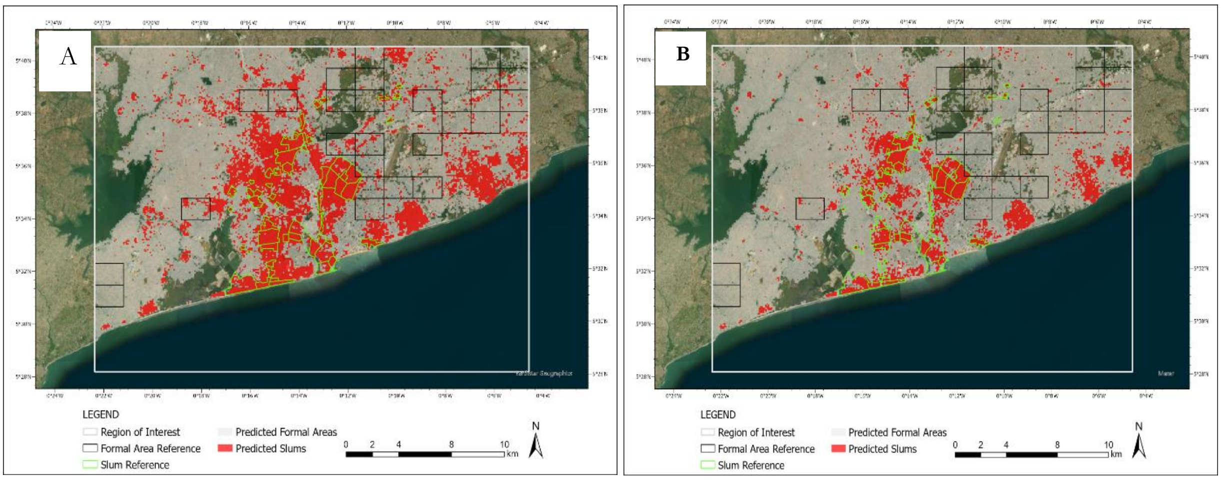


Figure 28: Models Predictions at city scale. Left: All-features model. Right: Top-20 features model. Slum reference data is from Accra Metropolitan Assembly and Basemap is sourced from Earth Geographics.

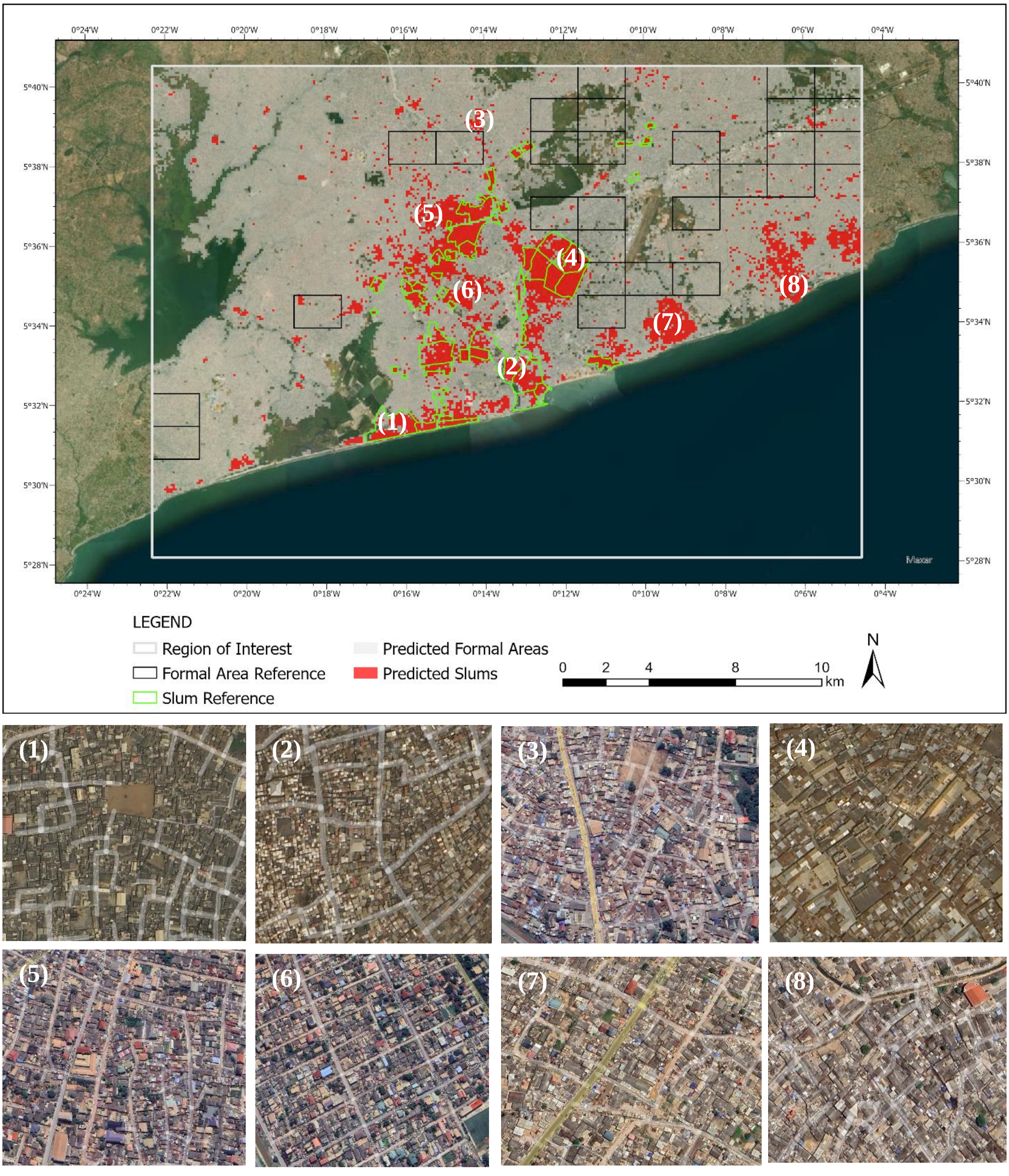


Figure 29: Examples of instances of accurate and inaccurate predictions from the top-20 model. The top four shows accurate predictions and the bottom four shows inaccurate predictions. Slum reference is from Accra Metropolitan Assembly, Basemap is sourced from Earth Geographics and validation images are from Google Earth.

4.4. Expert Evaluation of Models

The expert validation of the model results was conducted via an online discussion with local experts from the two cities. Local experts included a slum mapping expert who work with community mappers in Nairobi and a PhD student who has been working on slums in Accra since 2021. These experts possess substantial experience and local knowledge, which was instrumental in validating the output.

In discussions with the Nairobi expert, we observed that both models generally produced similar predictions, with only minor discrepancies highlighted in Figure 30. The expert acknowledged the models' proficiency in slum prediction, although overprediction was noted in certain high-density areas or regions with older colonial-style buildings, such as Shauri Moyo, Kuma Rock, and Huruma, as illustrated in Figure 30. The models' capability to accurately predict complex slum areas was also recognized, with Kawangware slum being a prime example. Despite some overestimation, this was deemed acceptable due to the dispersed nature of slums within the area, unlike the more concentrated slums like Kibera.

Figure 30: Sample Areas used for validation by local experts in Nairobi. Basemap is sourced from Earth Geographics.

In the case of Accra, the expert observed a tendency for overprediction of slums, particularly in the inner city, by both models. However, the expert noted that the output of the top-20 feature model was closer to reality (Figure 29), as it resulted in fewer overpredictions of slums compared to the all-feature model. The all-feature model, which predicted almost the entire city as slums, was deemed to be significantly less accurate (Figure 28a). The expert added that the model output in some areas, is not what the people in Accra will call a slum.

4.5. Feature Importance Analysis

4.5.1. Citizen ranking

The analysis of feature importance from a citizen science perspective, as depicted in Figure 31, provides valuable insights into the community's perception of factors distinguishing slums from formal areas. The density group of factors was ranked as the most important in three communities, Pumwani, Waruku, and Kibera, highlighting the significance of building density-related features such as distance between buildings in identifying slum areas. This group also ranks high in Mukuru while it ranks moderately in Kariobangi, indicating its relevance across different local contexts.

The diversity group of features, which includes aspects such as different shapes, areas, and heights of buildings, is ranked first in Mukuru and holds the second position in Pumwani, Waruku, and Kibera, indicating a recognition of the varied characteristics within slum environments. In Kariobangi, it ranks fourth, still reflecting a notable level of importance.

Additionally, the physical hazard group is perceived as the most important in Kariobangi and ranks second in Kibera, suggesting that factors like proximity to natural disasters are top concerns in these areas. However, this group is deemed less significant in Mukuru and Waruku, due to differing local conditions.

The spatial distribution group of features, which includes the building orientation and shared wall ratio, received high importance, emerging second in Kariobangi, fourth in Kibera, and third in the other three communities. These outcomes reflect the importance of spatial patterns in distinguishing slums and formal areas from the citizen's perspective.

Figure 31 encompasses the collective perception of all surveyed communities regarding feature importance in differentiating slums from formal areas. The density group emerges as the most significant, receiving the highest rank. The results support the perception that building density and its associated factors are pivotal in identifying slum characteristics.

In contrast, greenery, which encompasses the presence of trees and other vegetation, ranks lower across all communities, indicating that while these factors contribute to understanding slum characteristics, they are not seen as primary indicators by the citizens involved in the study.

Physical hazard and connectivity are perceived to have equal importance, reflecting concerns over safety and accessibility within urban landscapes. Meanwhile, access to facilities and the dimension group also receive attention, albeit to a lesser extent, indicating their role in the urban fabric yet not as critical as the top-ranked features.

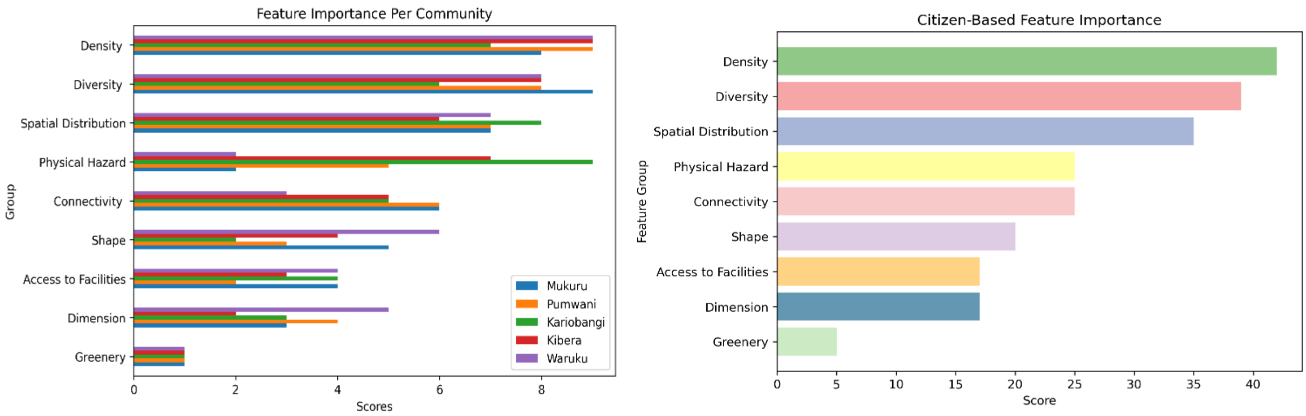


Figure 31: Feature importance from citizen perspective at individual community level (left) and overall importance (right).

4.5.2. Model Perspective

Figure 32 shows the top 20 features and their contribution to the model predictions. The feature importances are based on the Gini impurity which ranges between 0 and 1, with 1 indicating most important and 0 indicating least important. From the top 20 features, 7 features are from the density group, 5 are dimension features, 3 diversity features, 3 spatial distribution features, 1 access to facilities feature, and 1 physical hazard feature. These results highlight the model's dependence on density-related metrics as slums are seen to have higher built-up densities.

Specifically, the area of a tessellation cell stands out as the most significant feature, suggesting that the spatial extent of individual tessellation cells plays a pivotal role in model predictions. This is followed by the mean inter-building distance, which reflects the average distance between buildings, and building counts per grid, indicating the concentration of structures in a given area.

Additionally, distance to dumpsites emerged as a significant feature supporting the claim from slum dwellers that illegal dumpsites are created in these areas. Also, floor area ratio and gross floor area ratio emerged as significant factors indicating the importance of building height-related metrics to predict slums as slums are expected to have lower heights.

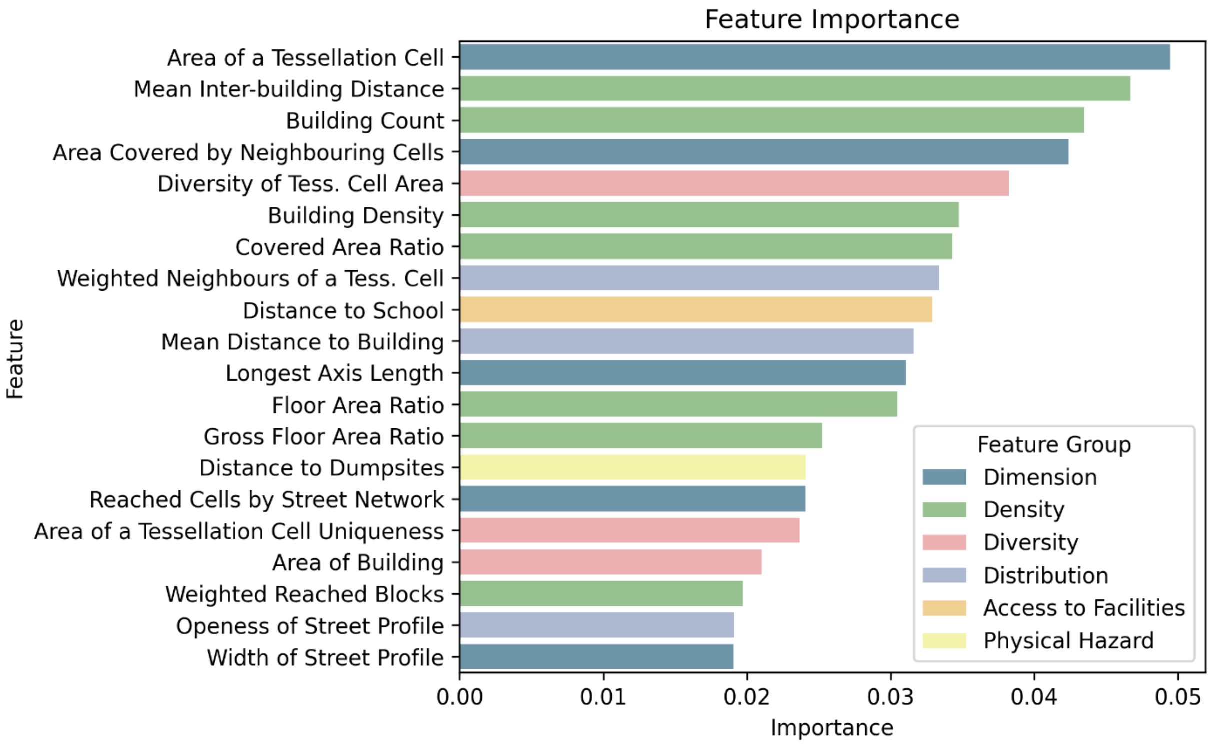


Figure 32: Top 20 Important features from the all-features model. The colour indicates the feature group.

4.5.3. Comparison of Feature Importance from Citizen and Model Perspectives

Figure 33 provides a comparative analysis of feature importance from a model and citizens' perspectives. The model's perspective highlights the area of a tessellation cell as the most significant feature influencing slum predictions. Notably, seven density group metrics including building density and mean building distance, emerged as strong influencing features among the top 20 features. These findings align with the citizens' emphasis on density-related factors as the most important to distinguishing slums from formal areas.

The absence of greenery-related features, such as the NDVI, in the model's top 20 features corresponds with its lower ranking by citizens, indicating a shared understanding of its lesser relevance in this context.

However, there is a notable divergence regarding the dimension group of factors. While the model includes five dimension-related features in its top 20, suggesting their importance in predicting slums, citizens ranked this group relatively low. This discrepancy reflects differences in the perceived impact of physical characteristics of the individual elements versus other more immediate and observable factors of the urban space. Additionally, the model includes three spatial distribution metrics as strong influencing predictors including the road network pattern and street openness. This also aligns with the citizen ranking of spatial distribution as the third most influencing factor given that the slums have very narrow and not well-connected roads if any exist.

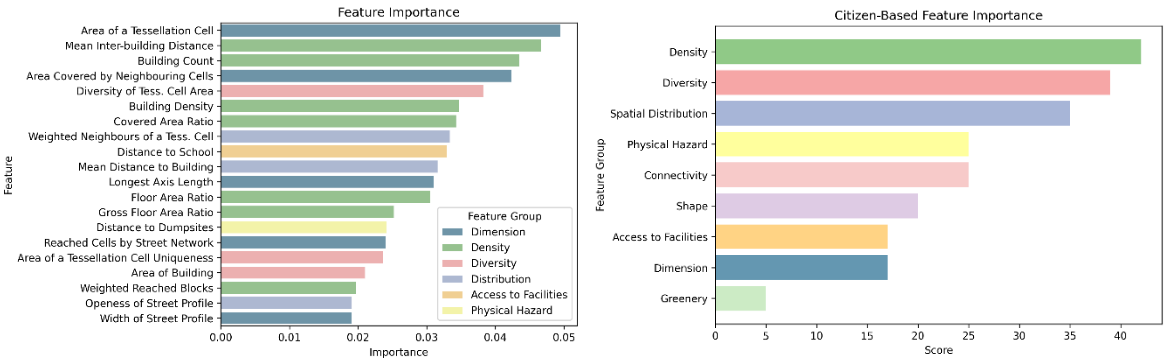


Figure 33: Comparison of model-based and citizen-based feature importance. Left: Top 20 features from the model perspective with colour indicating feature group. Left: Overall feature group ranking from citizens' perspective.

5. DISCUSSIONS

This chapter discusses the findings of our study including the ability of the proposed methodology to identify slums and to be transferred, a comparative analysis of model-derived and citizen-derived perspectives on important features, and finally, addressing the limitations of our approach.

5.1. Summary of main findings

Our study findings provided insights into utilising an urban morphology-based framework and citizen science methods to identify slums and formal areas at the city scale using open geospatial data and ML. First, we proved that we could map slums using urban morphology and open data, overcoming the need to work with cost-intensive approaches that are limited in transferability. We also confirmed that the proposed methodology is transferable across cities, especially in supporting the claim that slums have similar morphologies that can be utilised to improve their detection with a single model that is trained on diverse morphologies. Lastly, we confirmed that the perception of citizens on the importance of slum mapping features such as building density and road conditions have a significant positive correlation with how ML models identified and utilised these factors for slum mapping.

5.2. Urban Morphology-Based Framework in Identifying Slums

This study identified a comprehensive set of morphological features (Tables 2 and 3) that can be used to distinguish slums from formal areas through a combination of literature review and citizen science methods. The Random Forest models, trained on all features and the top 20 features, both performed well, achieving an overall accuracy of over 80%, which is similar to performances in other studies (e.g., Engstrom et al., 2015; Owusu et al., 2023). Additionally, this indicates that the selected urban morphology features are effective in distinguishing between slum and formal areas. Appendix 7.3 quantitatively validates the relationship between slums and formal areas based on selected urban morphology features, using boxplots for Nairobi and Accra. From Appendix 7.3, we observe that in terms of density, slums exhibit a high number of building counts per 100m×100m grid, as indicated by their wide boxplots and their upper limit whisker at around 100. In contrast, formal areas generally have fewer buildings, with the maximum number of buildings per grid around 50, as represented by the upper limit of their whiskers in the boxplot distribution.

The findings of this study proved that the proposed methodology could predict slums and formal areas with high accuracy. The Random Forest models achieved high accuracy, precision, recall, and F1 scores, indicating RF high prediction accuracy and their effectiveness in classifying urban built-up spaces into slum and formal areas (Owusu et al., 2021). We employed a spatial block strategy for data splitting to avoid the problem of spatial autocorrelation, leading to more reliable results (Meyer et al., 2019). The models' performance on the spatially distinct validation set demonstrated their ability to generalize well to unseen data. However, our results should be interpreted with caution as the models tend to overpredict slums in high-density formal areas, especially those with small building sizes and less vegetation cover.

Additionally, our study found that both models: one trained with all 113 features and the other trained with the top 20 features, achieved similar results in terms of accuracy, precision, recall, and F1 score. This suggests that the top 20 variables were informative and sufficient for the classification task. The comparison between models, trained on all variables versus the top 20 variables, provided valuable insights into the importance of feature selection in improving model efficiency without compromising performance. This demonstrates that a simpler model trained on a few relevant and informative features can produce similar results to a more complex model (Kuffer et al., 2016).

Moreover, this study has proven that urban morphology and open geospatial data can effectively map slum areas with high accuracy, aligning with the findings of Owusu et al. (2023). However, it should be noted that the developed models tend to predict high-density formal areas as slums, indicating a need for improvement. This issue, which was also noted in Owusu et al. (2021), arises from the models' reliance on density-based metrics to identify slums (Figure 32). To address this, incorporating innovative approaches such as the use of accurate building height and socio-economic data to refine the models could improve the models' ability to differentiate between slums and formal areas. This could work because formal areas, despite having high densities similar to slums, typically feature taller buildings. The additional feature of building height and social aspects can provide relevant information for machine learning models, reducing their over-reliance on density metrics, and adding a focus on height, as was suggested by other studies (e.g., Kuffer et al., 2016). It should be noted that our study experimented the impact of building height on the model prediction, however, given the general underrepresentation of the data and the course resolution (90m), this did not have a strong influence on the model predictions. We experimented with this data because building height data is difficult to get in slums and this is the only 3D data globally available with open access.

5.3. Spatial Transferability Of the Urban Morphology-Based Framework in Identifying Slums

Notably, our proposed methodology demonstrated robust spatial transferability, achieving an accuracy of more than 80% in distinguishing slums and formal areas in Accra. This finding supports the recommendation by Owusu et al. (2023) that models can be trained based on the morphological features of one city and can be used to map another city, given that the training data is representative of the morphological diversities. In addition to using the model trained on all features, we also tested the model trained on the top 20 features from Nairobi on the Accra dataset. This model also showed good results. However, upon comparing the performance of the two models visually, we found that the model trained on the top 20 features performed better in Accra overall than the model trained on all features. The high over-prediction of slums by the all-features model can be as a result that the model is confused by the many features and the unique local context of Accra. Nonetheless, it should be noted that the all-features model achieved high accuracy in predicting known slums, all situated in the inner city of Accra, compared to the top-20 features model. It indicates that some features present in the all-features model, such as the amount of vegetation and distance to rivers, which were not included in the top-20 model, may play important roles in Accra's urban morphology.

By successfully applying the model trained on Nairobi data to the Accra dataset, we confirmed the model's potential for transferability across different urban contexts. Additionally, given that this methodology is nearly cost-free compared to other methods (Abascal et al., 2024; Stark et al., 2020), it can easily be transferred to other cities. Worth noting is that the high statistical accuracies achieved by the models in Accra are influenced significantly by the location and distribution of the reference data. The reference data were skewed towards the inner city and the southern part of the study area, and the trained models were able to predict these areas with high accuracy. In contrast, the visual validation of the models' output in Accra, especially the all-features model, exhibited overpredictions of slums beyond the reference areas. Moreover, given that the reference data is derived from inner cities, there is an absence of reference data to quantitatively validate the model results beyond the inner city, such as the periphery areas, requiring local expert validation.

Overall, the current results highlight the model's ability to generalize and accurately predict slums and formal areas with diverse urban morphologies, validating the approach of leveraging urban morphology and citizen science for slum mapping. This reinforces the potential for this methodology to be adopted by city authorities and urban planners in various contexts, helping to address the dynamic nature of slum development and providing a cost-effective tool for urban planning and slum upgrading initiatives.

5.4. Citizen Science Insights and Feature Comparison

The inclusion of slum stakeholders in this study helped to identify and understand key features that are indicative of slums and formal areas based on local knowledge. The input from the slum stakeholders provided an essential basis for understanding and better interpreting the input features and the model outputs effectively. Unlike many studies (Owusu et al., 2023; and Stark et al., 2020) that determine a comprehensive set of features considered relevant for slum mapping, our approach incorporated insights from slum stakeholders, which revealed additional critical features that might have been overlooked by modelers alone. The need to include slum stakeholders in slum mapping was supported by Kuffer et al. (2021) and Owusu et al. (2021).

For instance, the number of police posts suggested as an indicator of high crime rates necessitating increased security in Nairobi slums, might have been missed without stakeholder input. Similarly, the prevalence of rectangular and elongated building shapes in slums, visible from satellite imagery, was interpreted as a strategy to maximize rental income by constructing elongated structures and dividing structures into multiple small rooms. These findings provide added insights about the features gathered that traditional methods alone might not have revealed. Engaging with citizens created a sense of involvement and facilitated knowledge sharing, enabling them to contribute to potential solutions for issues affecting their lives (Abascal et al., 2024).

CS also captured the perception of residents regarding the importance of identified slum mapping features and allowed a comparison with the model's perspective. The feature importance rankings derived from community discussions provided valuable insights into local perceptions of what defines slums and formal areas. The local context significantly influenced the perceived importance of features across different communities. For example, in Kariobangi, a slum community near the Dandora dumpsite, physical hazards were voted the most important feature group due to the significant health and safety risks posed by the nearby landfill site. Similarly, Kibera, located close to a river and prone to flooding, prioritized physical hazards highly. These variations highlight the need for models to be adaptable to local conditions. Overall, communities prioritized building density-related metrics as the most important factors in distinguishing slums from formal areas.

From the model's perspective, the most important feature was the area of a tessellation cell, serving as a standardized proxy for a plot and helping to understand the area covered by a single building. Appendix 7.1 shows that slums have smaller tessellation areas compared to formal areas, supporting the notion that slums have smaller building sizes. The next most influential factor was the mean inter-building distance, reflecting the dense nature of slums with shorter average distances between buildings (Appendix 7.1).

Comparing the feature importance from both perspectives revealed valuable insights. The model's inclusion of seven density-related metrics among the top 20 most influential features aligns with the citizens' ranking of building density, street density, and related metrics as most important. This finding is consistent with

Abascal et al. (2024). The inclusion of diversity and spatial distribution features highlights the model's consideration of the heterogeneity of urban areas and the arrangement of buildings, essential for capturing nuanced differences between slums and formal areas. The presence of features representing access to facilities and physical hazards, though fewer in number, indicates the model's ability to consider the availability of essential services and environmental risks, which are critical aspects of urban living conditions, as noted by Abascal et al. (2024) and Owusu et al. (2023).

Notably, the model includes five-dimension features in the top 20 influential features. In contrast, the citizen ranking placed dimension features second to last, indicating that citizens do not prioritize features such as building size as highly as density-related metrics. This discrepancy may arise from how the metrics were understood or explained to participants.

Overall, leveraging citizen science helped identify and interpret key features distinguishing slums and formal areas. However, it should be noted that citizen science approaches have limitations, including resource constraints and process efficiency if not well-guided (Abascal et al., 2024). Participants sometimes may not pay the necessary attention, affecting their responses and impacting the results generated.

5.5. Limitations

The first limitation of this study relates to the datasets that were used and how the quality was assessed. The reference data for slum areas come with inherent boundary uncertainties, which have influenced the results. Notably, the Accra slum reference data are confined to the inner city, posing a challenge for validating predictions beyond this area. Such a skewed distribution means that models accurately predicting these characteristics will inherently show high statistical results, as observed with the all-features model's transfer results. Additionally, we missed ground-truth formal area reference data. We collected the samples using satellite imagery guided by two locals and a classified slum map by ESRI, which may have introduced some level of uncertainties, further affecting model performance.

Additionally, the building height datasets used, released in 2015 with a spatial resolution of 90m, might be outdated and lack the granularity needed for building-level analysis. This limitation likely contributed to the underrepresentation of building heights in our findings. Considering the dynamic nature of urban development, particularly in slums, the dataset does not account for structures built after 2015. Also, our approach overpredicted slums, especially in high-density formal areas with smaller buildings and limited vegetation, due to the models' reliance on density metrics. Future studies should incorporate high-resolution and up-to-date building height data to better differentiate between high-density formal areas and slums. Additionally, the local experts recommended enhancing the models' predictive accuracy in high-density formal areas by incorporating social factors, such as population density and room occupancy rates. Such additions are expected to refine the models' learning ability, allowing for a more nuanced differentiation between slum and formal areas.

Moreover, the 100m grid size used for this analysis, while beneficial for generating high-resolution maps at a city scale, does not adequately capture the finer details of urban morphology. This is particularly evident in heterogeneous areas where the grid may encompass characteristics of both slums and formal areas. In such cases, the dominant class within a grid is likely to determine the model's prediction, potentially leading to misclassification. Smaller grid sizes would mitigate this issue by capturing the distinct features of a single class, thereby reducing the likelihood of mixed classifications. Smaller spatial units would significantly enhance the accuracy of slum identification and improve the model's learning capability.

The study engaged 50 participants from 5 communities, chosen due to the convenience of ongoing projects and particular attention was not given to demographics of participants. Future studies need to ensure that participants represent a diverse demographic, including variations in gender, age, socio-economic status, and urban contexts, to mitigate potential biases and strengthen the generalizability of the results. Moreover, participant engagement levels varied, with some not providing the necessary attention, which influenced their responses and, consequently, the study's outcomes. Additionally, fieldwork was conducted exclusively in Nairobi, not extending to Accra due to time and resource constraints. This limitation means that the citizen insights gathered may not reflect the perceptions that might exist in Accra, highlighting the need for broader field engagement in future research.

Also, the urban morphology features employed exhibit high correlation, such as building count and density, which both reflect the concentration of buildings per grid. Despite the RF model's robustness to high dimensionality, the inclusion of highly correlated variables can impact the results and feature importance rankings. Future research should consider reducing redundancy by excluding highly correlated variables or combining them into composite features.

Lastly, we acknowledge that assessing the quality of the data used in this study is paramount. However, we could only conduct a visual assessment of the data given the time constraints in completing this thesis. This assessment fails to quantify the uncertainties in the datasets, which could impact the study's conclusions. Future studies should include a more thorough and quantitative assessment of data quality to ensure more reliable results.

5.6. Societal Relevance

Our study contributes significantly to the domain of slum mapping, specifically in Nairobi, Accra, and Africa at large. The methodology developed in this study, which leverages urban morphology and citizen science to predict slums, has significant societal implications. Given the dynamic nature of slums and the rapid urbanisation in many cities, tools for identifying and mapping slums are critically needed. Traditional methods of identifying slums through field surveys are time-consuming and resource-intensive, and our approach addresses these challenges efficiently.

This approach's primary advantage lies in its potential to assist city authorities and urban planners in effectively identifying slum areas, whose locations are not known and are typically underrepresented in official datasets. The identified gap hinders the ability to cater to the needs of slum dwellers and integrate their habitats into urban planning. Our methodology enables authorities to frequently update urban maps, ensuring that slum areas are recognised and included in development plans. However, the effectiveness of this approach is contingent upon the temporal accuracy of the datasets used.

Moreover, the reliance on open data makes this methodology cost-effective and accessible, especially for city authorities with limited resources, thereby lowering the barriers to implementing slum identification and improvement initiatives. With this tool in hand, city planners can make informed decisions towards the efficient allocation of resources and prioritise slum upgrading programs.

Furthermore, the study's use of citizen science adds a unique and valuable perspective by incorporating local knowledge into the slum identification process. Not only does this local knowledge improve the accuracy of the tool but it also fosters community engagement and ownership of urban development initiatives.

Overall, our study provides a practical and innovative approach to identifying slums, and answering where they are located. The approach offers a scalable and transferable methodology that can be adopted by cities worldwide to improve urban planning and contribute to the achievement of SDG 11.

6. CONCLUSIONS AND RECOMMENDATIONS

6.1. Conclusions

This study aimed to improve the accuracy and spatial transferability of slum mapping models using an urban morphometric-based framework and citizen science methods. We established four sub-objectives: 1) to identify relevant morphological features that can distinguish slums and formal areas from literature review and CS methods. 2) to train an ML model from the identified morphological features to predict slums and assess the performance. 3) to assess the spatial transferability of the ML model developed for slum mapping and 4) to compare the most important morphological features that distinguish slums from formal areas from citizens' and the model's perspectives.

We successfully identified 113 urban morphology features relating to buildings, streets and neighbourhood level characteristics computed using morphological tessellation, categorized into nine groups, including density, dimension, diversity, spatial distribution, connectivity, shape, physical hazards, and access to facilities and services. Two Random Forest models were trained, mapping slums in Nairobi with over 80% accuracy, one on all features and the other on the top 20 important features. The top 20 features indicated a strong influence of density-related factors, such as mean inter-building distance, building density, and counts. Testing the model's transferability in Accra yielded high accuracies of over 80% but also revealed a tendency for overprediction. A comparison of feature importance rankings showed a significant alignment between the perspectives of slum dwellers and the model's evaluations.

Overall, our study demonstrated the potential to map slums using urban morphology and citizen science methods and achieved high accuracy. The proposed methodology offers a cost-effective, transferable, and scalable alternative to map slums, particularly beneficial for LMICs facing rapid urbanisation and the need for regular updates of slum maps. The approach aligns with the open data movement, supporting local decision-making and contributing to the efforts towards achieving SDG 11. While our results are promising, however, attention must be paid to the quality of the datasets used, as inherent errors could impact the model's performance.

6.2. Recommendations

While the results of this study are promising, to further improve the reliability of the methodology, based on the study the following is recommended:

- First, ground-truth samples for formal areas are required. Future studies should prioritise collecting ground truth data from the field to effectively train and evaluate models' performance. The reference data should capture the different types of formal areas including varying densities and vegetation, providing a robust training and statistical assessment of model performance, and mitigating over-optimistic results.
- Second, it is advisable to consider the exclusion of highly correlated features in modelling to prevent redundancy. Although the all-features model may be relevant across different contexts, identifying and focusing on key features that significantly contribute to model transferability could improve the approach.
- Moreover, given that the foundation of this study rests on open datasets. Incorporating accurate and current building height datasets might improve the model's performance, particularly in distinguishing between slum and high-density formal areas based on building heights and densities.

- Additionally, given the sensitive nature of slum classification, future studies should approach the task as a probability outcome rather than as a binary classification. This would address the stigma associated with labelling areas as slums and provide a gradient of urban development levels.
- While the model has shown promising transferability to Accra, testing its transferability to other cities, especially within Africa, is essential. Each urban area's unique characteristics may necessitate local tunning of the model to ensure accuracy and relevance.

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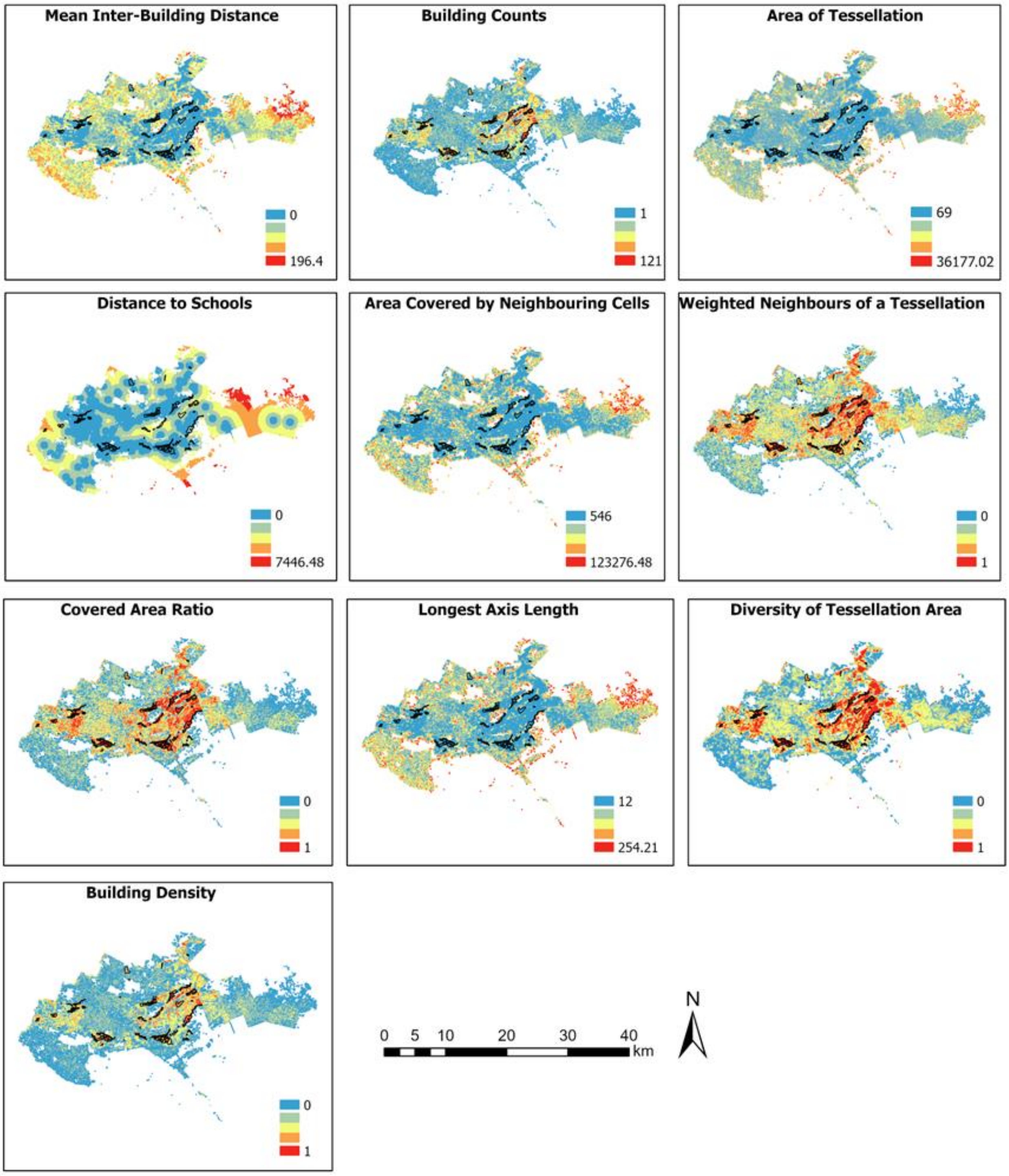
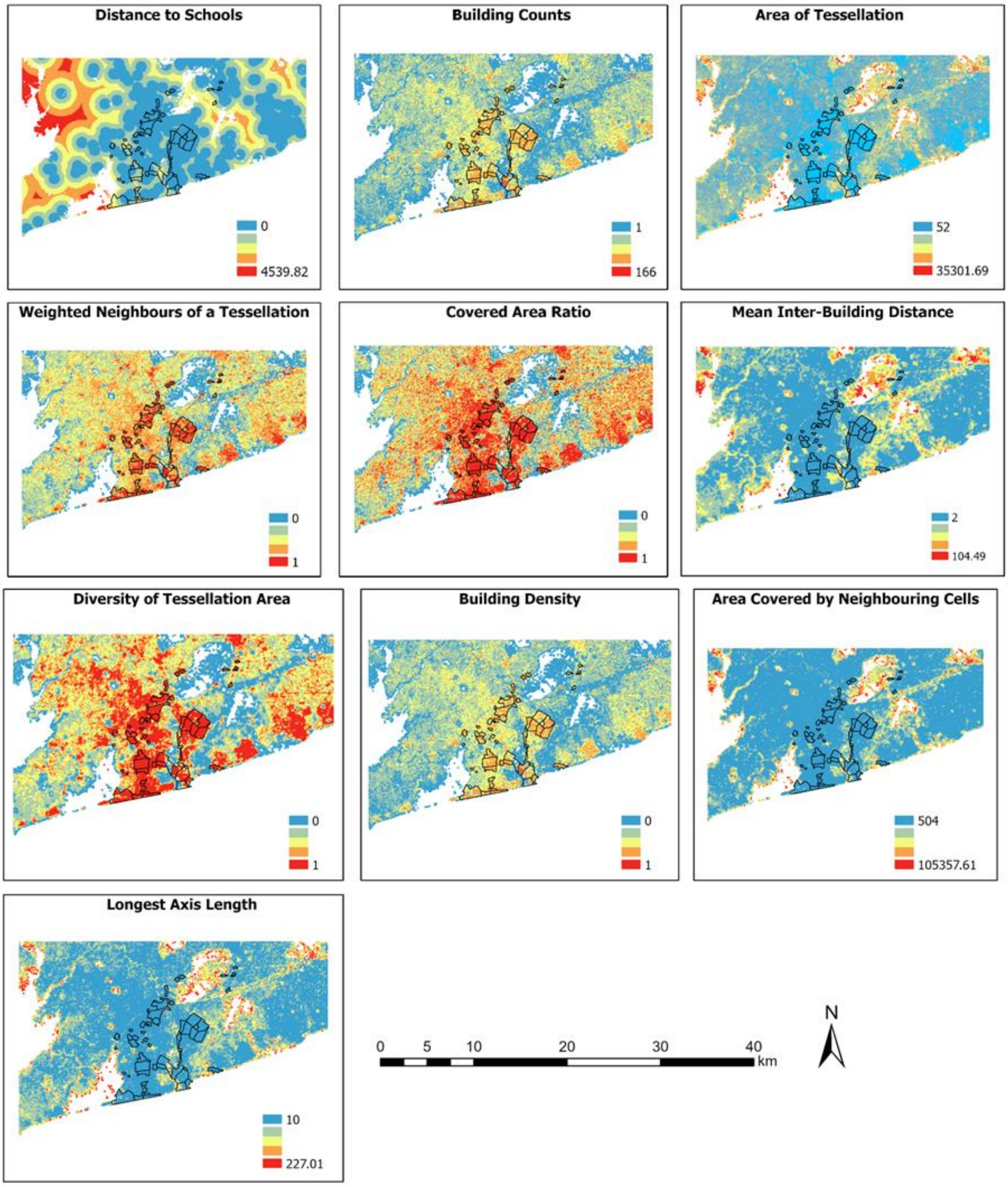
7. APPENDICES

7.1. Appendix 1: Independent Variables Distribution

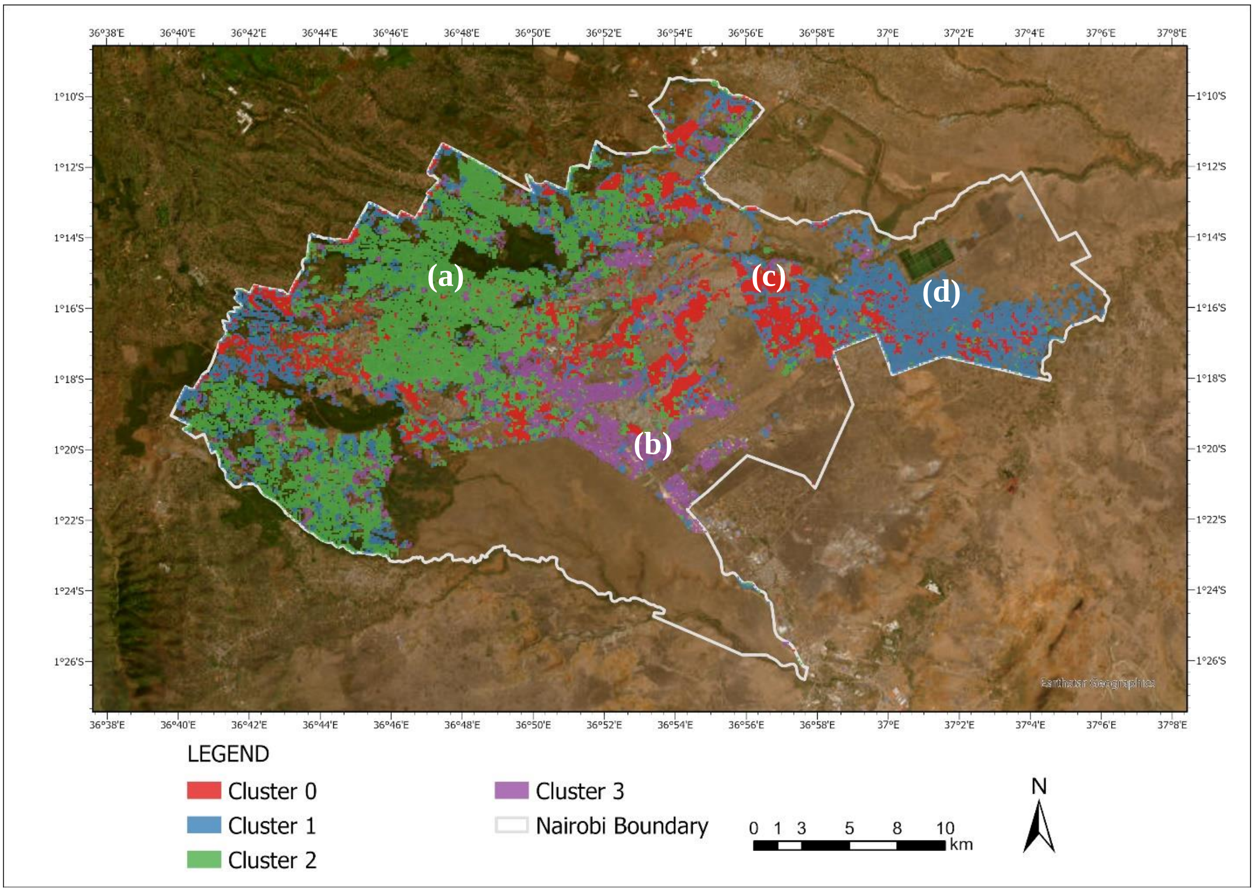
7.1.1. Nairobi



7.1.2. Accra


Distance to Schools
0
4539.82
Building Counts
1
166
Area of Tessellation
52
35301.69
Weighted Neighbours of a Tessellation
0
1
Covered Area Ratio
0
1
Mean Inter-Building Distance
2
104.49
Diversity of Tessellation Area
0
1
Building Density
0
1
Area Covered by Neighbouring Cells
504
105357.61
Longest Axis Length
10
227.01
0 5 10 20 30 40
km
N

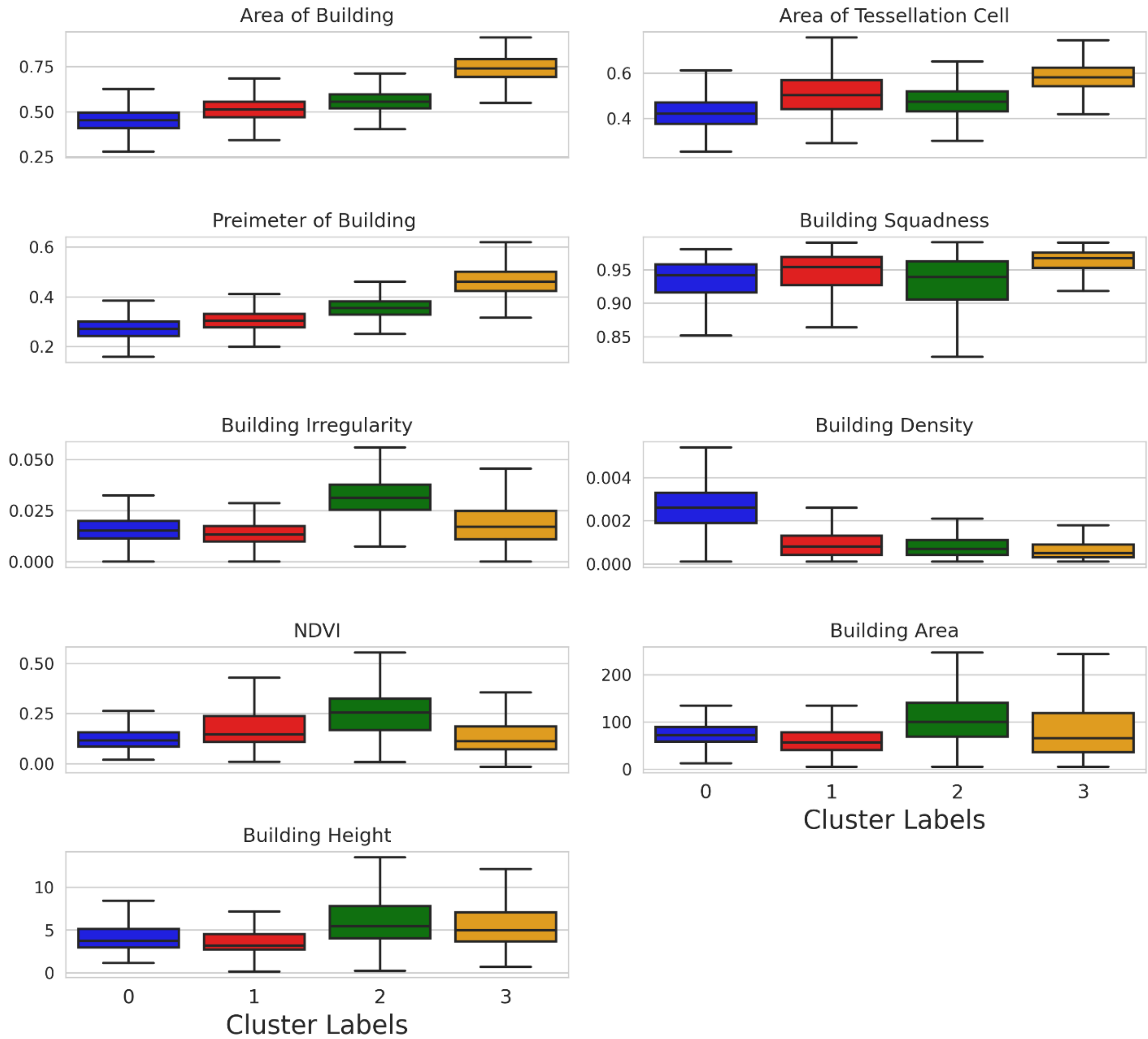
7.2. Appendix 2: Clustering Insights



Summary Table of Clusters

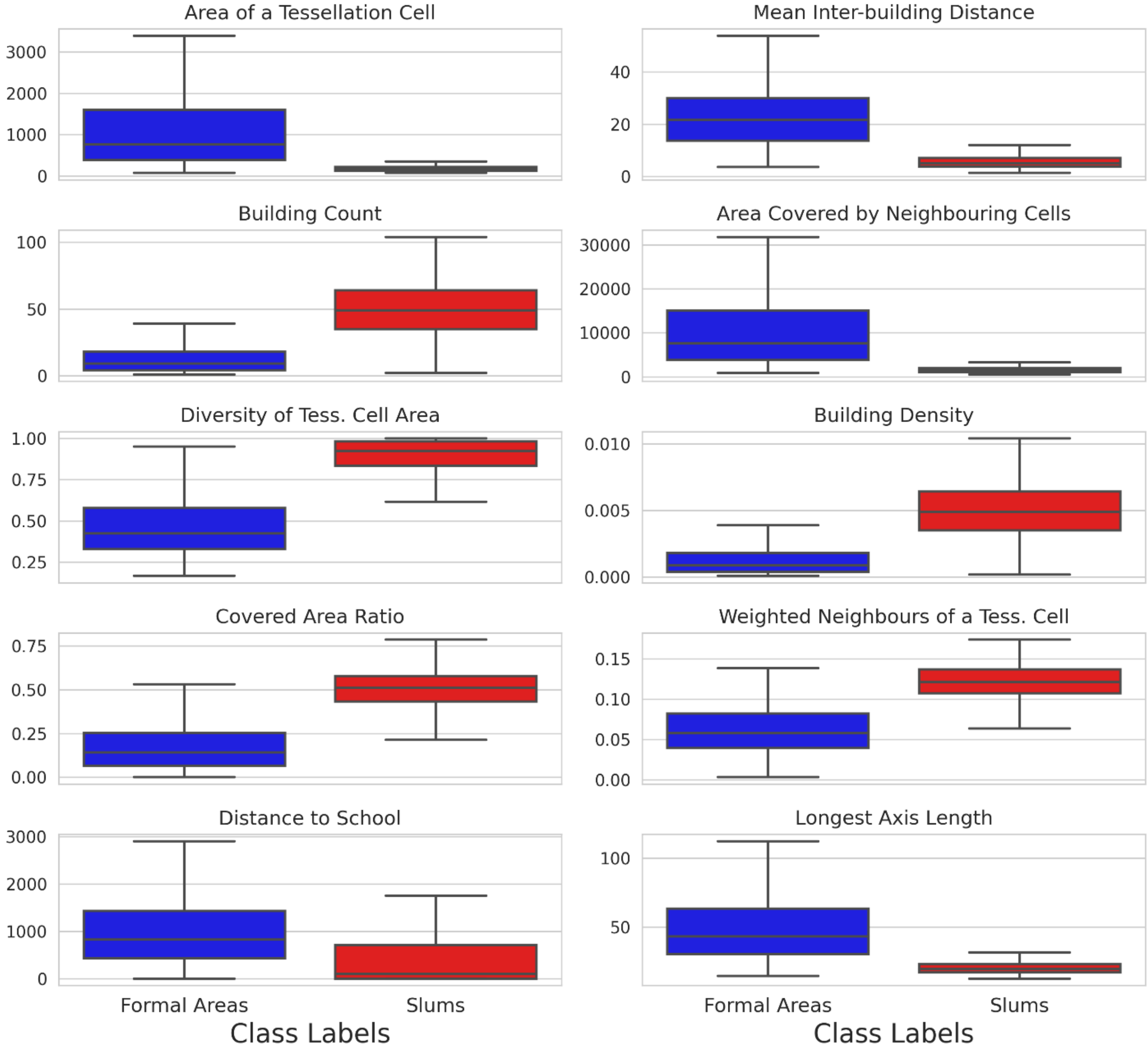
Cluster 0	Cluster 1	Cluster 2	Cluster 2
• High density • Less vegetation • Small building sizes • Small building heights	• Medium to high density • Considerable amount of vegetation • Small building sizes • Buildings heights of maximum 3 floor with more buildings with 2 floors	• Medium to low density • High amount of vegetation • large building sizes • Tall buildings with height about 4-5 floors	• Low density • Less vegetation • Large building sizes, mostly industry type of buildings • Medium building heights above 2 floors

7.2.1. Understanding the different clusters using boxplots for selected features

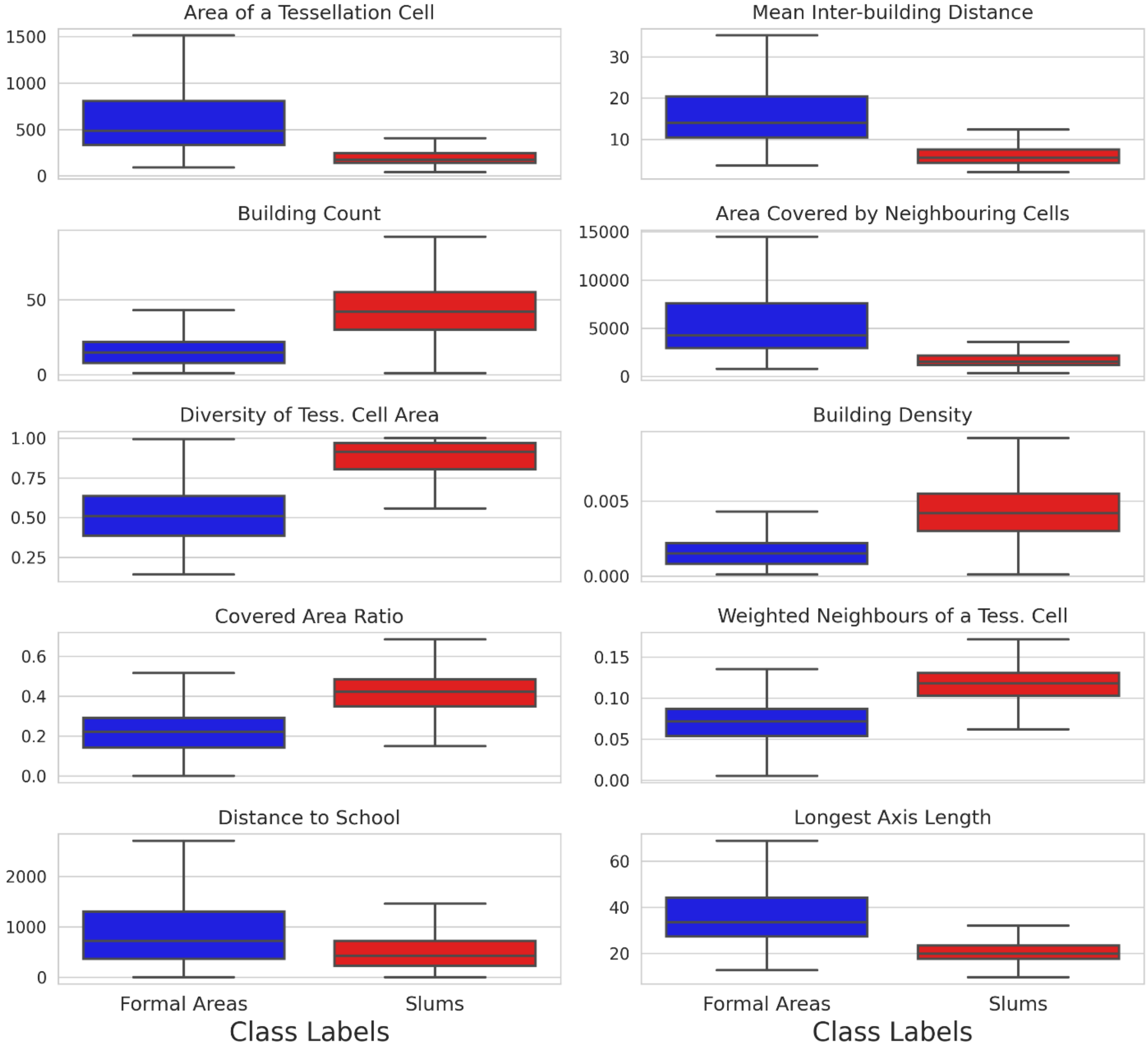


7.3. Appendix 3: Experiment Relationship Between Slum And Formal Areas In Accra And Nairobi Using The Training Data To Gain More Insights

7.3.1. Nairobi



7.3.2. Accra


Area of a Tessellation Cell
1500
1000
500
0
Mean Inter-building Distance
30
20
10
Building Count
50
0
Area Covered by Neighbouring Cells
15000
10000
5000
0
Diversity of Tess. Cell Area
1.00
0.75
0.50
0.25
Building Density
0.005
0.000
Covered Area Ratio
0.6
0.4
0.2
0.0
Weighted Neighbours of a Tess. Cell
0.15
0.10
0.05
0.00
Distance to School
2000
1000
0
Longest Axis Length
60
40
20
Formal Areas
Slums
Class Labels
Formal Areas
Slums
Class Labels

7.4. Appendix 4: Validation of predictions

We validated our model prediction in the Kawangware slum using point reference data of slums from the United Nations (UN). UN-Habitat carried out a mapping exercise on a sample of informal settlements in Kenya to establish the gaps they have in accessing key services during COVID-19. The dataset was created in 2020 and was accessed through Informal Settlement Mapping Point Data - Overview (arcgis.com).

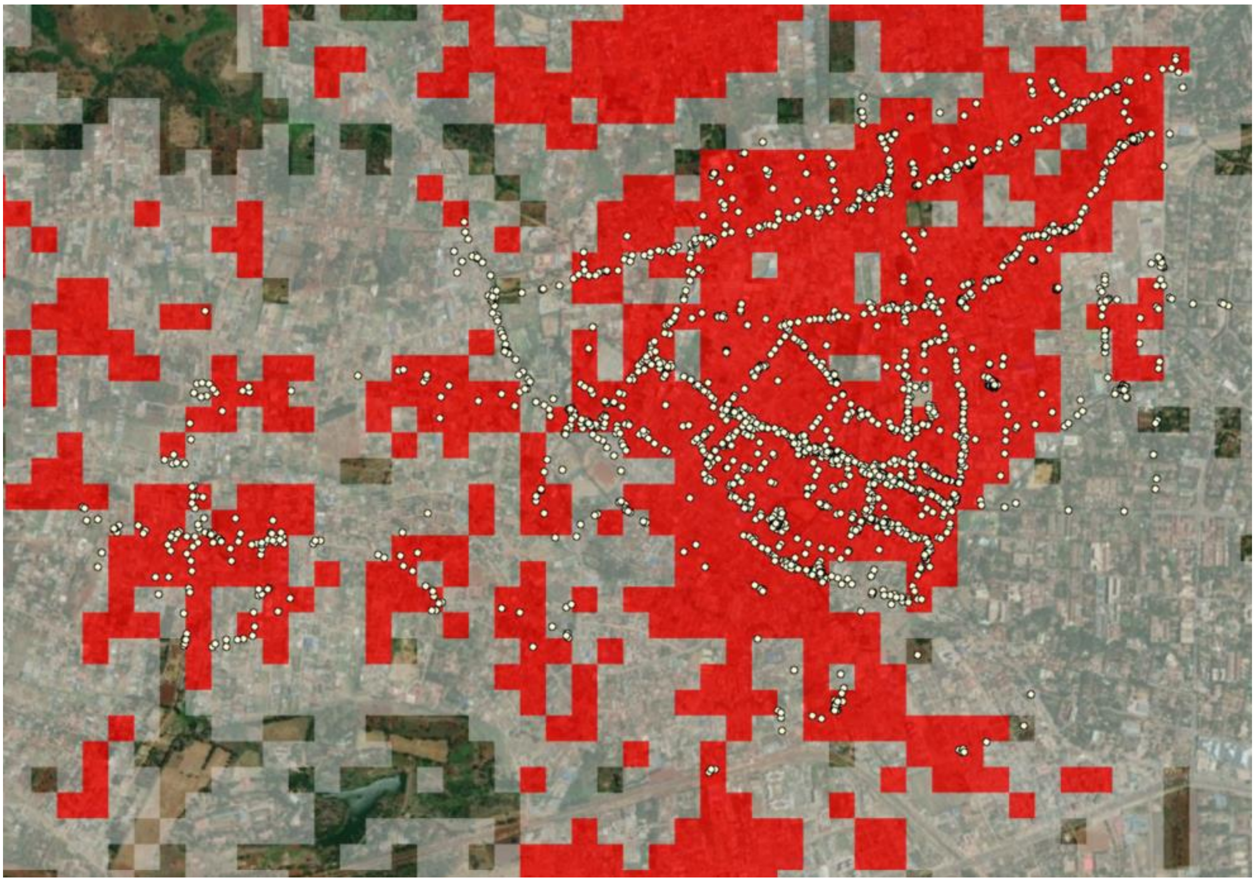


Figure 34: Validation of our model prediction in Kawangware using reference slum point data from UN-Habitat

7.5. Appendix 5: Ethical Considerations, Risks And Contingencies

In the realm of slum mapping is the issue of privacy and slum dwellers' fear of eviction and stigmatization that arrives when areas that are not slums are mapped as slums. This major concern governs how this study is conducted and how data and information will be shared with the public. Slum dwellers' permission will be sorted regarding their willingness for the data to be shared.

Additionally, the consent of slum dwellers' will be sought prior to the data collection, and the study objectives and all other necessary information such as the potential impacts of the study on their lives will be explained to create total awareness.

The unit of analysis considered in the study is 100m, this aggregates information at a coarser scale helping to overcome the privacy issues of revealing individual buildings and households that are slums, and hence minimising issues related to privacy and fear of eviction. The building datasets from Google contain plus codes that can be used to identify every single building on the map putting slum dwellers at risk of eviction, the aggregation of information, will help minimise the risk.

In terms of reproducibility, a data management plan will be developed to ensure effective storage and sharing of data. The original format, source, and year of data acquisition will be made known in tabular format. Also, all datasets used will be stored in both original and processed format in Google Drive to ensure long-term storage and usage. All freely available datasets used in the study follow the usage and sharing principles of the Open Data Commons Open Database License (ODBL) (https://opendatacommons.org/licenses/odbl/).

To ensure all datasets are correct, all datasets derived from Google and Microsoft will be locally checked as the accuracy may vary from place to place to avoid the use of inaccurate datasets. Regarding the sharing of data, all datasets are freely available for global access except the samples for the training data preparation acquired from ITC and as such should follow the ITC data sharing guidelines.

7.6. Appendix 6: Workplan

Table *12* shows the proposed work plan for the rest of the months towards a successful completion of the proposal.

Table 12: Work Plan

Task	Status	Sept	Oct	Nov	Dec	Jan	Feb	March	April	May	June	July
Thesis topic development		✓	✓									
Proposal writing		✓	✓	✓								
Proposal Defence				✓								
Internship						✓	✓	✓				
Fieldwork								✓				
Literature Review		✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Desktop Data Collection			✓	✓	✓	✓						
Data Preprocessing					✓	✓						
ML model training and testing							✓					
Midterm							✓					
ML model Transferability testing								✓				
Inference from results							✓	✓	✓			
Discussions								✓	✓	✓	✓	✓
Presentation Preparation											✓	✓

Final Defense											✓	✓

7.7. Appendix 7: DATA MANAGEMENT PLAN

The table below offers detailed information about all datasets that were used in the study. Regarding storage for long-term use, data will be stored in an effective file format and on a cloud platform (Google Drive). All codes used are stored and available on a GitHub platform[16] to ensure the reproducibility and replicability of the analysis.

Table 13: Data Management Plan

Data	**Source**	**Format**	**Resolution**	**Year**
Building footprints	Google open buildings	Geojson		2023
Building height	World Settlement Footprint 3D	Raster	90m	2015
Street	Microsoft	Geojson		2022
Slum boundaries	IDEAtlas	Shapefile		2022
Formal area reference	ESRI	Shapefile		2021
Public facilities	OSM	Shapefile		2023
NDVI	Sentinel-2	Raster	10m	2023
Slope	ALOS PALSAR	Raster	12.5m	2006-2011

[16] https://github.com/abdulcisseyWA/Abdul-MSc-Codes-.git

7.8. Appendix 8: Fieldwork materials

7.8.1. Appendix 9: Consent Letter

FACULTY OF GEO-INFORMATION SCIENCE AND EARTH OBSERVATION
UNIVERSITY OF TWENTE, ENSCHEDE, THE NETHERLANDS

Dear respondents,
I am Umar Abdul-Raheem, a final year student at the Faculty of Geo-information and Earth Observation, University of Twente. I am soliciting information on "Using urban morphology and citizen science for improved transferability of slum mapping models" in partial fulfilment for an MSc degree. I would be glad if you could please answer the following questions. Every piece of information provided shall be treated as confidential and for only academic purposes. You are allowed to opt-out at any point in time. The discussion is estimated to last for **2-3 hours.**
I want to express my sincere gratitude to you for joining this effort. Your insights and experiences within the community play a crucial role in enhancing our understanding of the local context, ultimately contributing to more effective and inclusive slum mapping. Your participation is invaluable.
The purpose of our conversation today is to gather your perspectives on various aspects of the community, particularly those physical features that might influence how we identify and map slum areas. We also intend to rank the variables according to their importance in helping to identify slum areas.
Your firsthand knowledge is incredibly important, and by sharing your insights, you are contributing to the development of models that can better capture the reality of slums.
Your input will make a significant impact, and I am genuinely thankful for your willingness to be a part of this activity.

Respondent's consent Do you voluntarily agree to participate in this discussion? Yes [ ] No [ ]

Code: ____
County/District: ____
Community: ____
Date: ____
Start Time: ________________
Name of Translator: __________________________________
Translator phone number: __________________________________
Name of community leader: __________________________________
Community leader phone number: __________________________________
End Time: _____________

General Observation(s): ____
____

7.8.2. Appendix 10: FGD Guide

FGD Guide: Citizen Perspectives on Slum Mapping Variables

Main Questions to understand the local context. (45mins)

Based on the map provided and your knowledge about your community.

1. What are the key physical features and characteristics (the things you can see) that describe the better-to-live areas and worse-to-live areas?
2. What characteristics specific to the buildings do you think are indicative of slum areas?
3. What characteristics specific to the streets do you think are indicative of slum areas?
4. Based on the mentioned characteristics, can you point out buildings, streets, and or areas that are indicative of slums?

Guiding questions

Auxiliary Variables

1. What physical conditions negatively affect slum areas?
   a. Main hazards
   b. Greenery
2. Are there accessibility challenges within slum areas?
   a. Are there factors such as access to schools and hospitals that influence how an area is perceived?
3. What environmental aspects do you think contribute to the identification of slums?
   a. Are there specific environmental aspects, such as waste management, that influence how an area is perceived?

Is there any additional information you would like to share?

Introduce the pre-established list of variables and their broader categories. Explain to them what they mean, and why we need the broader groups (to ensure effectiveness and efficiency of variable comparison).

Add any new variables that may have come out from the discussion so far.
Ask if they agree with the variable groupings.

RANKING OF VARIABLES. (45mins)

Introduction

In this sub-section, we will group the identified variables into main classes and rank the main groups of variables according to their importance level in helping us to identify slums from imagery. Specifically, you will be presented with pairs of groups to choose which you consider more important to identifying slums. This will help us to identify the most important group to the least important. I am seeking your input on prioritizing the variable groups. Please think about the two variable groups that will be compared and give your responses.

Recap: Remind them of variables. Use pairwise ranking**.**

- **Morphological and auxiliary variables**

Question 1: Between variables A and B which do you think is more important?
Question 2: Why do you think A is more important than B?

OR

Likert scale of importance. From extremely important (1) to least important (9).

Rank	Dimension	Shape	Intensity	connectivity	Spatial distribution	Diversity	Facilities and services	Physical hazard	Greenery
1									
2									
3									
4									
5									
6									
7									
8									
9									

Is there any additional information you would like to share?

Thank you for your time!

7.8.3. Appendix 12: Sample maps used to identify slums and formal areas during fieldwork.

Figure 35: Sample map of a section of Kibera used for fieldwork discussion.
Basemap source: Google Maps