PERCEIVED TENURE INSECURITY WITHIN DEPRIVATION: FROM A GEOSPATIAL PERSPECTIVE

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July, 2021

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ABSTRACT

Most cities in the Global South accommodate many people living in urban deprivation with a high level of perceived tenure insecurity due to the persisting threats of eviction and unwillingly loss of their land and other properties. There is an urgent need for up-to-date information to address this problem for promoting tenure security for all urban dwellers and make cities and human settlements safe and inclusive towards achieving the Sustainable Development Goals (SDGs). However, such information is often rare, outdated or incomplete. Though recent studies on urban deprivation have been applying earth observation as an alternative way to obtain timely information on urban deprivation, further application of earth observation to understand tenure insecurity has not been explored. In addition, the variation of perceived tenure insecurity within urban deprived areas and its relationship to spatial characteristics of these areas has not been investigated.

Therefore, this research analyses the potential of earth observation-based information and other spatial information to measure and predict the variation of perceived tenure insecurity in urban deprived areas based on the city of Kigali, Rwanda. The research started by identifying variation of perceived tenure insecurity based on household survey data. These data were analysed through Multiple Correspondence Analysis (MCA) to obtain the indices representing that variation. The research applied hierarchical clustering to validate the latter, allowing the creation of four clusters corresponding to very high, high, moderate and low trends of perceived tenure insecurity. Hence, the research spatially mapped these clusters and evaluated their spatial distribution across the study area.

Furthermore, the research extracted the land cover information and texture features from the VHR Google Earth image and additional spatial information such as slope and zoning plan maps, as indicators based on four buffer areas around households: 10, 15, 20 and 25 meters. Later, the research undertook several modelling processes using a random forest regression model to understand the relationship between image-based spatial indicators alongside other spatial information as indicators and the variation of perceived tenure insecurity. In addition, the study analysed the importance of each indicator for measuring and predicting the variation of perceived tenure insecurity.

Findings revealed that respondents with a similar variation of perceived tenure insecurity are spatially concentrated due to the common factors inducing their perceptions. Moreover, the findings revealed that spatial characteristics from VHR images and other spatial information have the potential to capture the variation of perceived tenure insecurity in urban deprived areas. Furthermore, the research found that textural features present high importance in capturing such variation due to their capacity to capture the spatial arrangement of objects in the image. Moreover, additional spatial information describing location has significant prediction importance.

These findings can assist municipalities and stakeholders to make evidence-based decisions for unjust city development. Besides, the research is a basis for further researches concerning the spatial measurement of tenure security trends and monitoring the implementation of the SDGs, especially goal 1(target 1.4) on tenure security for all and goal 11 addressing the issues of safe, inclusive and sustainable cities and human settlements.

Keywords: deprivation, perceived tenure insecurity, earth observation, spatial information

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CNN	Convolution Neural Networks
FAO	Food and Agriculture Organization of the United Nations
GE	Google Earth
GLCM	Grey Level Co-occurrence Matrix
GLTN	Global Land Tool Network
LTR	Land Tenure Regularization
MCA	Multiple Correspondence Analysis
OBIA	Object-Based Image Analysis
PTI	Perceived Tenure Insecurity
SDGs	Sustainable Development Goals
SVM	Support Vector Machine
UN-Habitat	United Nations Human Settlements Programme of the United Nations
VHR	Very High Resolution

1. INTRODUCTION

1.1. Background: deprivation, tenure security, and perceived tenure insecurity

The world's population is increasing fast, and it is expected to reach a total of 9.7 billion by 2050 (United Nations, 2019). In general, many countries are experiencing rapid urbanisation than ever before, and more than half of the world's population is currently living in cities (United Nations, 2018). It is projected that by 2050, 68% of the world's population will be living in cities (United Nations, 2018). However, the number of urban poor, especially people living in deprivation, is also increasing in many cities in the Global South. At present, about 1 billion of them are living in deprived areas (UN-Habitat, 2016). Deprivation is regarded as a lack of benefits considered to be basic necessities in a society and is linked to the way people live and work (Baud, Sridharan, & Pfeffer, 2008). Most of the urban poor population that lack such necessities live in urban deprived areas, also known as slums and informal settlements (Friesen et al., 2020; Kuffer et al., 2020). Failure to adopt planning policies for inclusive cities and lack of capacity for adequate city planning and development leaves the poor urban population to live in those urban deprived areas.

Urban deprived areas often exhibit physical and socio-economic aspects characterised by lack of basic infrastructure, poor housing, overcrowding, unhealthy living conditions, poverty, social exclusion, and tenure insecurity (UN-Habitat, 2003). These characteristics are presented in the so-called dimensions of deprivation (see chapter 2, section 2.2), and among them, tenure insecurity is a lack of assurance that a person's rights to land or property are recognised and protected (Chigbu, Alemayehu, & Dachaga, 2019). It is the opposite of land tenure security which is regarded as the certitude that a person's rights to land and property are recognised and protected in cases of challenges (FAO, 2002). Feeling less tenure security is linked to the likelihood of losing land or property without someone's willingness and is regarded as perceived tenure insecurity (Van Gelder, 2009). Perceived tenure insecurity increases when the legal system and institutions do not recognise and protect the rights to land and properties of their holders (Simbizi, Bennett, & Zevenbergen, 2014; Reerink & Van Gelder, 2010). However, perceived tenure insecurity may also increase when the legal system recognises their rights to land and properties, but the implementing institutions are weak and do not protect their land and property rights.

The need to address tenure insecurity, especially for the poor and the vulnerable groups, was identified as one of the essential steps towards sustainable development as highlighted in goal 1, target 1.4 and 11 of Sustainable Development Goals (SDGs), aimed at increasing tenure security for all and making safe and inclusive cities and human settlements (United Nations, 2015). The Global Land Tool Network (GLTN) and United Nations Human Settlements Programme (UN-Habitat) are also advocating the need for recognition of tenure security for all (UN-Habitat & GLTN, 2017). Furthermore, the Food and Agriculture Organization of the United Nations (FAO) recommends the provision of tenure security to all and protecting them against forced evictions and other threats (FAO, 2012).

However, solutions for tenure insecurity in urban deprived areas are difficult to implement due to a lack of reliable information on the tenure status of urban deprivation dwellers. Though governments and international organisations collect information on deprivation, such as its spatial appearance and socio-economic characteristics, the information about tenure insecurity is often not considered. Like other socio-economic information in deprived areas, the common sources of such information are surveys. However, information from surveys is often rare, outdated, unreliable and hard to access, and presents discrepancy to the reality on the ground due to methods applied, time and resources constraints (Kuffer et al., 2018).

Moreover, some countries and organisations use different methods and indicators to collect information on tenure insecurity, which results in incomparable information on regional, continental and global level (The World Bank, FAO & UN-Habitat, 2019). To have comparable data on tenure insecurity, different organisations (The World Bank, FAO & UN-Habitat, 2019 and Prindex, 2019) suggest measuring tenure insecurity based on the perceptions of land and property holders. Prindex, the Global Property and Rights Index initiative, is at the forefront of producing global up-to-date and comparative information of perceived tenure security based on survey data (Prindex, 2020). The data used to produce that information is collected through interviews with randomly selected respondents across countries. However, the information obtained is at a coarse scale (country level) and does not focus specifically on the urban deprived areas.

1.2. Motivation

Lack of information about tenure status in urban deprived areas is a challenge for monitoring the implementation of goal 1 target 1.4 and goal 11 of SDGs. Given the challenges of the existing methods of sourcing information about tenure status, there is a need for other methods that address these challenges and hence provides useful updated information on tenure status.

Timely and adequate information about the tenure status of dwellers of urban deprived areas is recognised as crucial for implementing urban redevelopment policies (UN-Habitat, 2018). Furthermore, it provided a guideline for ensuring justice and equal opportunities for poor and low-income urban dwellers, who predominantly reside in urban deprived areas, to live and benefit from cities (Chigbu, Alemayehu, & Dachaga, 2019). In this regard, information about tenure status depicts the situation concerning spatial and social (in)justice that arises from the implementation of urban development policies (Moroni, 2018).

Most developing countries are improving cities by establishing and implementing urban redevelopment policies (UN-Habitat, 2016). However, the implementation of those policies involves property development arrangements that require demolition of existing inadequate housing facilities and displacement of their dwellers, leading to unwilling loss of land and property for the affected households (Nikuze et al., 2019; Chigbu, Alemayehu & Dachaga, 2019). Like other developing countries, Rwanda, especially its capital city of Kigali, is a typical example of the implementation of urban redevelopment policies that are often controversial and are said to affect perceptions of land and property holders, especially urban poor living in deprived areas (Uwayezu & de Vries, 2019).

Kigali city has experienced rapid urbanisation induced by high population growth and migration over the past two decades. However, the urbanisation process was not well planned and resulted in the growth of informal settlements across the city (Manirakiza et al., 2019). About 65% of the built-up residential areas of Kigali city are occupied by informal settlements, which accommodate 79% of urban dwellers in small and congested houses characterised by low-quality building materials (Hitayezu, Rajashekar, & Stoelinga, 2018). The government of Rwanda acknowledges the existence of informal settlements, and different urban redevelopment policies were established to solve the problem of informal settlements. Of these policies, the master plan aims to improve urban dwellers' living conditions by ensuring adequate land use, provision of modern housing solutions, provision of adequate transportation, and a healthy environment (City of Kigali, 2019).

Though the implementation of the Kigali master plan is acknowledged to be successful, it is also criticised and accused of being disadvantageous to the urban poor living in deprived areas and threatening their tenure security (Goodfellow, 2014). The implementation processes target urban deprived areas attractive to investors, which expose dwellers to eviction and displacement, leading to perceived tenure insecurity for dwellers of deprived areas (Uwayezu & de Vries, 2019). Though the implementation is accused of threatening tenure security for urban dwellers living in deprived areas, it is generally assumed that tenure security has improved due to the Land Tenure Regularization (LTR) program, which aimed to secure land rights for the land and property holders through land registration and land titling (Ali, Deininger, & Goldstein, 2014). This brought attention to a broad concern that land registration and titling are not always the solution to tenure insecurity, especially for vulnerable people living in urban deprived areas (Prindex, 2019). Therefore, it is worth exploring the variation of perceived tenure insecurity across deprived areas in such areas and exploring whether spatial information of these areas can help measure and predict such variation.

Moreover, the need for up-to-date information about deprived areas has triggered the use of earth observation as an alternative way to source information that helps understand the physical and socio-economic aspects of deprivation (Kuffer, Pfeffer, & Sliuzas, 2016). Earth observation can capture detailed information enough for spatially identifying and characterising urban deprivation (Kuffer et al., 2018; Mahabir et al., 2016). However, despite the effectiveness of earth observation-based information for spatially characterising and understanding urban deprivation, deprivation is multidimensional, and earth observation-based information is not very efficient for capturing multidimensional deprivation, which challenges understanding deprivation in a holistic approach (Abascal et al., 2021). Therefore, it requires extensive understanding by studying each of its dimensions separately.

Earlier researches demonstrated that spatial information derived from earth observation has the potential to explain the variations in socio-economic conditions such as poverty, population density, wealth, and health in urban settlements (Yeh et al., 2020; Wurm & Taubenböck, 2018; Arribas-Bel, Patino, & Duque, 2017). In this context, earth observation-based information has been used in different scenarios to understand deprivation. It was used to understand the nature, evolution and growth of deprived areas (Wang et al., 2019; Arribas-Bel, Patino, & Duque, 2017; Kuffer et al., 2017; Mboga et al., 2017; Kohli, Sliuzas, & Stein, 2016), socio-economic conditions in deprived areas (Baud et al., 2008; Tapiador et al., 2011; Wurm & Taubenböck, 2018), as well as health and environment conditions in deprived areas (Friesen et al., 2020; Georganos et al., 2019). However, despite the effectiveness of earth observation-based information for understanding such variations, its potential for sourcing information about tenure insecurity in urban deprived areas is neglected in most of the researches employing earth observation-based information to understand urban deprivation. This is due to the lack of spatially referenced data on tenure status in most surveys (Abascal et al., 2021). Given the important role of information about tenure insecurity in monitoring for implementing and achieving goal 1 target 1.4 and goal 11 of SDGs as well as other urban development policies, as highlighted previously, it is also important to explore the extent to which earth observation-based information can capture the variation of such information in urban deprived areas.

In this regard, though data about perceived tenure insecurity in deprived areas is scarce, this can also be bridged by using earth observation-based information extracted from VHR remote sensing image as an alternative approach to measuring the variation of perceived tenure insecurity across urban deprived areas. Moreover, integrating this information with other spatial information characterising the area would provide an enhanced understanding of such variation. Therefore, this research assesses whether perceived tenure insecurity in deprived areas can be measured using VHR earth observation images by relating all the spatial information with the variation of perceived tenure insecurity as a socio-economic threat in deprived areas. This would provide up-to-date essential information for supporting the development of urban deprived areas.

1.3. Research problem

Deprivation is a more general term that describes the lack of basic necessities in a society (Baud, Sridharan, & Pfeffer, 2008). The term deprivation is a holistic description of the multidimensional absence of basic living standards, as illustrated in the previous sections. Few researchers have attempted to understand urban deprivation through its different dimensions (e.g., Duque et al., 2015; Wurm & Taubenböck, 2018). However, little attention has been paid to perceived tenure insecurity in urban deprived areas since the information about tenure insecurity is rare, outdated and hard to obtain (Abascal et al., 2021), which make it hard to monitor the implementation of goal 1 (indicator 1.4) and goal 11 of SDGs and other urban development policies.

As mentioned above, different researchers argue that earth observation is the potential alternative source of information for understanding aspects of urban deprivation. However, further application of earth observation to understand more detailed aspects of urban deprivation, such as tenure insecurity, has not been explored. In addition, the variation of perceived tenure insecurity within urban deprived areas, as well as its relationship to urban deprivation, has not been investigated. Therefore, this research intends to explore the potential of earth observation-based information extracted from VHR image and other spatial information for measuring and predicting variation of perceived tenure insecurity across urban deprived areas. Thus, the general idea of this research is to employ earth observation to detect spatial characteristics of deprived areas using VHR remote sensing image alongside other spatial information and relate the results with information regarding the variation of perceived tenure insecurity in urban deprived areas. This would contribute to the understanding of aspects of cities' appearance in relation to perceived tenure insecurity and support in the formulation and implementation of urban development policies for achieving equitable, safe and inclusive cities and human settlements.

1.4. Research objectives

1.4.1. General objective

This research aims to leverage the power of spatial information, especially that observed by satellite sensors, to measure the variation of perceived tenure insecurity within the urban deprived areas. It attempts to identify the variation of perceived tenure insecurity from survey data and further analyse its relationship to the spatial characteristics of urban deprivation.

1.4.2. Sub-objectives and research questions

1. To characterise perceived tenure insecurity within the urban deprived areas.

    1.1 What are the major indicators of perceived tenure insecurity in urban deprived areas based on the literature?

    1.2 What is the variation of perceived tenure insecurity in the study area?

2. To extract spatial characteristics of urban deprived area from VHR remote sensing image.

    2.1 What is the appropriate deep learning model for detecting spatial characteristics of urban deprived areas in the study area?

    2.2 What are the spatial characteristics of urban deprived areas in the study area?

3. To analyse the relationship between spatial characteristics of urban deprived areas and the variation of perceived tenure insecurity.

    3.1 Which spatial characteristics of urban deprived areas can be related to the variation of perceived tenure insecurity in the study area?

    3.2 How are these characteristics related to the variation of perceived tenure insecurity in the study area?

1.5. Thesis structure

The thesis is structured into seven chapters. The first chapter outlines the background and justification of the research, the research problem, objectives of the research and the research questions. The second chapter presents a conceptual framework and theories on deprivation and perceived tenure insecurity. The third chapter presents the description of the study area and the research data. The fourth chapter is the research methods and presents the research approach, data collection and data analysis methods. Chapter five presents the results of the research. Chapter six presents the discussion of the results and limitation of the research. Finally, chapter seven presents the conclusions and recommendations.

2. THEORIES AND CONCEPTUAL FRAMEWORK

This chapter will be discussing the theories and concepts of deprivation and perceived tenure insecurity, which forms the elements of conceptual frameworks for this research. The first section presents the conceptual framework for the research. The second section discusses deprivation and its multi-dimensionality. The third section discusses tenure insecurity and its perception in urban deprived areas. Lastly, the fourth section discusses deprivation from a geospatial perspective.

2.1. Conceptual framework

This research conceptualises deprivation as a multi-dimensional concept encompassing socio-economic aspects such as poverty, social exclusion and tenure insecurity and physical aspects such as poor housing, overcrowding and lack of basic infrastructure (Abascal et al., 2021; Thomson et al., 2019; UN-Habitat, 2015). In the socio-economic aspects of deprivation, the research is limited to tenure insecurity and narrows to perceived tenure insecurity. Thus, the research collected data concerning perceived tenure insecurity from the households living in the urban deprived area based on a field survey. Hence, the research identified the variation of perceived tenure insecurity based on the collected data.

From the earth observation point of view, the research approaches physical aspects of deprivation by extracting spatial characteristics of deprived areas regarding their built environment, ecology and services. Moreover, the research takes into consideration other spatial information characterising the urban deprived areas. In this context, the areas presenting the physical aspect of deprivation are referred to as deprived areas. Furthermore, the research investigates the linkage between the variation of perceived tenure insecurity and spatial characteristics of deprived areas. It explores the potential of earth observation alongside other spatial information of urban deprived areas for measuring and predicting the variation of perceived tenure insecurity. This would contribute to the timely collection of up-to-date information on perceived tenure insecurity that serves as a basis for inclusive city planning and monitoring the implementation of goal 1 (target 1.4) and goal 11 of the SDGs. The concepts and their relations are presented in figure 1.

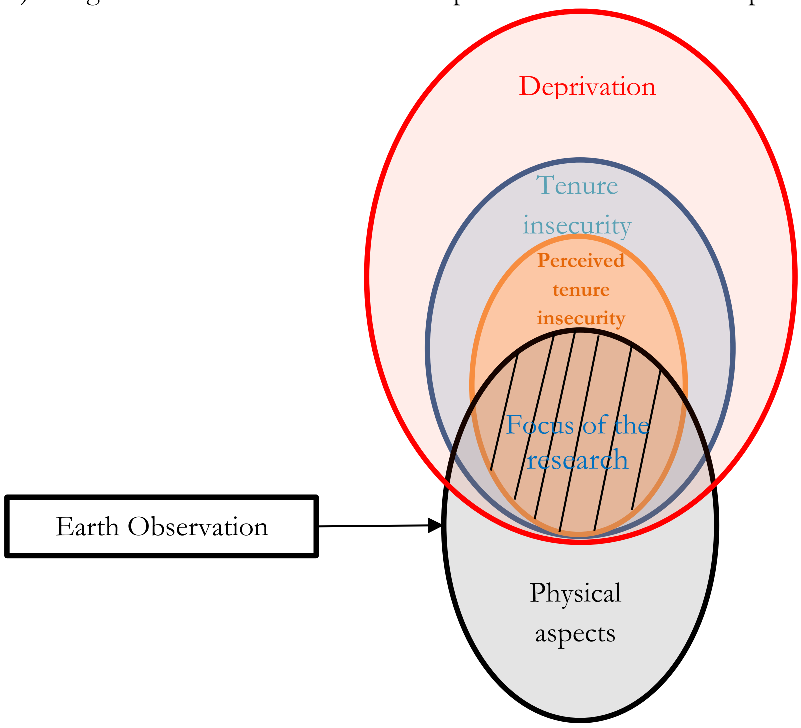


Figure 1: Research concepts

2.2. Deprivation and its multi-dimensionality

The urban population is rapidly increasing, which require a well-planned and arranged urban development process to accommodate the population (UN-Habitat, 2016). The increase in urban population has been one of the global challenges over the past decades. However, cities, especially in developing countries, have not met the pace for dealing with the challenge of urban population growth (Mahabir et al., 2016). The high increase in urban population has exceeded the capacity of developing countries in urban planning, provision of adequate and affordable housing, and infrastructure provision to most urban dwellers. Moreover, the lack and failure of urban redevelopment policies and spatial injustice has forced high proportions of urban dwellers to live in deprivation.

The term deprivation is conceptualised in many different ways, but in general, it is often used to indicate the lack of a wide range of necessities in a society (Baud, Sridharan, & Pfeffer, 2008). The lack of necessities in life is often used interchangeably with poverty in some social studies. However, urban scientists use the term deprivation instead of poverty, and it goes beyond poverty. Deprivation depicts multiple social, environmental (built and natural) and ecological aspects that significantly impact dwellers of urban deprived areas (Kuffer et al., 2020). It is crucial to note that some aspects are specific for deprivation while others are not (Thomson et al., 2019). For instance, environmental and ecological aspects such as flood plain and slope can also exist in non-deprived areas, whereas poor sanitation and inadequate housing are specific to deprived areas.

In a more general sense, deprivation represents multi-dimensional factors that describe sub-standard socio-economic and physical living conditions (UN-Habitat, 2015; Lilford et al., 2019). Researchers group these factors in domains to elaborate more comprehensive frameworks for measuring urban deprivation. For instance, Thomson et al. (2019) described a framework that groups deprivation factors in five domains: social and environmental risk, lack of facilities, unplanned urbanisation, contamination, and tenure insecurity. Very recently, the research by Abascal et al. (2021) conceptualises deprivation in the so-called Domains of Deprivation Framework. It encompasses concepts resulting from the review of various literature on deprivation alongside the validation by experts. This framework presents sixty-seven indicators grouped in nine domains. These domains are also under three mains levels: household level, within area and area connected. Details of the domains and indicators of that framework are presented in *Table 1*.

The Domains of Deprivation Framework allows a detailed understanding of deprivation, and the data for all its dimensions play a crucial role in its understanding (Abascal et al., 2021). However, its multi-dimensionality requires a broad range of data that is not easily available or obtainable. Lilford et al. (2019) recognised three essential methods for obtaining data about deprivation: household surveys for socio-economic data, ground surveys for identifying physical features, and earth observation to identify physical features. Though surveys provide reliable data, they are time-consuming, economically inefficient and do not reflect the fast-changing pace of urban deprived areas. Earth observation is an important source of up-to-date information in deprived areas. It is more efficient for capturing spatial and temporal physical properties of urban deprived areas.

Moreover, earth observation alongside advanced machine learning and deep learning methods have shown the potential to capture socio-economic information. In this context, it is claimed that the physical appearance of deprived areas reflects the socio-economic status of their dwellers (Arribas-Bel et al., 2017; Duque et al., 2015). However, though recent conceptualisations of deprivation acknowledge the importance of tenure status for identifying and understanding deprivation, tenure status is not often included due to the lack of data. The following sub-section describes tenure insecurity and its perceptions in the context of deprived areas.

Table 1: Domains and indicators of deprivation (Source: Abascal et al., 2021)

Household-level	Within area level	Area connect level
Socio-economic status	**Physical Hazards and Assets**	**Facilities and services**
-Assets (e.g. car, bike, TV, fridge, phone)	-Natural hazard (e.g. slope, flood zone)	-Access/financial, social
-Crowding	-Natural assets (e.g. biodiversity)	- Availability/distance-commercial
-Demographics	-Non-specific/multiple	-Availability/distance-municipal
-Education, literacy and training	**Contamination**	-Availability/distance-recreation/culture
-Employment and occupation	-Air pollution	-Availability/distance-worship
-Ethnicity and migration	-Garbage accumulation	-Availability/distance and quality-health
-Healthcare utilisation	-Industrial pollution (including toxic waste)	-Availability/distance and quality-schools
-Health, nutrition and disability status	-Noise or small pollution	-Availability/distance-all or other
-Income, expenditures (except housing), debt, credit and saving	-Water pollution	**Infrastructure**
-Insurance	-Non-specific	-Roads and walkways
-Public social services recipient		-Street lighting
-Sense of freedom, security and support	**Social Hazards and Assets**	-Transportation and traffic
-Sense of fulfilment, self-esteem and concentration	-Crime, safety, conflict (reported)	-Waste management
-Subjective property	-Security (perceived)	-Water, sewer
-Urbanicity	-Food security, distribution and nutrition	-Non-specific/multiple
-Non-specific/multiple	-Livelihood opportunities	**Governance**
	-Mobility	-Access to information
Housing	-Socio-economic inequality	-Civic participation, inclusion and fairness
-Energy for lightening, heating and cooking	-Savings and loan initiatives	-Corruption and accountability
-Property type, ownership and affordability	-Social capital and identity	-Finance and bureaucracy
-Sanitation	-Stigma	-Integrated planning
-Structure quality and attributes	**Unplanned Urbanisation**	-Legal and policy frameworks
-Tenure	-Building or population density	
-Water	-Building morphology (area, shape, arrangement, height)	
	-Building quality (roof materials)	
	-Building uses or functions	
	-Coverage or area of green space	
	-Land cover	
	-Land use	
	-Plot size	

2.3. Tenure insecurity and its perceptions in urban deprived areas

Tenure security protects land and property holders against arbitrary eviction and provides them with certitude that they will not lose their land and properties (UN-Habitat, 2008). It also encourages land and property holders to invest in land and housing (Chigbu, Alemayehu, & Dachaga, 2019). However, there is still a journey to achieve tenure security, especially for people who dwell in urban deprived areas in developing countries (Prindex, 2019).

Tenure insecurity is a predominant characteristic of urban deprived areas, and the absence of any official documentation, recognition and protection that empowers the dwellers to occupy the land or properties is one of the proofs of deprivation (UN-Habitat, 2003). The presence of tenure insecurity is one of the main reasons why urban deprived areas have persisted because tenure insecurity does not motivate the dwellers to improve their properties and neighbourhood (UN-Habitat, 2007). Without tenure security, households are discouraged from planning for sustainable livelihood due to fear of losing their properties and land (FAO, 2002). The most adverse manifestation of tenure insecurity for the urban poor is eviction, though it is not the only one; tenure insecurity also impacts access to services, vulnerability to risks and other hazards (Durand-Lasserve, 2012).

Contrary to tenure insecurity, tenure security is a prerequisite for access to economic and social opportunities such as credit, public services and livelihood opportunities. Tenure security is a gateway for the poor and marginalised urban population to have equal access to urban resources and opportunities. Providing tenure security to dwellers of urban deprived areas is one of the most significant characteristics in establishing acceptable and tolerable living conditions for human beings, especially for urban deprived areas dwellers (Berger, 2006). It is claimed that urban deprived areas where dwellers possess and benefit from tenure security, either formal or informal, have a high chance of success for community-led slum improvements initiatives (UN-Habitat, 2007; Van Gelder & Luciano, 2015).

Literature often represents tenure security in three forms: legal, perceived and *de facto* tenure security. According to Van Gelder (2009), legal tenure security assumes that tenure security is attained through the provision of legal titles or certificates of ownership, perceived tenure security is closely related to the feeling of losing land or property in unwilling circumstances, while *de facto* tenure security relies on social and political recognition of people's land or property rights. Moreover, *de facto* tenure security is accomplished by the official recognition of different extra-legal factors such as the existence of urban deprived areas and their dwellers, payment of property taxes, payment of utility bills and occupation time (Kim et al., 2019).

All three forms of tenure security are interrelated (Alizadeh et al., 2019). For instance, different land and property registration limitations, such as high cost and complex processes, hinder the poor and low-income populations from benefiting from property and land registration (Deininger & Feder, 2009), leading to tenure insecurity for them. Moreover, in the context of urban deprivation, though dwellers can have their properties and land registered or their rights on land and properties recognised, it does not automatically reflect the enhancement of tenure security. Dwellers of urban deprived areas can still unwillingly lose their land and properties due to the unjust implementation of urban development policies (Uwayezu & de Vries, 2019) and speculative land and property market induced by urbanisation (Payne, Piaskowy, & Kuritz, 2014). In this way, affected dwellers may feel less tenure secure. Therefore, it is essential to consider that providing only legal tenure security or *de facto* tenure security cannot necessarily change the perceptions on tenure insecurity but may influence and have impacts on the perceptions of the dwellers.

Among other forms, perceived tenure insecurity express the proxies for how an individual assesses the risk of losing their land and property. It defers from other forms of tenure insecurity since it does not depend either on jurisdiction or assessed by tracking the number of individuals or households having access to land through tenure arrangement recognised or protected by the government (UN-Habitat, 2018). Instead, perceived tenure security is often assessed by tracking individuals' or households' feeling or threats to unwilling loss of their land and properties due to circumstances such as eviction or conflicts. Besides, perceived tenure security can be assessed in the existence or absence of legal or *de facto* tenure security (Nakamura, 2016).

Perceived tenure security relies on individual's understanding of their tenure situation (Van Gelder, 2009). The perceived tenure status is the basis for the land and property holders to make decisions related to land and property (Ma et al., 2015). It is influenced by previous experience of eviction, low trust in the legal system and authorities, and lack of knowledge of one's rights on land or property, among others (Prindex, 2020). Perceived tenure insecurity reflects a threat to the injustice that may arise due to events like eviction or displacement of urban poor living in deprived areas. Such events are commonly induced by the unfair distribution of urban resources to all urban dwellers, which results in unequal access to resources and opportunities for dwellers of urban deprived areas (Moroni, 2018). The UN-Habitat relates perceived tenure insecurity to the inadequate housing development process in urban deprived areas since dwellers cannot formally develop adequate housing and do not invest more because they are threatened by eviction and displacement (UN-Habitat, 2015). Nakamura (2016) backed this by pointing out that dwellers of urban deprived areas tend to build houses that reflect the level of tenure security they perceive to minimise the loss in case of eviction or displacement.

Perceived tenure security may differ from household to household within the same location depending on the cause, who perceives it, how such tenure has been acquired, which players have been involved in securing the tenure for specific households and what is perceived as secure (De Souza, 2001). Moreover, several critics have argued that perceived tenure security instead of legal and *de facto* tenure security is the most underlying factor for housing improvements (Van Gelder, 2009). It corresponds to the perceptions of security that come from the likelihood estimation of the chance of eviction or other elements that endanger the prevailing tenure and bring about forced relocation (Ma et al., 2015).

Perceived tenure insecurity may result from circumstances such as threats of eviction aggravated by political factors, large-scale land acquisitions by investors and influential individuals and groups, the social stigmatisation of poor communities, non-compliance with planning and construction standards, and market pressure, among others (Chigbu, Alemayehu, & Dachaga, 2019). For instance, urban redevelopment processes aiming to improve deprived areas with compliance to modern and futuristic cities (UN-Habitat, 2016) involve slum upgrading, new housing development, and public infrastructure provision. However, in most developing countries, those activities are often implemented with injustice and threaten dwellers' tenure security (Uwayezu & de Vries, 2020). Dwellers of urban deprived areas are subjected to unfair compensation or forced to sell their properties to investors, leading to the unwilling loss of their interests on land. Hence, the increase in perceived tenure insecurity.

The increase in perceived tenure insecurity discourages dwellers of deprived areas from investing in housing and property development, which has various direct and indirect impacts not only on the single dweller but also on the settlement as a whole (Payne et al., 2014). This can be observed through the appearance of these urban deprived areas. For example, they are characterised by non-permanent, weak and old materials, small house units, high density and unstructured arrangement. Therefore, it is important to understand how tenure insecurity varies across such areas, which in turn provides essential information for solving tenure insecurity challenges.

International organisations and researchers interested in land rights have developed different approaches for measuring tenure security for evaluating the implementation of land policies (Prindex, 2019; UN-Habitat, 2018; Uwayezu & de Vries, 2018; Simbizi, 2016; FAO, 2012) and SDGs goal 1 indicator 1.4 on ensuring tenure security for all (The World Bank, FAO & UN-Habitat, 2019). This research identified the indicators for measuring perceived tenure insecurity in deprived areas based on the existing indicators for measuring tenure security. The identification was made by considering that tenure insecurity is the opposite of tenure security and recognising that perceived tenure insecurity is a subset of tenure insecurity. Besides, other researchers such as (Alizadeh et al., 2019; Moroni, 2018; Nakamura, 2016; and Payne et al., 2014) have also demonstrated that perceived tenure insecurity affect the way deprived areas dwellers invest in their land and properties. From this perspective, the research also identifies such physical environment among indicators to measure tenure insecurity. Table 2 illustrates the scope of the indicators adapted to measure perceived land tenure insecurity in deprived areas.

Table 2: Indicators for measuring perceived tenure insecurity in deprived areas identified from the literature

Indicator	**Research**	**Comment**
Duration of land or property ownership	(The World Bank, FAO & UN-Habitat, 2019); (UN-Habitat, 2018); (Prindex, 2019); (FAO, 2012); (Uwayezu & de Vries, 2018); (Simbizi, 2016)	The long or short period that landholder occupy the land/ property and living or nor living in fear of losing the land/property induce the perception of tenure insecurity
Land or property acquisition		Informal or formal land acquisition
Expected occupation period in the future		The likelihood of living or holding the land/property in the coming period of time
Types of rights to land/property		Bundle of rights to land enjoyed by the land and property holders
Recognition and protection of rights to land/property		Legal or *de facto* recognition of rights to land/property
Proof or evidence for rights to land/property		Documents proving the rights to land/property of land and property holders
Experience of eviction		Previous eviction and the causes of it
Likelihood to lose land/property unwillingly in the coming period of time (5 years)		Fear of event that can happen and make land/property holders to lose their rights to land/property
Physical/environmental characteristics	(Alizadeh et al., 2019); (Moroni, 2018); (Nakamura, 2016); (Payne et al., 2014)	Feeling insecure reduces the willingness to invest in land/property. Thus, areas with high tenure insecurity can be characterised by inadequate housing and environmental conditions.

2.4. Deprivation from a geospatial perspective

2.4.1. Spatial characteristics of urban deprived areas

Urban deprived areas present physical aspects such as poor structural quality of housing, overcrowding, high building density, solid waste management, environmental conditions (such as proximity to the wetland and steep slopes), and inadequate access to infrastructure such as roads, water supply, electricity (UN-Habitat, 2015). Different researches (e.g. Lilford et al., 2019; Kuffer et al., 2018; Wurm & Taubenböck, 2018; Taubenböck & Kraff, 2014) describe urban deprived areas as areas characterised by high building densities, small buildings, irregular arrangement of buildings and street networks as well as their location, which, in some cases is high-risk zones. The physical characteristics of deprived areas differ across locations and can be explained differently depending on the context (Kuffer et al., 2020). However, urban deprived areas present similar morphological characteristics. Kohli et al. (2012) conceptualised these morphological characteristics in three levels, namely object, settlement and environs, in the generic of slum ontology. Object-level represents characteristics such as building roof type, footprint, shape and orientation. The settlement level presents characteristics such as the irregular shape of roads and building density. Lastly, environs level presents characteristics linked to the location, such as proximity to hazardous places, such as flooding areas, wetland areas and steep slopes. Lilford et al. (2019) have extended the concept of slum ontology by including more physical characteristics to describe urban deprived areas. They suggested that deprived areas can be characterised based on their built environment, ecology, and services, but the main characteristics remain the same as presented in slum ontology.

Different researches studying urban deprivation have identified the spatial characteristics of urban deprived areas that can be extracted using earth observation methods. Those characteristics serve as guidance for efficient use of earth observation to produce reliable information on deprived areas. In this regard, this research gathered spatial characteristics of deprived areas based on a series of literature on deprivation and categorised them in three main categories adapted from (Lilford et al., 2019). Table 3 illustrates a compilation of spatial characteristics of urban deprived areas.

Table 3: Spatial characteristics of deprived areas from literature

Category	Characteristic	Research	Comment
Built environment	▪ Small buildings; ▪ High building density; ▪ Irregular building layouts; ▪ Poor roofing materials; ▪ Low road coverage, ▪ Presence of unpaved roads; ▪ Irregular road networks; ▪ Lack of access to electricity; ▪ Lack of streets lightning	(Wurm & Taubenböck, 2018), (Lilford et al., 2019), (Kohli et al., 2012), (Kuffer et al., 2018), (Kuffer et al., 2020), (Taubenböck & Kraff, 2014). (Graesser et al., 2012), (Kohli et al., 2016), (Georganos et al., 2019), (Arribas-Bel et al., 2017), (Friesen et al., 2020)	Image analysis techniques are used to extract these characteristics from VHR remote sensing images. Mapping night light from VHR remote sensing image indicate the existence of electricity services in areas
Ecology	▪ Gradient and altitude (floodplain, steep slope for land slides, other hazards) ▪ Green spaces ▪ Air quality		The use of multispectral remote sensing images and the Digital Elevation Model (DEM) to get information on topographic conditions of areas can reveal the possibility of disasters such as landslides or flood.
Services	▪ Presence of open sewers and solid waste disposal		Detected from VHR remote sensing images and reveal the unhealthy living conditions.

Extracting detailed spatial information about urban deprived areas from a remote sensing perspective depends on VHR earth observation image quality. Characteristics of urban deprived areas such as small building size, roofing materials and conditions are mostly hard to extract (Kuffer et al., 2017). Therefore, other useful spatial characteristics such as spectral features and texture features are often extracted and used as an alternative. Spectral features are extracted from images to represent the spectral characteristics of the object in the image. Spectral information is used in mapping urban deprivation for characterising the roofing material and other physical characteristics based on their colours (Kuffer et al., 2017). In contrast, texture features are based on Grey Level Co-occurrence Matrix (GLCM) and describe the intensity values in an image, representing information such as contrast, variance and homogeneity, which depicts the spatial arrangements of objects in the image (Ruiz et al., 2011). These are used to characterise the morphology of urban deprived areas.

2.4.2. Geospatial techniques for extracting spatial characteristics of urban deprived areas

Earth observation has shown the advantages of detecting high spatial and temporal characteristics of urban deprived areas useful for effectively monitoring and tracking urban deprived areas' growth and providing essential information to support urban development policies formulation and implementation (Mahabir et al., 2016). Besides, the availability of VHR earth observation images has increased the application of earth observation for producing adequate information about urban deprived areas (Kuffer et al., 2016). Therefore, researchers have employed different methods and algorithms for detecting spatial characteristics of urban deprived areas from VHR remote sensing images and aerial images.

The methods such as Object-Based Image Analysis (OBIA) and machine learning have been used to detect spatial characteristics of areas from VHR remote sensing images (Kohli et al., 2016). OBIA segments input image into several homogeneous contiguous groups before classification (Blaschke, 2010). OBIA approaches have shown capabilities of detecting both area and object-based information in deprived areas mapping (Kuffer et al., 2016). Random Forest, a machine learning approach, has shown the potential to achieve relatively high performance for urban mapping (Sun et al., 2017). The Support Vector Machine, which is also a machine learning method, was shown to have improved accuracy for detecting features from earth observation data (Huang & Zhang, 2013).

Though the above-mentioned methods have gained more credit for detecting spatial characteristics of areas from VHR remote sensing images, they present challenges for detecting spatial characteristics of complex spatial contextual and texture features (Sameen, Pradhan, & Aziz, 2018) and intra-class spectral variability (Chen et al., 2014) mostly in case of mapping urban deprived areas due to their morphology. Therefore, the increase in VHR images' availability and the challenges associated with the commonly used methods have left researchers' room to explore and propose new approaches for detecting spatial characteristics of areas from VHR remote sensing images.

There is a trend in applying deep learning methods for mapping urban deprived areas since they have shown the advantage of automatically learning and extracting spatial features from images with high accuracy than the commonly used methods (Bergado, Persello, & Gevaert, 2016). Deep learning models have gained popularity for analysing remote sensing images. They originated from artificial neural networks developed as an advance in perceptron, and they consist of three categories of layers: the input layer, hidden layers, and output layers (Lecun, Bengio, & Hinton, 2015).

Deep learning models are built to learn from the known data and predict the other data based on what they learnt. Typically, CNNs, a type of deep learning models, have gained more popularity in processing image through image classification, and if this classification occurs at a pixel level in an image, it is called semantic segmentation (Sameen et al., 2018). CNNs are built of one or more convolutional layers made of sliding filters over the input. The advantages of CNNs are that they are found in different architectures, and they allow flexibility for modification whereby the layers can be modified according to the user's need (Indolia et al., 2018).

In the context of image processing, deep learning through CNNs had demonstrated its potential for remote sensing image analysis. Therefore, since their breakthrough in semantic segmentation, known as image classification in remote sensing (Shelhamer, Long, & Darrell, 2017), different researchers have applied CNNs with different architectures to analyse VHR earth observation and aerial images in urban studies. Researchers (e.g., Ajamie et al., 2019; Wurm & Taubenböck, 2018; Kuffer et al., 2017; Persello & Stein, 2017) employed deep learning methods to map urban deprived areas and illustrated deep learning result in more relevant spatial information compared to other methods. Deep learning methods have illustrated the advantage of classifying the image into some predefined labels at higher accuracy than commonly used methods such as Support Vector Machine (SVM) and Random Forest (Sameen et al., 2018). The advantage of deep learning methods over other commonly used method is their capacity to learn spatial contextual information from image and produce more accurate results (Bergado et al., 2016).

Moreover, the research by Mboga et al. (2017) explored the performance CNNs for detecting informal settlement from VHR images, and they compared their performance to that of SVM and found out that CNN was able to lead to better classification accuracy. Wang et al. (2019) explored CNN's performance through U-Net architecture for identifying pockets of deprivation and found that the U-Net architecture used was able to detect and map the distribution and variation of deprivation. Sameen et al. (2018) benefited from the flexibility of CNNs and designed the architecture that could classify VHR aerial photo with high accuracy.

3. STUDY AREA AND DATA DESCRIPTION

This chapter consists of two sections. The first section presents the study area, and the second section explains the available data.

3.1. Study area description

Kigali city is the capital and the largest city of Rwanda. It is made of three districts, namely Gasabo, Kicukiro and Nyarugenge, and covers 730 km². The districts are further composed of three lower administrative levels: sectors, cells, and villages. (REMA, 2013). Kigali city is one of the fastest-growing city in Africa and home to more than 1 million people (Hitayezu et al., 2018). It lies on a hilly land surface with an altitude ranging from 1,300 m to 1,850 m, and its topography alternate with hilly and wetland valley areas (REMA, 2013).

Kigali city is comprised of mixed land-use types of commercial, residential, industrial and infrastructure, wetland, agriculture, forest, vacant spaces, public facilities and rivers. The new proposed master plan elaborates the city redevelopment in terms of infrastructure, housing and environment development (City of Kigali, 2019). Figure 2 shows the land use map (2019), and figure 3 shows the proposed zoning plan of Kigali city.

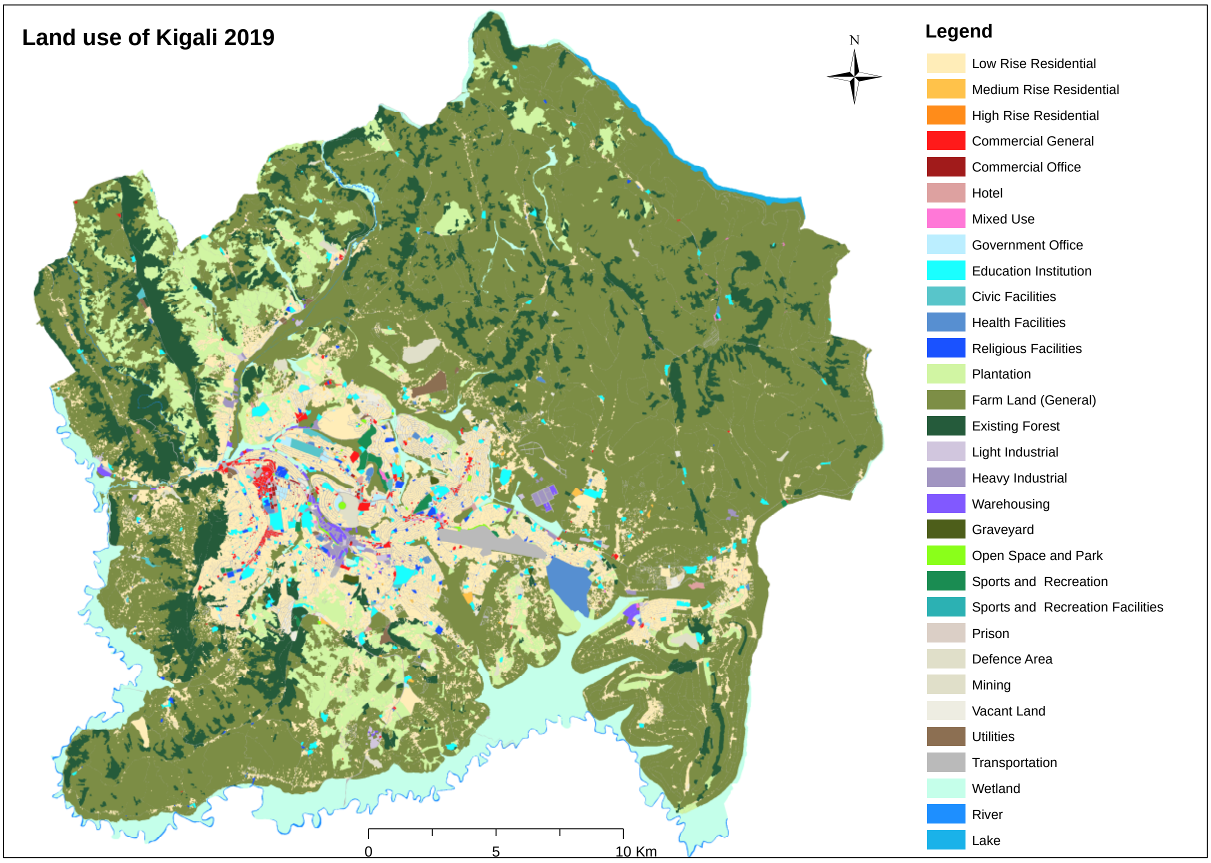


Figure 2: Land use map of Kigali city (2019). (Source: City of Kigali, 2019)

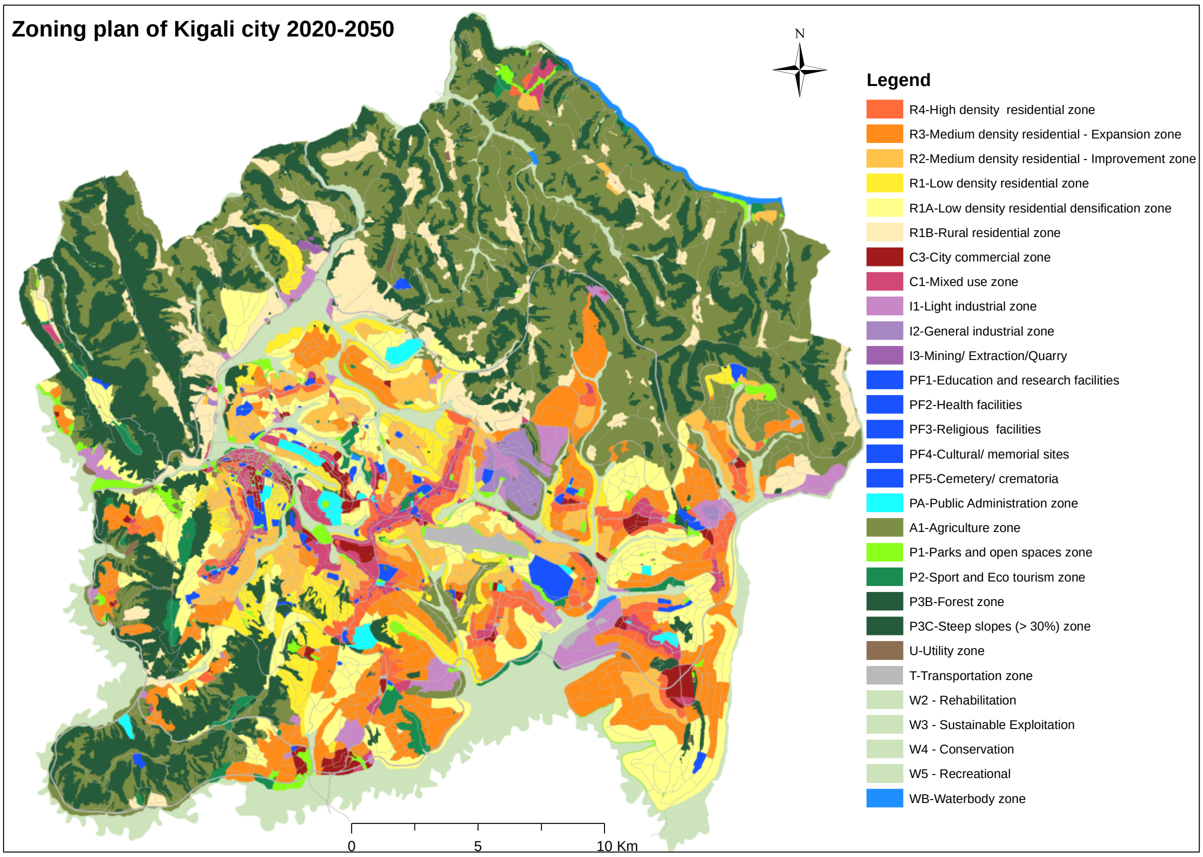


Figure 3: Zoning plan of Kigali city (2020-2050). (Source: City of Kigali, 2019)

Kigali is undergoing remarkable development changes. These changes are achieved through policies that aim to develop and redevelop commercial areas, business offices, infrastructure and industrial zones. These go hand in hand with the Clean city policy, which made the city recognised as one of Africa's cleanest and greenest cities (Manirakiza et al., 2019). The development changes of Kigali city are for solving long-standing challenges of the city such as informal settlements, which resulted from different factors such as high population growth, inefficient land use and lack of inclusion of urban poor in city development scheme (Hitayezu et al., 2018). The transformation of Kigali city is following the implementation of the Land Tenure Regularization (LTR) program across the country.

LTR program was implemented to cope with land issues such as tenure insecurity, unequal access to land and inefficient land use, inherited during the precolonial and colonial regimes, and independence until the 1990s (Ngoga, 2016). LTR program included components such as legal framework, institutional framework and land registration and titling. The main goal of the LTR program was to improve tenure security and ensure effective land use and management for the social and economic development of the country (Ali et al., 2014). The LTR program brought considerable improvements in equal access to land for men and women, increased security in land tenure and increased market value for the land (RCSP, 2017). Specifically, the implementation of the LTR program in terms of land registration and titling resulted in 11.4 million land parcels registered and assuring land titles to landholders (Government of Rwanda, 2013).

LTR program played a crucial role in developing the national land use and development plan and Kigali master plan (Government of Rwanda, 2019). The Government of Rwanda considered the LTR to be a basis for achieving adequate urban land use by entitling land and property holders with long-term lease contracts that are subjected to renewal upon developing land according to the land use plan and master plan (Government of Rwanda, 2013).

For implementing the master plan, informal settlements are mainly targeted for urban transformation and redevelopment (Hitayezu et al., 2018). Nevertheless, informal settlements dwellers are threatened by a lack of capacity to develop in accordance with the master plan and disasters such as flood and landslides due to the location of these informal settlements. Furthermore, the city authorities support land acquisition for master plan implementation as acts of public interests. However, the process of land acquisition is blamed for being unjust and resulting in the displacement of deprived areas dwellers, reflecting the loss of their land and properties (Nikuze et al., 2019). Though such loss should follow the legal procedures concerning evictions and expropriation, Uwayezu and de Vries (2019) revealed that strategies for implementing the master plan of Kigali do not follow the formal rule nor respect and protect tenure security of the affected urban dwellers despite their land being registered through the Land Tenure Regularization (LTR) program. These factors induce the dwellers to have perceived tenure insecurity though they possess land titles (Nikuze et al., 2019).

Given the conditions of Kigali city in terms of undergoing city redevelopment strategies, the research has identified three research sites: Gitega, Kimisagara and Gatsata. These sites were purposively selected because of three main reasons: (1) they are officially delineated as informal settlements and present major characteristics of deprived areas such as high buildings density and limited access to roads; (2) they are among priority areas for urban transformation in accordance to the implementation of the master plan (City of Kigali, 2019); (3) lastly, they are located on diverse topography such as steep slope for Kimisagara site, low land and proximity to ditch for Gitega site, and partly within the wetland and partly on a steep slope for Gatsata site, which allowed the researcher to explore further the contribution of the topography to the variation of perceived tenure insecurity across the study area. Figure 4 shows the research sites.

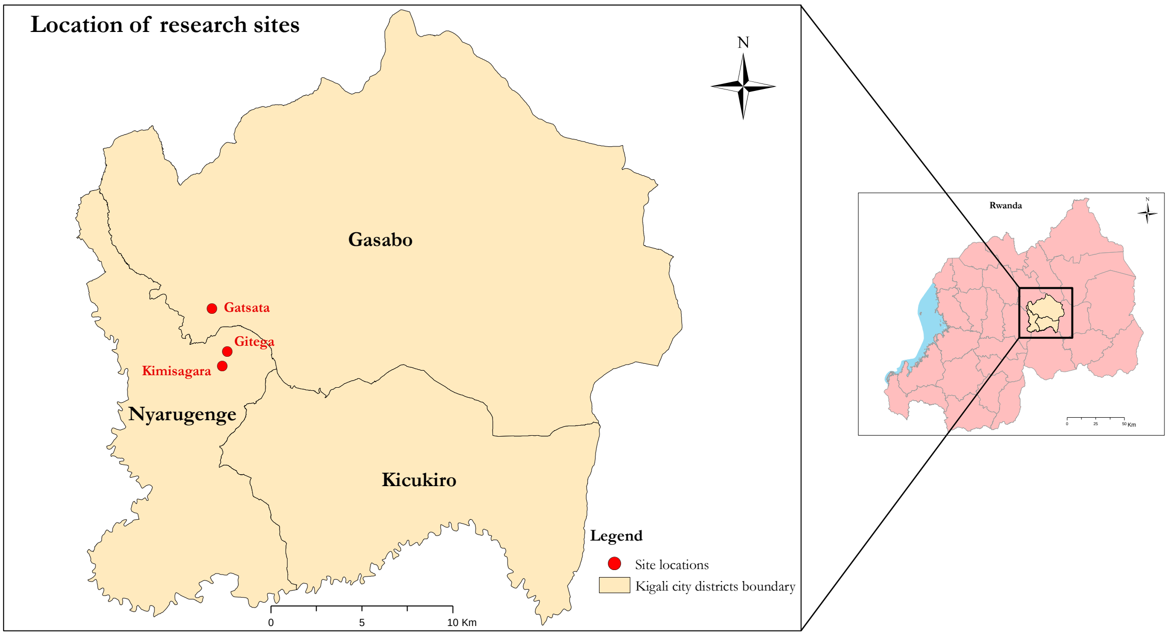


Figure 4: Map of Kigali city and the selected research sites.

3.2. Data description

In order to inspect the potential of earth observation in capturing the perceived tenure insecurity, it was obviously the first step to acquire samples to study the characteristic and spatial patterns of perceived tenure insecurity. To obtain such information, local knowledge alongside availability and access to the spatial data was crucial in selecting the study area for this research. Unfortunately, though a set of satellite images could be obtained from different sources covering different areas, socio-economic data, especially data on the perceptions of urban dwellers on tenure insecurity, were difficult to obtain. Thus, this research used the data on perceived tenure insecurity from a field survey conducted in Kigali city and data collected from literature review alongside VHR earth observation image and other spatial information.

3.2.1. Perceived tenure insecurity data

The reliable data on perceived tenure insecurity from the study area was only available from the field survey since such data were not available from the Rwanda National Institute of Statistics or other institutions. Moreover, Prindex's datasets on global perceptions of urban land tenure insecurity (Prindex, 2020) were not suitable for this research since they are collected at a coarse scale. The field survey was based on a questionnaire developed based on indicators of perceived tenure insecurity identified through the literature review (section 2.3). In addition, the questionnaire involves questions asking the justification of the answers provided by the respondent to ensure the validity of the answers provided. The questionnaire was developed in English, and questions on it were translated into Kinyarwanda (local language of respondents) during interviews to allow respondents to understand and express correctly what is reflected in the questionnaire. The questionnaire consisted of structured and open-ended questions such as *"How likely is that you could lose the rights on your land/property in the next 5 years against your willingness?",* and questions on the physical condition of their properties and their neighbourhoods such as *"How do you characterise the location of your neighbourhood?"* and *"How would you characterise the property/house you live in?".* A detailed questionnaire is attached in Annex 1 of the Appendix.

The field data collection assistant carried out the survey, and he was briefed about the survey through an online session to ensure that the expected data would be collected correctly. Data was collected based on household level from the study area through a geolocated respondents survey. The survey used respondents' interviews to collect the data, and the households' location coordinates were recorded using GPS (Global Positioning Satellites System) receiver. Thus, the coordinates of households' location served as the base for spatially linking each household in the study area with its corresponding survey data.

The survey was conducted in three research sites. Each site is made of different sub-sites corresponding to the small administrative units locally known as *"Imidugudu"*. A purposive sampling technique was used to ensure that each subsite is represented to select a representative sample. Due to the limitation in time, 3 to 5 samples were collected based on a sub-site area. To ensure the distribution of respondents at fine-scale, respondents were evenly distributed in sub-sites to allow the households' proper representation. Therefore a total of 120 respondents were surveyed. Table 4 indicates research sites, the number of sub-sites, and samples for each research site.

Table 4: Research sites

Sites	Subsites	Number of respondents per research site
Gitega (Akabahizi)	11	35
Kimisagara (Katabaro)	12	42
Gatsata (Nyamugari)	12	43
Total numbers of respondents		**120**

From the interviews, the research gathered information regarding the physical environment of the neighbourhood and the respondents' property, information regarding tenure rights of the households, and information regarding perceptions on tenure insecurity. Household representatives (head) were the preference for the survey and assumes that household members have the same perceptions of tenure insecurity by ignoring the intra-family disputes that may also read to one household member's high perception of tenure insecurity.

3.2.2. Earth observation data and other spatial data

Furthermore, the research employed a VHR Google Earth (GE) image of Kigali city, which was downloaded with enough zoom level similar to VHR imagery with sub-meter pixel size. The image was downloaded using the SAS Planet tool, a free and open tool for downloading high-resolution satellite images from Google Earth (GE), Bing and Esri Imagery services (http://www.sasgis.org/sasplaneta/). The VHR GE image comprised of 3 visible bands: Red, Green and Blue. Though the VHR GE image quality may be lower than some VHR remote sensing imageries acquired by different commercial platforms, VHR GE images are freely available to the public (with respect to their terms and conditions). VHR GE images' availability gives an advantage for areas and cities with limited resources for purchasing standard VHR satellite images. For instance, VHR GE images have been used to study living environment deprivation in Liverpool, England (Arribas-Bel et al., 2017), to explore the potential of machine learning for automatic slum identification in Latine America (Duque, Patino & Betancourt, 2017), and to map squatter settlements in South Africa (Gunter, 2009). These studies illustrated that using VHR GE image is a good alternative to commercial VHR images for their respective applications.

Apart from the survey data and VHR GE image, the research used administrative boundaries sourced from the Institute of Statistics of Rwanda and informal settlements boundaries in Kigali city sourced from the Rwanda Land Management and Use Authority. The research also employed the data sourced from the literature, including the spatial characterisation of deprived areas and physical proxies for characterising perceived tenure insecurity in deprived areas and the model for detecting spatial characteristics of deprivation. Table 5 illustrates the data used for this research.

Table 5: Summary of the data used in the research

Data	Source	Acquisition year	Specification
Household data for 120 respondents and their locations	Field survey	2021	Characteristics of physical environment and perceptions of respondents on tenure insecurity + locations
Satellite image	Google Earth/ SAS Planet	2020	VHR GE image (RGB) with sub-meter pixel resolution (0.65m)
Administrative boundaries	National Institute of Statistics	2012	Shapefile
Informal settlements in Kigali city	Rwanda Land Management and Use Authority	2018	Shapefile
Literature	Online libraries/publishers	Various years	Deprivation, perceived tenure insecurity, spatial characteristics of deprived areas, deep learning model for detecting spatial characteristics of deprived areas

4. RESEARCH METHODS

This chapter follows by describing the research methodology used in this research. It starts with the research approach, followed by a method for identifying perceived tenure insecurity in the study area, a method for detecting spatial characteristics of deprived areas in the study areas, and ends with a method for relating the spatial characteristics of deprived areas and variation of deprived areas perceived tenure insecurity.

4.1. Research approach

This research has adopted a mixed methods research approach. This approach was identified since the research needs to find answers to research questions that require quantitative and qualitative data. According to Creswell (2014), the mixed methods research approach provides a deep understanding of the problem. Quantitative data consists of numerical data, whereas qualitative data consists of categorical and textual data. Therefore, this research uses this approach by using primary data collected from the study area through household survey and secondary data collected from literature review alongside VHR earth observation image and other geospatial datasets (details are presented in sub-section 4.3.5). Figure 5 summarises the research steps.

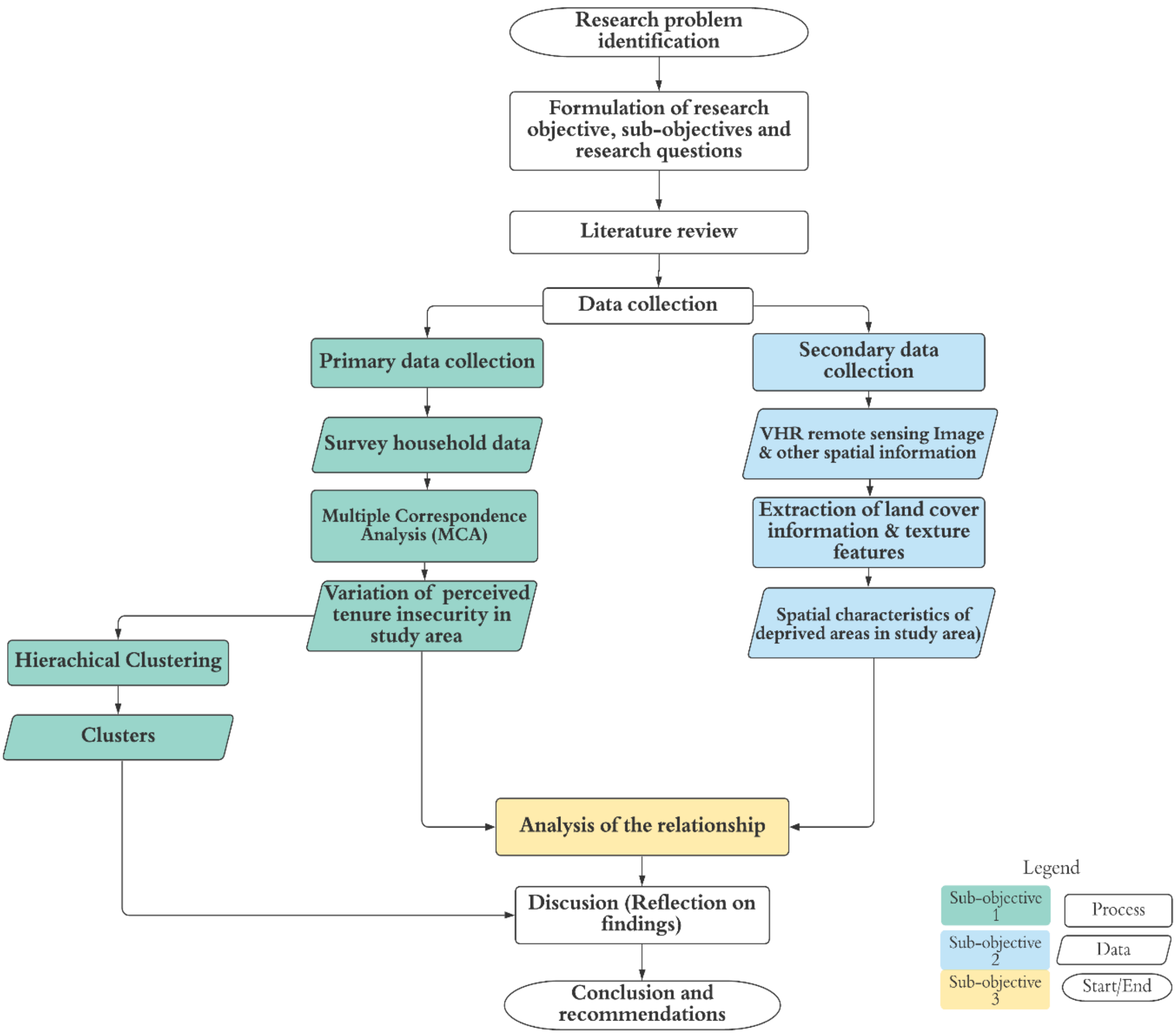


Figure 5: Research steps

4.2. Method for characterising perceived tenure insecurity in deprived areas

The research employed the literature review alongside the information gathered from the field survey to understand how the perception of tenure insecurity is characterised and described. The information obtained from the literature review was the basis for analysing the variation of perceived tenure insecurity in the study area.

The research employed a comprehensive search of the literature based on title and quick scanning of the abstract, introduction, and conclusion (Jaidka, Khoo, & Na, 2013). Literature was sourced from peer-reviewed and published papers, books, book sections, policies and reports from different scientific databases and online. The keywords used in the literature search include deprivation, deprived areas, slum, informal settlement, tenure security, perceived tenure insecurity. Different search queries combining these keywords were used to retrieve scientific papers within different scientific databases.

The research has reviewed different articles and reports on measuring and assessing tenure status. The main focus was to review the literature published from 2015 when there was concern about ensuring tenure security for all and measuring individuals' rights to land to monitor the implementation of the SDG goal 1 indicators 1.4.2. However, the research identified the FAO's voluntary guidelines on the responsible governance of tenure of land, fisheries and forests of 2012 as an additional potential source of information on measuring perceptions on tenure insecurity (FAO, 2012). Therefore, this research summarised and synthesised perceived tenure insecurity indicators in deprived areas based on all this literature. The obtained indicators served as the basis for the design of the questionnaire used for the field survey.

In addition to the literature, the field survey was carried out to collect respondents' perceptions of tenure insecurity. The obtained survey data for this research was detailed household data from 120 households collected from the study area. The survey contained data about the physical environment indicators of the neighbourhood and households, data about the indicators of tenure rights and perceptions of household respondents on tenure insecurity. The data consisted of categorical variables and was kept with categorical variables for preliminary data processing. The preliminary data processing helped to explore and understand the data. It consisted of descriptive statistical analysis. During the descriptive statistical analysis, frequencies of the answers given for each question were assessed, and only 25 indicators from which all respondents did not have similar answers were selected for further analysis.

Further analysis consisted of aggregating all the respondents' answers to the selected indicators to end up with an index for each respondent, which in the case of this research can is called the Perceived Tenure Insecurity (PTI) index and represents the variation of perceived tenure insecurity. The research used Multiple Correspondence Analysis (MCA) to analyse survey data and build PTI indices. MCA is an effective technique that allows the study and visualises a categorical variable dataset in dimensional space, which allows identifying variation in the dataset (Di Franco, 2016). Moreover, MCA works without making further assumptions on data to avoid that some indicators may have extremely more influence than others. MCA follows the same approach as Principle Component Analysis (PCA), but it is uniquely designed to deal with categorical variables (Ayele, Zewotir & Mwambi, 2014). Therefore, MCA was identified as a potential analysis approach for this research.

The research used MCA to compute the Perceived Tenure Insecurity (PTI) index for each respondent from the MCA's first dimension (component). The main purpose of applying MCA was to develop a PTI index for each respondent that could be connected to spatial characteristics of deprived areas retrieved from the VHR GE image. Recent researches on deprivation, poverty and health have followed the same approach and applied MCA to analyse their data. For instance, MCA was used to construct a deprivation index to identify the degree of deprivation of slums for an Indian city (Ajami et al., 2019). Another study showed the use of MCA in calculating wealth index from socio-economic data in South African urban informal settlements (Lawana & Booysen, 2018). Moreover, MCA was used to assess household socio-economic status changes in rural South Africa based on household asset indicators (Kabudula et al., 2017) and characterise people's socio-economic and demographic situation in an area prone to malaria in Brazil (Lana et al., 2017). These studies clearly show the advantage of using MCA for identifying patterns in qualitative and categorical data.

The MCA produced various outputs for this research which allowed the understanding of the PTI indices. The most important outputs were: the coordinates of respondents aggregated from their response in n-dimensional space (also known as components), scatter plots visualising the point cloud of respondents in 2-dimensional feature space, and squared correlation between indicators and dimensions demonstrating the potential of each dimension to describe indicators.

Further, this research used a hierarchical clustering method to validate the obtained PTI indices and deeply understand how perceived tenure insecurity varies across the study area and evaluate whether the obtained PTI indices express the real variation of perceived tenure insecurity. The hierarchical clustering method is frequently used to analyse social data and works by constructing clusters of individuals with an order from top to bottom (Liu et al., 2008). In addition, it is a statistical method useful for identifying patterns in data based on unsupervised classification (Liu et al., 2008). Therefore, it was useful for this research to find the patterns in the PTI indices.

The hierarchical clustering method allowed the creation of four clusters corresponding to the very high, high, moderate and low variation of perceived tenure insecurity. These clusters were based on the respondents that share similar characteristics. In addition, the research described and characterised clusters based on the indicators, variables, and dimensions to link the obtained clusters to perceived tenure insecurity for a deep understanding of the obtained clusters. Therefore, the research evaluated the p-values of each indicator to find which ones best characterise the clusters. The p-value expresses the probability that the results obtained are random (Liu et al., 2008). A small p-value shows that there is less possibility that the observed results have occurred by chance (Liu et al., 2008), and hence the more they significantly characterise the clusters. Additionally, the research evaluated the test statistic of each variable to determine variables that best characterise each of the clusters and describes the discriminating power of a variable for a certain cluster. In this context, variables with the test statistic value above 2 highly characterise a particular cluster (Greenacre & Blasius, 2006).

The obtained clusters were spatially mapped to evaluate their spatial distribution across the study area and assess whether perceived tenure insecurity is spatially concentrated across the study area.

4.3. Method for extracting spatial characteristics of the deprived area in the study area

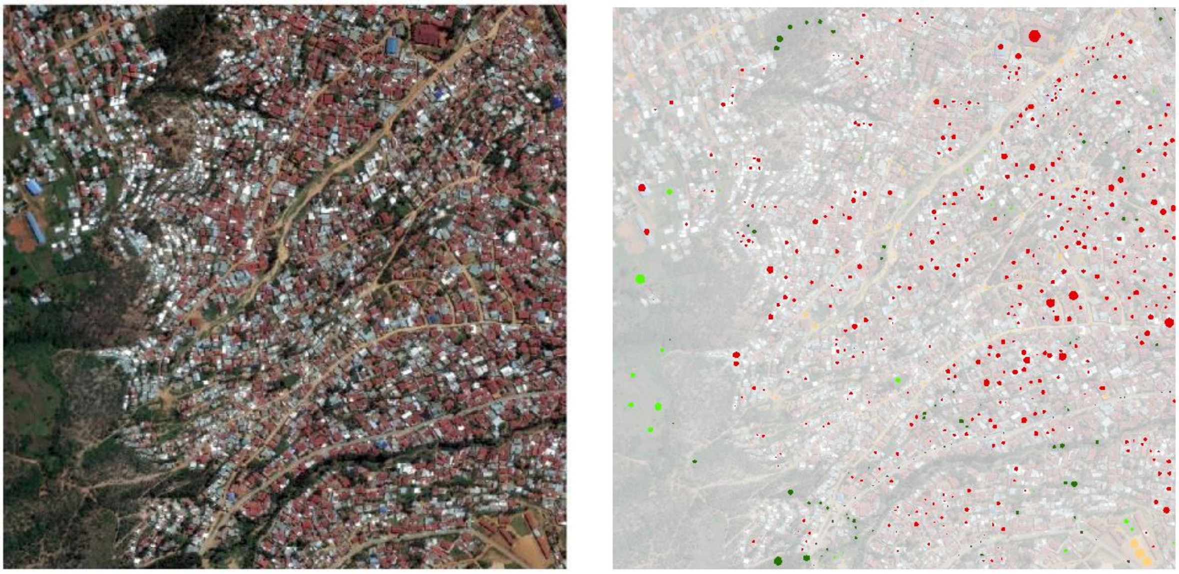
This research adopted dense segmentation for land cover classification to extract deprived areas' spatial characteristics using deep learning due to its efficiency, as shown in chapter 2, sub-section 2.4.2. This was achieved by reviewing publications concerning geospatial techniques for extracting spatial characteristics of urban deprived areas from remote sensing image analysis. The review aimed to identify a deep learning model for detecting spatial characteristics of deprived areas from VHR GE image.

A quick content analysis of these reviewed publications has revealed that most reviewed publications have used CNNs in different architectures for remote sensing image analysis through a pixel-wise classification and demonstrated that CNNs are suitable for analysing images with a spatial component, especially for VHR earth observation images (Sameen et al., 2018). Therefore, this research has identified CNN as the model for detecting a deprived area's spatial characteristics from the VHR earth observation image.

The CNN-based method for detecting spatial characteristics in the study area is based on a supervised VHR earth observation image classification. The CNN model learns from a set of ground truth data, also called training data, to predict and classify the image. Training data is a set of observations expected by CNN as examples of all classes to be classified (Chen et al., 2014). This means that the CNN model uses the training data as an example for classes, and hence when new data are passed, it predicts their classes based on what it learnt from the training data.

4.3.1. Image pre-processing and reference data preparation

The VHR GE image covering all the study sites was first split into 15 tiles of 1500×1500 pixels for each. Then, the reference data used to train the CNN model was manually prepared. The research extracted sample polygons for five land cover classes: built-up, low green space, paved roads, dense green space and unpaved roads and bare lands, through visual image interpretation. The labels for each land cover class were randomly collected across on top of the VHR GE image (sparse labelling). After collecting the reference labels, labels were converted in a raster format. Since the collected labels were sparse, pixels that were not labelled were assigned a value of 0 and were excluded in the model's training. Figure 6 (a) shows the example of image tile and (b) its corresponding sparse labels, respectively.



(a) (b)

Figure 6: Example of image tile (a) and its corresponding sparse labels (b)

4.3.2. Image processing

During this step, the VHR GE image tiles and their corresponding labels were prepared as input to the model for extracting land use cover information of the study area. Following the architecture of deep learning models, the input image needs to be split into small image patches before being fit to the size of the input layer of the model. Therefore, the VHR GE image tiles and their corresponding labels were split into small input images called patches of the size compatible with the model. The image patch size used for this research ranges from 64×64, 128×128 and 256×256 pixels, and the optimum patch size was determined based on the model results. The patch size plays a significant role in computational cost in terms of the memory required and the model's accuracy. Reducing the image tiles into small patches help to deal with computational limitations. The image patches were randomly split into two parts, namely 80% as training set and 20% for the test set. The training set was used for training the model, whereas the test set was used to evaluate the model's performance. The research used more training data than testing data to ensure that enough training data are fed to the model to identify the features in the input images.

4.3.3. Training the CNN model for detecting spatial characteristics of deprived areas

This research adopts the CNN model architecture that is a U-Net model. The U-Net architecture was accessed through ArcGIS API for Python. The importance of employing the existing model architecture is that it has been established and tested for its scalability for a trusted Geographic Information System software Company (ESRI). Additionally, the research wanted to put more effort into identifying the variation of perceived tenure insecurity and analysing their relationship with spatial characteristics of urban deprived areas rather than starting the development and training of the new model for extracting spatial information from the VHR GE image.

The U-Net model used in this research comprises two main parts like other Fully Connected Network models. The first part is an encoder that uses a downsampling process to detect features on an image. This encoder part utilizes a pre-trained classification network of the RestNet model with a series of convolutional blocs and maxpooling. The second part is a decoder that builds the model using the input image size and applies the upsampling and concatenation processes to reconstruct the image's pixels for spatial information.

The model training process was aimed to train the model to do land cover classification. The model training used a learning rate of 0.001 and 100 epochs. The process took place on a personal computer with Intel(R) Core(TM) i7-9750H CPU at 2.60 GHz, a RAM of 16 GB, and dual GPU: Nvidia Quadro T1000 and Intel(R) UDH Graphics 630.

The implementation was evaluated through model accuracy on the test set and metrics such as precision, recall and F1-score (Nivaggioli & Randrianarivo, 2019). Precision measures the ratio of correctly classified pixels to the total number of all classified pixels in the classified map. The recall measures the ratio of correctly classified pixels in a classified map to the total number of pixels in the reference map. Finally, the F1-score is obtained based on the precision and the recall value and indicates the model's performance by showing the harmonic value balancing both precision and recall.

Furthermore, after the training process, the trained model was saved for deployment. The research deployed the model to generate a classified raster map. The research benefited from ArcGIS API capabilities for faster deployment of the trained model using parallel processing and obtained the classified raster map. The obtained map consisted of land cover information of the study area.

After obtaining land cover information of the study area, the research extracted this information based on the location of each respondent. As indicated in chapter 3, section 3.2, respondents were spatially illustrated by the geographic coordinates of their households. The research considered the buffer of 10, 15, 20 and 25 meters for each household location coordinate and extracted percentages of each land cover information. The same approach of employing buffer to extract spatial characteristics has been applied by Georganos et al. (2019) to model wealth index using VHR remote sensing image and Perez-Heydrich et al. (2016) to study the influence of demographic and health survey point displacements using raster analysis. The buffer consideration allows the extraction of important spatial characteristics. Therefore, land cover classes obtained were aggregated at the buffer area levels, and the percentage of each land cover class was derived as a predicting variable for predicting perceived tenure insecurity across the study area.

4.3.4. Texture and spectral features as spatial characteristics of deprived areas

The texture features serve as complementary information to the extracted land cover information because it was difficult to extract more detailed land cover information due to the quality of the VHR GE image used. Therefore, through the GLCM, eight texture variables were extracted, namely contrast, correlation, dissimilarity, entropy, homogeneity, mean, second moment and variance using ENVI 5.6 software. Structure features were computed using all band on the VHR GE image at a greyscale quantisation level of 64 using a 3×3 kernel window. The obtained results were aggregated on the buffer area to derive texture variables for predicting perceived tenure insecurity in the study area.

4.3.5. Additional spatial information

The research used supplementary spatial information characterising the study area to evaluate whether they can improve the ability to relate spatial information to perceived tenure insecurity, as illustrated in table 6 below. The additional spatial information was identified based on survey data regarding the reasons behind respondents' perceptions of tenure insecurity (Annex 2).

Table 6: Additional spatial information

Spatial layers	Source	Description
Slope	Rwanda Land Management and Use Authority	Derived from Digital Elevation Model of the study area (with 12.5 m resolution)
Zoning plan	Rwanda Land Management and Use Authority	Plan indicating detailed land use plan for the study area
Road network	OpenStreetMap	Road network of the study area

Table 7 below presents all variables (image derived variables and other spatial information derived variables) used to predict the variation of perceived tenure insecurity in the study area.

Table 7: Variables for predicting perceived tenure insecurity in the study area

Category	*Variable*	*Description*
Land cover	Built-up area	Percentage of built-up areas
	Dense green space	Percentage of dense green spaces
	Low green space	Percentage of low green spaces
	Paved roads	Percentage of paved areas
	Unpaved roads and bare lands	Percentage of unpaved roads and bare lands
Texture features	GLCM_Contrast	Texture features extracted through GLCM contrast
	GLCM_Correlation	Texture features extracted through GLCM correlation
	GLCM_Dissimilarity	Texture features extracted through GLCM dissimilarity
	GLCM_Entropy	Texture features extracted through GLCM entropy
	GLCM_Homogeneity	Texture features extracted through GLCM homogeneity
	GLCM_Mean	Texture features extracted through GLCM mean
	GLCM_Second Moment	Texture features extracted through GLCM second moment
	GLCM_Variance	Texture features extracted through GLCM variance
Additional spatial information	Distance to road	Accessibility to road
	Distance to wetland	Proximity to wetland
	Slope	Slope(%) derived from DEM representing the topography
	Residential_R1	Planned low residential zone derived from the zoning plan
	Residential_R1B	Planned rural residential zone derived from the zoning plan
	Transportation facilities	Planned transportation facilities derived from the zoning plan

4.4. Method for relating spatial characteristics of the deprived area to variation of perceived tenure insecurity

This section provides an overview of steps for modelling processes for measuring and predicting the variation of perceived tenure insecurity using spatial characteristics derived from the VHR GE image. To find the relationship between different spatial characteristics of deprived areas and perceived tenure insecurity, the research employed a Random Forest model to predict the variation of perceived tenure insecurity and find how the spatial characteristics contribute to the prediction. Random Forest was identified because it is one of the tree-based and non-parametric supervised machine learning algorithms resistant to overfitting (Breiman, 2001). In addition, it has a low number of hyper-parameters to set for model optimisation, presents the ability to handle multi-collinear datasets, and can work as a classifier or regressor (Stevens et al., 2015). Moreover, the research selected the Random Forest model because of its capacity to model complex non-linear relationships among spatial characteristics derived from images and socio-economic data (Georganos et al., 2019).

The research extracted image-based spatial characteristics (land cover and texture features) and additional spatial information for each buffer area to analyse the relationship between earth observation-based information and other spatial information with the variation of perceived tenure insecurity. Hence, the research computed the relation between the extracted spatial characteristics and variation of perceived tenure insecurity. Figure 7 summarises the workflow for relating spatial characteristics of the urban deprived area with perceived tenure insecurity using the Random Forest regression model.

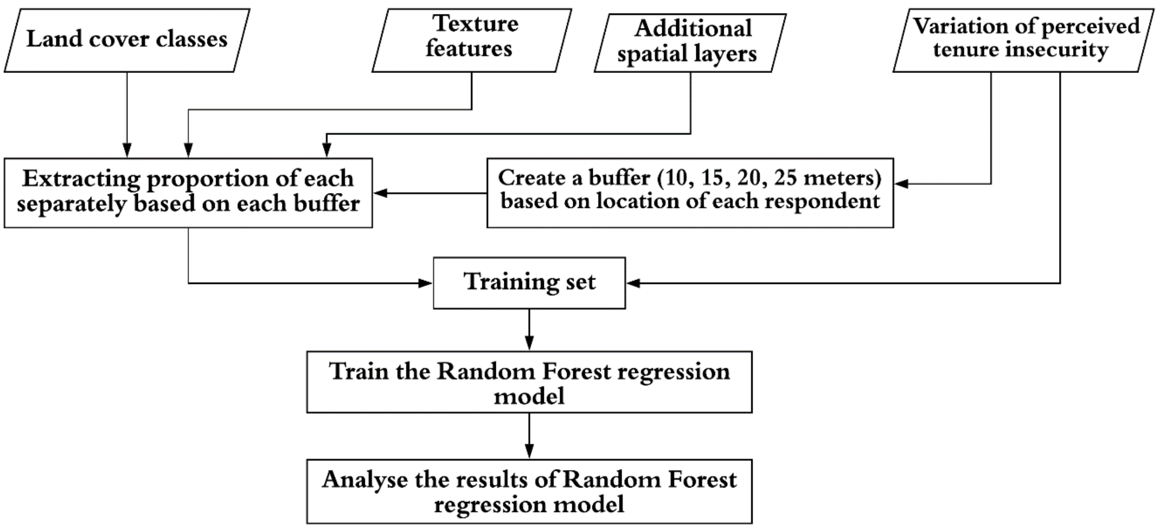


Figure 7: Workflow to relate spatial characteristics with the variation of perceived tenure insecurity

5. RESULTS

This chapter presents the results of this research. It includes three sections: section 5.1 presents results on the characterization of perceived tenure insecurity in deprived areas. Section 5.2 presents the results of extracted spatial characteristics of deprived areas. Finally, section 5.3 presents the relationship between spatial characteristics of deprived areas and the variation of perceived tenure insecurity.

5.1. Characterisation of perceived tenure insecurity in deprived areas

5.1.1. The variation of perceived tenure insecurity across the study area

The research used the survey data collected based on indicators of perceived tenure insecurity identified from literature (chapter 2, section 2.3) to characterize the variation of perceived tenure insecurity in deprived areas. As explained in chapter 4 (section 4.2), the research used MCA to analyse survey data and build the PTI indices. The PTI indices were built based on data from 120 survey respondents. The MCA used 25 qualitative indicators from each of 120 respondents and created 44-dimensional spaces to find variation in the data. As a result, the MCA produced a point cloud of respondents across each dimensional spaces. The scatter plot in figure 8 gives the overview of the point cloud of respondents across the first and second dimensions.

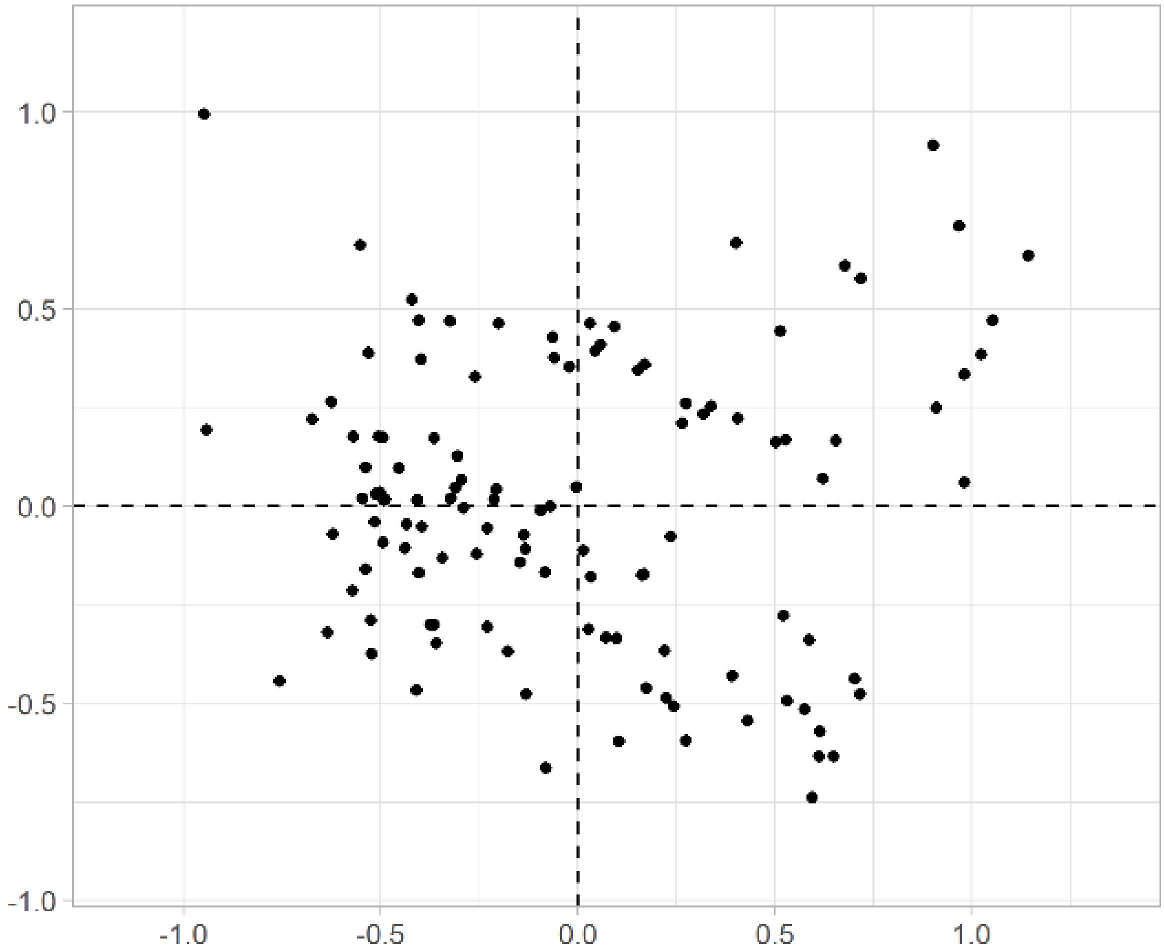


Figure 8: Scatter plot of respondents in 2-dimensional space on the first and second dimension of MCA

The respondents closer to each other are closely related and have similar indicators and variables of perceived tenure insecurity. However, respondents far from each other are different. This means the closer respondents have similar perceptions of tenure insecurity, whereas respondents far apart have significantly different perceptions of tenure insecurity. The interpretation of obtained PTI indices is simplified by extracting MCA's first dimension's value to represent the PTI indices, as shown in chapter 4, section 4.2. Figure 9 indicates the plot of each respondent's corresponding index. The indices in red are below the average (-0.01) and represent 65 respondents with high tenure insecurity. The indices above the average are in green and represent 55 respondents with low perceived tenure insecurity.

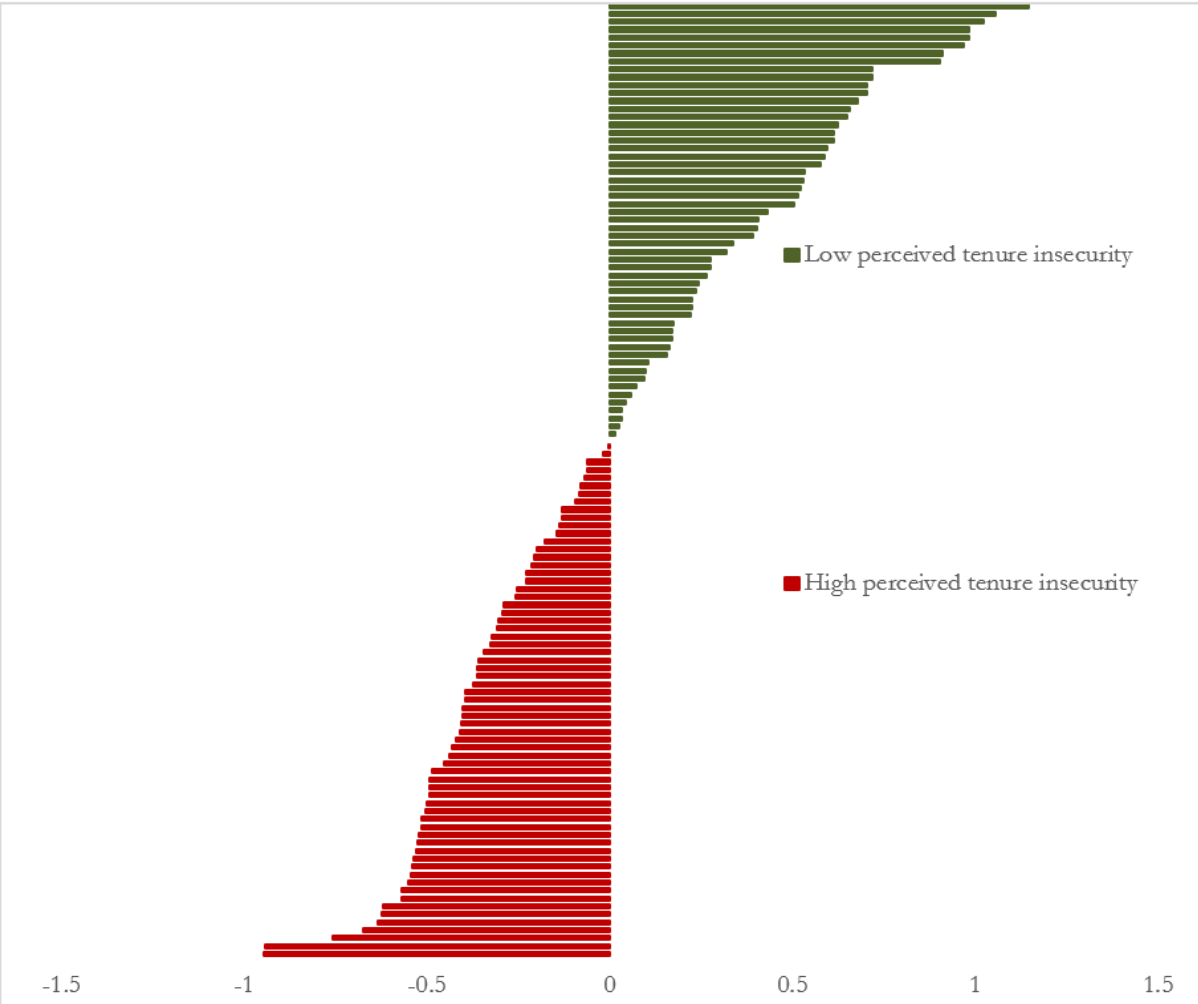


Figure 9: Plot of respondents along the first dimension of MCA

The indicators used for measuring perceived tenure insecurity did not contribute equally to the creation of the PTI indices. The squared correlation of indicators with the first dimension provides an overview of the contribution of the indices, as shown in figure 10. The higher the value of squared correlation, the more the indicator contribute to the creation of indices. This means the indicators with a high value of squared correlation are essential for characterising the variation of perceived tenure insecurity in the study area. In this regard, wall materials, household access to water, likelihood to lose property in the next five years, occupation time in the future, and the house's size are five the most indicators contributing to the creation of PTI indices. This implies that they are the most critical indicators for characterising the variation of perceived tenure insecurity in the study area.

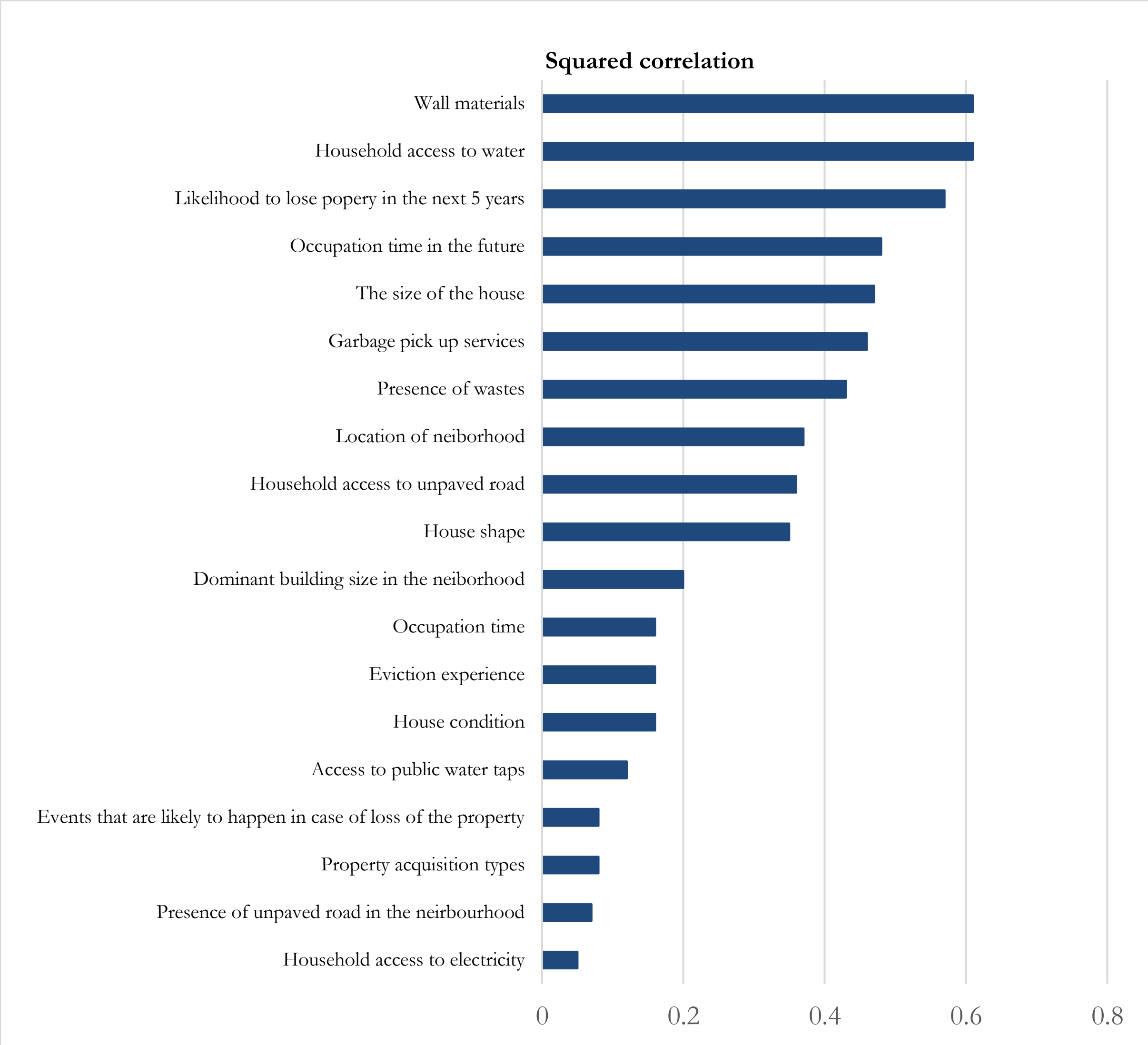


Figure 10: Squared correlation indicators with the first dimension of MCA

5.1.2. Validation of the variation of perceived tenure insecurity across the study area

The indices obtained from MCA characterise the variation of perceived tenure insecurity in the study area from a general perspective. However, the research is also concerned with validating the obtained variation, as shown in chapter 4, section 4.2. Thus, the research explored the level of perceived tenure insecurity and whether there is a spatial concentration of respondents with the same perceptions of tenure insecurity across the study area.

The perceptions of tenure security were not constant among all respondents, as shown by the MCA results in the previous sub-section (5.1.1). However, some respondents present almost similar indicators of perceived tenure insecurity. Therefore, the research grouped the respondents in four (4) clusters based on the similarity of their indicators.

Furthermore, the research described each cluster based on the indicators, variables, and dimensions to relate the clusters to variation of perceived tenure insecurity. Then, the research evaluates the p-value to find indicators that best characterise all clusters. The indicators that best characterise the clusters are shown in table 8. They are sorted from the best indicators.

Table 8: Indicators that best characterise the clusters

Indicators	P-value
Wall materials	3.21×10^{-26}
Location of the neighbourhood	1.56×10^{-21}
Household access to water	4.58×10^{-15}
Likelihood to lose popery in the next 5 years	7.65×10^{-12}
House condition	8.80×10^{-12}
Occupation time	9.94×10^{-12}
Events that are likely to happen in case of loss of the property	1.21×10^{-11}
The shape of the house	1.72×10^{-10}
Presence of wastes	9.17×10^{-10}
Garbage pick up services	4.71×10^{-9}
Feelings of staying in the same property in the future	5.04×10^{-9}
The size of the house	7.70×10^{-9}
Dominant building size in the neighbourhood	5.01×10^{-7}
Household access to the unpaved road	2.33×10^{-6}
Property acquisition types	1.39×10^{-4}
Eviction experience	9.20×10^{-4}
Access to green space	7.89×10^{-3}
Presence of unpaved road in the neighbourhood	1.29×10^{-2}
Access to public water taps	2.56×10^{-2}
Presence of unpaved footpath	4.13×10^{-2}

Each indicator consisted of different variables. For instance, wall materials as an indicator consisted of variables such as wood, unburnt brick, concrete and stone. The similarity of variables also characterises respondents in the same cluster. Therefore, by checking the test statistic value of each variable in the clusters, similar variables in each cluster were identified. Table 9 illustrates significantly characteristic variables for each cluster based on their absolute test statistics. The variables are sorted from those that best describe the clusters to those that describe clusters a little less, keeping only the variables with a significant link with the clusters.

Table 9: Variables that best characterise each cluster

Cluster 1

Variables	*Test statistic*
Event in case of loss of property: Relocation	6.61
Location of the neighbourhood: Proximity to wetland	5.35
Location of the neighbourhood: Proximity to ditch	4.48
Eviction experience: No	3.79
Property acquisition: Inherited from my family	3.7
Likelihood to lose popery in the next 5 years: Very likely	2.93
Household access to water: No	2.79
Wall material: Unburnt brick	2.65
Dominant building size in the neighbourhood: Medium	2.57
Access to green space: Yes	2.49
Access to public water taps: No	2.25
Protection in case of loss: Very strongly	2.18
Location of the neighbourhood: Proximity to the road	2.17
House condition: Old	2.14

Cluster 2

Variables	*Test statistic*
Household access to water: No	6.59
Wall material: Unburnt brick	6.43
Location of the neighbourhood: Steep slope	6.38
Dominant building size in the neighbourhood: Small	5.87
House size: Small	5.5
Presence of wastes: No	5.47
Garbage pickup: No	5.33
Occupation time: Between 5 and 10 years	5.14
Likelihood to lose popery in the next 5 years: Very likely	5.14
Household access to unpaved road: No	3.76
House shape: Simple shape	3.16
Unpaved roads: No	2.92
Event in case of loss of property: Land readjustment	2.75
Household access electricity: No	2.16

Table 9: Continued

Cluster 3

Variables	*Test statistic*
Wall material: Burnt brick	7.29
Presence of wastes: Yes	5.09
Occupation time: Longer than 10 Years	4.81
Garbage pickup: Yes	4.76
Household access to water: Yes	4.45
Occupation time in the future: Longer than 10 Years/lifelong	4.41
Likelihood to lose popery in the next 5 years: Unlikely	4
House condition: Old	3.72
House size: Medium	3.71
Dominant building size in the neighbourhood: Medium	3.55
Event in case of loss of property: Upgrading	3.18
Location of the neighbourhood: Moderate slope	2.91
Household access to unpaved road: Yes	2.46
Household access to footpath: No	2.13
Location of the neighbourhood: Proximity to watershed	2.01
Unpaved roads: Yes	2

Cluster 4

Variables	*Test statistic*
Wall material: Concrete	7.92
House condition: New	7.27
House shape: Complex shape	5.99
Household access to water: Yes	5.47
Occupation time: Between 1 and 5 years	4.51
Occupation time in the future: Longer than 10 Years/lifelong	4
Location of the neighbourhood: Moderate slope	3.93
Household access to unpaved road: Yes	3.93
Likelihood to lose popery in the next 5 years: Somewhat likely	3.77
Occupation time: Between 5 and 10 years	3.72
House size: Medium	2.89
House size: Large	2.69
Likelihood to lose popery in the next 5 years: Very unlikely	2.69
Eviction experience: Yes	2.67
Property acquisition: Bought from the private individual	2.59
Event in case of loss of property: Land readjustment	2.37
Garbage pickup: Yes	2.09

Finally, the research characterised the clusters based on MCA dimensions. The description of clusters by axes shows that the first and second dimensions allow the best separation of the clusters from MCA results based on test statistics of each cluster along these dimensions. This means the plane defined by the first and second dimensions gives a visual idea of distances that distinguish the respondents according to their clusters. Table 10 indicates test statistics on the first and the second dimension for all clusters.

Table 10: Indicators that best characterise the clusters

	Test statistic			
	Cluster 1	Cluster 2	Cluster 3	Cluster 4
First dimension	-3.797	-6.298	4.331	6.788
Second dimension	-2.970	3.581	-7.023	5.517

The results indicate that respondents in cluster 1 have lower coordinates on the first dimension and lower coordinates on the second dimension. Respondents in cluster 2 have the lowest coordinates significantly on the first dimension and high coordinates on the second dimension. Respondents in cluster 3 have high coordinates on the first dimension and significantly lower coordinates on the second dimension. Finally, respondents in cluster 4 have significantly high coordinates on the first dimension and significantly high coordinates on the second dimension. Figures 11 illustrate the graph indicating the distribution of respondents in clusters along the first dimension on the x-axis and the second dimension on the y-axis.

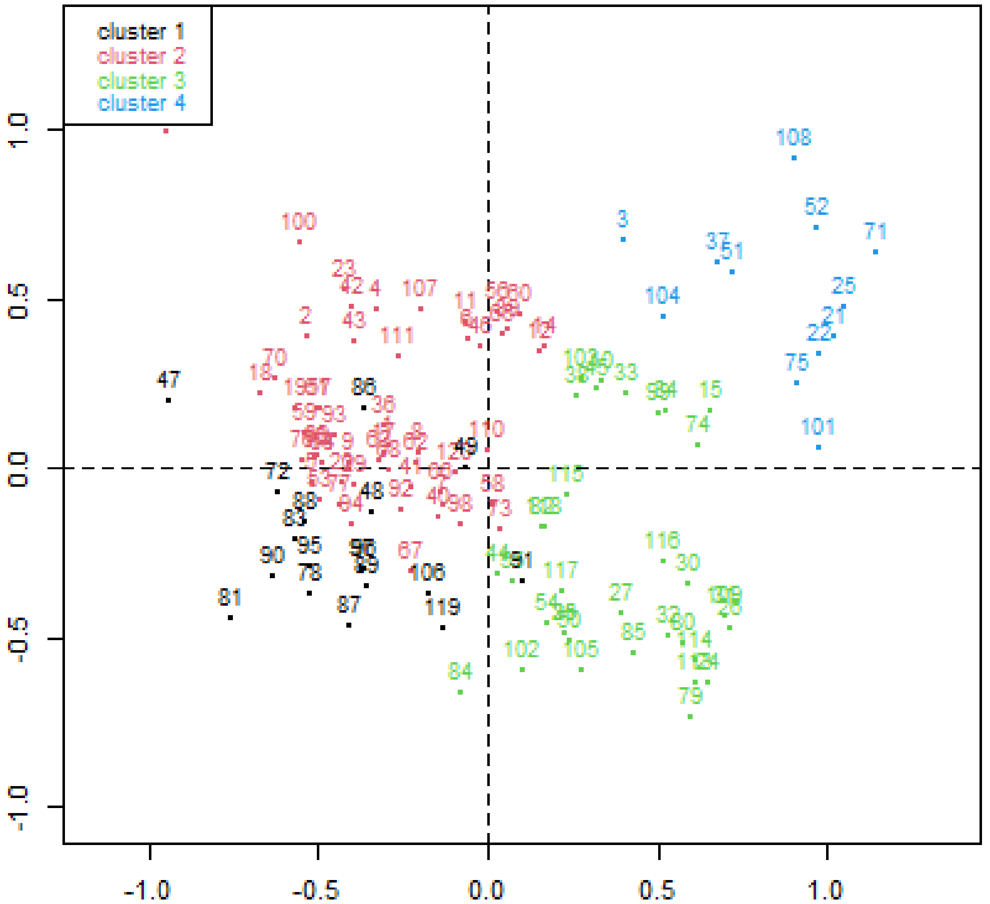
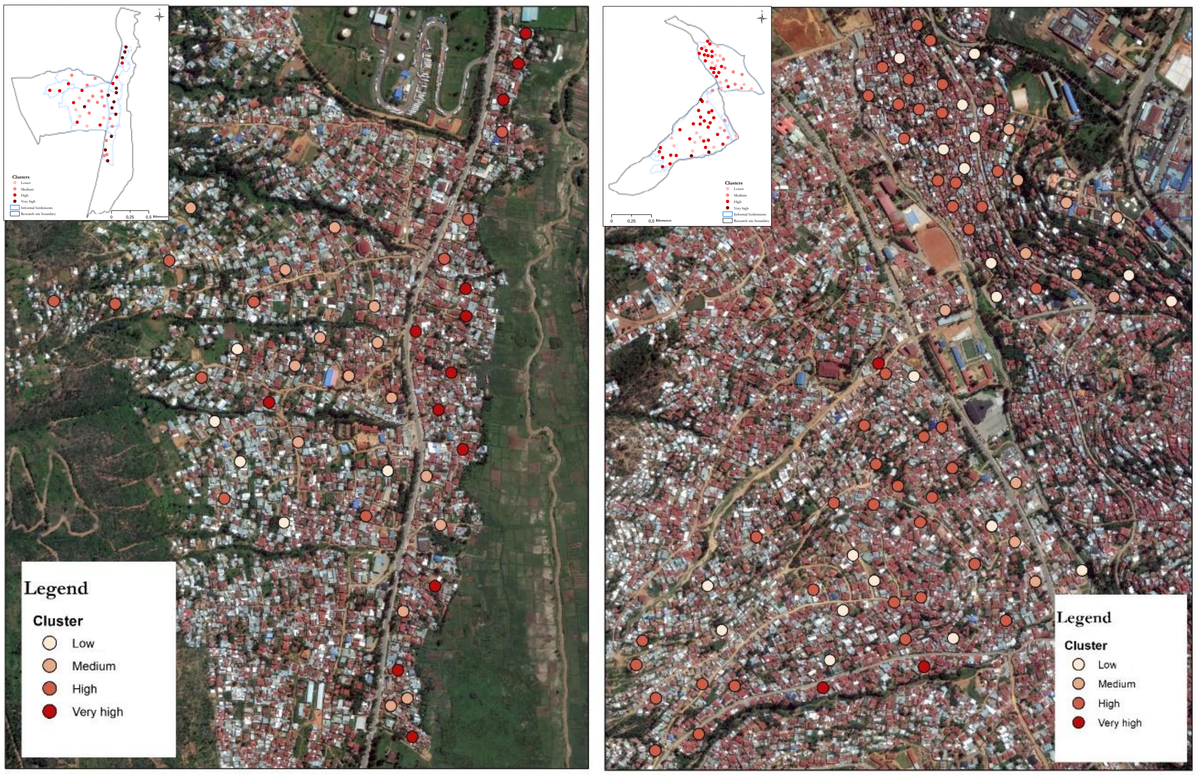


Figure 11: Clusters of respondents on along first and second dimension of MCA

Therefore, by bringing together the characteristics of the clusters based on indicators, variables and dimensions, cluster 1 is the one with respondents that have common variables representing very high perceived tenure insecurity, followed by cluster 2 with high perceived tenure insecurity, cluster 3 with medium perceived tenure insecurity and cluster 4 with low perceived tenure insecurity. Moreover, visual representation of the clusters on the map shows that respondents in the same clusters are spatially concentrated across the study area, as shown in figures 12 (a) and (b).



(a) (b)

Figure 12: The variation of perceived tenure insecurity across the study area

5.2. Spatial characteristics of the urban deprived area

The research relied on how different studies on deprivation conceptualise and spatially characterise urban deprived areas using information derived from earth observation. Typically, the research took advantage of the spatial characteristics of urban deprived areas gathered through the literature review as indicated in chapter 2 (sub-section 2.4.1, *Table 3*). Hence, spatial characteristics such as land cover information and texture features across the study were extracted area.

The research used the deep learning model to extract five land cover classes across the study area, as explained in chapter 4 (section 4.3). The model was trained on different patch sizes of input images. After different experiments, the model trained on the patch size of 128×128 pixels had the best performance compared to 64×64 and 256×256 pixels. Therefore, the model was deployed to extract land cover information for the study area.

The accuracy of the model on the test set was good, and the visual results are satisfactory given the quality of the image and the sparse training data (labels). The model performance was evaluated through the recall, precision and F1-Score metrics for each land cover class. The frequently seen classes had high accuracy than the rare class, which means the model had a better performance on dominant classes such as built-up area and dense green space than other classes. Table 11 illustrates recall, precision and F1-Score for each land cover class.

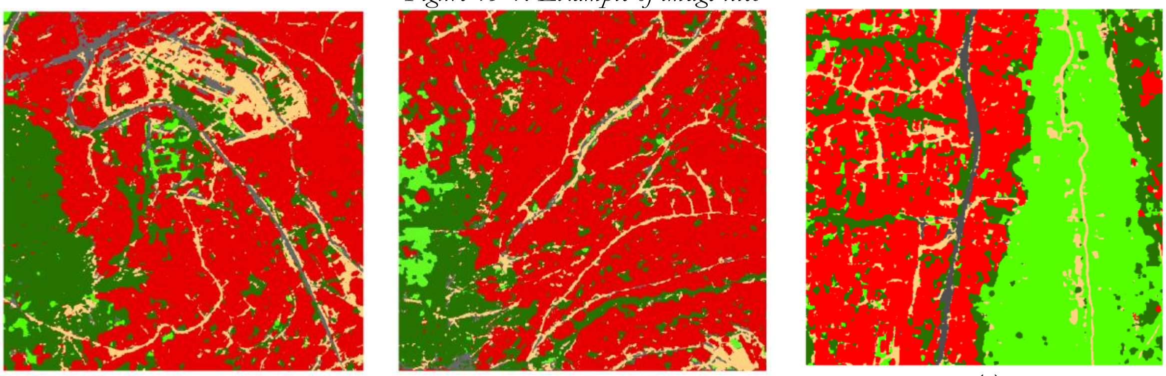
Table 11: Accuracy metrics for each land cover class

Land cover class	Recall	Precision	F1-Score
Built-up area	0.92	0.90	0.91
Low green space	0.88	0.89	0.88
Dense green space	0.93	0.91	0.92
Paved roads	0.85	0.84	0.84
Unpaved roads and bare lands	0.85	0.86	0.85

Figure 13-1 presents the samples of image tiles, and figure 13-2 presents the classification results of the U-Net model. The results show that the model performance to classify the study areas was quite good.

(a) (b) (c)

Figure 13-1: Example of image tiles



(a) (b) (c)

Built-up areas , Low green spaces , Dense green spaces , Paved roads ,
Unpaved roads and bare lands

Figure 14-2: Example of land cover classification results from the model

The results obtained were land cover features that characterise the study area in terms of built-up areas, low and dense green spaces, paved roads, and unpaved roads and bare lands. Therefore, land cover information obtained was aggregated based on 10, 15, 20 and 25 meters, respectively, to obtain land cover variables. These buffer areas were the main spatial analysis units for this research. The variables aggregated were: percentage of built-up area, low green space, dense green space, paved roads, and unpaved roads and bare lands. In addition to the information about land cover, the research extracted the information about texture features from the VHR GE image to complement land cover information. The research derived texture features from GLCM. These features were adapted as an alternative to other detailed information about the urban deprived area related to variation, such as building layouts and roofing conditions that could not be extracted from the VHR GE image due to its quality. Figure 14 visualises the texture features extracted from the sample of the VHR GE image tile of the study area.

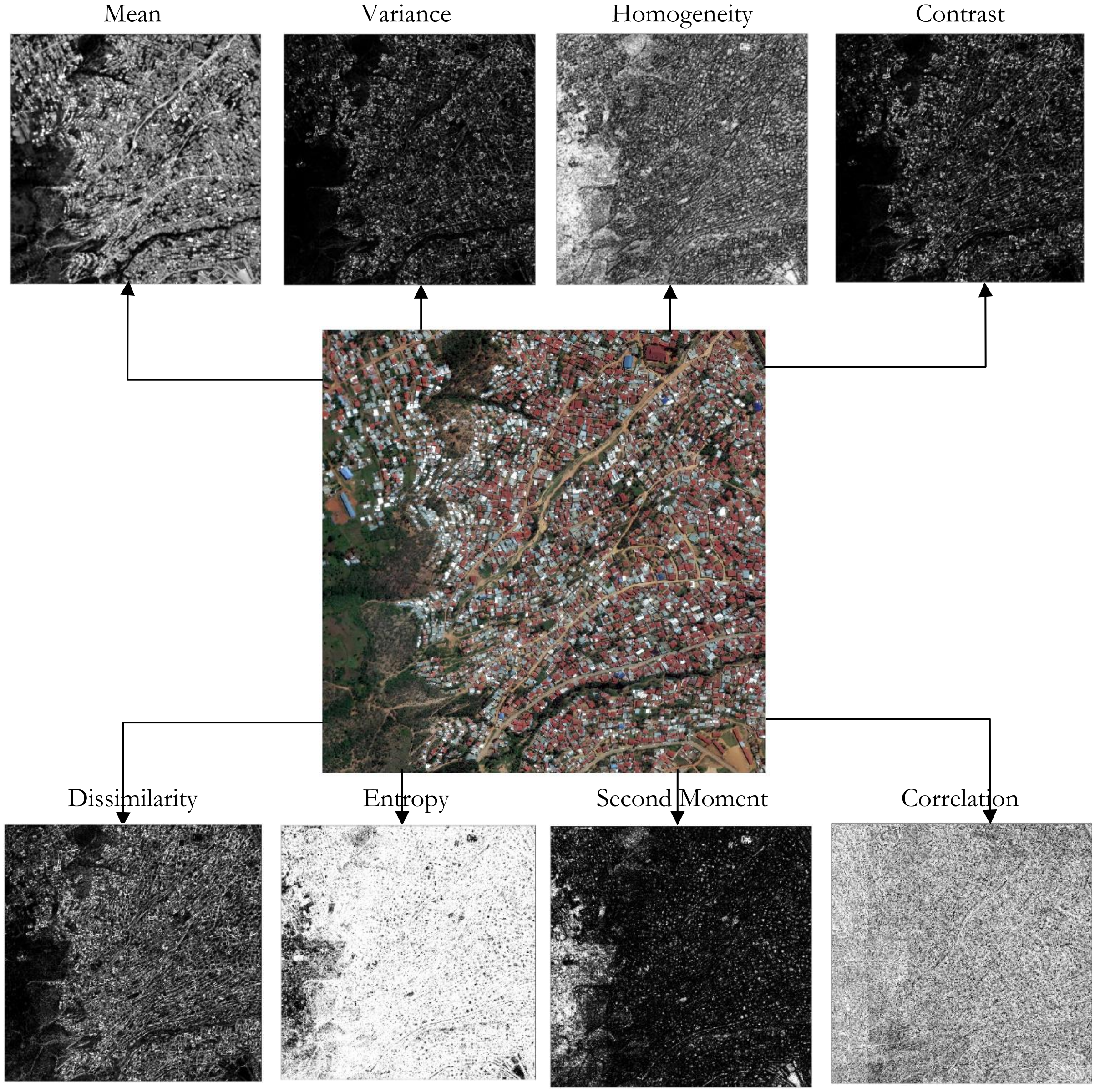


Figure 15: Example of GLCM texture features extracted from image tile

The GLCM texture features obtained were also aggregated based on the buffer areas (10, 15, 20 and 25 meters). Therefore, after extracting all spatial characteristics: image-based (land cover and texture features) and additional spatial information, the variables to establish the relationship with the PTI indices representing the variation of perceived tenure insecurity were obtained. The following section presents the results of that relationship.

5.3. Relationship between spatial characteristics of urban deprived areas and variation of perceived tenure insecurity

This section presents the relation between spatial characteristics of urban deprived area derived from the VHR GE image alongside other spatial information of the study area and the variation of perceived tenure insecurity derived from survey data. The section first presents results on spatial characteristics of the urban deprived area of the study area related to the variation of perceived tenure insecurity in the study area. Then follows the results on the relationship between spatial characteristics of urban deprived areas and variation of perceived tenure insecurity in the study area.

5.3.1. Spatial characteristics of urban deprived area related to the variation of perceived tenure insecurity in the study area

The research used the results presented in chapter 5, sub-section 5.1.1 (*Table 8*), to identify the physical environment indicators, among others, that best characterise the variation of perceived tenure insecurity in the study area. Furthermore, the research utilised the results on spatial characteristics of deprived areas obtained from the VHR GE image of the study area in section 5.2. Hence, identify spatial characteristics that describe the variation of perceived tenure insecurity in the study area. Table 12 summarises the spatial characteristics identified.

Table 12: Spatial characteristics describing the variation of perceived tenure insecurity in the study area

Physical indicators (from survey data)	**Spatial characteristics (detected from VHR GE image)**	**Comment**
Wall materials	-	Difficult to capture but can be captured using oblique VHR Unmanned Aerial Vehicle image
Location of the neighbourhood	-	Not detected (Slope was used instead)
House condition	+	Partially detected through GLCM texture and spectral features
Shape of the house	+	Partially detected through GLCM texture features
Presence of the wastes	-	Not detected
Size of the house	+	Partially detected through GLCM texture features
Dominant building size in the neighbourhood	+	Partially detected through GLCM texture features
Household access to the unpaved road	++	Detected as the unpaved road land cover class
Access to green space	++	Detected as the dense and low green spaces land cover class
Presence of unpaved road in the neighbourhood	++	Detected as the unpaved road land cover class
Presence of unpaved footpath	+	Not fully detected, but a portion of it detected as unpaved roads and bare lands

++ directly detected, + indirectly detected, – not detected

The results obtained after analysing the survey data through MCA have indicated that the physical environmental conditions of the neighbourhood and properties were among the indicators contributing to the perceived tenure insecurity of respondents. The results in *Table 12* identified physical environment indicators of perceived tenure insecurity in the study area that were detected through the earth observation approach. Unfortunately, the research could not extract very detailed and explicit information from the VHR GE image. However, it was possible to extract some useful information based on the physical environment that influences perceptions of respondents on tenure insecurity. Therefore, the research used land cover information, texture information and other spatial information to characterise the study areas spatially. The obtained spatial characteristics served as input variables to establish their relationship with the variation of perceived tenure insecurity, as illustrated in the following sub-section.

5.3.2. Relating spatial characteristics of urban deprived and variation of perceived tenure insecurity in the study area

The research developed the solution to the question of relating the variation of perceived tenure insecurity with spatial characteristics of urban deprived areas. The research used spatial characteristics derived from the VHR GE image and other spatial information characterising the area as variables for predicting perceived tenure insecurity.

The intention was to evaluate how spatial characteristics derived from the VHR GE image as well as other additional spatial information can predict perceived tenure insecurity across the study area. Therefore, the research undertook four modelling processes using Random Forest (a tree-based) regression model to establish the relationship between image-derived spatial characteristics of urban deprived areas and other spatial information with perceived tenure insecurity. The research used squared correlation coefficient (R^2) to evaluate the performance of all the modelling processes based on the relationship between image-derived variables and the combination of image-derived variables and additional spatial information. The available variables were split into two sets, whereby one set was used to train the model and the other for evaluating the modelling processes. The value of R^2 on the test set for each modelling processes are illustrated in table 13.

Table 13: Correlation coefficient between spatial characteristics of urban deprived areas from each buffer areas and the predicted variation of perceived tenure insecurity

	Buffer-wise squared correlation (R^2)			
Buffer (in meters)	10	15	20	25
Only VHR GE image derived spatial characteristics	0.22	0.27	0.45	0.44
With additional spatial information layers	0.40	0.36	0.60	0.61

Modelling processes using only image-derived spatial characteristics showed good performance for spatial characteristics extracted on a buffer area of 20 meters (R^2 = 0.45), followed by those extracted on a buffer area of 25 meters (R^2 = 0.44). Besides, the modelling processes using only image-derived spatial characteristics showed poor performance on characteristics extracted based on the buffer of 10 meters (R^2 = 0.22) and 15 meters (R^2 = 0.27), respectively.

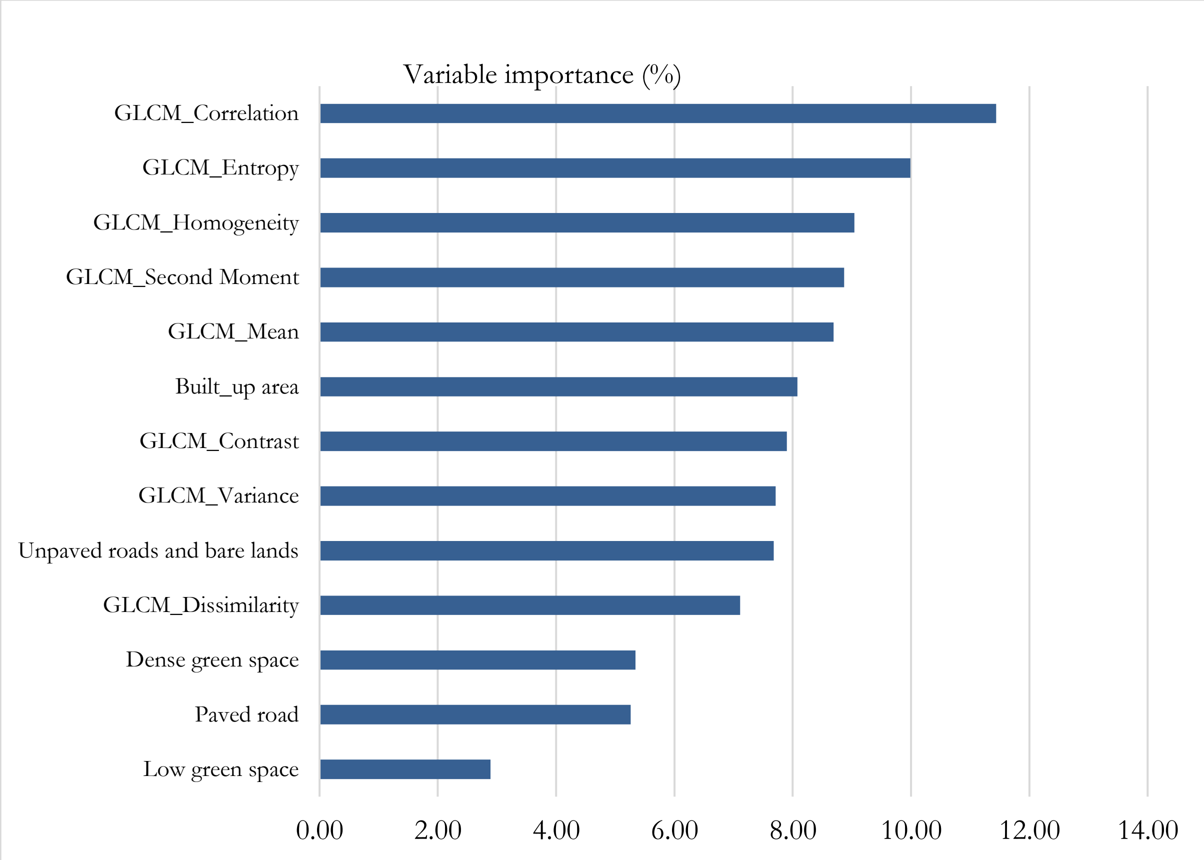


Figure 16: Variable importance based on image-based spatial characteristics extracted at the buffer of 20 meters

In addition to evaluating modelling processes through the values of R^2, the research also visualises the variable importance to understand the relevance of each variable in predicting perceived tenure insecurity. Figure 16 illustrates the variable importance of the modelling process based on the spatial characteristics extracted on the buffer of 20 meters, which illustrated the good performance.

Modelling processes using image-derived spatial characteristics and additional spatial information showed good performance for spatial characteristics extracted based on the buffer area of 25 meters ($R^2 = 0.61$), but not significantly different to the result of the modelling process using spatial characteristics extracted based on the buffer area of 20 meters ($R^2 = 0.60$). Furthermore, the modelling processes using image-derived spatial characteristics and additional spatial information showed low performance on characteristics extracted based on the buffer of 15 meters ($R^2 = 0.36$) and 10 meters ($R^2 = 0.40$), respectively. Figure 16 illustrates the variable importance of the modelling process based on the spatial characteristics extracted on the buffer of 25 meters, which illustrated the good performance.

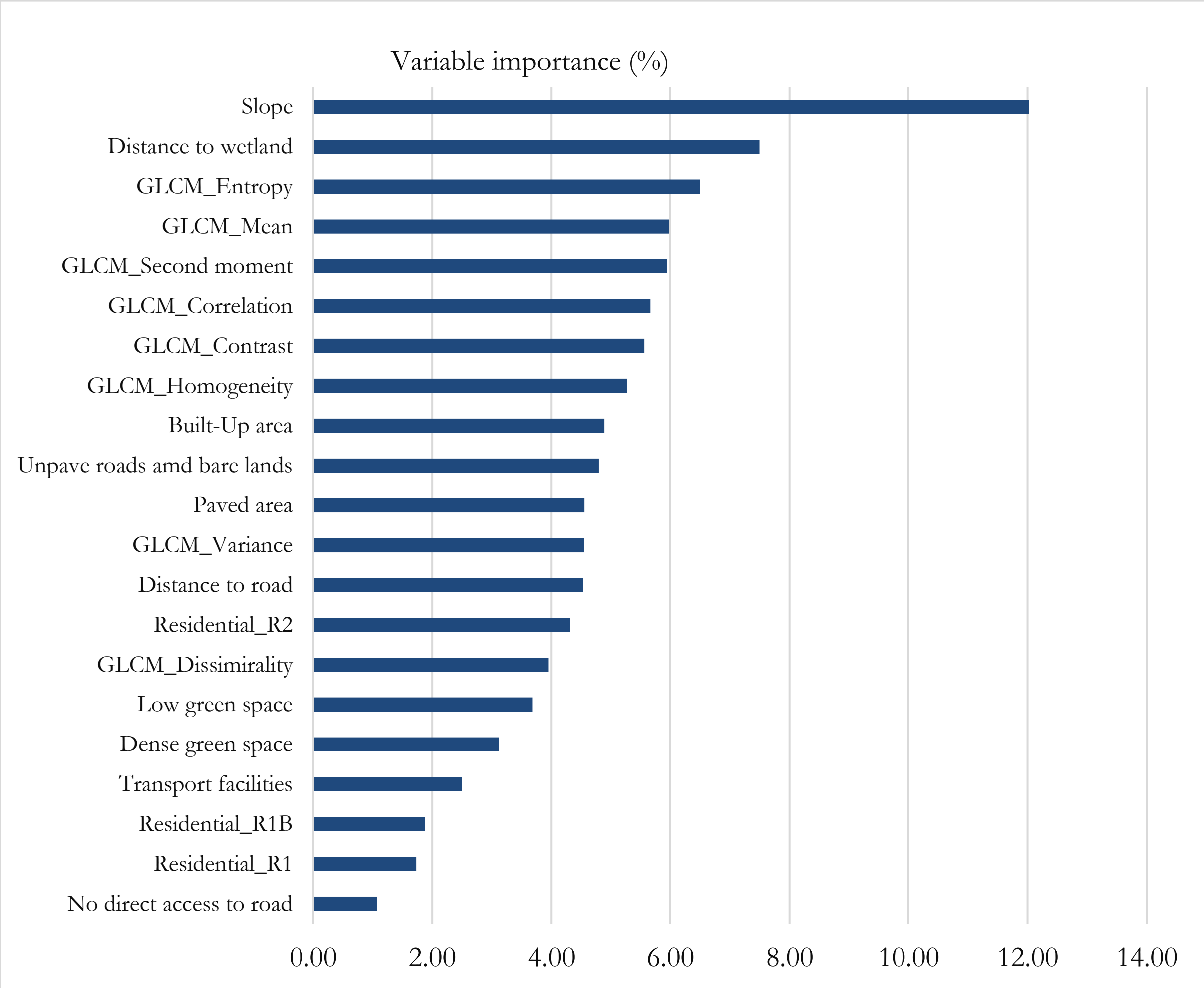


Figure 17: Variable importance based on image-based spatial characteristics and additional spatial at the buffer of 25 meters

The results show that correlations between image-derived spatial characteristics of the urban deprived area and perceived tenure insecurity are low (R^2 = 0.22 on the buffer of 10 meters and R^2 = 0.27 on the buffer of 15 meters) and moderate (R^2 = 0.45 on the buffer of 20 meters and R^2 = 0.44 on the buffer of 25 meters). Furthermore, the correlations between image-derived spatial characteristics alongside additional spatial information and perceived tenure insecurity are also moderate for the buffer of 10 meters and 15 meters(R^2 = 0.45 and R^2 = 0.36). However, the correlations between image-derived alongside additional spatial information and perceived tenure insecurity are almost high on the buffer areas of 20 and 25 meters (R^2 = 0.45 and R^2 = 0.36).

6. DISCUSSION

The previous chapter presents the results of this research. This chapter presents a discussion drawn from the analysis of results and limitations. It also presents the transferability assessment.

6.1. Results discussion

This research investigates the relationship between deprivation and perceived tenure insecurity by assessing the potential of earth observation-based information to measure and predict the variation of perceived tenure insecurity across the urban deprived areas. As mentioned in chapter 1, different researchers explored the capability of earth observation-based information to study and understand urban deprivation. This research is a continuation and evaluates whether there is a relationship between image-derived spatial characteristics of urban deprived areas and the variation of perceived tenure insecurity.

6.1.1. The variation of perceived tenure insecurity in the urban deprived area

The research started by identifying the indicators of perceived tenure insecurity in the urban deprived areas through the literature review (chapter 2, section 2.3). After that, a questionnaire was designed based on these indicators, and the survey data were collected and analysed. The purpose was to build Perceived tenure index (PTI) indices that represent the comprehensive variation of perceived tenure insecurity across the study area by covering all the indicators identified in the study area. The research used the MCA approach to analyse, visualise and identify variation (Di Franco, 2016) in the collected survey data, which resulted in PTI indices. The latter captured the variation of perceived tenure insecurity relying on survey data without assumptions or weights introduced to some data. Though the research agrees that some indicators may have more weight than others, weighting those indicators might introduce assumptions that may change the respondents' viewpoints. The application of MCA was considered to avoid bias that might arise from weighting categorical qualitative data, as Di Franco (2016) shows.

The results in chapter 5, sub-section 5.1.1 *Figure 10* show that apart from indicators related to tenure rights and perceptions on tenure rights, physical environment indicators contributed much to creating PTI indices. These indicators played a significant role in indicating the variation of perceptions of individuals on tenure insecurity. This was in line with Alizadeh et al. (2019), Payne et al. (2014), and other authors showed in chapter 2. The authors argue that perceived tenure insecurity is linked to the physical environment since people perceiving tenure insecurity are less likely to invest in their land and properties. Moreover, it is linked to the physical environment since it also increases due to political pressure for non-compliance to planning regulation, as shown by UN-Habitat (2016) and Chigbu, Alemayehu and Dachaga (2019). This aligns with the results obtained since the research sites are among the recognised informal settlements that will be redeveloped in the near future, as shown in the Kigali Master plan (City of Kigali, 2019). Therefore, it is important to note that the physical environment influences people's perceptions of tenure insecurity in the study area.

After the identification of PTI indices, the research clustered respondents into 4 clusters based on PTI indices, as shown in section 5.1.2. Clustering respondents allowed the research to understand the variation of perceived tenure insecurity among the respondents in a detailed way. This followed the same principle of clustering used by Liu et al. (2008) for identifying variation in data based on unsupervised classification. However, though clusters represent the respondents with similar perceptions of tenure insecurity, clusters were comprehensive when spatially mapped. Therefore, the spatial distribution of respondents based on their clusters was important for the study to spatially understand the variation of perceived tenure insecurity across the study area.

Interestingly, the result (see *Figure 12* in chapter 5, sub-section 5.1.2) shows that respondents in the same clusters were spatially concentrated. This revealed that respondents closer to each other have similar perceptions of tenure insecurity. Therefore, the concentration of respondents in the same cluster indicates that perceptions of tenure insecurity are a common problem across a certain area. Also, the spatial concentration of respondents in the same cluster can be justified by the existence of common causes inducing their perceptions of tenure insecurity. As shown in chapter 3 (section 3.1), the study area consists of informal settlements which are mainly targeted for the master plan implementation and mainly such areas across the city are acquired by large scale investors hence living dwellers in fear of losing their land and properties (Nikuze, Sliuzas, & Flacke, 2020). However, it is also important to consider other factors such as proximity to steep slope and wetland influenced the fear of losing the land and properties due to existing settlements and wetlands management regulations (Government of Rwanda, 2013). This also aligns with Durand-Lasserve (2012), who showed that tenure insecurity is also induced by vulnerability to risks and other hazards. Moreover, though all land parcels in the study area are registered, and owners were issued titles through the LTR program, the results confirm that dwellers still feel less secure, which is in line with Uwayezu and de Vries (2019), who showed that people can still feel less tenure security due to certain circumstance regardless whether they have land titles, as depicted in chapter 2, section 2.3.

Identifying the variation of perceived tenure insecurity served as a basis for identifying the relationship between spatial characteristics of urban deprived area and variation of perceived tenure insecurity. The reason to focus on identifying and measuring the variation of perceived tenure insecurity was the need to have a comprehensive variation of perceived tenure insecurity that would make the relationship real and understandable. This means moving from PTI indices towards the understandable variation of perceived tenure insecurity across the study area. This added significance to the meaning of the PTI indices derived from MCA using the survey to identify perceived tenure insecurity and the need to explore its linkage to the spatial characteristics of the study area.

6.1.2. Spatial characteristics of the urban deprived area

Urban deprived areas present different physical characteristics that can be spatially detected through earth observation, as shown by different researches (e.g. Lilford et al., 2019; Kuffer et al., 2018; Wurm & Taubenböck, 2018). The research applied a U-Net model architecture of CNN to extract land cover information that spatially characterises the study area. The land cover information extracted consists of existing built-up areas, paved roads, unpaved roads and bare lands, low and dense green spaces, as shown in chapter 5 (section 5.2). The use of land cover information to characterise the urban deprived areas for this research was in line with other researches that followed the same approach. For instance, Arribas-Bel et al. (2017) used the land cover information as basic variables for predicting living environment deprivation, and Georganos et al. (2019) used land cover information to model household wealth. Though the research could not detect detailed land cover information, it bridged this barrier by extracting GLCM texture features from the VHR GE image of the study area. Texture features play an important role in spatially characterising urban deprived areas (Kuffer et al., 2017; Kohli et al., 2016). These have been used in urban deprivation studies as an alternative for characterising spatial arrangements of objects of an area in an image, as shown in chapter 2 (sub-section 2.4.1).

Although the research did not derive much detailed land cover information from the VHR GE image due to the quality, the results were encouraging. Instead of employing a commercial VHR earth observation image with enough resolution to detect many details, the research was limited to the freely available VHR GE image. Most researches (e.g. Wang et al., 2019; Ajamie et al., 2019; Bergado et al., 2016) on urban deprivation, as shown in chapter 2, employed VHR remote sensing images. However, as indicated in chapter 3 (sub-section 3.2.2), those images are available for a high cost, limiting institutions and countries with limited financial resources to use them. Therefore, it was a privilege for this research to take advantage of the freely available image data.

6.1.3. Relationship between spatial characteristics of urban deprived area and variation of perceived tenure insecurity

The research did four modelling processes to find the relationship between only image-derived spatial characteristics of the urban deprived area with the variation of perceived tenure insecurity across the study area. The research has indicated that spatial characteristics of urban deprived area derived from VHR GE image can predict the variation of perceived tenure insecurity with R^2 of 0.45 and 0.44 at the buffer of 20 and 25 meters, respectively. Furthermore, the research did modelling processes using both spatial characteristics derived from the VHR GE image and additional spatial information. The combination of image-derived spatial characteristics and additional spatial information had more potential to predict the variation of perceived tenure insecurity with R^2 increased to 0.60 and 0.61 at the buffer of 20 and 25 metres, respectively.

The buffer of 20 and 25 metres enabled the extraction of more important spatial characteristics around the location of sample respondents than buffers of 10 and 15 metres. The effect of the buffer can be linked to the spatial concentration of respondents with similar perceptions of tenure insecurity. This means respondents in the same areas have almost the same perceptions concerning perceived tenure insecurity and share similar spatial characteristics. Thus, allowing the model to learn more important spatial characteristics improved the results. The research considered buffer areas as a basic analysis unit for extracting spatial characteristics since considering the administrative unit as a basic analysis unit would be meaningless due to the variation in the size of an administrative unit that is officially delineated as deprived areas. Thus, buffer areas helped to avoid incorporating irrelevant information in modelling processes. In addition to the buffer consideration, the research also considered the multicollinearity among all the spatial characteristics of urban deprived areas extracted from the study area. Multicollinearity between spatial characteristics would cause the model to give poor results. The research applied the Random Forest model, one of the tree-based models, and is resistant to multi-collinearity (Arribas-Bel et al., 2017). Thus, the research was able to use all the extracted spatial characteristics in the modelling processes and allowed the research to find the importance of each characteristic in an interpretable manner.

The research found that texture features play an important role with high predictive significance. This reflects how urban deprivation is conceptualised and spatially characterised (e.g. see Abascal et al., 2021; Kuffer et al., 2020; Thomson et al., 2019; Lilford et al., 2019; Kohli et al., 2012), as illustrated in chapter 2 (section2.2 and sub-section 2.4.1, respectively) and discussed earlier. Therefore, using detailed spatial characteristics sourced from commercial VHR images instead of texture features would increase the significance of this research since texture features are not very comprehensive to humans. So there is a trade-off between using costly VHR images and using freely available VHR images.

Interestingly, despite the quality of the VHR GE image used, the relationship obtained was impressive. This can be attributed to the fact that the physical conditions influencing perceived tenure insecurity in the study area as identified from survey data (see chapter 5 sub-section 5.3.1) were similar to the physical characteristics of urban deprived areas, as depicted in chapter 2 subsection 2.4.1. Moreover, it is important to note that perceived tenure insecurity exists as one of the challenges faced by urban deprived dwellers (UN-Habitat, 2003). Therefore, it was interesting to see that earth observation can capture the variation of perceived tenure insecurity.

Moreover, additional spatial information had a high predictive significance, mainly slope and distance to wetland. This can be traced back to the existing regulations and current activities of displacing people living in urban deprived areas and high-risk zones in Kigali city (see Uwayezu & de Vries, 2020 and Nikuze et al., 2019). Generally, the additional spatial information was linked with the factors inducing the perceptions on tenure insecurity for the people of the study area. This information is closely related to regulations such as zoning regulation and urban redevelopment policies in Kigali city (City of Kigali, 2019). Therefore, it is worth considering that the importance of additional spatial information for predicting the variation of perceived tenure insecurity opens the door to the possibility of exploring other spatial information that may have a strong significance.

The important outcome of this research is the identification of the variation of perceived tenure insecurity in urban deprived areas and the potential of earth observation-based information alongside other spatial information to measure and predict such variation. Thus, the research demonstrates the potential of geospatial information for understanding perceived tenure insecurity across urban deprived areas. Another significant outcome of this research is the contribution to the literature on the usefulness of earth observation to measure and predict perceived tenure insecurity in urban deprived areas. Though earth observation-based information can not fully replace ground survey for measuring tenure insecurity, the research demonstrates that earth observation can estimate perceived tenure insecurity where there is a lack, gap, or outdated information about tenure insecurity. Therefore, the research serves as a basis for further exploration of earth observation-based information in measuring tenure insecurity for obtaining the required information to monitor the implementation of SDGs goal 1 (target 1.4) and goal 11. Besides, this research complements other existing research in the same field on providing methods for obtaining useful information for inclusive urban policies formulation and implementation.

6.2. Limitation

As highlighted several times in the text, the VHR GE image used was freely accessed, and it has low quality compared to VHR images acquired from commercial providers. In addition, the VHR GE image used in this research has poor spectral information since it only has visible bands, Red, Green and Blue (Hu et al., 2013). This affected its ability to discriminate against some land cover classes such as water. It also had a negative impact on the results of image classification due to the shadow. Furthermore, the physical environment indicators such as building size, shape and condition that contributed to respondents' perceptions on perceived tenure insecurity were hard to detect using the available VHR GE image directly. Though texture features were used to consider that detailed information, there are not well comprehensive to humans.

The other limitation to highlight is the field survey data that measured respondents' perceptions of tenure insecurity. This kind of information is often not available in most census data. The research relied on the sample of data collected from the study area. However, the sample was collected across three research sites based on the administrative level, which is small in size, and the sample collected from these sites was not sufficient due to the time limitation, resources and constraints of the Covid-19 pandemic during which the research took place. This might have caused some uncertainty in the results since the research employed a tree-based model proven to have the best performance on a large dataset.

6.3. Transferability assessment

This research provides new evidence about the potential of earth observation-based information alongside other spatial information to measure the variation of perceived tenure insecurity. It is important to consider that the spatial characteristic of urban deprived areas conceptualised depending on the place (Kuffer et al., 2020). Besides, the variation of perceived tenure security is linked to several events and regulations, which also differ from place to place. In this regard, the scalability and transferability of this research must focus on the overall methods employed rather than considering spatial characteristics and the variation of perceived tenure insecurity used in this research because they are location dependent. Therefore, methods used in this research such as MCA, clustering, CNN model and Random Forest regression model can be transferred to other contexts by feeding them with new sample data. Though new CNN architecture or other types of tree-based models can be introduced, and tuning of their hyperparameters may differ from what is employed in this research, but the general analytical framework remains the same.

7. CONCLUSION AND RECOMMANDATION

The previous chapter discusses the results of this research. It discusses results on identifying variation of perceived tenure insecurity across the study area, spatial characteristics of urban deprived areas detected in the study area, and the relationship between those spatial characteristics and variation of perceived tenure insecurity in the study area. This chapter concludes the research and presents the recommendations for the possibilities for further research.

7.1. Conclusion

The general objective of this research is to leverage the power of earth observation to study the variation of perceived tenure insecurity within the urban deprived areas and further analyse its relationship to spatial characteristics of deprivation. There is a continuous need to explore the capabilities of earth observation-based information for bridging the gap of the lack of up-to-date information about urban deprivation. In this regard, different researches have explored the potential of earth observation-based information to understand different aspects of urban deprivation due to the lack of base data on tenure insecurity. In this regard, tenure insecurity, one of the challenges within deprived areas, was not given more attention. Therefore, this research focused on exploring the potential of earth observation-based information and other spatial information for understanding the variation of perceived tenure insecurity. To achieve the main objective of this research, three sub-objectives were identified, and the main objective was achieved by answering their related research questions.

The first sub-objective is to characterise perceived tenure insecurity within the urban deprived areas. Two research questions guided this sub-objective: The first is "what are the major indicators of perceived tenure insecurity in urban deprived areas based on the literature are?". The second is "what is the variation of perceived tenure insecurity in the study area?" The research identified indicators for measuring perceived tenure insecurity based on the literature to answer those research questions. The identified indicators were the basis of the design of the questionnaire used for survey data collection across the study area. The research has collected the survey data and employed MCA to identify and understand patterns in survey data. The research relied on MCA as the primary analysis method to create indices of perceived tenure insecurity. The indices were used to understand the variation of perceived tenure insecurity across the study area. Each index was assigned to the respective respondents, and respondents were clustered based on their indices' value. Four clusters were obtained. They represent respondents with very high, high, moderate and low perceived tenure insecurity. Clusters were spatially mapped, and the research identified the spatial concentrations of the respondents having similar perceptions of tenure insecurity across the study area.

The second sub-objective is to extract spatial characteristics of deprived areas from VHR remote sensing image. This sub-objective has two research questions. The first research question is "what is the appropriate deep learning model for detecting spatial characteristics of urban deprived areas in the study area? " The second research question is "what are the spatial characteristics of urban deprived areas in the study area? " The research answered those research questions by reviewing the literature concerning the application of deep learning to analyse VHR earth observation images. The research identified CNN as the best deep learning model for detecting spatial characteristics of the urban deprived area. Furthermore, the research has applied the CNN model through U-Net architecture to detect spatial characteristics of the study area. The research extracted five land cover classes and eight extracted texture features, and other spatial information to complement the land cover information of the study area. All the extracted information spatially characterised the study area and were aggregated based on buffer areas across each survey respondent.

The last sub-objective is to analyse the relationship between spatial characteristics of urban deprived areas and variation of perceived tenure insecurity. This sub-objective consists of two research questions: The first research question is "which spatial characteristics of urban deprived areas can be related to the variation of perceived tenure insecurity in the study area? " The second research question is "how are these characteristics related to the variation of perceived tenure insecurity in the study area? " Those research questions were answered based on the identification of spatial characteristics detected from the study area and the indicators of perceived tenure insecurity identified in the study area. Therefore, the research has applied the modelling processes to establish how those spatial characteristics can predict the variation of perceived tenure insecurity. The research demonstrated that image-derived spatial characteristics of the deprived area could predict the variation of perceived tenure insecurity with R^2 equals to 0.45 and 0.44 on the buffer of 20 and 25 metres, respectively. R^2 increased to 0.60 and 0.61 on the buffer area of 20 and 25 metres by adding additional spatial information. Furthermore, the research illustrated spatial characteristics with the high potential of predicting perceived tenure insecurity in the study area.

The study measured the variation of perceived tenure insecurity. Besides, the study extracted spatial characteristics of urban deprived areas from the VHR GE image and additional spatial information that characterise the urban deprived areas. Moreover, the research established the relationship between spatial characteristics of the urban deprived areas and the variation of perceived tenure insecurity. Therefore, based on the results, research demonstrated a promise of earth observation-based information to measure the variation of perceived tenure insecurity across urban deprived areas.

7.2. Recommendations

Chapter 6 (section 6.2) highlights the limitations of this research. Finally, this section lists possible directions for further research regarding the presented limitations:

- This research used the VHR GE image with low quality and poor spectral information, which did not allow the extraction of more detailed spatial information of the study area. Further research could explore the possibility to use an ultra-VHR image with good spectral information. This would allow the extraction of detailed and easily understandable spatial information of urban deprived areas such as building layouts, building size and conditions.
- Additional spatial information of the study area has shown the capability to improve the results of the modelling processes. However, it would be advantageous for further research to explore the potential of adding different spatial information in the analytical workflow.
- This research also employed survey data collected from the study area to identify the variation of perceived tenure insecurity. However, the available data was not enough. Therefore, it could be more efficient for further research to consider more samples to identify the variation of perceived tenure insecurity.
- This research showcased the potential of earth observation-based information to measure and predict the variation of perceived tenure insecurity across the urban deprived areas. Further researches could test the implementation of this approach on different urban deprived areas based on larger areas or city level with different morphology to evaluate the scalability of the presented approach. Therefore, this would be one of the steps to upscale the presented approach, which could result in regional, continental and global layers of areas with levels of perceived tenure insecurity in support of SDGs goal 1 target 1.4 and goal 11.

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APPENDIX

Annex 1: Questionnaire for survey

This interview is part of field data collection to support academic research on "Perceived tenure insecurity and its relation to deprivation: From a geospatial perspective". The research is part of the fulfilment of the requirement for the Degree of Master of Science in Geo-information Science and Earth Observation at the Faculty of Geo-information Science and Earth Observation, The University of Twente, the Netherlands. The answers given to this questionnaire will be kept confidential and will be used only for academic research purpose.

Location:

Sector ………………………….

Cell……………………………...

Village…………………………..

Date: /   /   Household given number ☐

Household given number

Respondent Gender: Male ☐ Female ☐

Position household: Head of Family ☐ Other, specify ………..……………………...

SECTION 1: PHYSICAL ENVIRONMENT

1. Which of the following exist in your neighbourhood? (Select all that apply and if possible, indicate approximate percentage)
   - ☐ Paved roads
   - ☐ Unpaved roads
   - ☐ Paved footpaths
   - ☐ Unpaved footpaths
   - ☐ Electricity
   - ☐ Public water taps
   - ☐ Garbage/wastes
   - ☐ Open sewers
   - ☐ Greenspace
   - ☐ Open space (vacant space)

   Dominant building sizes
   - ☐ Small
   - ☐ Medium
   - ☐ Large
2. How do you characterize the location of your neighbourhood? (Select all that apply)
   - ☐ Steep slope
   - ☐ Proximity to watershed
   - ☐ Proximity to wetland
   - ☐ Lowland
   - ☐ Other, specify……………………………………………………………………….

3. How would you characterize the property/house you live in?

Size:
- ☐ Very small
- ☐ Small
- ☐ Medium
- ☐ Large

Shape:
- ☐ Simple
- ☐ Complex

Building condition:
- ☐ New
- ☐ Old

Roof materials:
- ☐ Plastic/Polythene
- ☐ Tile
- ☐ Iron sheets
- ☐ Concrete
- ☐ Other…………………………………

Wall materials:
- ☐ Wood
- ☐ Wood and mud
- ☐ Unburnt brick
- ☐ Burnt brick
- ☐ Stone
- ☐ Concrete
- ☐ Others…………………………

4. Does your property/house has access to:
- ☐ Water supply
- ☐ Electricity
- ☐ Paved road
- ☐ Unpaved road
- ☐ Reliable garbage pickup
- ☐ Latrine/toilet facility

SECTION 2: ASSESSMENT OF TENURE RIGHTS

1. How long have you lived in this area? (land/property)
- ☐ Less than 1 year
- ☐ Between 1 and 5 years
- ☐ Between 5 and 10 years
- ☐ Longer than 10 Years

2. How did you acquired this land/property?
- ☐ Inherited from my family
- ☐ Bought from private individual
- ☐ Acquired by donation
- ☐ Acquired from government
- ☐ Acquired from exchange
- ☐ Squatted
- ☐ Others, specify……………………………………………………………………….

3. How long do you think you will continue to live here? Your best estimate is fine.
- ☐ Less than 1 year
- ☐ Between 1 and 5 years
- ☐ Between 5 and 10 years
- ☐ Longer than 10 Years/lifelong
- ☐ Don’t know

4. What type of tenure rights do you have on this land/property?
   - Freehold
   - Leasehold
   - Sub-lease
   - Other, specify ………………………………………………

5. Do you have documentation of the tenure/property rights on this land/property?
   - Yes
   - No

   If yes, what kind of document do you have on this land/property?
   - Land registration certificate
   - Freehold title
   - Lease agreement
   - Other, specify, ………………………………………………

SECTION 3: ASSESSMENT OF PERCEPTION ON TENURE RIGHTS

1. Have you ever been moved out/expropriated from your land/property?
   - Yes
   - No

   If yes, What were the reasons:
   - Slum upgrading
   - Urban (re)development/ masterplan
   - Infrastructure development
   - Other, specify………………………………………………

2. How likely is that you could lose the rights on your land/property in the next 5 years against your willingness?
   - Very likely
   - Somewhat likely
   - Unlikely
   - Very unlikely

What are the source of potential loss of your land/property if very likely or somewhat likely? (Select all that apply)
   - Proximity to wetland
   - Steep slope
   - Proximity to drainage/sewage canal
   - No access to infrastructure (road, water, electricity, etc.)
   - Urban (re)development/ masterplan
   - Slum upgrading
   - Expropriation
   - Seizure of my land property by government or companies
   - Other, specify…………………………………………………………………………

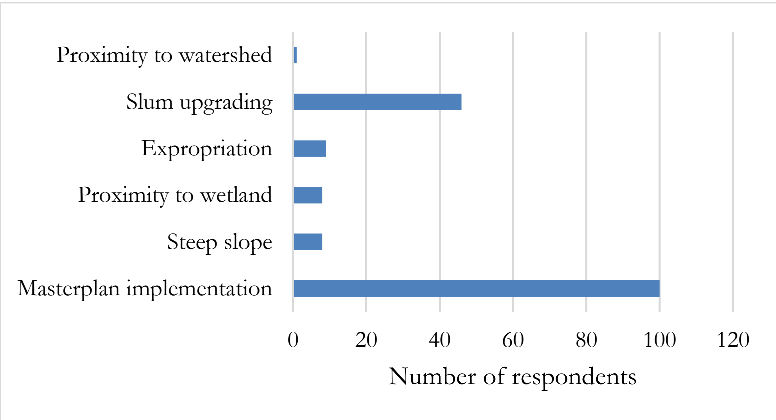
3. Which of the following are likely to happen to you in case of unwilling loss of your land/property?
   - Eviction
   - Relocation
   - Upgrading

- ☐ Land readjustment
- ☐ Joint development with investors
- ☐ Fair compensation
- ☐ Unfair compensation
- ☐ Others, specify……………………………………………………….

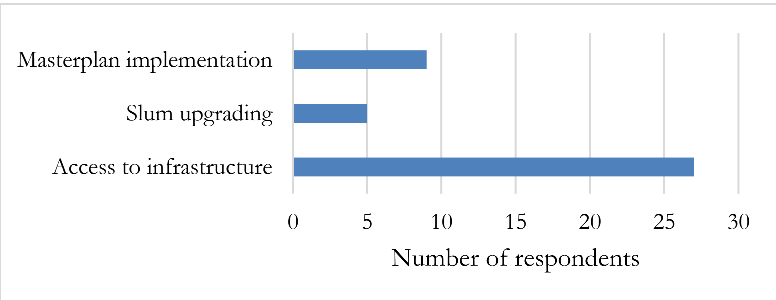
4. How strongly do you feel the authorities would protect you in case of potential loss of your land/ property?
   - ☐ Very strongly
   - ☐ Fairly strongly
   - ☐ Not strongly
   - ☐ Not at all
   - ☐ Neutral

Annex 2: Reasons for respondent's perceptions of tenure insecurity in the study area

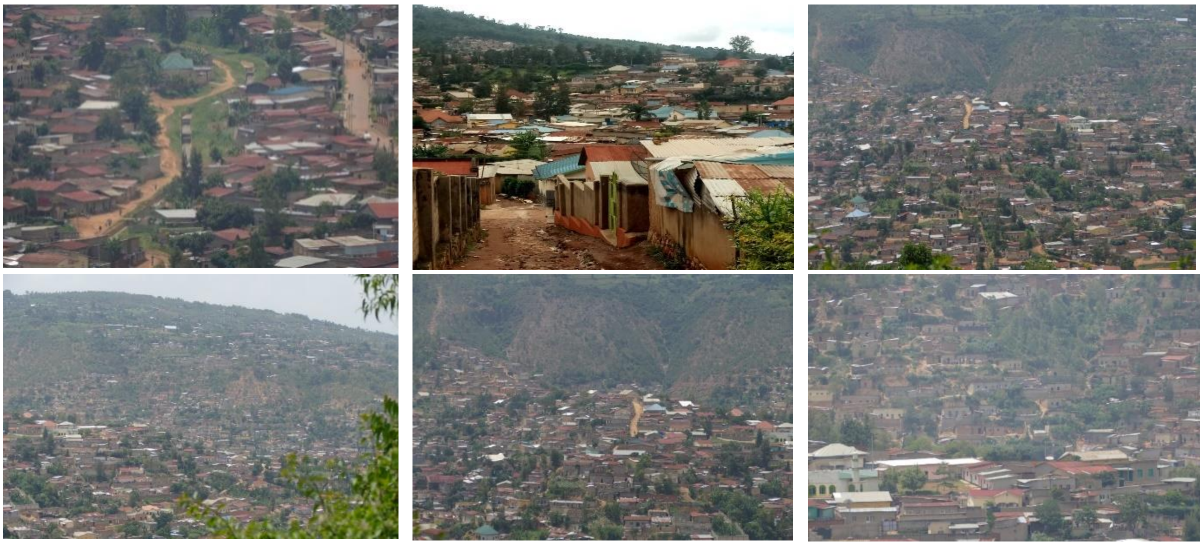
Possible causes for people likely and somewhat likely to lose their properties in next coming 5 years



Reasons for experienced eviction



Annex 3: Examples of photos displaying the ground situation of the study area



Annex 4: Training samples

Land cover	Number of sample
Built-up area	484,479
Low green space	68,157
Dense green space	79,579
Paved roads	33,110
Unpaved roads and bare lands	67,916

Annex 5: Model training loss graph