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An Analysis of Urban Land use land cover (LULC) Changes in Lilongwe City, Central Malawi (2002–2022)

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Abstract

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Zola Manyungwa

Lilongwe, Malawi's capital city, has grown nearly tenfold in the last 40 years with a 4-5% annual population growth rate, and the city's population is projected to double over the next decade. Rural to urban migration and natural increase are the driving factors of the city's urban expansion. Characterised by the urbanisation of poverty, Lilongwe is experiencing uncontrolled and unplanned urban expansion that has led to the growth of informal settlements. Urbanisation leads to land use land cover (LULC) changes that negatively impact the quality of life and the environment. Lilongwe faces many challenges, including high levels of poverty, inequality, poorly built infrastructure, lack of access to safe sanitation and clean water, urban flooding, and poor waste disposal. Effective land use planning is important in mitigating future urbanisation's adverse effects. To prepare and plan for the inevitable future urban growth of the city, studies of historical land use land cover changes are essential in understanding the urbanisation trajectory of the city. This study used post classification change detection and the SLEUTH urban growth model to analyse land use land cover changes in Lilongwe from 2002 to 2022. Results revealed that Lilongwe's urban growth is characterised by the expansion of built area coverage within and on the edges of already existing urban clusters. While urban growth is apparent in all parts of the city, it is concentrated in the northwest, southwest, and southeast.

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1 Introduction

Africa is one of the fastest urbanising continents in the world, with the Sub-Saharan Africa (SSA) region registering the world's highest urban growth rate of 5% per year since the early 1970s (Agyemang, 2019; Hove et al., 2013). Driven by various factors, urbanisation in Sub-Saharan Africa is mainly uncontrolled and uncoordinated due to governments' liberation of the housing sector in attempts to bridge the housing gap caused by the rapidly growing urban population (Yiran et al., 2020).

The urban population growth in Malawi is higher than the national population growth rate, with 16% of the national population living in urban areas. By 2050, 20% will reside in urban areas (National Statistical Office, 2018). Attributed to various factors, urbanisation in Malawi is unplanned and has resulted in the multiplication and expansion of informal settlements, poor infrastructure and poor service delivery in both established and emerging towns, resulting in increased vulnerability to disasters (Manda, 2013; Phiri et al., 2019). Rapid and unplanned urban growth has adverse health, environmental and socio-economic consequences, such as the development of slums, traffic congestion, urban flooding, the outbreak and spread of diseases such as cholera, pollution, crime and overcrowding.

Urbanisation leads to land use land cover (LULC) changes due to the growing population's demand for land. The terms land use land cover jointly refer to human utilisation of the earth's physical landscape, and LULC changes indicate changes in humans' utilisation and function of the land. In the urban context, changes comprise the natural landscape mainly being replaced by an impervious surface which has negative impacts on the ecosystem, the hydrological processes, biodiversity, microclimate, the ecological habitat, water quality, air quality and the environment (Das & Angadi, 2022; Li et al., 2014). Urban planners must be aware of the potential implications of urban expansion on land use land cover (LULC) for effective planning and sustainable development.

Integrating remote sensing methods and quantitative spatial analysis can be used to analyse LULC changes. Geospatial technologies and remote sensing LULC changes at high temporal precision and lower costs than traditional methods (Hegazy & Kaloop, 2015). Studies of urban

LULC changes using remote sensing data, such as those provided by the Landsat program, are essential for land management and urban land use planning (Alqurashi & Kumar, 2013; Mawenda et al., 2020). Urban expansion prediction and simulation models using different algorithms have also been developed to enhance urban growth studies.

Lilongwe, Malawi's capital city, has grown nearly tenfold in the last 40 years with a 4-5% annual population growth rate, and the city's population is projected to double over the next decade, with a population of approximately 2 million by 2033 (Strachan et al., 2021). Despite this recorded and projected growth, most of the city remains unplanned. The city faces many challenges, some of which can be attributed to the unplanned urban sprawl, and these include high levels of poverty, inequality, poorly built infrastructure, lack of access to safe sanitation and clean water, urban flooding, poor waste disposal and crime (Phiri et al., 2019). Despite the stated challenges, Lilongwe's urban research is quite limited (Mwathunga & Donaldson, 2018). This study, therefore, analyses the changes in LULC in Lilongwe from 2002 to 2022 using remote sensing and the SLEUTH urban growth model.

2 Literature review

2.1 Urbanisation in Africa

The African continent is one of the fastest urbanising continents in the world, and its total population is projected to reach almost 2.5 billion people by 2050, with about 55% of the population expected to live in urban areas (Güneralp et al., 2017). By 2050, the African urban population will account for 20.2% of the total global urban population (Saghir & Santoro, 2018). Rural-urban migration significantly contributes to the rapid urban growth in most African urban cities (Hegazy & Kaloop, 2015; United Nations, 2018; Yiran et al., 2020). People move from predominantly poor rural areas for social and economic opportunities. In recent years, the adverse consequences of climate change have been an additional factor in rural-urban migration. The increased immigration and rapidly growing urban population increase the demand for built infrastructure like housing, resulting in the unorganised development and occupancy of undeveloped urban spaces and the expansion of urban land uses into rural areas (Yiran et al., 2020).

2.2 Urbanisation in Sub-Saharan Africa

Sub-Saharan Africa (SSA) has had the world's highest urban growth rate, averaging 5% per year, since the early 1970s. It is expected to play a leading role in future global urbanisation patterns (Agyemang, 2019; Hove et al., 2013). Although some researchers attribute the rapid urban growth in Africa to rural-urban migration (Hegazy & Kaloop, 2015; United Nations, 2018; Yiran et al., 2020), the United Nations, Department of Economic and Social Affairs, Population Division (2019) argues that the trend of urbanisation in Sub-Saharan Africa has happened concurrently with dropping mortality and fertility rates characteristic of the demographic transition. Hove et al. (2013) state that the growth can be attributed to some African governments adopting post-independence macro-economic policies that increased urbanisation dramatically to nearly 40% presently. Regardless of the various explanations suggested for the rapid growth of urban areas in Sub-Saharan Africa, it is undeniable that the region's cities are expanding at an alarming rate. Rapid and unplanned urban growth has adverse health, environmental and socio-economic consequences, such as the development of slums, traffic congestion, urban flooding, the outbreak and spread of diseases such as cholera, pollution, crime and overcrowding (Fabiyi, 2006). Urban slum dwellers face the most significant exposure to environmental and health consequences of urbanisation.

The capacity of urban planners to successfully plan for and cater to the growing population is inadequate, and in regions such as Sub-Saharan Africa, inadequate urban planning has been identified as a risk factor. Saghir and Santoro (2018) explain that when rapid urbanisation is inadequately planned and occurs alongside widespread poverty, countries increase their vulnerability to the adverse effects of urbanisation and reduce their resilience. Rapid urbanisation in Sub-Saharan Africa frequently results in the uncontrolled and uncoordinated expansion of cities beyond their borders, as many governments have liberalised the housing sector to allow for the private sector to provide housing services in order to bridge the housing gap caused by the rapidly growing urban population (Yiran et al., 2020). The encroachment of urban land use on rural land blurs the spatial segregation between urban and rural areas, and this has implications in rural areas, such as a threat to food security due to reduced farmland and an increased cost of living. Proper urban planning can be a valuable strategy to reduce the adverse effects of urbanisation.

2.3 Urbanisation in Malawi

Some reports present Malawi as one of the fastest urbanising countries (Phiri et al., 2019), while others (Manda, 2013b; Mwathunga & Donaldson, 2022) suggest that it is still in an early stage of urbanisation, and its urban population is growing at a relatively moderate pace. Nonetheless, the 2018 Population and Housing Census revealed that urban population growth in Malawi is higher than the national population growth rate. Therefore the Government of Malawi (GoM), through the Ministry of Lands and Housing, acknowledges rapid urbanisation as a critical national development concern (Manda, 2013). The 2018 Population and Housing Census found that out of the 17.6 million people in Malawi, 16% of the national population lives in urban areas of various sizes, and it is projected that 20% of the country’s population will be living in urban areas by 2050 (National Statistical Office, 2018).

Malawi's urban population growth is primarily a result of rural-urban migration and natural increase (Manda, 2013; Mwathunga & Donaldson, 2022; Phiri et al., 2019). Push factors for rural-urban migration include challenges connected with rural life, such as rural poverty, unemployment, poor health care services and the negative consequences of climate change, which result in low and insufficient agricultural production. The growth of the urban population has resulted in categorising previously rural areas as urban and extending the administrative urban boundaries (Phiri et al., 2019), undermining the city's attempts at urban planning.

The urbanisation of poverty characterises Malawi's urbanisation, as most migrants to cities are poor (Mwathunga & Donaldson, 2018). Also, urbanisation in Malawi is not matched by the increased availability of much needed infrastructure, housing and service delivery. Unplanned urbanisation has resulted in the multiplication and expansion of informal settlements, poor infrastructure and poor service delivery (Manda, 2013). The infrastructure in the informal settlements, where the majority of the urban population resides, is made of substandard construction materials that cannot withstand disasters. These settlements are also in unsafe locations with poor access to services such as water, sanitation and waste management (Manda, 2013). Poor access to these services leads to the spread of waterborne diseases like cholera. Rapid population growth in informal settlements causes overcrowding and encroachment on areas intended for natural drainage, worsening the impact of disasters caused by rapid environmental degradation and deforestation (Manda, 2013; Phiri et al., 2019). The informality of urban regions, urban population expansion, and the absence or inadequate implementation of legal and administrative regulations worsen the situation in urban areas (Phiri et al., 2019).

In recent years, Malawian urban areas have experienced floods, a phenomenon previously associated with rural areas (Strachan et al., 2021). When floods occur in areas with a prevalence of informal settlements, the risk of infrastructure damage and sanitation-related disease transmission is very high (Manda, 2013). Also, poorly developed informal settlements cannot withstand other natural disasters like earthquakes and strong winds. In addition to the stated conditions, Malawian urban areas have an insufficient electricity supply, and the roads lack traffic regulation facilities like traffic lights, road signs and even road markings (Manda, 2013).

Proper land-use planning regulates urban expansion and mitigates the disaster risk in urban areas. Unfortunately, regulatory-based land use planning in Malawian urban areas has generally been ineffective (Phiri et al., 2019). This has resulted in uncontrolled and unregulated development of established and emerging towns, resulting in increased vulnerability to disasters (Manda, 2013; Phiri et al., 2019). When utilised, urban land-use planning in Malawi is said to be discriminatory specifically to low-income residents creating formal and informal spaces, with informal spaces being neglected in city planning activities (Phiri et al., 2019). This neglect leaves poor urban dwellers in informal settlements at risk and vulnerable to urban disasters. Effective and non-discriminatory urban land-use planning is necessary to mitigate the current risk of disasters in urban areas and ensure that future development is regulated and aligned with health and safety regulations and disaster management strategies.

The urban planning system in Malawi faces challenges ranging from the institutional and administrative framework of urban planning, legal challenges and contradictions, land rights and inherent spatial planning contradictions, to political and economic factors (Mwathunga & Donaldson, 2018). With an overall deficiency in the number of planning-related professional positions and professionally qualified planners, the planning system is unable to fulfil its mandate of effectively administering and managing urban land. The lack of technological capacity results in the continued use of outdated or inaccurate geospatial data, making accurate, informed, and evidence-based urban development challenging (Mwathunga & Donaldson, 2018). The deficiencies result in inadequate development control enforcement, a lack of territorial control, an excessive responsibility on the state to conduct monitoring and surveillance techniques, insufficient land supply, and increased encroachment (Mwathunga & Donaldson, 2018). In order to enhance efficient planning and sustainable growth, it is essential to investigate changes in land use and land cover (LULC) (Mawenda et al., 2020).

2.4 Urbanisation and land use land cover (LULC) change.

Urbanisation leads to land use land cover (LULC) changes to cater to the growing population's needs. The difference between land use and land cover is often overlooked, and the terms are used interchangeably. In essence, they are different and refer to varying characteristics of the landscape. Land use refers to how people utilise the land for social and economic purposes (Li et al., 2014; Shetty et al., 2021). Examples of land use include commercial, agricultural, recreational, and residential. Land cover describes the land surface Field's natural, anthropogenic, and physical characteristics and patterns (Li et al., 2014; Shetty et al., 2021). Land cover includes developed/built areas, grassland, and water. Information on urban growth and LULC change is essential to local government and urban planners to improve future city physical development plans (Hegazy & Kaloop, 2015). However, in situations where land use changes are rapid and undocumented, which is the case in most developing countries, observations of land cover changes provide essential information on human activities and utilisation of the landscape (Das & Angadi, 2022; Hegazy & Kaloop, 2015; Ruiz Hernandez & Shi, 2018). Therefore, the terms land use and land cover are jointly used to refer to human utilisation of the earth’s physical landscape, and land use land cover (LULC) changes indicate changes in the utilisation and function of the land by humans.

Land use land cover changes in the urban context are comprised of the natural landscape being mostly replaced by an impervious surface which has negative impacts on the ecosystem, the hydrological processes, biodiversity, microclimate, the ecological habitat, water quality, air quality and the environment (Das & Angadi, 2022; Li et al., 2014). When changes in LULC are uncontrolled and haphazard, the impacts lead to several social, economic, and environmental problems in the urban space, such as pollution, urban flooding, the spread of diseases like cholera, and the development of the Urban Heat Island effect. Urban expansion and LULC changes will undoubtedly continue in the years to come. In order to reduce the adverse effects of urbanisation-induced LULC changes and to efficiently utilise the limited land in urban areas, there is a need for effective planning. LULC maps are essential for landscape monitoring, planning, and management and researching the effects of climate change and human intervention on ecological processes and services (Shetty et al., 2021). Recent developments in geospatial technologies have made it possible for quantitative and statistical analysis of the LULC changes and urban expansion patterns.

2.5 Change detection

Change detection is the process of identifying the spatiotemporal differences in the state of an object or phenomenon (Alqurashi & Kumar, 2013). Geospatial technologies and remote sensing are vital for identifying landscape changes because they can monitor LULC changes at high temporal precision and lower costs than traditional methods (Hegazy & Kaloop, 2015).

Remotely sensed data properties such as synoptic view, repeated coverage, and real-time data capture enable the identification of patterns of change in LULC from one period to the next (Hegazy & Kaloop, 2015). The repeated coverage of an area makes available the much-needed historical data helpful in identifying LULC patterns and predicting future changes. Change detection has proven useful in disaster response, wildlife conservation, disaster monitoring, and mapping urban expansion.

Change detection is helpful for urban planners as they conduct urban growth monitoring. Urban growth monitoring determines or maps spatiotemporal land use land cover (LULC) changes using remotely sensed data (Hegazy & Kaloop, 2015). Rapidly urbanising and developing nations need reliable information about ongoing LULC changes. Therefore, studies of urban LULC changes using remotely sensed data, such as those provided by the Landsat program, are essential for land management and urban land use planning (Alqurashi & Kumar, 2013; Mawenda et al., 2020). The availability of remotely sensed imagery and the wide adoption of machine learning algorithms enhance the mapping of extensive and complex urban landscapes at a high level of detail. Using remotely sensed data alongside machine learning algorithms usually leads to better overall classification accuracies compared to more traditional, parametric methods (Maxwell et al., 2019). This, in turn, results in accurate change analysis and pattern identification that helps planners to predict and prepare for future urban expansion.

2.6 Urban growth models

In recent decades, the use of satellite remote sensing and geographic information systems (GIS) in mapping out urban areas have grown in popularity. Alongside developing various tools and methods of mapping out the urban space, models of urban expansion prediction and simulation using different algorithms have been developed. Aside from simulating and predicting urban expansion, these models also enhance understanding of urban growth trajectories (Agyemang et al., 2019). Kumar and Agrawel (2022) explain that machine learning links image spectral information to independent factors and supplementary data, improving urban growth modelling. Some of these include cellular automata (CA) coupling with fuzzy logic, artificial neural networks, Markov chain with a modified genetic algorithm, weights of evidence, and non-ordinal and multi-nominal logit estimators (Bihamta et al., 2015; Das &

Angadi, 2022). Multiple studies have shown that the cellular automata (CA)-based spatial models properly simulate and predict the spatial process of urban growth (Bihamta et al., 2015). These models are composed of grids with cells that have their states updated based on neighbouring cells' states and through the application of predefined rules. However, CA models rely heavily on very particular geospatial data availability.

2.6.1 The SLEUTH urban growth model

The SLEUTH urban growth model is an open-source package developed by Dr. Keith Clarke, based on the CA city expansion development theory, that uses historical geospatial data to calibrate parameters (Bihamta et al., 2015; Du, 2016). It simulates urban growth and land use change based on rules and assumptions about how cities expand over time. SLEUTH is an acronym for the required spatial input data: Slope, Land use, Exclusion, Urban extent, Transportation and Hillshade. Kumar and Agrawal (2022) explain that the SLEUTH urban growth model can provide greater accuracy when predicting urban variation, and it is robust to input data spatial resolution, as it can achieve a good model fit on data of up to 30 m spatial resolution. Given that Landsat data are freely available at a spatial resolution of 30 m, the SLEUTH urban growth model is a highly suitable and cost-effective option for urban growth prediction.

Urban growth is defined by four growth types or rules: spontaneous growth, new spreading centre, edge growth, and road-influenced growth, which are controlled by diffusion, breed, spread, slope, and road gravity coefficients (Bihamta et al., 2015; Watkiss, 2008). Table 1 summarises the four growth rules and the coefficients that control them. An exclusion layer and slope are the additional controlling factors.

Table 1:Summary of Growth Rules and Controlling Coefficients

Growth Rules	Controlling Coefficients	Description
Spontaneous Growth	Dispersion/Diffusion	Spontaneous growth defines the occurrence of random urbanisation of land. The coefficient controls the number of times a pixel will be randomly selected for possible urbanisation.
New Spreading Centre	Breed	New spreading centre growth determines whether any new spontaneously urbanised cells will become new urban spreading centres. The coefficient determines the probability of the spontaneous growth pixel becoming a new spreading centre.
Edge Growth	Spread	Edge growth is the expansion of already existing spreading centres. The coefficient determines the probability that any pixel is part of a spreading centre.
Road Influenced Growth	Road Gravity, Dispersion/Diffusion and Breed	Road-influenced growth refers to expansion determined by the existing transportation infrastructure. The coefficients control the probability of growth along the transportation network.
Slope Resistance	Slope	Reduces the probability of urbanisation on steep slopes. A slope gradient of greater than 21% cannot be built up.
Exclusion Layer	User Defined	Represents areas where development is restricted or prohibited (parks and protected areas)

Source: (*Project Gigalopolis*, n.d.)

The calibration process involves brute force Monte Carlo runs through the historical datasets, and the outputs of the calibration provide important information about the urban growth trajectory of the study area (Agyemang et al., 2019; Du, 2016; *Project Gigalopolis*, n.d.; Watkiss, 2008). Each parameter has possible values ranging from 1 to 100. Calibration consists of three phases: coarse, fine, and final, with each phase applied to a dataset of varying spatial resolution and sequentially narrowing the range of coefficient values. The model's internal statistical metrics assess the fitness of each combination of the coefficients to the historical growth of the area of study (Agyemang et al., 2019). The best-fit coefficient values are selected to run the model's prediction function.

3 Research questions

Integrating remote sensing methods and quantitative spatial analysis can be used to analyse land use land cover (LULC) in urban areas. This study analyses the changes in LULC in Lilongwe from 2002 to 2022.

1. How did Lilongwe's urban land use and land cover (LULC) change between 2002 and 2022?

    - I quantified changes in urban LULC during the 20 years in this question. The changes in built-up/developed area coverage that reflect urban growth are of particular interest.
    - Landsat 5 Thematic Mapper (TM) and Landsat 8 Operational Land Imager (OLI) multispectral satellite images with a spatial resolution of 30 m were used to answer this question. The post-classification change detection approach was used to quantify changes in LULC.

2. How are the observed land use and land cover changes similar and different to those simulated by the SLEUTH model?
    - For this question, I used the SLEUTH model to simulate the expected urban expansion in 2022, given the urban situations of the years prior to 2022.
    - The results from the simulation were compared to the changes observed in question one and the actual landscape conditions.

4 Study area

Lilongwe is the capital city of Malawi, and it was named after the river that runs through it. Located in the inland plains of the country with an area coverage of 403 square kilometres, it is the country's largest city constituting 5.6% of Malawi's total population (National Statistics Office, 2019). Figure 1 presents the location of Lilongwe. It was once a colonial city and has been an administrative centre since the early 1900s. The emergence of Malawi's tobacco industry and the city's strategic location at the junction of major north-south and east-west roadways increased its importance as an agricultural market centre in the 1920s (Strachan et al., 2021). It replaced Zomba as the capital city in 1975 and has had high population growth.

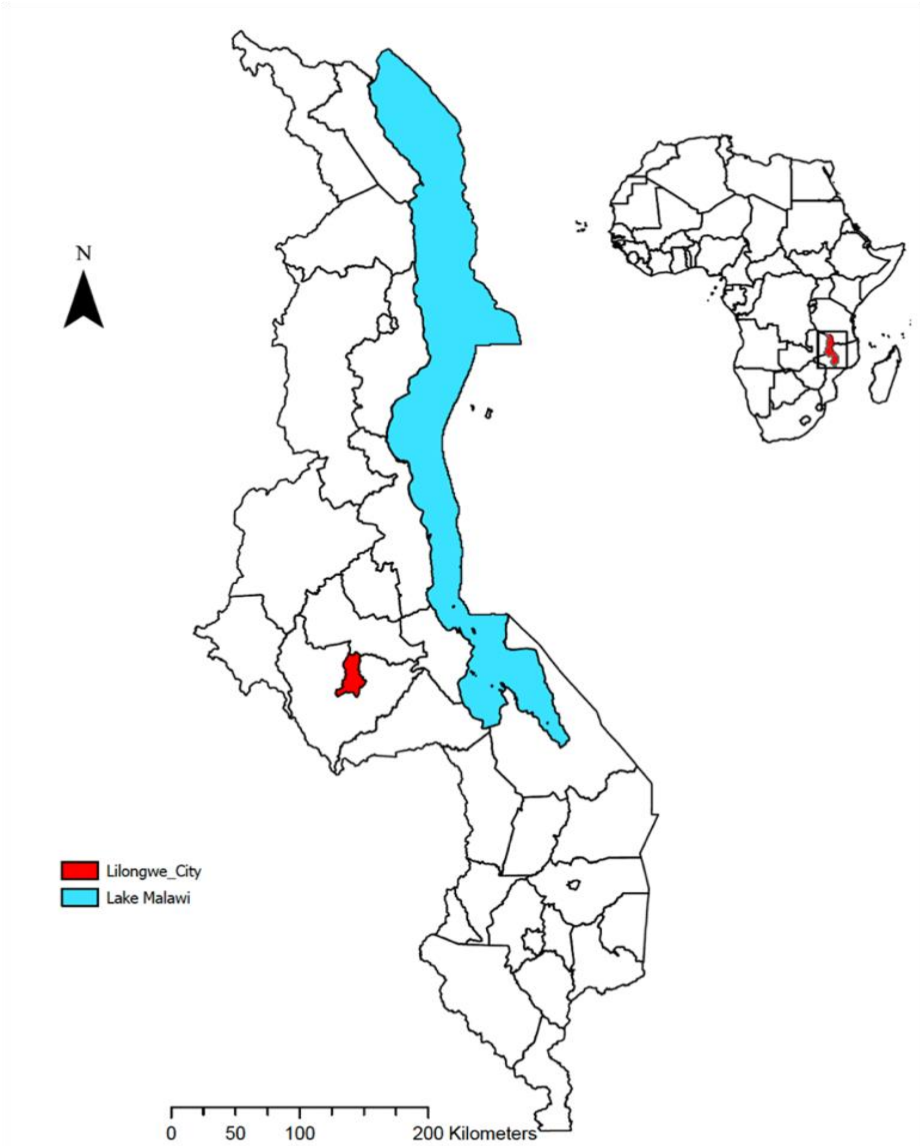

Figure 1: Location of Lilongwe.

Lilongwe’s population grew rapidly from 19,425 to nearly 100,000 in the decade after independence (Manda, 2013). With an estimated population of 989,318 in the 2018 population census and a 4-5% population growth rate, future predictions indicate that the city’s population will nearly double to approximately 2 million by 2033 (Strachan et al., 2021). Rural-urban migration is the primary driver of the city’s urban expansion and is influenced by financial resources and investments in the city and its social and economic development (Manda, 2013; Ngalande & Odera, 2023). The adverse effects of climate change in rural areas also influence rural-urban migration, and the World Bank Groundswell report suggests that Lilongwe will emerge as a climate in-migration hotspot by 2030 (Rigaud et al., 2018). In response to urban growth, the 2030 Master Plan, an urban development plan, was developed to manage the city's expansion (Ngalande & Odera, 2023).

It has been observed that the city’s built-up area increased significantly from 1973, two years before Lilongwe became the capital city, to 2020 (Ngalande & Odera, 2023). Despite the existence of the master plan, the city lacks an adequate supply of land in designated residential areas and affordable formal housing in the traditional housing areas to accommodate the influx of rural migrants (Ngalande & Odera, 2023). The inadequate supply of land in designated residential areas and the high cost of building in traditional housing areas have led to unplanned and uncontrolled urban expansion as migrants resort to settling in informal settlements (Ngalande & Odera, 2023). Unplanned urbanisation leads to the encroachment of urban land use in rural areas, which results in the reclassification of these areas, and further expansion of urban development and land use confuses rural-urban boundaries. The administrative border often does not correspond with the built-up area, as shown in Figure 2, causing challenges for the city authorities (Manda, 2013).

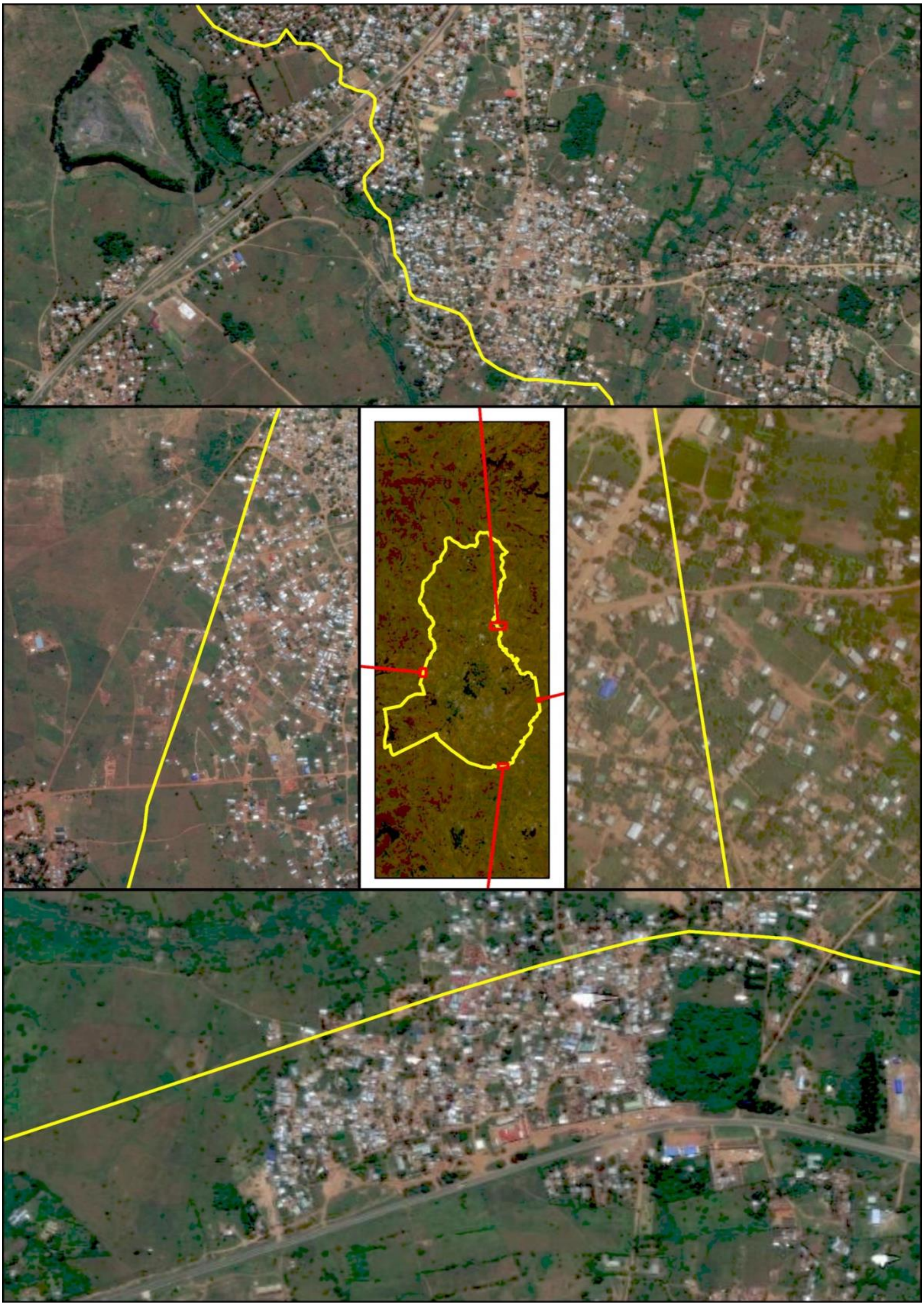

Figure 2: Overflow of the built landscape. Image Source: Maxar.

Urban sprawl and unplanned settlements are apparent in all parts of the city, with dominance along the edges of the city (Manda, 2013; Ngalande & Odera, 2023). Although urban expansion is apparent along the edges in all parts of the city, it is concentrated in the southeast, southwest and northwest, characterised by high to medium density suburbs were houses are constantly constructed (Ngalande & Odera, 2023). Urban growth is less concentrated in the northeast and upper northwest due to the presence of formal low density suburbs and the restricted Kanengo industrial site in the northwest, and the expansion of wetlands that are unsuitable for development in the upper northwest and the eastern parts of the city (Ngalande & Odera, 2023).

Lilongwe faces many challenges, including high levels of poverty, inequality, poorly built infrastructure, lack of access to safe sanitation and clean water, urban flooding, poor waste disposal and crime (Phiri et al., 2019). The challenges leave urban dwellers vulnerable and at risk of natural disasters and disease outbreaks. Phiri et al. (2019) wrote that Malawi's Department of Disaster Management Affairs (DoDMA) reported floods in December 2017 and March 2018 in Lilongwe that killed over six people, displaced twenty thousand people and left over six thousand homeless. They further explain that most of the townships within the city have faced a reoccurrence of floods and mudslides, which have been attributed to environmental degradation due to the prevalence of informal settlements, especially along the riverbanks. In 2020, flash flooding affected parts of Lilongwe, and over 1,500 people from around 400 households were affected (Strachan et al., 2021). Regardless of its rapid urbanising nature, urban research on Lilongwe however remains sparse, and the limited scholarly research on Lilongwe has been primarily focused on the city's urbanisation following its capital relocation from the colonial capital of Zomba (Mwathunga & Donaldson, 2018).

5 Methods

The SLEUTH Urban Growth model used the post-classification change detection approach to assess and study Land Use and Land Cover (LULC) changes in Lilongwe from 2002 to 2022. Figure 3 highlights the main steps in the methods employed in this study.

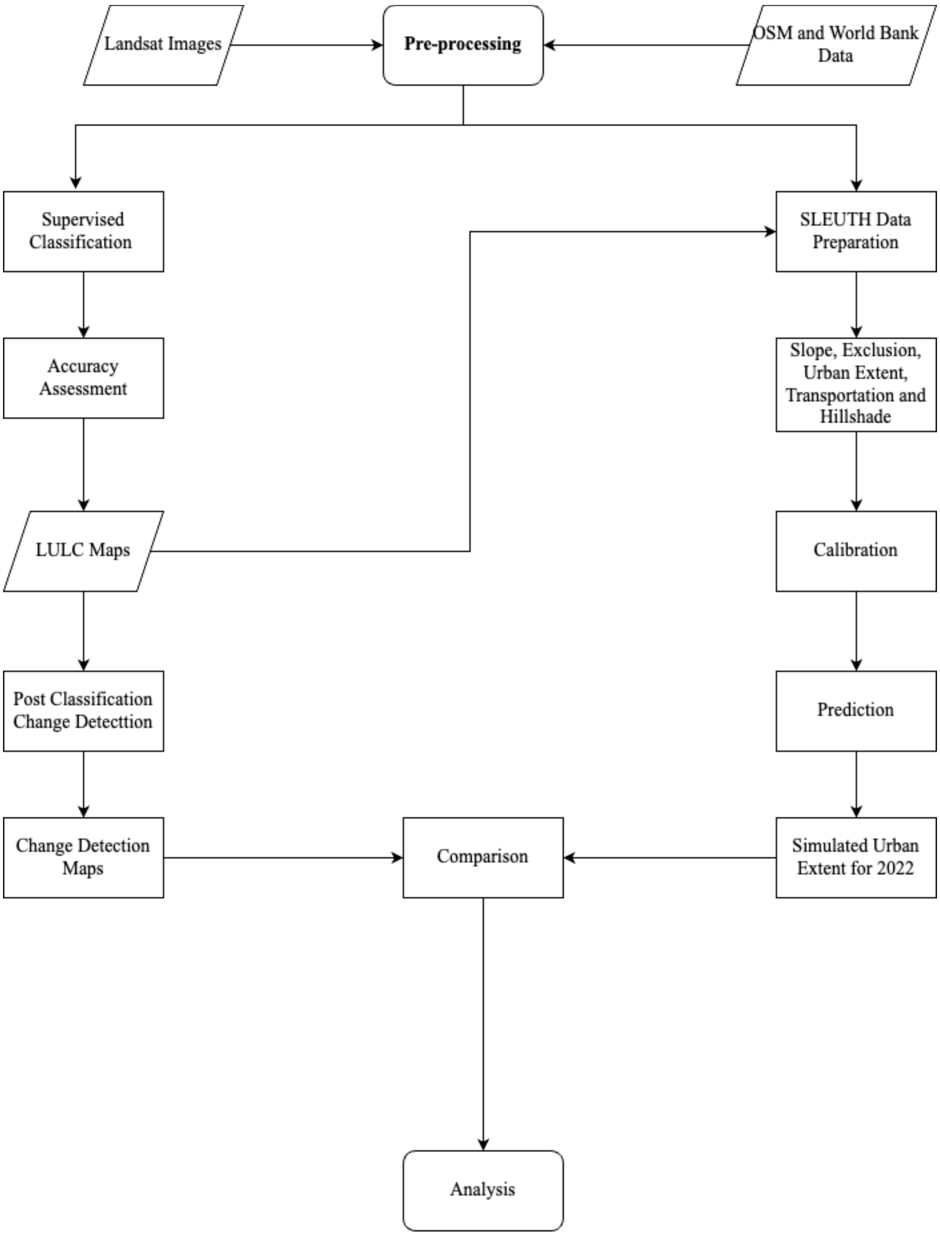

Figure 3: Flow chart conceptualising methods implemented in this study.

5.1 Data description

Using the post-classification change detection method and the SLEUTH urban growth model in the study necessitated the availability of various datasets. The study made use of Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI) satellite imagery from Path 168/Row 70 with a 30 m spatial resolution and a 16-day repeat cycle obtained from the United States Geological Survey (USGS) Earth Explorer website. The study also used other data, and Table 2 summarises all the data used. The coordinate system of all datasets was uniformly set to WGS_1982_UTM_Zone_36S.

Table 2: Data used in the study.

Data Type	**Collection Date**	**Data Source**
Landsat 5 Satellite imagery	2006 and 2011	USGS
Landsat 7 Satellite imagery	2002	USGS
Landsat 8 Satellite imagery	2014, 2018 and 2022	USGS
Google Earth Imagery	2002, 2006, 2011, 2014, 2018 and 2022	Google Earth Pro
Roads Shapefile	2010	The World Bank Data Catalogue
Roads Shapefile	2020	OpenStreetMap
Excluded areas shapefile	N/A	OpenStreetMap and on-screen digitizing
Slope	N/A	DEM from United States Geological Survey (USGS) Earth Explorer
Hillshade	N/A	United States Geological Survey (USGS) Earth Explorer

5.2 Land use land cover classification

The performance of machine learning-based classification algorithms, as quantified by the accuracy of the resulting thematic maps, is influenced by a variety of factors, including the heterogeneity/complexity of the study area, sensor characteristics (e.g., spatial, temporal, spectral, and radiometric resolution), the number of classes, the availability of ancillary data, the scale and purpose of the target land cover map, and the classifier chosen (Shetty et al., 2021).

Random forest (RF) supervised classification was used in this study. RF is an ensemble classifier composed of many decision trees in which a random subset of the available training samples is used to train each tree in the ensemble. The training samples used in each tree are selected using random sampling with replacement (i.e., bootstrapping). The classifier also allows selecting from a subset of the available predictor variables at each decision node. The goal is to create an ensemble of weak classifiers that are collectively strong due to a reduced correlation (Breiman, 2001; Shetty et al., 2021). RF has been applied to map urban land cover, surface mines, agriculture, and general land cover, among other landscape characteristics and features. Its many strengths include ease of optimisation, the capacity to assess predictor variable importance, robustness to noisy input data and mislabelled training samples, and the ability to accept a complicated and high dimensional feature space (Maxwell et al., 2019).

Land use land cover was divided into four classes: developed, water, undeveloped land, and vegetation. Descriptions of the LULC classes are presented in Table *3*. Visual interpretation of the satellite images was used to identify the LULC types, and the samples for the different LULC classes for the individual six image data were manually selected and collected using the Training Samples Manager in ArcGIS Pro. Resulting thematic maps were generalised using a sieve filter, which removed small contiguous areas of a class and replaced the land cover assignment at the cell with the surrounding and more dominant class. Contiguous areas of only one or two cells were removed.

Table 3: Land use land cover types.

Land use land cover Type	Description
Developed	All built-up or made structures, such as roads, pavements, buildings, and all artificial surfaces.
Water	All water bodies
Vegetation	All green and healthy vegetation such as trees, shrubs, forests, and agricultural fields.
Undeveloped land	All areas characterised by bare soils, dry grasslands and abandoned land croplands

5.3 Accuracy assessment

Conducting accuracy assessments before making decisions based on the results obtained is essential. Image classification is subject to various errors that occur during the classification process. An accuracy assessment is required to document the common sources of error in remotely sensed data, such as detectors and cameras, spacecraft platform movement, ground control errors, and classification mistakes (Alqurashi & Kumar, 2013). In thematic mapping from remotely sensed data, the term accuracy is typically used to express the degree of correctness of a classified map (Samal & Gedam, 2015). Metrics used to assess the accuracy of land cover maps include overall accuracy, user's accuracy, and producer's accuracy, all of which can be derived from a confusion matrix. Confusion matrix-based accuracy assessment is a widely used approach that includes a simple cross-tabulation of the mapped class label against that observed on the ground (i.e., reference data) for a sample of cases at specified locations (Samal & Gedam, 2015). A confusion matrix was used to measure the accuracy of the classification of satellite imagery in this study.

The availability of classified data extracted from the classified raster and ground truth data, which serves as the reference or known information, is required to produce a confusion matrix. To ensure a representative and unbiased sample, stratified random sampling was used to generate 500 accuracy assessment points for each of the six LULC thematic maps, with the classified LULC as the stratification variable. Accuracy assessment points that overlapped classification sample points were removed. This resulted in at least 450 accuracy assessment points for each thematic image. Google Earth Pro imagery was used as reference data.

5.4 Post classification change detection

Change detection processes analyse, describe and quantify differences between images of the same scene at different times (Hegazy & Kaloop, 2015). LULC change was quantified using the post-classification change detection method. In post-classification comparison, the images are classified separately, pixel-by-pixel, minimising the atmospheric and sensor differences between the two dates (Alqurashi & Kumar, 2013). Alqurashi & Kumar (2013) state that this is the most commonly used technique in change detection. It is an accurate procedure and has the advantage of indicating the nature of changes (Alqurashi & Kumar, 2013). Post-classification change detection was used to quantify LULC changes from 2002 to 2022 using two classified raster grids to compute categorical change raster grids.

5.5 SLEUTH input data preparation

The SLEUTH urban growth model was used to simulate the 2022 urban extent for Lilongwe. Five spatial data input layers were utilised for the calibration and prediction processes. These input layers include topographic slope that was derived from Lilongwe's digital elevation model (DEM); five urban extent layers representing the urban extent of the city for the years 2002, 2006, 2010, 2014 and 2018; an exclusion layer representing areas that are resistant to urbanisation; two transportation layers representing the road networks for the years 2010 and 2020; and a hillshade layer, derived from the city's DEM, that was used as a base map and to provide spatial context.

The model requires all data layers to be in grayscale GIF format with the same extent and spatial resolution as the row and column counts stay consistent (Project Gigalopolis, n.d.; Watkiss, 2008). For each of these input layers, a pixel value of zero is considered inactive or non-existent, while all values $0 < n < 256$ are considered active. Table 4 summarises how the data were prepared to ensure all input data layers meet the model requirements, and Figure 2 is a visual representation of the data layers. The model was first run in test mode to ensure it was working correctly and the data were in the accepted format.

Table 4: SLEUTH data preparation.

Input Data Layer	Preparation Processes
Slope	1. Slope derived from DEM. 2. Slope layer exported as TIFF. 3. TIFF converted to GIF.
Urban Extent (2002, 2006, 2010, 2014 and 2018)	1. Classification of Landsat Imagery. 2. Classified image resampled. - 0= nonurban - 0 < n < 256= urban 3. Resampled image exported as TIFF. 4. TIFF converted to GIF.
Excluded	1. On-screen digitisation to add to OSM import. 2. Vector to raster conversion. 3. Resampling. - 0 = locations available for urbanisation - 0 < n < 256 = excluded 4. Resampled raster exported as TIFF. 5. TIFF converted to GIF.
Transportation	1. Downloaded vector layers rasterised. 2. Resampling. - 0 = non-road - 0 < n < 256 = road 3. Resampled raster exported as TIFF. 4. TIFF converted to GIF.
Hillshade	1. Hillshade derived from DEM. 2. Hillshade layer exported as TIFF. 3. TIFF converted to GIF.

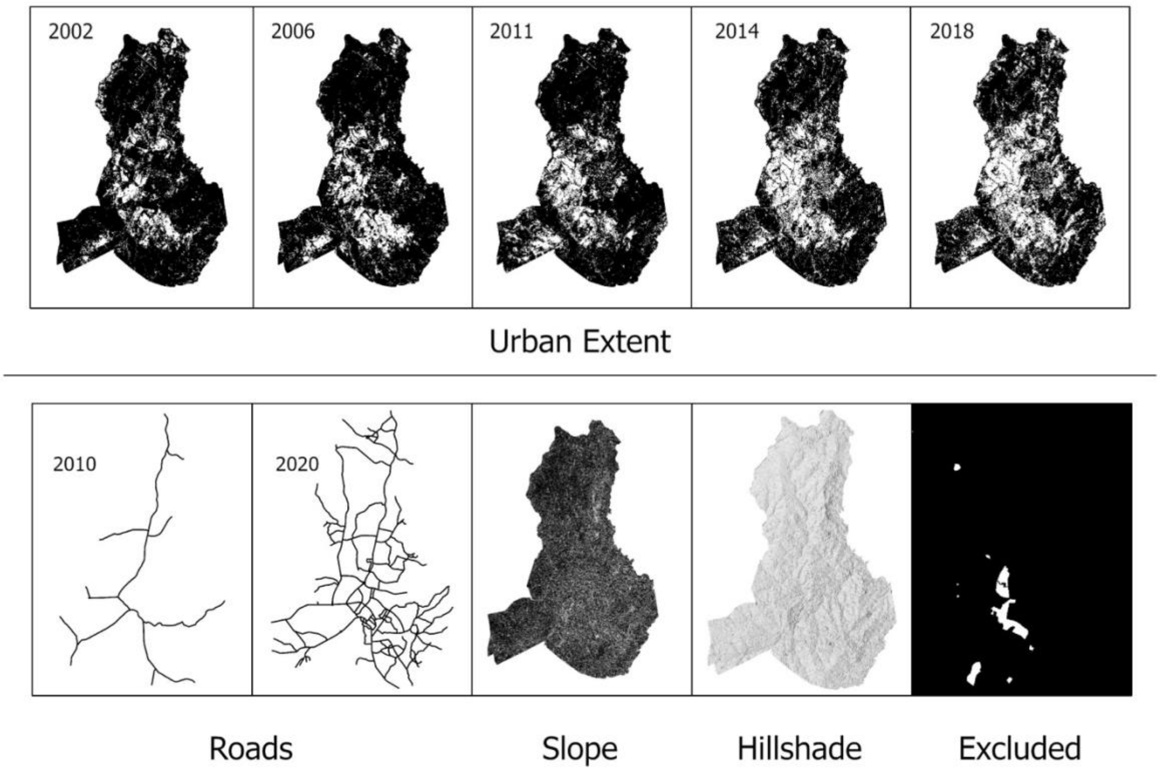

Figure 4: Lilongwe SLEUTH input layers.

5.6 Calibration

Running the model in calibrate mode performs brute force monte carlo runs through the historical data using every combination of the model coefficient values indicated (ranging from 0 to 100) (Project Gigalopolis, n.d.). The model required the data to be calibrated in three phases, sequentially narrowing the range of coefficient values and adjusting the spatial resolution for each Calibration phase (Project Gigalopolis, n.d.). Calibration was done at the coarse, fine and final phases. Each phase was applied to Lilongwe's dataset with different spatial resolutions. All data layers must have the same spatial resolution for the model to run, meaning the row and column count was to stay consistent. This required the derived resolution dataset above, which had a row x column count of 796 x 1204, to be resampled. Following the requirements of the model, coarse calibration was applied to a dataset with a row x column count of 199 x 301, representing a quarter of the full resolution. Fine calibration was applied to a dataset with a row x column count of 398 x 602, representing half of the full resolution, and the final calibration was applied to a dataset with the full resolution.

It is recommended that coefficient values for the coarse calibration phase are set to 0 (START), 100 (STOP), and 25 (STEP). The output of the coarse calibration phase included a control_stat.log file that stored values of the runs executed during the calibration phase. It is from this file that the coefficient values that were used in the subsequent phase were selected. The process of identifying these coefficients is an area of ongoing discussion among users, and no definitive 'right' way has been agreed upon (Project Gigalopolis, n.d.; Watkiss, 2008). Therefore, many statistics processing approaches may be applied at the user's discretion. With reference to similar work, the coefficient values were selected using the lee salle metric, which measures the degree of spatial match between the modelled extent and input data for each combination of variables (Project Gigalopolis, n.d.; Watkiss, 2008). The coefficients' best-fit values for this study's fine calibration phase were selected by sorting the lee salle metric values generated in the coarse calibration phase. The same was done to find best-fit values for the final calibration phase. The best-fit values derived through the final calibration phase were used to find the forecasting coefficients used to generate best-fit coefficient values for prediction.

6 Results and discussion

6.1 Post classification change detection

6.1.1 Classification results

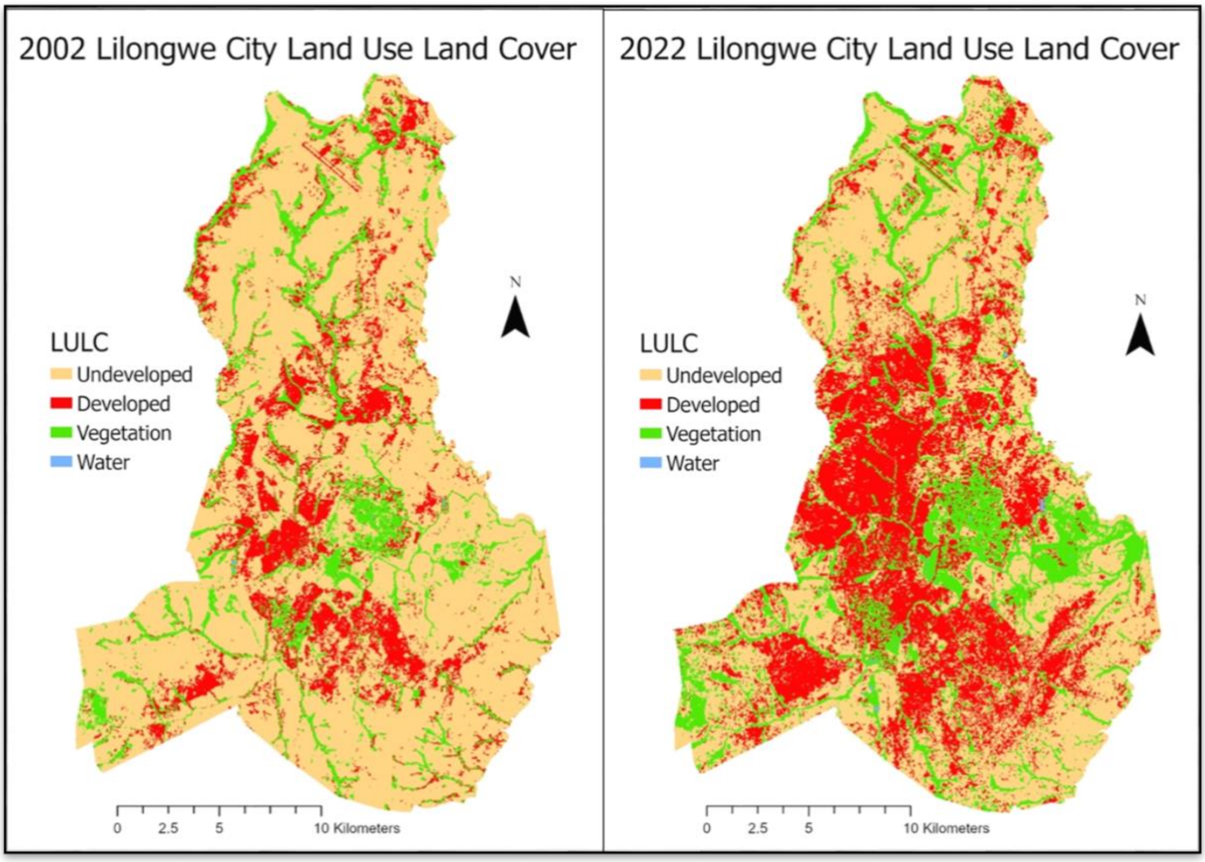

Figure 5: 2002 and 2022 Land use land cover maps.

The study employed the post-classification change detection method that used the 2002 and 2022 satellite images. The classified land use land cover maps obtained after pre-processing and supervised classification of the 2002 and 2022 images are displayed in Figure 5. The ground truth data obtained from Google Earth Pro was used to verify the classification accuracy. Table 5 and Table 6 represent the confusion matrices of the two classified images. Overall classification accuracy of Lilongwe for 2002 and 2022 are 91.6% and 90.9%, respectively.

Table 5: 2002 Confusion matrix.

		Reference Data					
		Water	Developed	Undeveloped land	Vegetation	Total	User's Accuracy (%)
Classified Data	Water	9	0	0	0	9	100
	Developed	0	44	25	0	69	63.8
	Undeveloped land	1	10	330	0	341	96.8
	Vegetation	0	0	3	56	60	93.3
	Total	10	54	358	56	479	
	Producer's Accuracy (%)	90.0	81.5	92.2	100		91.6

Table 6: 2022 Confusion matrix.

		Reference Data					
		Water	Developed	Undeveloped land	Vegetation	Total	User's Accuracy (%)
Classified Data	Water	5	1	3	1	10	50.0
	Developed	0	121	23	0	144	84.0
	Undeveloped land	0	12	231	0	243	95.1
	Vegetation	0	2	2	85	89	95.5
	Total	5	136	259	86	486	
	Producer's Accuracy (%)	100	89.0	89.2	98.8		90.9

A close look at the two tables shows classification confusion between the developed and undeveloped land class types. The user's accuracy represents the probability that the classified pixel in the thematic map represents the category on the actual landscape. The developed LULC type, which is of great interest, had user's accuracy of 63.8% and 84%, respectively. The classification confusion between the two classes can be attributed to varying factors.

The spatial resolution defines the level of spatial detail displayed in an image. It is frequently related to the size of the smallest ground feature that can be recognised within an image and the distinguishability of a ground feature as a separate entity in the image (Weng, 2012). According to Weng (2012), the resolution required for feature detection in an urban setting should be one-half the diameter of the smallest object of interest, with 0.25 to 0.5m being the minimum spatial resolution recommended for detecting buildings. Using the Landsat 30-meter spatial resolution imagery in this study led to poor detectability of sparsely distributed buildings. It led to underestimating the developed LULC type and overestimating Undeveloped land in subsections of the study area with sparsely distributed areas. Figure 6 presents an example of the explained scenario.

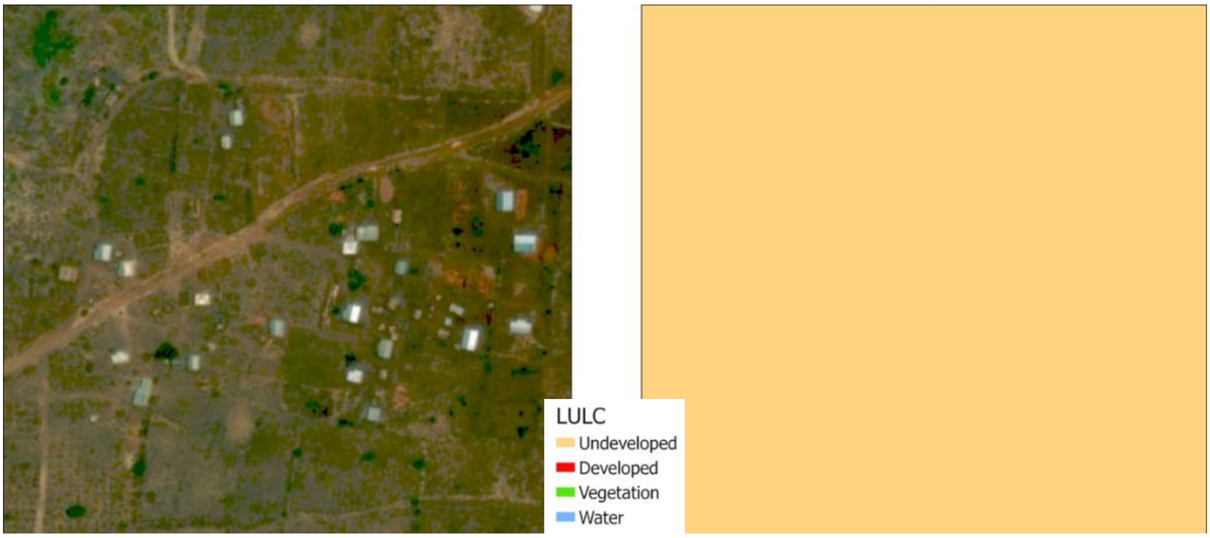

Figure 6: Underestimation of developed LULC.

Urban landscapes like Lilongwe are a complex blend of different features such as buildings, roads, grass, trees, and water. The complexity of urban environments leads to mixed pixels in coarse and medium spatial resolution remotely sensed satellite images, such as the 30m spatial resolution Landsat imagery used in this study (Zhang et al., 2015). Mixed pixels have been identified as a barrier to efficiently using remotely sensed data in land use land cover classification and change detection (Lu et al., 2011). When using pixel-based classification methods, such as the RF method used in this study, the presence of mixed pixels leads to the overestimation and underestimation of the land area of land cover classes depending on the dominant LULC type in the subsection of the study area. This confusion was not unique to Undeveloped and developed land but extended to other class types, as shown in Figure 7.

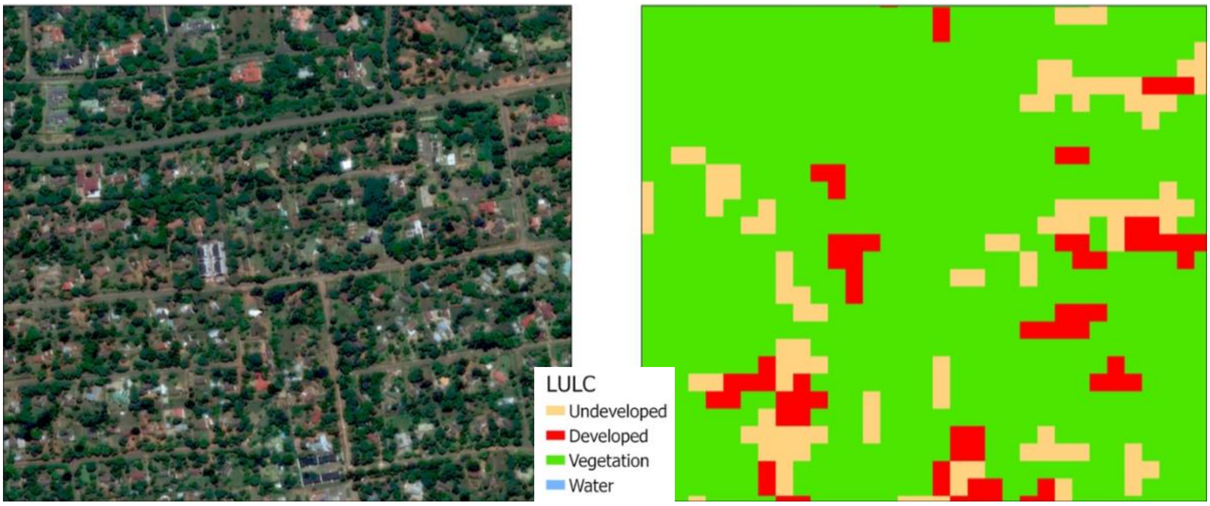

Figure 7: Mixed pixels.

The spectral confusion between the bare soils of the undeveloped land and artificial features was another source of misclassification. Spectral confusion in the land use land cover classification of Sub-Saharan African landscapes is most significant between impervious surfaces and undeveloped land, usually characterised by bare soils, dry grasslands and abandoned land croplands (Forget et al., 2018; Simwanda et al., 2019). Bare soils are spectrally similar to impervious surfaces, which makes the separation between built-up or developed areas and undeveloped land difficult, especially when the construction materials are made up of natural resources around the area (Forget et al., 2018; Zhang et al., 2015). Zhang et al. (2015) further explain that the complexity of impervious surfaces comprising various construction materials and associated reflection characteristics result in wide spectral variation and produces high spectral confusion among land cover classes. Various building materials characterise Lilongwe's built-up environment, including mud bricks and thatched roofs. This intermingling of building materials and the spectral similarity between bare soils and some impervious surfaces contributed to the confusion between the two classes, as shown in Figure 8.

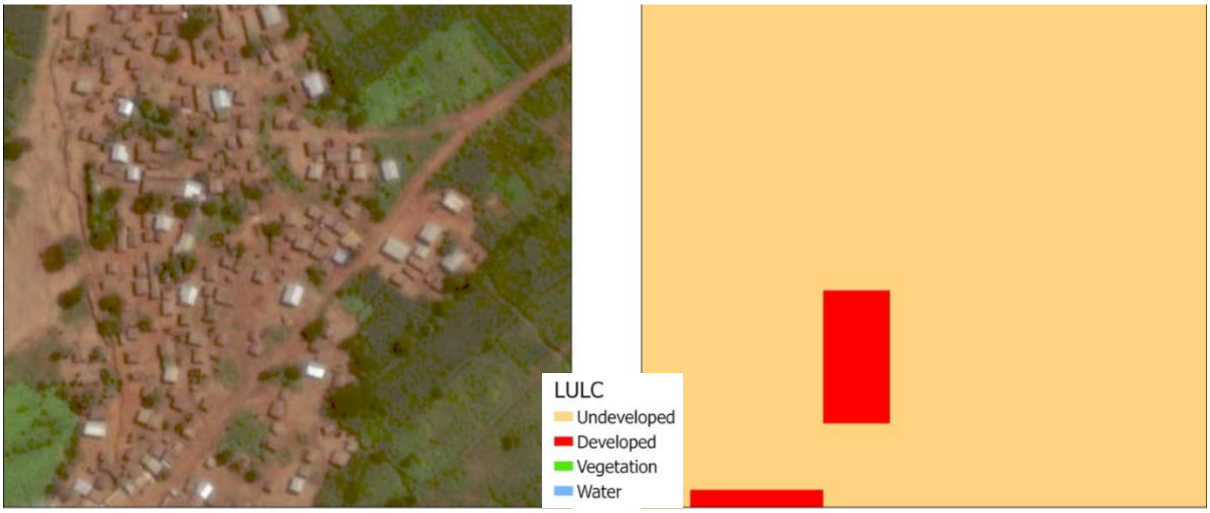

Figure 8: Spectral confusion.

The sources of misclassification in LULC change detection studies make it difficult to accurately measure the exact changes in area coverage of the different LULC types. Nonetheless, the post-classification change results reveal general land use land cover patterns and historical trends in a study area. Analysing the historical trends can provide significant information to understand the dynamics of the changing urban landscape and support future planning activities. The assessment also serves as a basis for forecasting and addressing any future challenges associated with LULC.

6.1.2 Urban Expansion

The increased area coverage of the developed LULC is immediately apparent through the visual interpretation of the LULC thematic maps in Figure 5. Image statistics indicate that the percentage coverage of developed LULC increased from 15% of Lilongwe's total surface area in 2002 to 31% in 2022, indicating urban expansion in the given time. Figure 9 is a visual representation of the post-classification LULC change detection. The map shows areas of the city that were developed in the given time. A large part of the urban expansion is characterised by the growth or extension of already existing built-up clusters. This indicates the occupancy and infill of vacant land parcels within and around existing urban clusters as opposed to the development of new urban centres in vacant land. The observed findings confirm Ngalande and Odera's (2023) and Manda's (2013) claim of urban expansion throughout Lilongwe with dominance along the city's periphery.

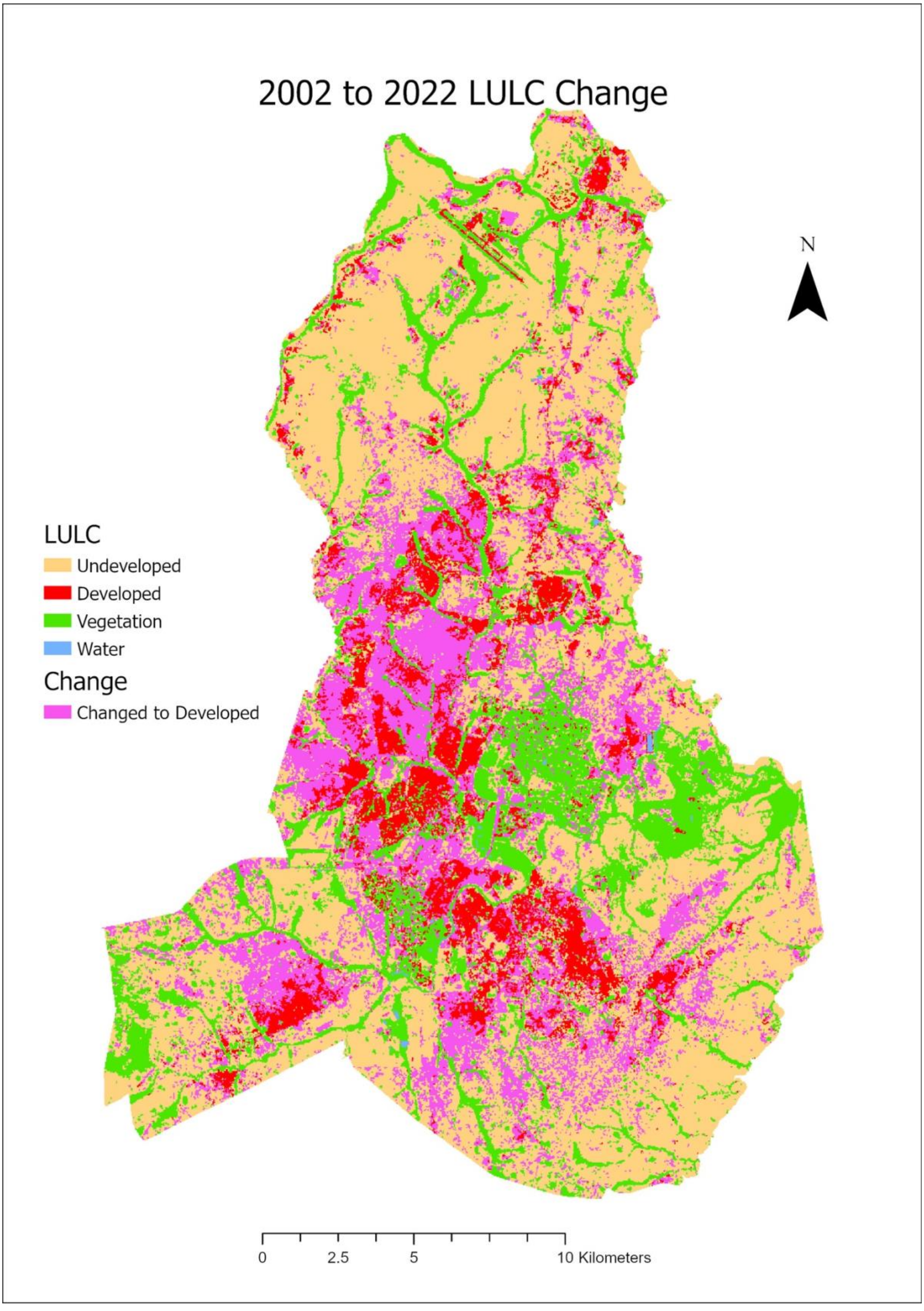

Figure 9: Post classification change detection map.

Figure 9 gives evidence to Ngalande and Odera's (2023) findings as it shows that while urban expansion is seen across the city, the northwest, southwest, and southeast areas had comparatively significant growth. Ngalande and Odera (2023) explain that the concentration of urban growth in the periphery of the city in the northwest, southwestern and south-eastern directions is due to the increase in rural-urban migration, which leads to high demand for residential housing. The inconsistent supply of plots in designated residential areas and the higher development cost in Traditional Housing Areas lead to migrants being drawn to the informal settlements in the city's peripheral or edges (Ngalande & Odera, 2023). The map also shows that urban growth was less concentrated in the northeast part of the city. This is because this part of the city consists of formal low-density suburbs and the Kenango industry sector, characterised by strict enforcement of urban development regulations and dispersed development (Ngalande & Odera, 2023). They further explain that another reason for the dispersed urban development in the east and uppermost northwestern is the expansion of wetlands unsuitable for development.

Table 7 presents the LULC change summary of the conversion from a particular land use land cover to another category. The results indicate that 64% of the city's landscape remained unchanged between 2002 and 2022. The most significant change in LULC was transforming 20% of Lilongwe's landscape from undeveloped land to developed. This indicates increased human activities and the occupation of vacant land. Increased human activity can be attributed to the City's 4-5% population growth rate, which led to the population growing from 669,532 to 989,318 between 2008 and 2018 alone (National Statistical Office, 2018; Strachan et al., 2021). Population growth leads to LULC changes, particularly the growth of the built-up environment, as humans alter the environment to cater to the growing population's needs. This is evident in Lilongwe, as evidenced by visual and statistical interpretation of the results.

Table 7: Summary of LULC change.

From	To	Area (km^2)	Area (%)
Water	Developed	0.0027	0.0%
Water	Vegetation	0.0585	0.0%
Developed	Water	0.0756	0.0%
Developed	Undeveloped land	17.0082	3.6%
Developed	Vegetation	7.9056	1.7%
Undeveloped land	Water	0.2511	0.1%
Undeveloped land	Developed	95.8266	20.2%
Undeveloped land	Vegetation	35.6553	7.5%
Vegetation	Water	0.3906	0.1%
Vegetation	Developed	4.8096	1.0%
Vegetation	Undeveloped land	8.2980	1.7%
Same	Same	304.2090	64.1%

The results also indicate that the developed LULC changed to different categories, with a 3.6% change of the city's landscape from developed to undeveloped land being the most significant, followed by a change of 1.7% to vegetation. An immediate look at the classification accuracy results alongside the change detection results suggests that land use land cover misclassification contributes to the indicated transformation results. Misclassification may not account for all the indicated transformation results, and other factors contribute to the indicated transformation.

An examination of prior research suggests that floods in the study period may have led to the loss of infrastructure. Flooding in Lilongwe is not uncommon and accounts for 48% of major disasters, with increasing frequency and severity (Strachan et al., 2021). Informal settlements in Lilongwe that are characterised by poorly built infrastructure and poor maintenance cannot withstand disasters, and some informal settlements are swamped with water in January and February every year (Manda, 2013; Strachan et al., 2021). Phiri et al. (2019) share that Malawi's Department of Disaster Management Affairs (DoDMA) reported floods in December 2017 and March 2018 in Lilongwe that killed over six people, displaced twenty thousand people and left over six thousand homeless. In 2020, flash flooding affected parts of Lilongwe, and over 1,500 people from around 400 households were affected (Strachan et al., 2021). Therefore, frequent floods are a possible contributing factor to the loss of built-up environment area coverage.

6.1.3 Conclusion

Machine learning algorithms like the random forest (RF) supervised classification used in this study model complex patterns in the data and enhance the mapping of extensive and complex urban landscapes. However, the spatial and spectral resolution of the input data influences the outputs' accuracy. Although the errors inhibit precise change measurements, the results still present important information about the urban landscape. Post-classification LULC change detection revealed the growth in developed LULC from the edges of existing urban clusters with a concentrated urban expansion in the northwest, southwest, and southeast areas. These results coincide with the findings of Manda (2013) and Ndalande and Odera (2023)

6.2 SLEUTH model simulation

6.2.1 Calibration results

The SLEUTH model was used to simulate the 2022 urban extent for Lilongwe. The calibration process consists of three phases: coarse, fine, and final, with each phase applied to a dataset of varying spatial resolution and sequentially narrowing the range of coefficient values. The output of each calibration phase included a control_stat.log file that stored values of the runs executed during the calibration phase. It is from this file that best-fit values were selected. The selected best-fit coefficient values for each calibration phase of the SLEUTH model are shown in Table *8* below. Note that it is recommended that the coefficient values for the coarse calibration phase, which is the first phase of calibration, are set to 0 (START), 100 (STOP), and 25 (STEP).

Table 8: Coefficients from calibration phases.

	Coarse		**Fine**		**Final**		**Forecasting Coefficients**	
Coefficient	**Range**	**Step**	**Range**	**Step**	**Range**	**Step**	**Range**	**Step**

Diffusion	0 - 100	25	0 – 25	5	1 – 5	1	1 -1	1
Breed	0 - 100	25	0 – 25	5	1 - 5	1	2 -2	1
Spread	0 - 100	25	25 – 75	10	35- 70	7	42 – 42	1
Slope	0 - 100	25	0 – 20	5	1 – 5	1	3 – 3	1
Road Gravity	0 - 100	25	0 – 75	15	0 – 60	15	15 - 15	1

The best-fit coefficient values for the prediction run were selected after running the model in calibration mode using the forecasting values derived by averaging the coefficient values of the many Monte Carlo iterations (*Project Gigalopolis*, n.d.). The model was run in prediction mode using this final set of coefficients presented in Table 9 below. The selected best-fit values for prediction reveal the urban growth trajectory of the City. The Lilongwe SLEUTH coefficient values are lower than those recorded in other African urban studies using the model (see calibration results from Agyemang et al., 2019; Watkiss, 2008).

Table 9: Best fitting coefficients for prediction.

Diffusion	**Spread**	**Breed**	**Slope**	**Road Gravity**
1	49	2	1	17

The spread coefficient value of 49 was relatively higher than the other coefficient values. This indicates a relatively higher probability of urban expansion from the edges of existing urban clusters. Visual interpretation of the map produced from the post classification change detection process affirms the finding of the SLEUTH model regarding the growth of already existing urban clusters. The results also support Manda's (2013) and Ngalande and Odera's (2023) claim of the city's edge growth. The possible reason for the growth of already existing urban clusters is the rural-to-urban migration of the relatively rural poor that are drawn to already existing informal settlements in urban areas (Manda, 2013; Mwathunga & Donaldson, 2022; Ngalande & Odera, 2023).

The results from calibration also show that existing road networks do not significantly influence the pattern of expansion in the city, as the road gravity coefficient of 17 was recorded. Lilongwe lacks basic road infrastructure, and most of the road network lacks maintenance and is in poor condition (Strachan et al., 2021). The lack of development attraction towards road networks may be attributed to the poor state of the road infrastructure. Also, the behaviour of migrants to typically settle in informal settlements due to the high cost of development in traditional housing areas (Ngalande & Odera, 2023), regardless of the presence or absence of a reliable road network, may explain this finding.

The city also registered very low diffusion and breed coefficient values of 1 and 2. This indicates that there was hardly any random development of vacant land that was not an extension of an already existing cluster, and the likelihood of an urbanised part of the city turning into growth nuclei was very low. Generally, people tend to settle in areas with access to needed goods and services, lowering the probability of developing new urban nuclei. The very low slope coefficient value of 1 indicates that the slope gradient does not influence an area's urbanisation. The relatively flat terrain of Lilongwe may explain this.

6.2.2 SLEUTH prediction results

The final growth parameters derived through calibration (Table 9) were used to run the model in prediction mode. The seed year was the most recent historical data's urban extent layer for 2018, and the prediction was run from 2018 to 2022. Output images of simulated urban extent for each year following 2018 to 2022 were produced. Figure 10 presents the image output produced for 2022, the year of interest for this study. This study used the default colour setting given in the model's scenario file presented in the table below.

Table 10: SLEUTH colour setting.

Colour	**Probability for Urbanisation**
Transaparent	0 to 49%
Dark green	50 to 79%
Light Green	80 to 94%
Red	95 to 100%
Yellow	100%- Already exisiting urbanised pixels from seed year

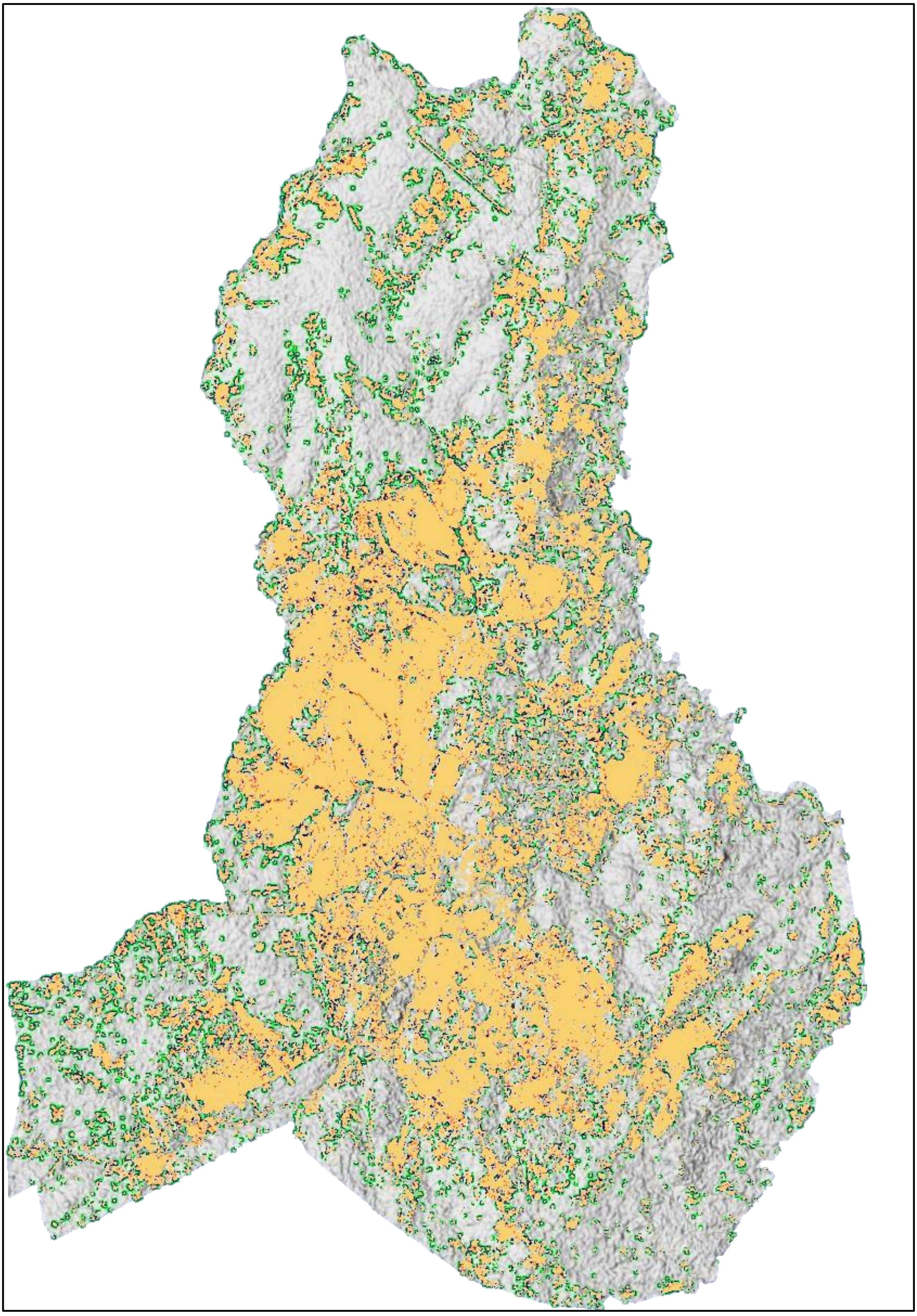

Figure 10: SLEUTH 2022 simulation.

The image represents the 2022 urban extent prediction, given the model's growth rules and the calibrated coefficients from the historical data. Yellow represents all existing urban pixels obtained from the 2018 seed year input. Newly urbanised pixels are allocated a colour depending on their percentage chance of urbanisation throughout the prediction process.

Visual interpretation of the prediction output reveals a very high probability (95 – 100%) of urban growth within already existing urban clusters, indicating the absorption of vacant land parcels within the urban areas. The results also show a high (80-94%) probability of urban growth from the edges of existing urban clusters. This edge growth is attributed to the spread coefficient acquired from the calibration of the historical data. The results support Manda's (2013) and Ngalande and Odera's (2023) claims regarding dominating outward expansion of the city along the edges and findings from the post classification change detection.

Numerical evaluation of the spatial extent of the SLEUTH model urban extent prediction indicates that 53.47% of Lilongwe's landscape was expected to remain undeveloped and 46.53% developed or covered with artificial surfaces. This contradicts the findings from the post-classification change detection that indicated that 31% of the city was developed in 2022, indicating an overestimation by the model.

6.2.3 Comparison of SLUETH output and actual 2022 urban extent

The SLEUTH model urban extent prediction and the actual 2022 urban extent were compared using the 2022 LULC map derived in the post classification change detection process. This was due to the lack of readily available datasets showing the 2022 urban extent. The developed LULC class was extracted from the classified LULC map and used as the urban extent for 2022. Pixels part of the seed year and those that fell in the model's 80% to 100% probability range were considered as the model's prediction urban extent.

Figure 11 is a visual representation of the results of the comparison. Blue indicates areas of the model overestimation because the prediction did not coincide with the 2022 urban extent. Red represents model underestimation. Green represents areas where the model's urban extent overlapped the extracted 2022 urban extent. A numerical evaluation of the comparison indicates that 21.29% of the model's urban extent is an overestimation, 6.1% is an underestimation, and 72.61% coincides with actual landscape conditions.

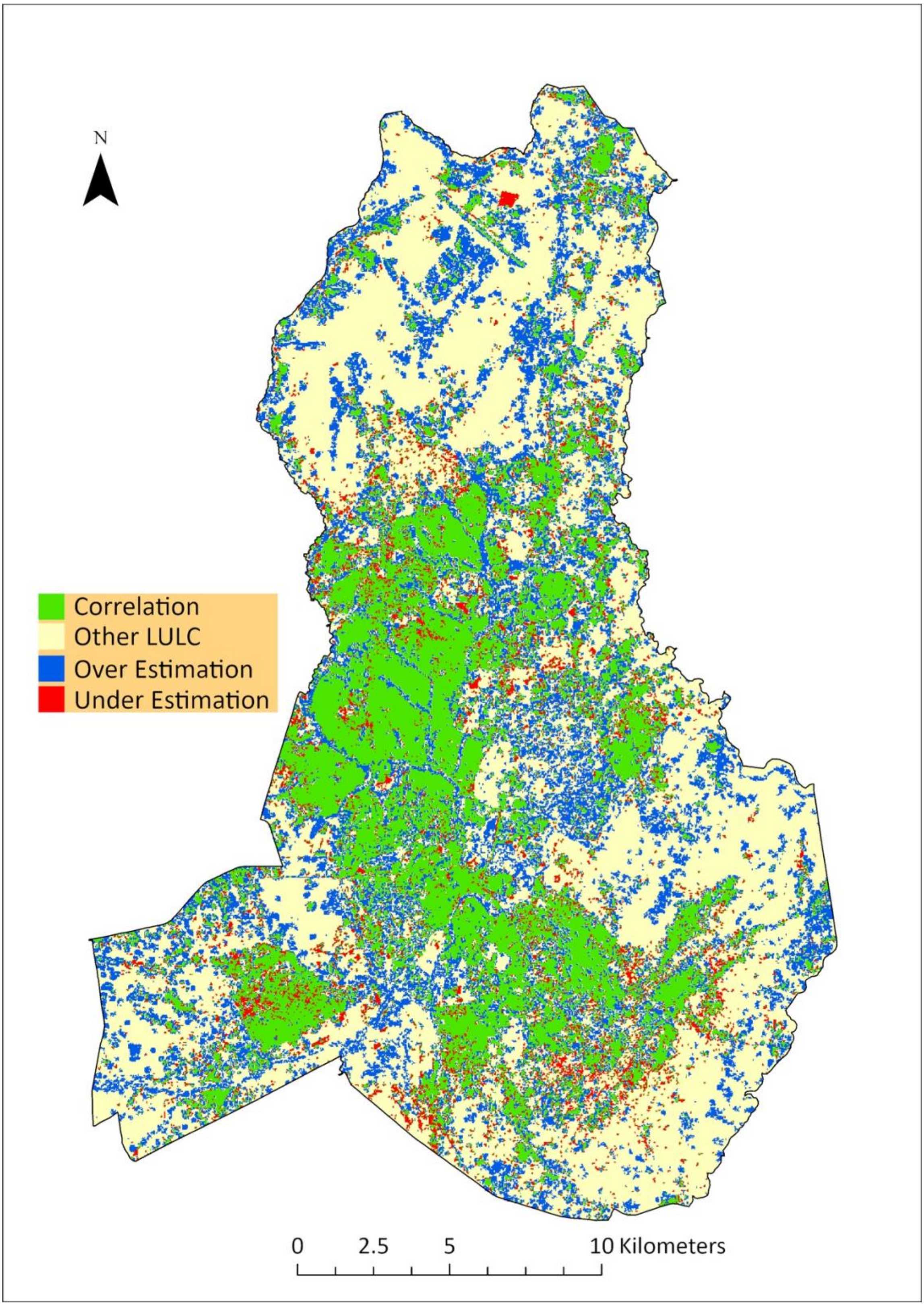

Figure 11: Model and actual landscape conditions comparison.

Model underestimation and overestimation are observed in all parts of the city. The differences between the model prediction and the 2022 urban extent may be attributed to differences or changes that occurred in the urban environment between the seed year 2018 and the end year 2022 that were not taken into account. Figure 12 represents a simple overlay of the model's predicted urban extent and the seed years' urban extent. The map overlay shows that the model's urban extent is an extension of the existing urban pixels in 2018. Therefore, it is clear that the prediction was heavily dependent on the urbanised pixels that existed in the seed year, as that is the nature of cellular automata models.

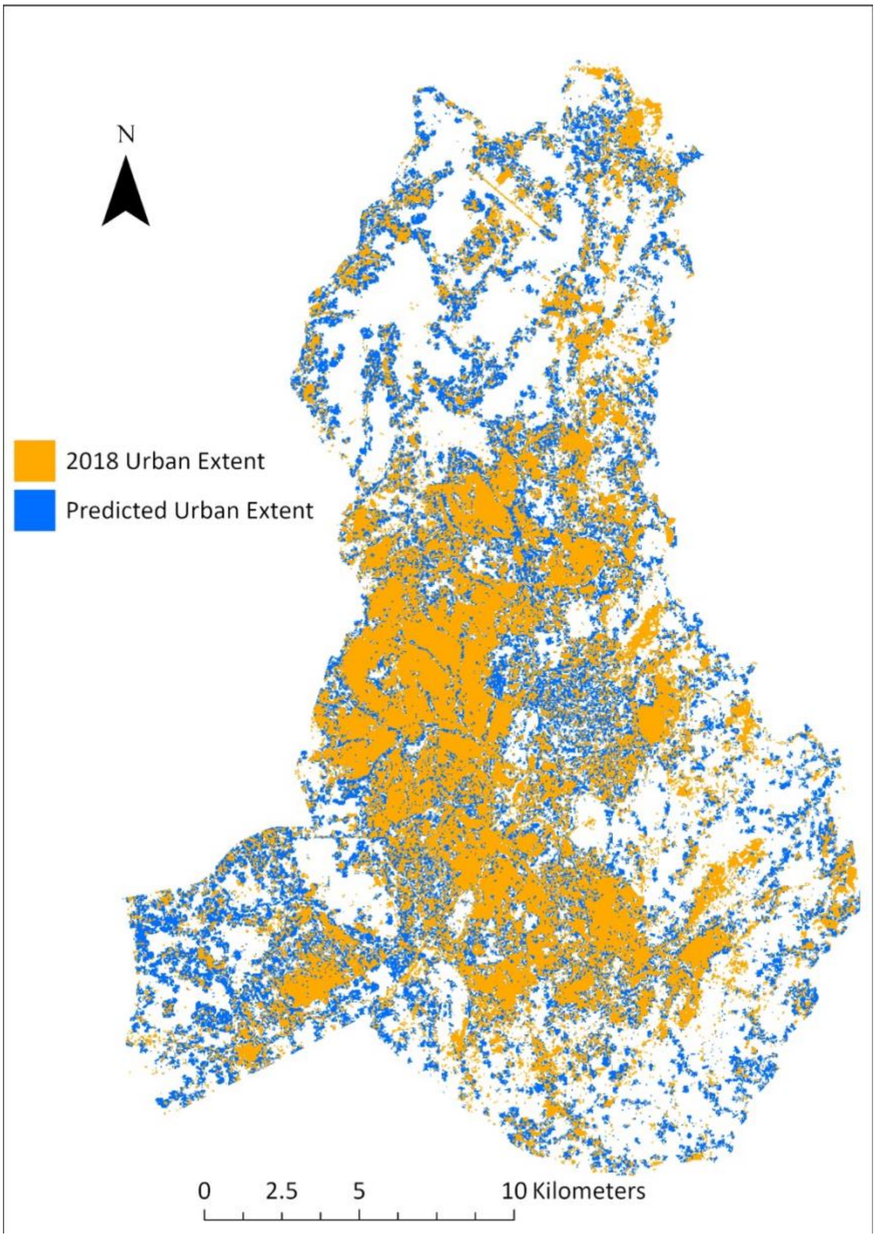

Figure 12: Predicted urban extent and 2018 urban extent overlay.

Misclassification of LULC in the seed year and the end year may have contributed to the differences between the model prediction and the 2022 urban extent. As already alluded to in prior sections of this study, an accuracy assessment of classification results revealed classification confusion in the produced LULC maps. The urban extent of the seed year and end year was extracted from the 2018 and 2022 classified LULC maps. Misclassification may have led to overestimating and underestimating the different classes between the two urban extents.

As previously stated, the frequent occurrence of floods in the city leads to the damage of infrastructure and in 2020, flash flooding affected parts of Lilongwe, and over 1,500 people from around 400 households were affected (Strachan et al., 2021). This may have led to the loss of built-up areas coverage by 2022 and therefore contributed to the overestimation in areas such as the Old Town in the southwest part of the city that has poor and unmaintained infrastructure that can not withstand disasters (Ngalande & Odera, 2023; Strachan et al., 2021).

The exclusion layer used in running the model contributed to the overestimation and underestimation observed. The exclusion layer defines all areas resistant to or restricted from development in a study area (*Project Gigalopolis*, n.d.). The exclusion layer for Lilongwe was not readily available from the data sources. The layer used in this study was derived from and importation of digitised cemeteries from OpenStreetMap and the user's onscreen digitising of other restricted areas. This led to the omission of some restricted areas, which were treated as vacant parcels of land available for development. For example, the airport in the northern part of the city was not included in the exclusion layer, and there was therefore predicted growth around it. This may have contributed to the overestimation of the simulated urban extent.

Additionally, areas with partial restrictions due to administrative restrictions or unsuitability of development were omitted from the exclusion layer. This was due to the lack of existing datasets delineating the areas with partial restrictions. The presence of formal suburbs in the east, the restricted Kanengo industrial area in the northeastern, and the presence of wetlands unsuitable for development in the city's uppermost northwest and eastern parts identified by Ngalande and Odera (2023) were not considered. The model, therefore, treated all vacant areas in the city with the same probability of development. This, therefore, may have led to the model overestimating development in areas that would otherwise not experience an increase in built-up coverage.

6.2.4 Conclusion

A comparison of the model's predicted urban extent and the 2022 urban extent revealed an overestimation of development in some areas and an underestimation in others. The differences in the predicted urban extent could be attributed to changes between the seed year and end year, misclassification, and omission of restricted and partially restricted areas in the exclusion layer. The comparison also revealed that despite the overestimation and underestimation in some parts, 72.61% of the model output overlaps with the 2022 urban extent, which represents the actual 2022 urban extent. Based on these findings, the research considers SLEUTH a valuable model for urban growth modelling and prediction.

7 Summary and conclusion

7.1 Summary

The study employed the post-classification change detection method that used the 2002 and 2022 satellite images. There was relatively significant classification confusion between the developed and undeveloped land. Factors that may have contributed to the classification confusion include the use of the Landsat 30 m spatial resolution imagery that led to poor detectability of sparsely distributed buildings; the presence of mixed pixels that led to the overestimation and underestimation of the land area of land cover classes depending on the dominant LULC type in the subsection of the study area; and spectral confusion between bare soils and artificial features. The sources of misclassification in LULC change detection studies make it difficult to accurately measure the exact changes in area coverage of the different LULC types. Nonetheless, the post-classification change results revealed general land use land cover patterns and historical trends in a study area.

The percentage coverage of developed LULC increased from 15% of Lilongwe's total surface area in 2002 to 31% in 2022, indicating urban expansion in the given time. The most significant change in LULC was 20% of Lilongwe's landscape from undeveloped land to developed. Most of the urban expansion was characterised by the growth or extension of already existing built-up clusters. Although expansion was observed in all parts of the city, some parts experienced more significant changes than others. The city's northwest, southwest and southeast parts experienced relatively significant growth than the east and northeastern parts. The concentration of urban growth in the stated areas is attributed to the migration of the rural poor that typically settle in existing informal settlements and the relatively cheaper development cost in the informal settlements. Formal suburbs and the Kanengo industrial site in the east and northeast contributed to the dispersed development of those areas. The results also revealed a loss of infrastructure, possibly due to floods.

The SLEUTH model was used to simulate 2022 urban extent for Lilongwe. The best-fit coefficient values acquired from the calibration runs for the prediction run were: Diffusion-1, Spread-49, Breed 2, Slope-1 and Road Gravity- 17. The calibration of historical data indicated that urban growth in the city was mainly characterised by edge growth of already existing urban clusters. The low breed value revealed the unlikeliness of the development of new urban nuclei. The existence of a road network did not have significant influence and development. That flat nature of the city's terrain also meant that slope gradient had little influence on the city's development. The values of the derived coefficients were reflected in the simulated 2022 urban extent from running the model in prediction mode.

Visual interpretation of the prediction output reveals a very high probability (95 – 100%) of urban growth within already existing urban clusters and a high (80-94%) probability of urban growth from the edges of existing urban clusters. The results coincided with the results from the post classification change detection and prior studies of the study area. Numerical evaluation of the spatial extent of the SLEUTH model urban extent prediction indicated that 53.47% of Lilongwe's landscape was expected to remain undeveloped and 46.53% developed or covered with artificial surfaces.

The SLEUTH model urban extent prediction and the actual 2022 urban extent were compared. A numerical evaluation of the comparison indicated that 21.29% of the model's urban extent was an overestimation and 6.1% was an underestimation. Model underestimation and overestimation were observed in all parts of the city. Differences between the model prediction and the 2022 urban extent may be attributed to misclassification and landscape changes between the seed year and the end year, like loss of infrastructure due to floods. Also, the exclusion layer used in the model omitted other restricted areas, areas unsuitable for development and those with partial restrictions. Regardless of the differences between the model output and the actual landscape, 72.61% of the model output coincided with the actual 2022 landscape conditions.

7.2 Conclusion

Post-classification change detection and SLEUTH modelling results provide useful information to planners. The results support the findings of Manda (2013) and Ngalande and Odera (2023). Manda (2023) claimed that urban expansion was dominant along the city's edges. Ngalande and Odera (2023) added that the concentration of urban expansion was in the periphery of the city's southeast, southwest and northwest parts.

Rapid and unplanned urban growth has adverse health, environmental and socio-economic consequences, such as the development of slums, traffic congestion, urban flooding, the outbreak and spread of diseases such as cholera, pollution, crime and overcrowding, conditions that already characterise Lilongwe. Urban growth in Lilongwe is inevitable due to its position as the country's capital city that poses as a location of better opportunities for the rural poor (Ngalande & Odera, 2023). Therefore, city officials must employ land use planning strategies to mitigate the adverse consequences of unplanned urban expansion. Based on the results, vacant land along the edges of the existing urban extent should be targeted for planning.

8 Limitations of study

The lack of an existing exclusion layer for the city was a significant limitation. The exclusion layer defines the areas resistant to or restricted from development. The exclusion layer used in the study was derived from importing already digitised cemeteries from OpenStreetMap and the onscreen digitising. As already stated, this led to the omission of other restricted or resistant areas (i.e., the airport) and not considering the partial restriction or resistance of other areas (i.e., wetlands and suburbs).

The use of 30m spatial resolution freely available Landsat data resulted in misclassification, evident in the overestimation and underestimation of LULC. The absence of ancillary data limited the possibilities of improving classification results. Using outputs from the classification process as inputs in the SLEUTH urban growth model led to the errors of misclassification being reflected in the model output.

The study was data intensive and required long hours of data preparation. Underestimation of the time required to prepare the data for the post classification change detection and to run the SLEUTH urban growth model led to the study omitting key informant interviews that aimed at collecting additional data to explain Lilongwe's urbanisation trajectory.

9 Recommendations

The study was data-intensive and required long hours of data processing and preparation. At least three weeks should be allocated to data preparation, with particular attention allocated to the exclusion layer for the SLEUTH urban growth model. The exclusion layer defines areas that are resistant to development, and the accuracy of the exclusion layer is essential for reliable prediction and forecasting. An exclusion layer containing all restricted and partially restricted areas should be created with the consultation of relevant city officials. This will enable a more accurate and precise prediction of urban expansion.

Urban expansion in Lilongwe is inevitable due to its social and economic development (Ngalande & Odera, 2023), and reports indicate that it will emerge as a climate in-migration hotspot by 2030 (Rigaud et al., 2018). Therefore, city officials must actively enforce administrative policies and measures to avoid uncontrolled urban expansion. Results from this study have revealed the trajectory of urban expansion in Lilongwe. City officials should use these results to allocate the limited resources for urban planning to areas that experience concentrated urban expansion. Based on the results, urban planners should target the edges of existing urban clusters with particular interest in the northwest, southwestern and south-eastern directions.

The study revealed that the SLEUTH urban growth model is an essential tool for urban growth prediction, and therefore, city planners should use it to predict future growth. The SLEUTH provides a simulation environment for researchers to explore the repercussions of policy decisions made by decision-makers (Bihamta et al., 2015). Lilongwe has the 2030 master plan (Ngalande & Odera, 2023) and policies regarding urban growth that lack reinforcement (Mwathunga & Donaldson, 2022). Before reinforcing the different policies, scenario-based modelling should be conducted to explore the possible repercussions of policies on the urban landscape.

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