Assessment of Spatial-Temporal Dynamics of Urbanization in Response to Rapid Urban Migration:

The Case of Dodoma City, Central Tanzania

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LIST OF ABBREVIATIONS AND ACRONYMS

ENVI:	Environment for Visualizing Images
ETM+:	Enhanced Thematic Mapper Plus
GIS:	Geographical Information Systems
GPS:	Global Positioning System
Ha:	Hectares
LULC:	Land Use/Land Cover
OLI:	Operational Land Imager
RS:	Remote Sensing
USGS:	United States Geological Survey

ABSTRACT

The purpose of this research was to assess the spatial-temporal dynamics of urbanization with respect to population growth in Dodoma City, Central Tanzania, as a response to rapid urban migration. Specifically, this research examined the spatial-temporal variations of several land use/land cover (LULC) classes including built-up areas, shrubs, wetlands, barren land and green vegetation, with the built-up class serving as a measure of urbanization within the study area. Satellite imageries datasets for 2001 and 2011 were obtained from Landsat 7 Enhanced Thematic Mapper Plus (ETM+), and for 2021 imageries from Landsat 8 Operational Land Imager (OLI) were acquired from the United States Geological Survey (USGS) earth explorer archive. Environment for Visualizing Images (ENVI) software was used for image classification and Arc map 10.8 software was employed for the LULC analysis phase. However, Cellular Automata (CA) and Markov models embedded in TerrSet software were used in the simulation of 2040 LULC changes, as well as the assessment of the urbanization dynamics. The results showed that between 2001 and 2011, built-up areas, green vegetation, and shrubs LULC classes positively increased, while wetlands and barren land decreased in terms of hectares (ha). Additionally, the results indicated that between 2011 and 2021, wetlands, built-up areas and green vegetation classes had a continued growth within the study area, while shrubs and bare land declined. In general, the city saw a greater transition of LULC classes between 2001 and 2021, with a higher gain in the built-up areas class, indicating a positive urbanization trend. However, a greater loss in barren land and shrubs LULC classes was observed as a result of human intervention on these classes for construction purposes. Furthermore, the results from simulated LULC classes of 2040, show that the built-up class will continue increasing from 14.61% in 2021 to 35.08%, showing that the city will steadily urbanize. On the other hand, bare land, green vegetation and shrubs will significantly decrease by 2040, due to human search for additional spaces for construction activities within the city. Geographical Information Systems (GIS) and Remote Sensing (RS) technologies have shown great capability in studying LULC dynamics in recent decades and have proven to be more effective and more advantageous in terms of cost-effectiveness and less time-consuming while giving high coverage and reliable results of the past, current and future urbanization scenarios. From the findings, it is concluded that the city is experiencing steady growth, indicated by a rapid increase of built-up areas with a high rate of barren and shrubs decrease within the city. Finally, it is recommended that due to the substantial increase of urbanization in the city, the government should increase proper land planning schemes for most unsurveyed plots, particularly on the city's peripherals. Also, the government and other stakeholders should take immediate and early measures of natural resource conservation programs, such as afforestation, grazing management and understanding of the natural landscape, climate and environment to control and reduce human stress on the natural environment as well as biodiversity conservation for the city’s sustainable development.

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CHAPTER ONE
INTRODUCTION

1.1 Introduction and Background

Urbanization is the process of transforming land uses of an area as a result of human interventions induced by population increase in urban areas, as a result of urban migration (Nourqolipour et al., 2016; Sahana et al., 2018). These transformations result in the modification of the existing environments and physical forms, as people increase, impinging their activities in forming urban locales (Dahal et al., 2018), which eventually grow into cities and megacities (Mondal et al., 2017). Urbanization highly accelerates urban growth and changes in lifestyle, housing conditions, social behaviour, culture and demographics in urban areas (UNDESA, 2018). Global statistics show that in recent times, about 55% of the global urban population lives in urban environments, and this is projected to increase up to 68% by 2050 (UNDESA, 2018), with a higher rate of urbanization in Africa and Asia (UNDESA, 2018). Rapid urbanization comes with environmental, economic and social challenges, including land deprivation, air pollution, disturbances in urban ecosystems, health challenges, crime and traffic congestion, among others (Elmqvist et al., 2019; Keys et al., 2019; Ranagalage et al., 2020).

In most African countries, cities are urbanizing fast. Africa had the least urban population, about 197 million by 1990. However, in 2020 it recorded the largest population in the world after Asia (AfDB, 2016). Rapid economic growth, industrialization and migration into cities are the major triggering factors of rapid urbanization (OECD, 2017). It is estimated that by 2050, Africa will be 56% urbanized (UNDESA, 2018). In Sub-Saharan Africa, high population growth is estimated from 1 billion in 2016 to 2 billion by 2046, whereby in 2100, Sub-Saharan Africa is expected to account for 35% of the global population, rising from 13% in 2016 (UNDESA, 2018), with countries such as Mozambique, Zambia, Uganda and Tanzania expected to treble in size in the coming years (UNDESA, 2018). Thus, there is rapid urban population growth in developing countries, compared to developed countries.

In Tanzania, most cities such as Dar es Salaam, Arusha and Mwanza, have experienced a high rate of urbanization attributed to an increase in urban population, with Dar es Salaam growing from a population of 2 million in 2000 to around 6 million people in 2020 and expected to double by 2035 (UN, 2020). Currently, Dodoma City has recorded a higher population growth since the relocation of government offices from Dar es Salaam to the city (Makonyo & Msabi, 2021; Msabi & Makonyo, 2020; Xinhua, 2018). All ministries and departments relocated their employees to the city, with about 2346 civil servants having been transferred to the city by July 2016 (Oforo, 2017). This relocation triggered expansion and initiation of various developmental, social and economic projects, such as industries, renovation and construction of new roads, hospitals, offices, residential houses, financial institutions, state houses, public universities and airport expansion among others, opening of various business centres such as shopping malls, hotels, lodges and new markets, which led to the migration of people from different parts of the country and beyond, to the city in search of socio-economic opportunities, which in turn resulted in the city's accelerated population growth. Relocation, natural increase and high rates of rural to urban migration are the major root factors of the rapid urban population growth within the city, as in other African cities, due to a disparity in development between rural and urban areas. However, these growth dynamics are associated with social-economic and environmental challenges in a given area over time, as in other parts of the world (Seto et al., 2011). These include degradation of land, wetlands, natural habitats, hydrological cycles and the local climate, among others (Kukkonen & Käyhkö, 2014; Seto et al., 2011). The impact of land use/land cover (LULC) changes is more serious in developing cities than in other areas as a result of pressure on land due to the high rate of construction activities (Wang et al., 2021), which acts as a good indicator of urbanization. Various studies have applied geospatial technologies in providing insights on the assessment of LULC changes monitoring and analyses in different parts of the country including; LULC changes prediction for Dodoma (Kabanda, 2019), analysis of the future LULC changes in the peri-urban areas of Dar es Salaam (Mnyali & Materu, 2021), evaluating historical and predicted long-term LULC changes in Dodoma (Mubako et al., 2022), modelling drivers of LULC in Usangu catchment and Kilombero Valley (Hyandye et al., 2015), analysis and modelling of urban growth in Dodoma (Kisamba & Li, 2022), with most of these focusing on the rural settings thus, leaving behind rapidly growing urban areas with inadequate information for future planning.

The advancement of science and technology, specifically GIS and RS, has easily and highly accelerated the study of urbanization patterns by employing spatial datasets, which have replaced the limitations of quantitative datasets facing most African countries (Ndzabandzaba, 2015). Regardless of the large spatial coverage of the remotely sensed datasets, the cost-effectiveness of the datasets is of vital importance in motivating researchers to widely study and model earth-related challenges for human prosperity. Satellite imageries acquired utilizing RS have capabilities of recording dynamics of LULC in a given area over time and thus, are a good source of information through which LULC information can be extracted and analysed for better planning (Liping et al., 2018). Various datasets such as LULC, soil datasets, surface temperature and population density among others, can be easily produced from remotely sensed datasets in various spatial-temporal resolutions (Alshari & Gawali, 2021; Murayama et al., 2021), and can easily guide scientific and logical land planning as well as foster social and economic developments (Liping et al., 2018). However, GIS is capable of providing volatile environments for the collection, storing, manipulation and displaying spatial datasets employed in LULC change analysis and detection (Khan et al., 2016). These techniques have been proven effective in mapping and analysing urbanization patterns as well as predicting future patterns (Abebe et al., 2022; Arumugam et al., 2021; Simwanda et al., 2020). Furthermore, these technologies have recently been the key to planning and developing of sustainable cities in many parts of the world (Murayama et al., 2021). Moreover, various LULC change detection and prediction models have been developed and applied. The most widely used models among others include; analytical equation models, statistical models, Cellular-Markov models, multi-agent models and multi-layer perception neural networks (Hyandye et al., 2015; Shamsi, 2010). However, in the current study, Cellular Automata (CA) and Markov Chain analysis models (CA-Markov) have been employed. This model can easily predict LULC change in an area as it considers space (spatial) and time (temporal) and provides the probability of change in an area, it is advantageous in simulating LULC dynamics (Liping et al., 2018). Various researchers have applied this model to understanding LULC change dynamics globally (Ghalehteimouri et al., 2022; Kafy et al., 2021; Onilude & Vaz, 2021; Rahnama & Society, 2021; Wang et al., 2021). Therefore, this study will assimilate GIS and RS in analysing the urbanization trends elicited by urban migration within Dodoma City, Central Tanzania. The results from the analysis will be used as a framework for the government, city planners, decision-makers and other stakeholders engaged in planning for sustainable development of the city, as well as understanding the spatial-temporal patterns of the city for future planning.

1.2 Statement of the Research Problem

Since the relocation of government offices from Dar es Salaam to the city in 2016, the city has experienced high pressure on land due to new developments and expansion of various social-economic interventions including; industries, hotels, residential buildings, expansion of roads, airports, business centres, hospitals, play grounds and government offices, among others (Msuya et al., 2021). These developments have accelerated the high rate of population growth coming from the city's peripherals and other inner parts of the country, as well as outside the country, in search of economic opportunities, resulting in a high rate of city's urbanization. Consequently, these interventions have altered the natural LULC in most parts of the city as well as changed the ecology of areas that were previously virgin and un-surveyed. However, high population growth not only affects natural LULC, but it is also associated with various socio-economic challenges including crime, cultural deterioration, health issues and disturbance of the natural ecosystem, among others. Several LULC studies have focused on the use of geospatial technologies in monitoring natural resources within the area including; the influence of urban expansion on institutional arrangements in the management of urban spaces (Boba, 2014); drivers of LULC changes (Kabanda, 2019), historical and predicted long term LULC changes (Mubako et al., 2022), and modelling of urban growth (Kisamba & Li, 2022). These studies provide useful insights into drivers of LULC changes but, despite the higher population growth associated with the high demand for land for human interventions within the city, there is little attention on LULC changes with respect to urbanization caused by high population growth within the city which is meaningful for future planning. Hence, this calls for the current study to assimilate the advantages of geospatial technology, which captures timely based LULC information of a given area over time to assess spatial-temporal dynamics of urbanization within the city, in response to population growth.

1.3 Research Objectives

1.3.1 General Objective

The main objective of this study was to assess the spatial-temporal dynamics of urbanization for the years 2001, 2011 and 2021, in relation to population growth in Dodoma City.

1.3.2 Specific Objectives

i. To determine Dodoma City's LULC classes for the years 2001, 2011 and 2021
ii. To examine Dodoma City's change in LULC trends for the years 2001, 2011, 2021, and 2001-2021
iii. To simulate Dodoma City's 2040 LULC and assess changes.

1.4 Research Questions

i. What are the Dodoma City's LULC classes for the year 2001, 2011 and 2021?
ii. What are the causes of Dodoma City's change in LULC trends for the years 2001, 2011, 2021 and 2001-2021?
iii. What are the simulated Dodoma City's 2040 LULC classes and changes?

1.5 Significance of the Study

The significance of the present study is to inform and increase awareness among the public, government and stakeholders, on spatial-temporal changes of urbanization trigged by population growth as a result of urban migration and its effects on the LULC changes within the study area. Unmanaged population growth poses serious challenges to the natural and man-made environments, human health, water sources and safety, as well as to city planning. Therefore, the findings from this study will provide an inventory of information to the society, stakeholders, authorities, practitioners and decision-makers, on the right trend of urbanization within the city since 2001, determine specific areas urbanizing fast within the city, as well as reveal which LULC category within the areas is diminishing as a result of urbanization, so that appropriate measures can be taken for sustainable city development.

1.6 Organisation of the Report

This research work is organised into five chapters. Chapter one comprises the background & introduction, a statement of the research problem, the objectives of the study, the research questions and the significance of the study. Chapter two covers the literature review, which includes the definition of key concepts, the empirical review and the conceptual framework. Chapter three covers the description of the study area, justification of the study area selection, data types and sources, data collection methods, data processing and analysis, as well as a methodological framework. The fourth chapter consists of the results and discussion, while the last chapter includes a summary of the findings, conclusion and policy recommendation, as well as references.

CHAPTER TWO
LITERATURE REVIEW

2.1 Definitions of Key Terms

2.1.1 Geographical Information Systems (GIS)

GIS is a computer-assisted system for collecting, storing, managing, analysing and representing geo-referenced data to help in spatial decision-making. It is useful for mapping and analysing real-world objects and events (Ali, 2020). It also allows users to create maps, query information, edit, analyse and present results from these operations.

2.1.2 Remote Sensing (RS)

RS is a technique of acquiring information, detecting, evaluating and monitoring the earth's surface features by recording reflected and emitted electromagnetic radiation without coming into contact with the object under investigation (Campbell & Wynne, 2011).

2.1.3 Geospatial Analysis

Geospatial refers to the mix of spatial software, analytical tools and datasets pertaining to a specific geographic location. Thus, spatial analysis is a collection of interconnected techniques used to select an inferential model that takes into consideration the geographical relationship between observable variables (Mücher, 2009).

2.1.4 Landsat Image Processing

This is the process of manipulating digital satellite imagery with various computer tools to extract relevant information for spatial decision-making. This technique includes band detection, band restoration, atmospheric correction (geometric and radiometric correction) and digital image analysis, among others (Tewabe & Fentahun, 2020).

2.2 Theoretical Review

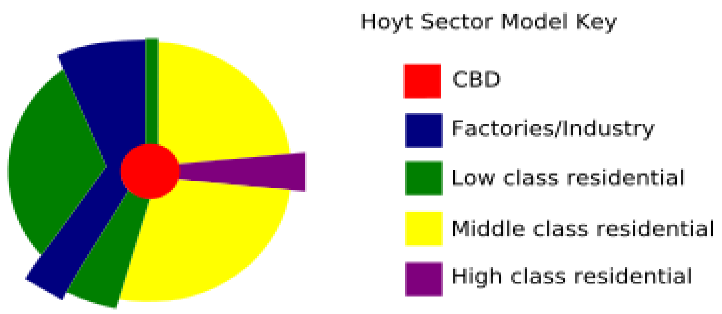
2.2.1 Spatial Theory of Development

The spatial theory was first introduced by Hotelling in 1929 through a seminal paper. The theory is built on the concept of distance, which may be of economic or ideological forms that span many disciplines such as social, economic, urban and geography studies among others (Hotelling, 1929). In this theory, the author tried to study the balance of locating two sellers with homogeneous products, based on spatial completion (space), thus allocating limited materials among different users. However, space is extended beyond the physical space, which includes position based on the characteristics of the product and political platforms. This is one of the building blocks in the political phenomenon analysis is the exemplification of preferences (Lancaster, 1979). The mechanics of the public choice method are halted in the absence of a technique for capturing the substance of goals and trade-offs for individual choices. While there are other theories describing preferences, the 'spatial' model is the most often utilized (Hinich & Munger, 2004). This model was previously used in classical economic games, in which both player's supplier and consumers operated within certain constraints, such as limited budget, demand and technology while maximizing utility and profit thus, after attaining mutual adjustment, the equilibrium will be attained (Olsson & Gale, 1968). Most spatial theories have been adopted and extended from economic theories in which traditional regional science and theoretical geography have been directed in the same narrative. This context implies that players can change utility and production functions as well as manipulate space. The limitation of this theory is that space was devaluated and considered dead due to its immovability. It is noted that most spatial theories have the same assumptions and behaviour as non-dimensional theories. Hence it is assumed that traditional spatial theories are valid and they are meant to engage them in the calculation of the optimal and equilibrium solutions, as well as deriving alternatives (Olsson & Gale, 1968). In this research, the spatial theory provides the basis to use different assumptions and choices of LULC classes, which are attributed to occupying space of known location, dimensionality and directionality in examining the spatial-temporal changes of urbanization, with respect to urban migration within Dodoma City.

2.2.2 Radial Sector Theory of Development

Homer Hoyt, an American land economist, proposed the sector theory of urban land use in 1939. His ideas were first published in 1939 under the title 'The Structure and Growth of Residential Neighbourhoods in American Cities,' by the United States Federal Housing Administration (Washington), (Hoyt, 1939). Hoyt had conducted a factual examination of residential rent patterns in twenty-five cities in the United States of America. According to Hoyt (1939), cities have five different types of land use zones: Central Business District (CBD), wholesale and light industry zone, low class residential zone, medium class residential zone and high class residential zone. Hoyt's model considers the entire city to be a circle, with various land use zones originating near the centre of the circle and migrating towards the periphery and the differences persisted as the city grew. Distinctive land use sectors, often cantered on major route ways, were likely to emerge from the city centre. Thus, high-class residential areas are the primary tool in shaping the city's land use structure. He further suggested that land use patterns are conditioned by the arrangement of transportation routes radiating out from the city centre, which created a sectorial system of land and rent values, which influences the urban land use pattern. Hoyt's concept of a wedge-like expansion of urban land use is an improvement on Burgess' earlier concentric model, in that it considers both the distance and direction of expansion, as well as the importance of transportation routes in city growth. In Hoyt's model, high class residential areas originate in the eastern quadrant of the city and would tend to extend outward along established lines of communication, thus producing the sector (Figure 2.1). Certain characteristics are dominant along this process, including homes of influential members of the community, open land free from the threat of flooding and open spaces without any physical barriers. The most expensive locations for new homes will be found along the perimeter of a district with high-class housing once it has been established. A zone of high-class housing eventually tends to be located on one side of a city due to urban expansion, rather than in the continuous ring as suggested by the concentric theory over time.

Figure 2. 1: Hoyt's Sector City Model (Hoyt, 1939)



Hoyt's sector theory provides a more thorough explanation of the residential organisation of the city. Thus, when it comes to the growth of residential areas, the sector theory is more relevant, with the advantages of considering the city's future growth and development, and acknowledges the significance of transportation pathways, particularly arterial streets and highways, in determining the city's overall land use pattern. Both the centre of the city and its periphery have different types of land use. However, as layers of homes are added to the edges of cities, it becomes more likely that the edges of buildings will display a concentric arrangement, even though better clan housing may extend outward in a sector. The critique of this theory is seen as representing a fundamental change, hence perceived as a refinement of Burgess' earlier concentric zone model. Additionally, the theory ignores the emerging ideas of edge cities and boom burbs that emerged in the 1980s, following the development of the model. Since its inception, the traditional Central Business District has lost some of its significance as a result of the relocation of numerous stores and offices to the suburbs. Therefore, this theory fits well and has been applied in the current research work to understand city development and various changes in land use patterns with time, as well as determining future city development within the study area.

2.3 Empirical Review

2.3.1 Urbanization: What is it?

Urbanization is the proportion of the number of people living in urban settings (Jones, 1991). It is a complicated socio-economic factor that changes and completely transforms the built setting of a given geographical area, and also changes rural locales into urban settings, while transforming rural spatial distribution into urban (UNDESA, 2018). This process includes the changing of former lifestyle, culture and behaviour, which eventually affects the demographic, economic and social structure of the rural and urban areas (Montgomery et al., 2013). Urbanization is associated with the increase in population size residing in urban areas and high human interventions on land as compared to rural areas moulded by spatial and urban planning, as well as by buildings and infrastructure (UNDESA, 2018). These cities that are transformed due to urbanization, usually become sustainable areas where both public and private basic services are easily accessible as compared to rural settings. Thus, in turn, urbanization has a positive influence on economic growth, poverty reduction, human development and prosperity.

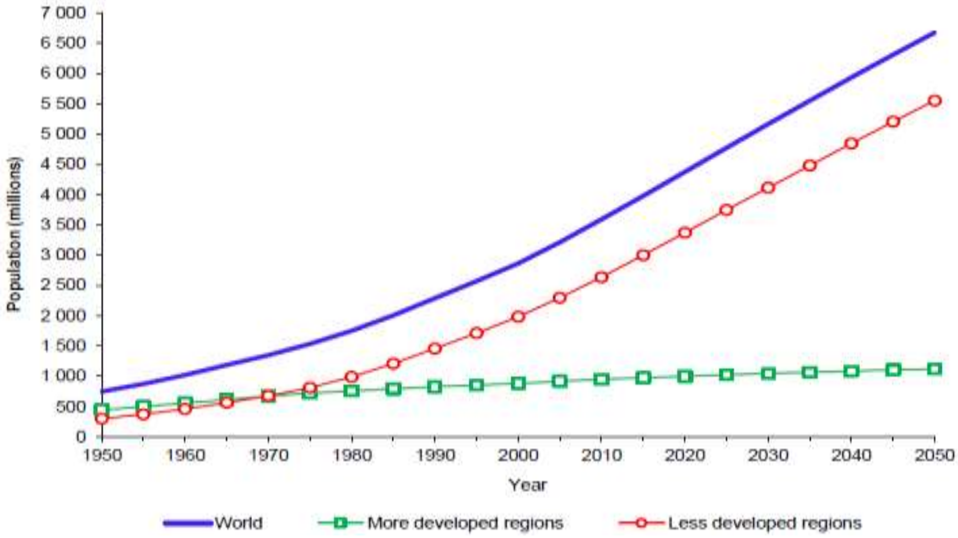
2.3.2 Urban Migration

Urban migration can be a pure permanent shift of people from residing in rural areas to living in urban areas (Hugo, 2015). In most cases, migration tends to be driven by aspirations in search of socio-economic opportunities worldwide. However, urban migration motives differ from country to country. In most African cities, the high rate of urban migration is triggered by the search for employment opportunities, better health and education facilities, among others (Mlambo, 2018). Urban migration rapidly results in urban population growth, which eventually transforms rural setting into urban environments, as more social services and better economic opportunities speedily emerge, resulting in the expansion of the urban settings. Population shift has played a great role in the growth of urban centres globally (Hugo, 2015), and has greatly influenced the socio-economic and demographic structure of urban settings, as well as the expansion and growth of urban centres (Montgomery et al., 2013). However, urban migration is highly contributed by rural-urban migration, internal and external migration (UNDESA, 2018). In most cases, urbanization and urban growth drivers are stimulated by three main components: natural increase, migration and reclassification. Thus, their role in urban growth varies depending on demographic changes, spatial planning policies, physical settings and country specific-conditions (Hugo, 2015; UNDESA, 2018).

2.3.3 Global Urbanization Trend

The world urban population is increasing rather rapidly and tremendously, the future global population will consequently be increasingly and predominantly in urban areas. In 1959 the world experienced the first 1 billion urban population hit and 2 billion in 1985. However, this population doubled to 4 billion in 2015, a period of only 56 years, and is projected to reach 6 billion in 2041, with the declining of its counterpart rural population (UNDESA, 2018). Thus, the global population is rapidly urbanizing from 30% in 1950 to 55% in 2018 with an expectation of 66% by 2050 (UNDESA, 2014) (figure 2.1). Global statistics show that in many regions of the world's developing urban population, the number and size of cities will grow and expand rapidly as a result of various factors including; rural-to-urban migration, urbanization of local centres and surplus of births over deaths in cities (Lerch, 2017), with low growth rate in developed countries.

Figure 2. 2: Global Urbanization Trend from 1950 to 2050 (UNDESA, 2014)



2.3.4 LULC Change and Urbanization

Urban growth is associated with the change in the LULC of a particular area because of human activities, such as industrial, residential and commercial developments. This growth is normally quantified through the use of LULC change analysis for specific LULC classes, identified fitting the purpose of the study, such as built-up areas, barren land, agricultural fields, forest and wetlands (Hall & Hossain, 2020). However, for the assessment of urbanization, defining which LULC class category to be considered urban is of vital importance. Urban LULC class is the spatial intensity of developed land, thus proportional to impervious surface per area of land (Hamer, 2003). Urban settings are considered human-developed areas that do not allow percolation such as buildings, walkways, parking spaces, roads, airways, railways and any other environment considered to be an urban setting.

2.3.5 Approaches for Urbanization Trend Mapping

GIS and RS techniques have rapidly replaced traditional methods of analysing LULC, which were done through in situ surveys and aerial photographs measurements, which could offer detailed information. However, these techniques were very expensive, time-consuming as well as spatially and temporally limited (Hall & Hossain, 2020). Since the launch of the Landsat Mission in 1972, mapping of urbanization has been more affordable using datasets acquired by optical satellite sensors, capable of differing spectral variations from various LULC categories on the earth's surface. Hence, it has made it possible to study urban growth (MacLachlan et al., 2017) as applied to urbanization studies elsewhere (Jeykumar & Chandran, 2019; Salamatnia et al., 2019). Furthermore, the use of supervised and unsupervised classification schemes is widely used to extract different LULC spectral signatures used in assigning LULC class values over space and time. However, other classification algorithms, which require significant data analysis and processing, such as linear spectral un-mixing and machine learning, among others, are also used.

2.3.6 LULC Change Detection Analysis

LULC change detection is undertaken to determine which LULC class is changing to what class over time and space. Change detection is employed in various LULC-related applications, such as cultivation, urban expansion and landscape variations (Tewabe & Fentahun, 2020). Thus, understanding the changes taking place on the earth's surface over time is of vital importance for the management of resources and sustainable planning. Satellite imageries of different years are employed to determine these changes. The commonly known LULC change analysis methods include; image overlay, evaluation of the differences of classified LULC statistics, change vector analysis, image rationing, principal component analysis (PCA) and supervised classification schemes, among others (Han et al., 2009). Thus, areas covered in each LULC class are determined from each classified LULC map of each year under analysis and then land cover statistics are used to determine these changes over space. However, from these statistical analyses, the spatial change trend is also determined. Thus, change detection has become a major application of remotely sensed data because of repetitive coverage at short intervals and consistent image quality (Twisa & Buchroithner, 2019). Furthermore, various LULC classes are employed in change analysis based on the purpose of the study and interest in built-up areas, agriculture, forests, water bodies and bare soil (Shah et al., 2021), built-up areas, bare land, vegetation, and water areas (Kisamba & Li, 2022).

2.3.7 Simulation of Future LULC Changes

2.3.7.1 Markov Chain Analysis

The Markovian chain analysis is used in the simulation of LULC changes over a time interval in which the transitional probability of the current state and the earlier determines the transition trends of different LULC states (Liping et al., 2018). This facilitates the simulation of future LULC changes (Wang et al., 2021). However, the model is insensitive to both system state and space (no spatial variables) (Liping et al., 2018). It produces a transitional probability matrix that shows which cell will change to another cell in the future as well as transitional areas which will change over a defined time interval. The Markov chain analysis model is expressed as in equation (Eqn) 2.1;

$$S_{(t,t+1)} = p_{ij} \text{ x } S_{(t)} \quad \text{.................................} \quad \text{Eqn 2.1}$$

Where:

$S_{(t)}$ is the system state at time t, $S_{(t+1)}$ is the state at time t+1, p_{ij} is the transitional probability matrix of the system (Khanal et al., 2019; Ma et al., 2012).

Thus, the earlier state of the system $S_{(t+1)}$ can be well determined by the later state $S_{(t)}$ within the Markov model by using (Equation 2.2).

$$p_{ij} = \begin{bmatrix} p_{11} & p_{12} & \cdots\cdots & p_{1n} \\ p_{21} & p_{22} & \cdots\cdots & p_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ p_{n1} & p_{n2} & \cdots\cdots & p_{nn} \end{bmatrix} \left(0 \leq \; p_{ij} \; \leq 1 \quad\right) \text{ .... Eqn 2.2}$$

Whereas:

P is the transitional probability matrix of the Markovian Chain Model, p_{ij} is the probability of transforming from current state i to another later state j. The low transformation will have a probability near 0 and a higher near 1 (Munthali et al., 2020; Wang et al., 2021).

2.3.7.2 Cellular Automata (CA) Analysis

CA analysis is one of the most used LULC modelling algorithms worldwide. The CA is a discrete model which employs changing spatially extended systems based on pre-defined transitional rules, relating the current state to the earlier LULC state and those of the surroundings (neighbourhood) (Munthali et al., 2020). CA is a stochastic model which is capable of providing complex and nonlinear processes of a spatial-temporal phenomenon in local, regional and global LULC change patterns (Liping et al., 2018). In CA, the change in a given cell is influenced by rules, thus the model consists of cells, cell space, rules, time and neighbourhood (Liping et al., 2018). These factors determine the transition probability of a cell from one state to another (Liping et al., 2018). Thus, the CA model can be expressed as (Equation 2.3).

$$s_{(t,t+1)} = f_{((st),N)} \text{ .... Eqn 2.3}$$

Whereas:

S is the set of finite cell states, N is the neighbourhood cells, t and t+1 are different time intervals and f is the transformation rule of the local space (Liping et al., 2018; Mohamed & Worku, 2020; Wang et al., 2021).

2.3.7.3 CA-Markov Analysis

The CA-Markov Model is a hybrid of the CA and Markov models. The models take the advantage of CA in the simulation of spatial change over time (spatial-temporal dynamics) and the transition probability from Markov to simulate the future spatial-temporal LULC change of a given area, as applied in other studies (Baqa et al., 2021; Ghalehteimouri et al., 2022; Wang et al., 2021; Zhang et al., 2021). Thus, the Markov Chain Model based on the transitional probabilities controls LULC, changes over time, while spatial changes are controlled by the defined set of rules within the CA model (Liping et al., 2018). However, the spatial prediction accuracy of the LULC map can be produced on the model.

2.3.8 Application of GIS and RS in Urbanization Studies

Currently, GIS and RS have been the most widely used spatial technologies in assessing spatial-temporal changes of urbanization worldwide (Serra et al., 2008). They have been advantageous due to their versatility in handling and managing large multi-disciplinary datasets. GIS provides an efficient environment for storage and analysis providing its powerful set of tools for collecting, storing, retrieving, transforming, and displaying spatial data from the real world for spatial decision-making, than conventional methods (Makonyo & Msabi, 2021). However, RS is advantageous in providing remotely spatial information and it is cost-effective, and less time-consuming, while providing a large coverage of information over time, which is useful in spatial-related problem solving (Kisamba & Li, 2022). It is the most widely used technology for the acquisition, quantification and mapping of various LULC characteristics on the earth's surface over time, due to its repetitive data detection capability and ability to quantify LULC changes over a wide range of spatial-temporal scales in a particular area, and differentiates various spectral signatures between LULC classes (Chen et al., 2005). Future LULC changes simulation models have been developed and incorporated within these technologies thus, offering a favourable environment to detect and plan for future changes, including the Cellular Automata (CA), Markov Model, the hybrid CA-Markov Model, and machine learning algorithms, among others. Hence, this study takes advantage of these methods and techniques, which are efficient in mapping urbanization trends and extents at different spatial scales within the city to enhance the availability of vital information for strategic decision-making in the study area.

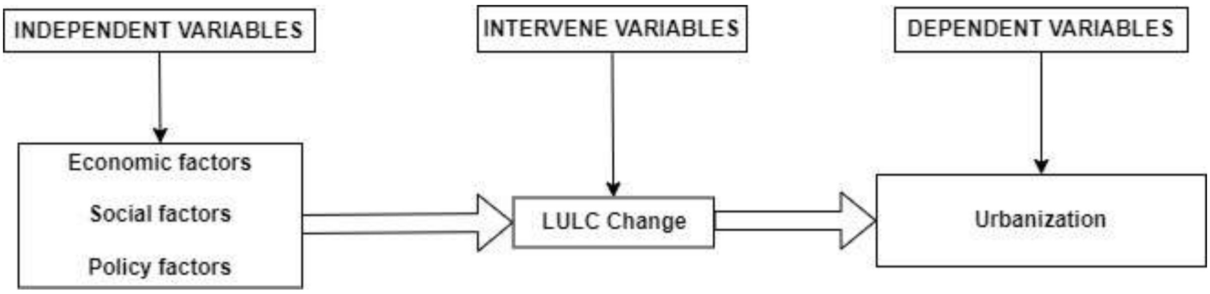
2.3.9 Dodoma City Development Governing Bodies

The transformation of Dodoma into capital and an international city was vested under the Capital Development Authority (CDA), founded through Government Notice Number 230 of October 1973, under the Parastatal Act of 1969, Number 17, with its amendment in 1992 (Kiduanga, 2014) and later dissolved in 2017. The authority applied decentralization by a deco-centration system to manage land and urban development activities within the city to assist the government in smoothly transferring to the city. It had to ensure the implementation of the decision of transferring Tanzania's capital city from Dar es Salaam to Dodoma, to prepare plans for Dodoma City developments to the targets of the capital city, to advise and assist the government on a well and orderly transfer of various government and other public offices to Dodoma, to ensure coordination of land surveying, plots allocation, issuance of leases, hold and control unauthorized developments, among others, which were then vested under the Dodoma Municipal Council (DMC). Due to rapid population growth, the failure of these authorities to fully engage people at the grass roots level, affected their performance in several ways, including the invasion of people in undeveloped land in search of building materials such as aggregates, sands and stones, causing loss of water catchments in some areas within the city. Furthermore, the emergence of squatters was due to the shortage and delayed survey of land in relation to increased demand, as well as the laxity of relevant officials in implementing laws and policies (Kiduanga, 2014). All these have triggered LULC change in different parts of the city, as people infringe on these areas for human development, rapidly transforming the areas into urban localities.

2.4 Conceptual Framework

The applied conceptual framework indicates that social, economic and policy factors influence change in the LULC of an area (figure 2.2). However, it shows the relationship between existing independent, intervening and dependent variables. Economic factors such as industrial and commercial activities highly influence urban growth, which eventually accelerates LULC change, leading to rapid urbanization in a given area (Kisamba & Li, 2022; Msuya et al., 2021). Studies also indicate that environmental and social factors are amongst the positive forcing factors of LULC change which trigger rapid urban growth, eventually resulting in high urbanization in most cities globally (García, 2010).

Figure 2. 3: Conceptual Framework Employed in the Current Study

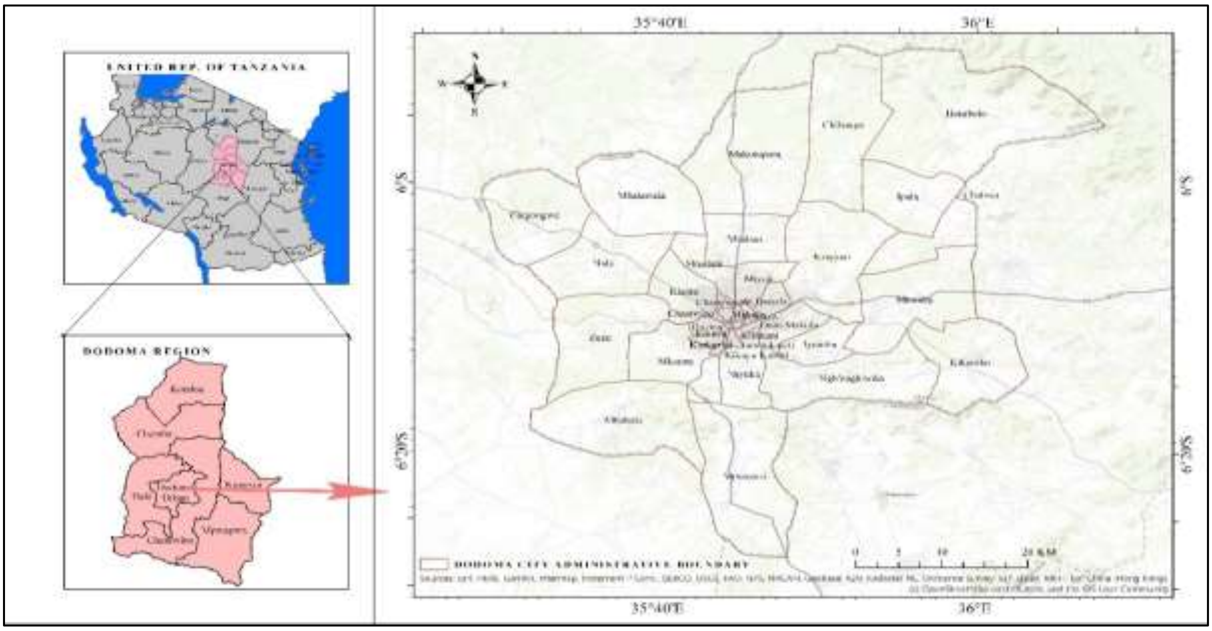


CHAPTER THREE
RESEARCH METHODOLOGY

3.1 Description and Location of the Study Area

Dodoma City lies in the central region of Mainland Tanzania. Dodoma was designated as the capital city of the country in 1974. However, the majority of government offices remained in Dar es Salaam, until major offices were transferred in 2016. The city was selected as the capital because the government needed to foster significant social and economic improvement in the central regions and have a more centralized capital, as by then Dar es Salaam was already urbanized. The city is situated 453 km away from Dar es Salaam (the largest city and financial hub of the country), and 441 km from Arusha (Headquarters of the East African Community), covering about 2,669 square kilometres, in which 625 square kilometres are urbanized (CCD, 2020). Topographically, the area lies at an elevation of about 1135 meters above the mean sea level within the central plateau of eastern Africa, characterized by semi-arid climatic conditions, with a long dry and short wet spell, with average annual precipitation of about 300 – 800 mm. Demographically, according to the Nation Bureau of Statistics (NBS) 2012, the city had about 410,956 residents, with an average household of about 4.4 people. The residents of the area are mostly the Gogo, Sandawe, Rangi and other tribes, who engage in small, medium and large-scale business activities, as well as social and administrative activities (figure 3.1).

Figure 3. 1: Location of the Study Area



3.2 Justification of the Study Area

Relocation of government offices from Dar es Salaam to Dodoma City stimulated high population growth, as a result of immigration of people in search of socio-economic opportunities, as well as displacement (Makonyo & Msabi, 2021; Msuya et al., 2021). To accommodate this growth, various development strategies were adopted by individuals and the government to expand existing as well as develop new infrastructure. This led to the booming of new buildings for residential, commercial and office use, thus infringing on virgin areas which were previously covered and used for other activities. As the city is rapidly urbanizing, there is a need for a thorough understanding of the dynamics of urbanization spatial patterns within the city, the magnitude of change and urbanization trends for effective and inclusive planning, management and sustainable city development.

3.3 Data Types and Sources

In the current study, three epochs of cloud-free Landsat imageries were analysed. Landsat 7 Enhanced Thematic Mapper Plus (ETM+) was acquired on November 06, 2001, Landsat 7 ETM+ on November 02, 2011, and Landsat 8 OLI on November 05, 2021, both acquired from the United States Geological Survey (USGS) Earth Explorer (https://earthexplorer.usgs.gov/), with path 168 and row 064. In Landsat 7 ETM+, band combinations involving bands 2, 3 and 4 were employed in LULC analysis for 2001 and 2011, while band combinations involving bands 3, 4 and 5 were employed in the analysis of 2021 LULC classes. These imageries were in standard format (rectified), with less than 10% scene and cloud cover both, with 30m spatial resolution and of the same season (month) to eliminate seasonal change and minimize cloud cover. However, a handheld Global Positioning System (GPS) device was used for field data collection (coordinates), employed in the validation stage of the classified imageries and assisting in the LULC classification phase.

3.4 LULC Classification Method

The selection of LULC classification methods is of vital importance, as it influences classification and results interpretation. In the current study, four LULC categories were identified and classified within the study area (table 3.1). These LULC classes include built-up areas, wetlands, green vegetation and barren land. Similar classes have been used in various similar studies worldwide (Wang et al., 2021).

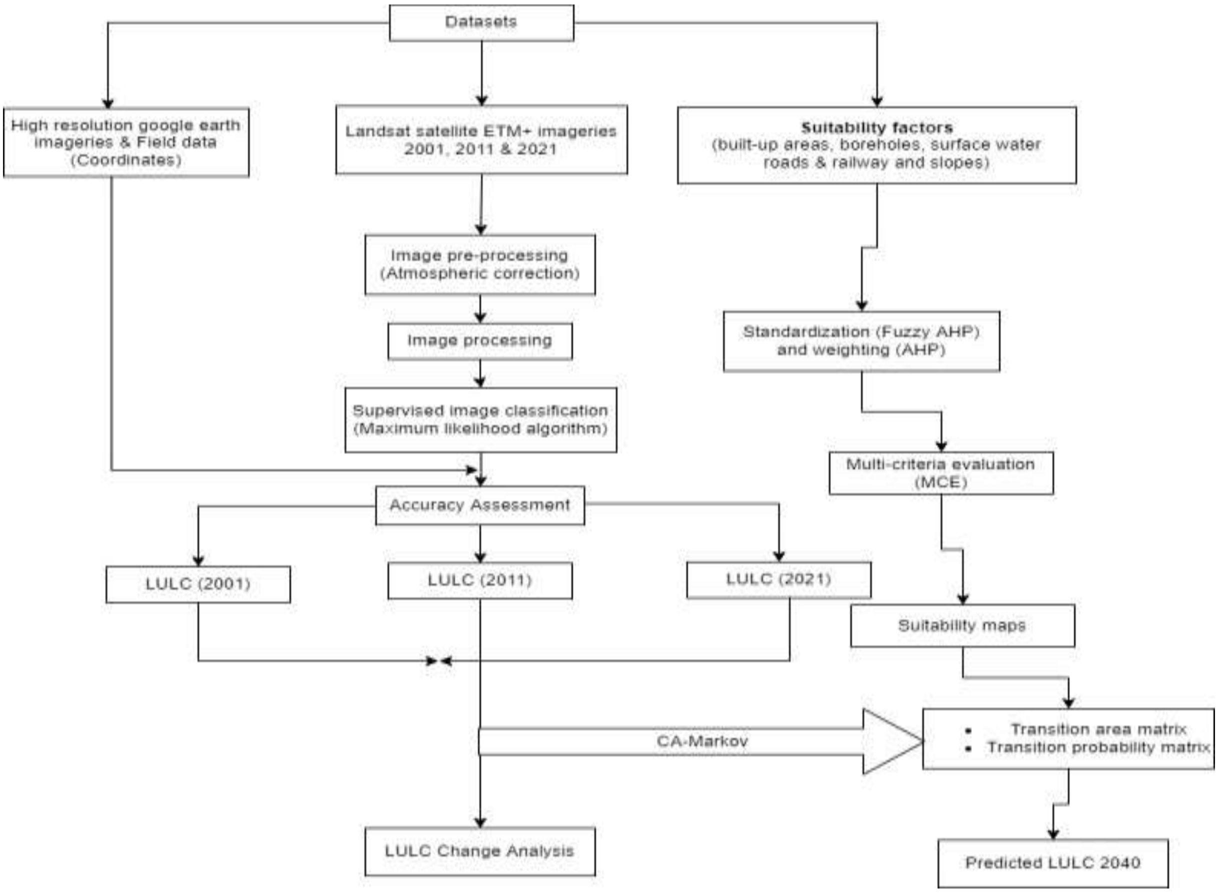
Table 3. 1: LULC Classification Scheme

LULC Types	Descriptions
Built-up areas	Commercial areas, settlements, industrial areas, government and institutional buildings, roads, hard surfaces, parking areas, recreational areas and airports
Barren land	Exposed soils, open landfills and rocks
Wetlands	Surface water, rivers, ponds, reservoirs and marshlands

Vegetation	Planted and natural vegetation

A detailed methodological flow (figure 3.2) shows the steps undertaken to accomplish this study.

Figure 3. 2: Methodological Framework Employed in the Current Study Modified From (Vinayak et al., 2021)



3.5 Digital Image Processing

Downloaded satellite imageries were both resized using extraction by mask toolset within ArcGIS 10.8 environment, in which the Dodoma City administrative boundary shape file was used to obtain imageries fitting the Area of Interest (AOI). Resized imageries were then imported into Environment for Visualizing Image (ENVI) software for further analysis. Using ENVI software, the raw downloaded imageries were transformed into Universal Transformation Mercator (UTM) Zone 36S Projected Coordinate System. Landsat imageries containing Digital Number (DN) values were then converted into Top of Atmosphere (TOA) then to surface reflectance, using the radiometric tool in the ENVI environment. Furthermore, both imageries were atmospherically corrected each at a time, including noise removal and de-stripping to remove missing scan lines in Landsat 7 ETM+ imageries (2011). At this stage, Landsat Gap-Fill Extension in ENVI software was used, in which a two-band gap fill (Local histogram matching) was employed. 30 m multispectral imageries were specified and Landsat 7 imagery (master image), with strips was firstly selected and lastly, Landsat 8 OLI imagery was secondly selected to assist in gap filling. Image enhancement was then performed to increase image visibility for easy visual image interpretation and for helping during the image classification stage. However, to properly examine and discern surface features, all the input satellite imageries bands 4, 5 and 6, were combined using the Red Green and Blue (RGB) colour composition. Additionally, before image classification mosaicking, band stacking and image sub-setting were conducted.

3.5.1 Pre-Processing

This is the first step undertaken on any spatial data before analysis. In this research, downloaded datasets such as lithology and soil were pre-processed, including editing and spatial reference transformation to a Universal Transverse Mercator (UTM) Zone 36S Projected Coordinate System. However, pre-processing for Landsat satellite imageries was undertaken through the following steps.

3.5.1.1 Atmospheric Corrections

Atmospheric correction is the process of eliminating the effects of the atmosphere on the reflectance values of an image taken by a satellite or any remote device (Pacifici et al., 2014). Atmospheric effects such as haze, water vapor and clouds, among others, usually tend to alter the spectral radiations reaching a remote sensor. Thus, the atmosphere tends to absorb or scatter radiation traveling from the sun to the object and again to the remote sensor, hence altering the quality of an image. The atmospheric correction undertaken in this study includes changing imageries Digital Numbers (DN) values to a physically interpretable measure of the Top of Atmosphere (TOA) corrections and Dark Object (DO) corrections, to improve the image visibility for visual interpretations and analysis.

3.5.1.2 Radiometric Corrections

Radiometric errors are the noises or effects caused by spatial or temporal variations in illumination quality and quantity, surface terrain and optical properties that tend to reduce image brightness signal relating to a certain surface cover taken by any remote sensor (Stow, 2017). Thus, radiometric correction involves the process of processing or removing these noises to improve brightness values in a digital image, hence improving the ability to visually interpret digital remote-sensed imageries as well as analyse them. Thus, these raw downloaded imageries were radiometrically corrected and enhanced using ArcGIS 10.8 software, before actual processing.

3.6 Image Classification and Accuracy Assessment

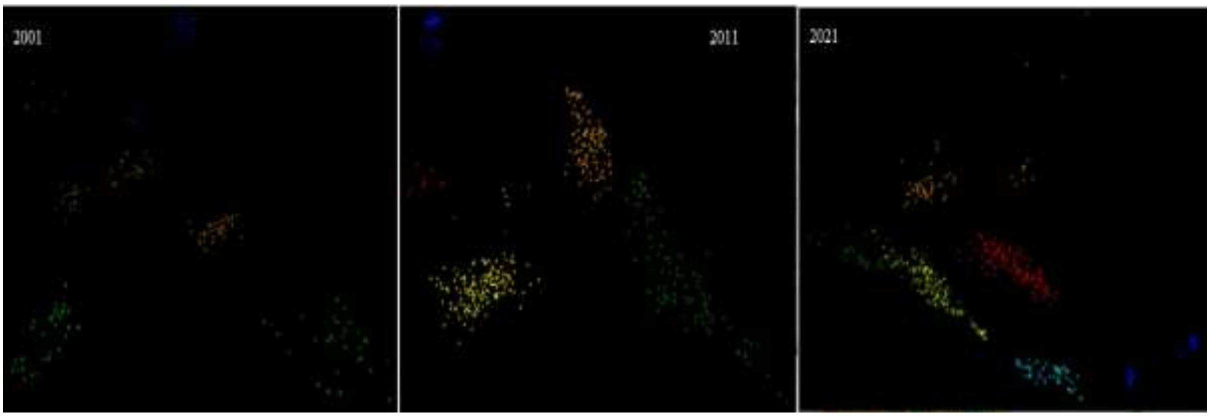
In the image classification phase, a supervised image classification algorithm was employed. The point type geometry method was used in selecting training samples in each epoch of the imagery. In this stage, various training samples were collected at each respective epoch combined image bands, in which built-up category, green vegetation, wetlands, shrubs and barren lands were produced by selecting pixel-by-pixel reflectance of each respective LULC class in each respective imagery. These training sample datasets were then saved and used in the maximum likelihood classification algorithm in ENVI software, to classify LULC categories for each epoch (2001, 2011 and 2021). Additionally, these training samples obtained were then used with the conjunction of the field-collected coordinates of the aforementioned LULC classes, for validation purposes. A modified Jeffries-Matusita and Transformed divergence separability measures metrics were used to establish the statistical separability between land cover categories for each variation in texture characteristics. These values range from 0 to 2 and a value greater than 1.9 indicates a good separability of classes, as obtained in this study (Table 3.2).

Table 3. 2: LULC classes pair separation and transformed divergences

LULC categories pair separation (2001)	Transformed Divergence	LULC categories pair separation (2011)	Transformed Divergence	LULC categories pair separation (2021)	Transformed Divergence
Wetlands and Shrubs	1.585	Built-up areas and Barren land	1.993	Built-up areas and Barren land	1.988
Vegetation and Barren land	1.995	Vegetation and Wetland	1.999	Vegetation and Wetland	2.000
Built-up areas and Shrubs	1.998	Vegetation and Barren land	1.999	Vegetation and Barren land	1.999
Built-up areas and Wetlands	2.000	Vegetation and Shrubs	1.999	Vegetation and Shrubs	2.000
Vegetation and Shrubs	2.000	Built-up areas and Vegetation	1.999	Built-up areas and Vegetation	1.998
Built-up areas and Vegetation	2.000	Built-up areas and Wetland	2.000	Built-up areas and Wetland	2.000
Wetlands and Vegetation	1.999	Wetlands and Barren land	2.000	Wetlands and Barren land	2.000
Barren land and Shrubs	1.999	Wetlands and Shrubs	2.000	Wetlands and Shrubs	1.999
Built-up areas and Barren land	2.000	Barren land and Shrubs	1.999	Barren land and Shrubs	1.985
Wetlands and Barren land	2.000	Built-up areas and Shrubs	2.000	Built-up areas and Shrubs	2.000

Furthermore, an n-D visualizer was used to clearly show the distribution of classes before performing supervised image classification (figure 3.3). This step is crucial in image classification as it enables checking class samples' boundaries to avoid interaction and mixing, which may lead to poor classification, hence maintaining the accuracy and quality of results.

Figure 3. 3: LULC Classes Training Samples Separability



3.7 LULC Change Analysis

This process is undertaken to determine the transition of LULC from one category to another over a defined period, from 2001 to 2021 within the study area, hence assessing the level of urbanization. Over a period of 20 years, a significant change, in terms of the area, will be determined due to the expansion of human settlement and human interventions on land because of population growth within the area, brought by rapid urban migration. Furthermore, confusion matrices are developed for each interval ranging from 2001 to 2011, 2011 to 2021 and 2001 to 2021, as well as the probability of LULC change of the projected 2040 map showing areal changes in terms of hectares (ha) from each respective LULC category in ArcGIS environment.

3.8 Accuracy Assessment

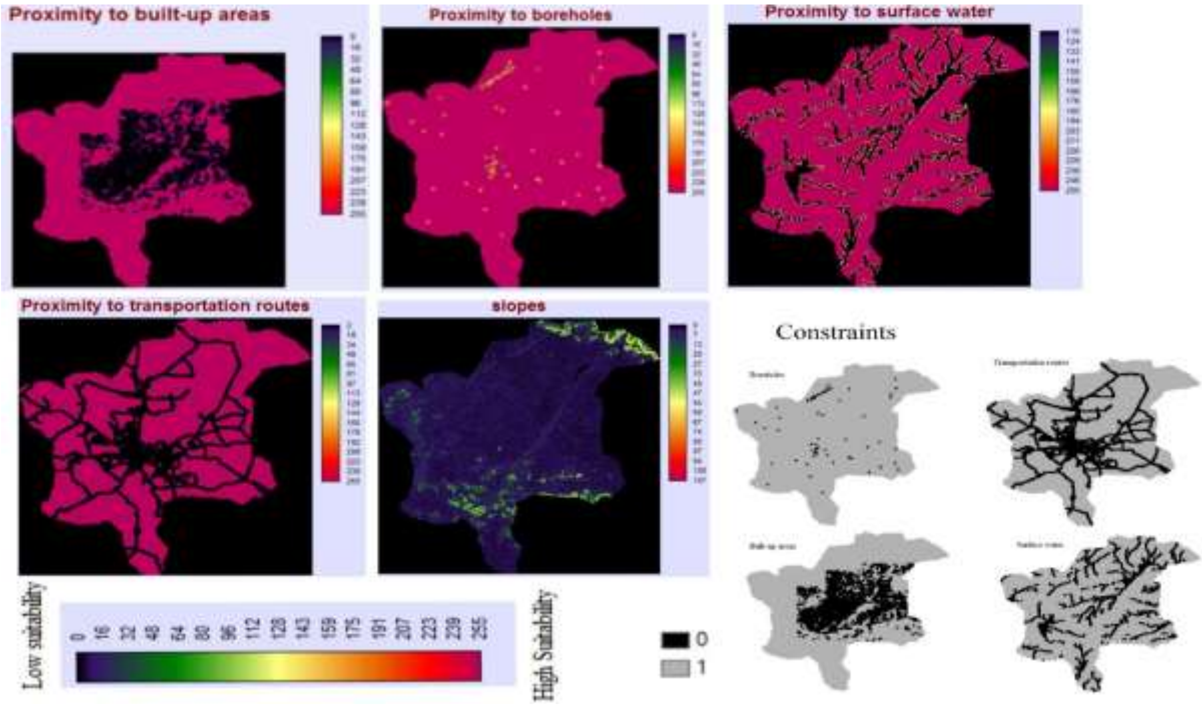
Accuracy assessment of the classified LULC maps of each respective epoch is of vital importance to assess how well the results have represented the earth's real features on the ground. Field data collection using handheld GPS devices was undertaken, in which spatial coordinates (ground truth datasets) of each respective LULC class of interest were collected. These points were then used to compare with the training samples datasets and an accuracy report was generated using a confusion matrix. The accuracy report includes overall user and producer accuracy. Overall accuracy represents the comparison between the correctly mapped reference sites against the total sites. The user's accuracy represents the error of commission, which shows the probability of reality in the classified image. Producer accuracy shows the error of omission which represents how often real features are accurately shown in the classified image (Vinayak et al., 2021). Furthermore, the Kappa Coefficient Index was computed. The index represents the proportion between the number of accurately classified pixels to the total pixel in the image (Cohen, 1960). Thus, if the index value is greater than or equal to 0.8, it indicates excellent agreement, 0.4 to 0.8, good agreement while less than or equal to 0.4 poor agreement (Foody, 2004).

3.9 Transitional Suitability Maps Preparation

The suitability maps generated in this study involved the use of various factors and constraints. The MCE method in TerrSet software was used to integrate various conditional factors to generate a single index of suitability for each LULC class involved in the analysis, which is a prerequisite for future change scenarios simulation (El-Hallaq & Habboub, 2014; Mishra et al., 2014). However, these driving factors may differ from place to place, based on the nature of the areas under investigation. In the current study, proximity to built-up areas, surface water, roads & railways, boreholes and slopes were used in the production of the suitability map of the built-up class, in which fuzzy membership function was employed in the standardization of the suitability map into a scale of 0 – 255, which represents low and high suitability, respectively using Sigmoidal, J-shaped and Linear fuzzy membership types available in TerrSet software. From these membership functions, different suitability levels were achieved based on available membership function shapes, such as monotonically increasing, decreasing and symmetric. However, constraints were also developed to limit the expansion of further development in developed areas and wetlands (Mishra et al., 2014). Existing built-up areas, surface water bodies, boreholes and transportation networks were used as the constraints. These were further standardized into a Boolean of 0 and 1, representing unsuitable and suitable for development respectively. Analytical

Hierarchy Process (AHP) techniques, using 1 to 9 Saaty's scale were employed in weighting these factors, in which scores of 0.2607, 0.4481, 0.1517, 0.0882 and 0.0513 were obtained for proximity to boreholes, surface water, built-up areas, roads and slopes, respectively (figure 3.4). Furthermore, Weighted Linear Combination (WLC) method was applied in aggregating these factors and constraints, generating a single built-up suitability map index of the study area. The other suitability maps were standardized from the transitional areas generated by the Markov Model, as used in various studies elsewhere (Kisamba & Li, 2022).

Figure 3. 4: Factors and Constraints Employed in the Construction of Suitability Maps



3.10 Future LULC Prediction

Future LULC change prediction was carried out using an integrated CA-Markov model embedded in TerrSet software. Transitional probability matrices for the years 2001 to 2011 and 2011 to 2021 were computed using the Markov Tool, which shows the probability of various LULC class changes in each respective year. Simulation of future LULC using the CA-Markov Model requires the basic land cover, transition area files and collection of the generated transitional suitability maps (Hyandye & Martz, 2017). The 2001 to 2011 transitional areas were combined with the suitability maps generated to simulate the 2021 LULC for validation purposes. On the other hand, the 2011 and 2021 transitional areas were combined with the suitability map to simulate the 2040 LULC map using the CA-Markov technique.

3.11 CA-Markov Model Validation

This is a critical phase in the CA-Markov modelling and prediction process. As a result, before employing the model in simulating future LULC maps, there should be a significant allowable agreement between the simulated and observed LULC maps. The

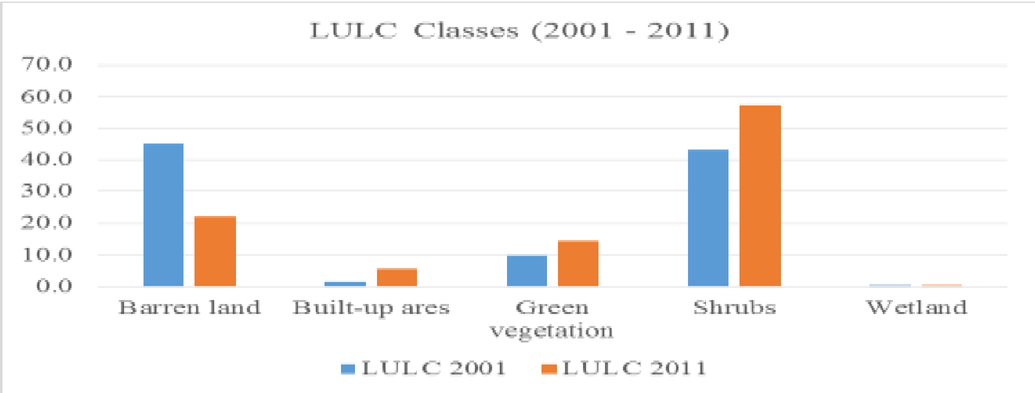
TerrSet software's Validate and Crosstab modules were used to generate various Kappa Index values, which measure the model accuracy using the observed and simulated 2021 LULC maps as inputs. Thus, Kappa Index values greater than 75% indicate that the model findings are at a higher degree of agreement, 50% to 75% indicate a medium or substantial level of agreement, and less than 50% indicate poor agreement (Keshtkar & Voigt, 2016; Pontius Jr & Schneider, 2001). In this study, Kappa for no information (Kno), Kappa for location (Klocation) and Kappa for standard (Kstandard) index values of the agreement were computed as suggested by various scholars (Mosammam et al., 2017). The future 2040 LULC map was finally simulated when the generated Kappa Index values were acceptable.

CHAPTER FOUR
RESULTS AND DISCUSSION

4.1 LULC Change From 2001 to 2011

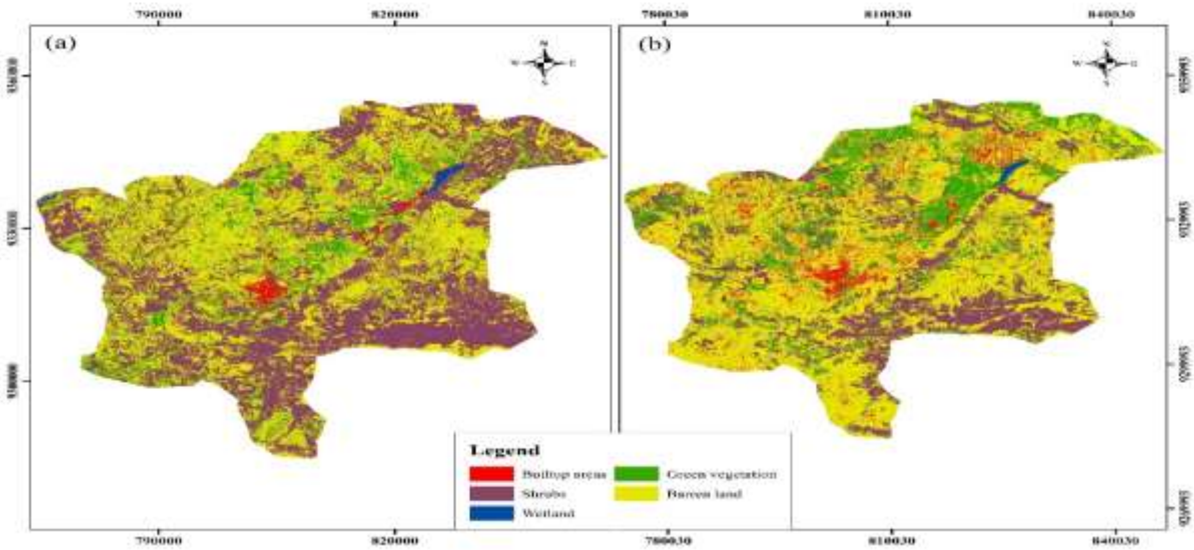
The results reveal that in 2001, Dodoma City was predominantly barren - almost 45.3% of the entire land area. Built-up areas and wetlands covered almost 1.4% and 0.4%, respectively. However, green vegetation and shrubs covered almost 9.9% and 43.1%, respectively (figure 4.1).

Figure 4. 1: Initial LULC Classes between 2001 and 2011



There was a sharp LULC transition between 2001 and 2011 LULC classes. Visually, the results show that there was a decrease in the barren land, wetland and green vegetation classes. However, the built-up areas class had shown a significant increase as compared to other classes (figure 4.2).

Figure 4. 2: LULC Maps for the Years 2001 and 2011



Results show a 20.85% decrease in the barren land class from 2001 and 2011. The decline could be the result of numerous increased human interventions, such as city infrastructure construction and settlement expansion as a result of rapid population growth. The built-up class, on the other hand, saw an increase of 4.32% in 2011. This is due to increased construction activities within the city which had accelerated the expansion of existing urban areas, as well as the growth of isolated centres which eventually became urban areas, accelerating the urbanization of the city. A positive growth of 4.67% was observed in the green vegetation class, which might be due to high rainfall and variations in climatic conditions. Furthermore, shrubs had an increase of almost 12.02%, which could also be attributed to climatic changes with increased rainfalls in 2011. Nevertheless, the results indicated a decrease in wetland areas by nearly 0.17%, in 2011, indicating that wetland areas might have been exploited as a result of the expansion of construction activities, including settlement and agricultural activities, as also identified by Kisamba and Li (2022).

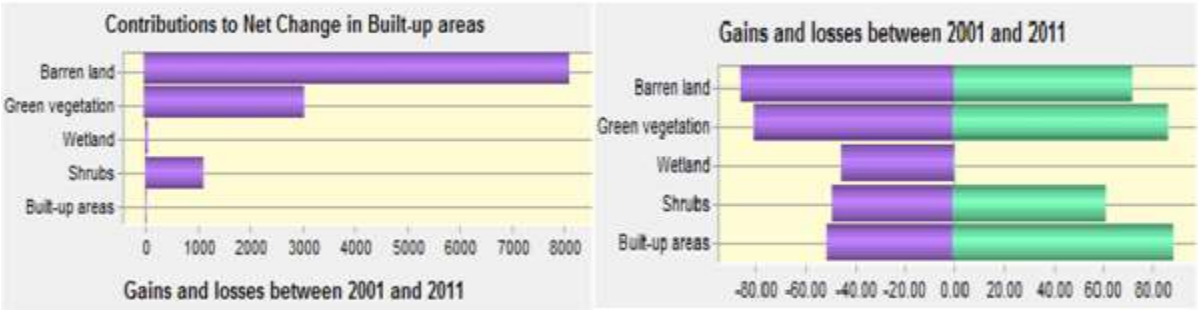
Table 3. 3: LULC Classes Areal Change for the Years 2001 and 2011

		LULC Classes 2011					Total
		Barren land	**Built-up areas**	**Green vegetation**	**Shrubs**	**Wetland**	
LULC Classes 2001	Barren land	41162.94	2054.95	12056.43	57235.27	0.05	**112509.64**
	Built-up areas	8.48	1822.45	685.13	1136.79	0.00	**3652.85**
	Green vegetation	832.39	3420.31	5172.51	16376.50	0.00	**25801.72**
	Shrubs	16053.71	7603.49	19777.09	74731.30	0.04	**118165.63**
	Wetland	15.97	43.40	295.57	65.83	507.58	**928.34**
	Total	**58073.49**	**14944.60**	**37986.73**	**149545.68**	**507.67**	**261058.17**

4.1.2 Contribution to Net Change in Built-Up Areas, Gains & Losses (2001-2011)

In the current study, the built-up areas LULC class is used as an indicator of urbanization, as applied by various researchers worldwide (Dinda et al., 2021; Mahmoud et al., 2021; Roy & Kasemi, 2021). However, barren land, vegetation, shrubs and wetlands were further used to assess their contribution to the net change in the built-up class in the study area. The analysis shows that barren land had a higher contribution to built-up change, followed by vegetation and shrubs, respectively (figure 4.3). Furthermore, gains and losses of each class were assessed to determine each quantity of LULC lost or gained for 10 years. Hence, the results indicate that barren land and wetland had decreased with an increase of other classes in the study area from 2001 to 2011.

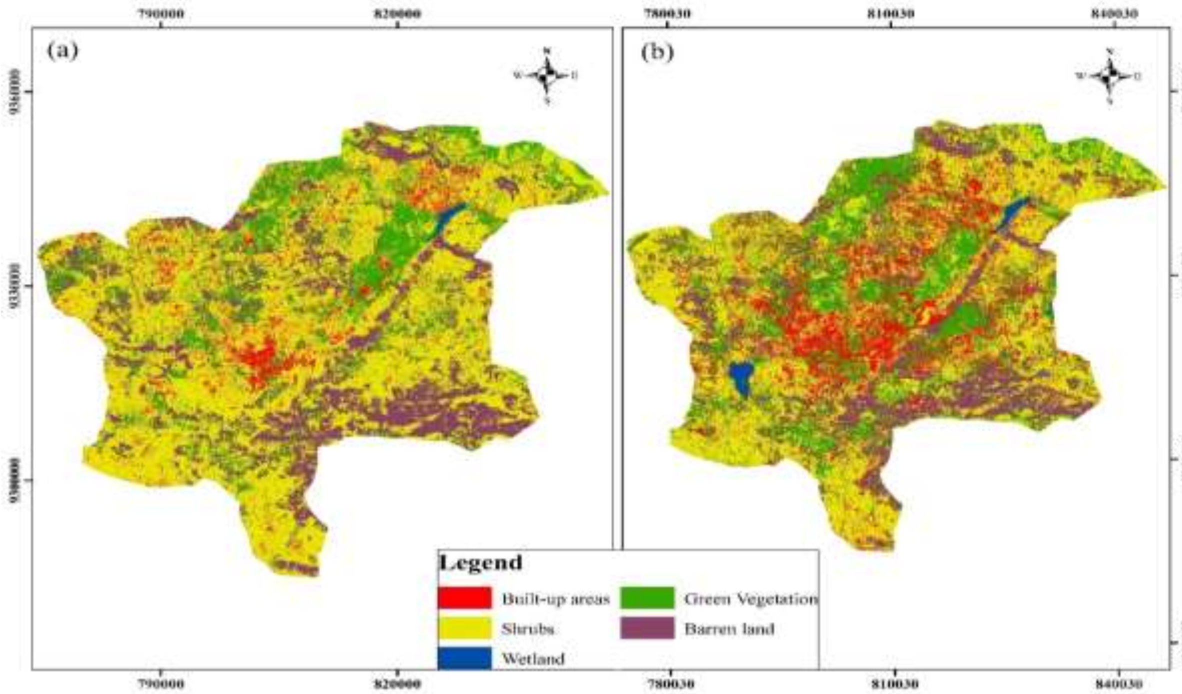
Figure 4. 3: Net Change in Built-Up Areas and Gains & Losses (2001-2011).



4.2 LULC Change From 2011 to 2021

From 2011 to 2021, LULC classes have experienced a high rate of transition from one category to another. The results reveal that barren land and shrubs have experienced a negative increase, while built-up areas, green vegetation and wetlands experienced a positive increase in ten-year intervals (figure 4.4).

Figure 4. 4: LULC Maps for the Years 2011 and 2021



The analysis reveals that from 2011 to 2021, barren land and shrubs have decreased by almost 3.03% and 13.89%, respectively, indicating that there was a great scramble for most virgin areas, for development purposes and other human interventions, due to high population growth within the city. On the other hand, built-up areas have increased by 8.87% over the last ten years, primarily due to high rate of construction activities within the city, attributed to the major shift of government offices and services from Dar es Salaam, which coincided with the construction of infrastructure, such as new roads, airport expansion, construction of government offices, residential buildings, hospitals, industries and parking spaces, among others, accelerating urbanization of the city and its peripherals. Green vegetation has also increased by 7.57% since 2011, which could be attributed to several environmental conservation interventions implemented by the City Council, such as *'Dodoma ya Kijani (A Green Dodoma),'* which have favourably accelerated the expansion of green areas within the city. The reduction in other classes is related to the increase in built-up areas and other human interventions, which threaten their existence. As the city's population grows, people are stretching their interventions to other barren and virgin areas for construction activities to meet human needs. These results have aligned with other authors, such as Kabanda (2019), who found that settlements within the city are mushrooming rapidly due to population increase within the city. On the other hand, Kisamba and Li (2022), also found that settlements and green vegetation are rapidly increasing within the study area (Table 3.4).

Table 3. 4: LULC Classes Areal Change for the Years 2011 and 2021

		LULC Classes 2021					**Total**
		Barren land	**Built-up areas**	**Green vegetation**	**Shrubs**	**Wetland**	
LULC Classes 2011	**Barren land**	26071.25	4045.12	10256.44	17115.21	76.81	**57564.82**
	Built-up areas	357.43	4496.05	3225.29	6564.61	256.70	**14900.08**
	Green vegetation	3847.32	5165.45	16464.57	11840.92	463.65	**37781.91**
	Shrubs	19410.23	24044.17	27401.90	76565.32	664.11	**148085.74**
	Wetland	33.83	6.97	37.49	47.73	381.66	**507.67**
	Total	**49720.1**	**37757.8**	**57385.7**	**112133.8**	**1842.9**	**258840.2**

4.2.1 LULC Gains and Losses in Various LULC Classes (2011 – 2021)

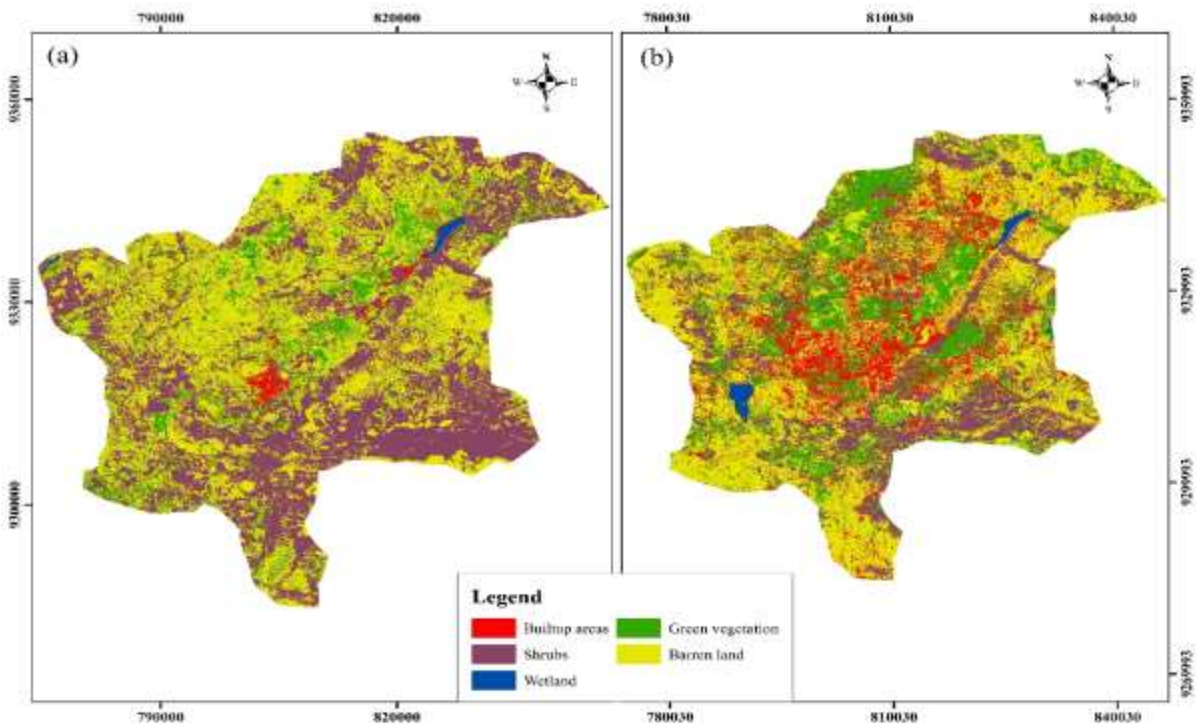
LULC gains and losses determine which class has gained or lost its area for the specified interval of time. The results depict that barren land, and shrubs have lost 7844.72 ha and 35951.94 ha of land, respectively, which has contributed to built-up areas, vegetation and wetlands within the study area. However, built-up areas, vegetation and wetlands have gained 22857.72 ha, 19603.79 ha and 1335.23 ha of land, respectively, indicating that human intervention on land greatly alters existed LULC classes (figure 4.5).

Figure 4. 5: LULC Gains and Losses for the Years 2011 to 2021

4.3 LULC Change From 2001 to 2021

According to the findings, Dodoma City has witnessed considerable changes in LULC over the last 20 years (2001-2021), because of human interventions caused by a high rate of urbanization, triggered by increased population growth. Owing to a variety of factors, there has been a significant transition of LULC classes from one form to another, with significant changes occurring over the last ten years (2011-2021). A substantial positive change in the built-up class and a decrease in barren land and shrubs is accelerated by the high rate of construction activities within the city and its peripherals (figure 4.6).

Figure 4. 6: LULC Maps for the Years 2001 and 2021



The findings indicate that over the last 20 years (2001-2021), the city has witnessed a greater gain in settlement expansion of around 34113.38 ha of land, as compared to other classes. Barren land has lost approximately 61914.41 ha of land, which is greatly contributing to the built-up class because of human activity infringing on virgin areas, in pursuit of settlement locations and other developmental activities. Furthermore, shrubs have decreased by around 4885.89 ha of land, which also contributed greatly to settlement expansion, as bushes are rapidly replaced by settlements. Wetlands and green vegetation, on the other hand, have increased significantly because of different conservation and intervention measures implemented by the government, including the *'Dodoma ya Kijani,'* campaign (Table 3.5).

Table 3. 5: LULC Classes Areal Change for the Years 2001 and 2021

		LULC Classes 2021					Total
		Barren land	**Built-up areas**	**Green vegetation**	**Shrubs**	**Wetland**	
LULC Classes 2001	**Barren land**	32228.66	10761.52	19343.24	48676.36	623.90	**111633.68**
	Built-up areas	37.40	1133.59	1180.67	1216.92	75.10	**3643.69**
	Green vegetation	1336.50	5321.95	6503.09	12058.68	398.41	**25618.62**
	Shrubs	16047.14	20484.61	30191.21	50050.23	247.31	**117020.51**
	Wetland	69.56	55.39	170.81	132.42	498.21	**926.40**
	Total	**49719.27**	**37757.07**	**57389.02**	**112134.62**	**1842.93**	**258842.91**

Furthermore, the analysis indicates that barren land had a significant transition to built-up areas, and vegetation with slight transition of shrubs and wetlands. However, this transition did not affect some of the original LULC classes since 2001, hence they remained unchanged for the past 20 years (Figure 4.7 & Figure 4.8).

Figure 4. 7: LULC Transition Map from 2001 to 2021

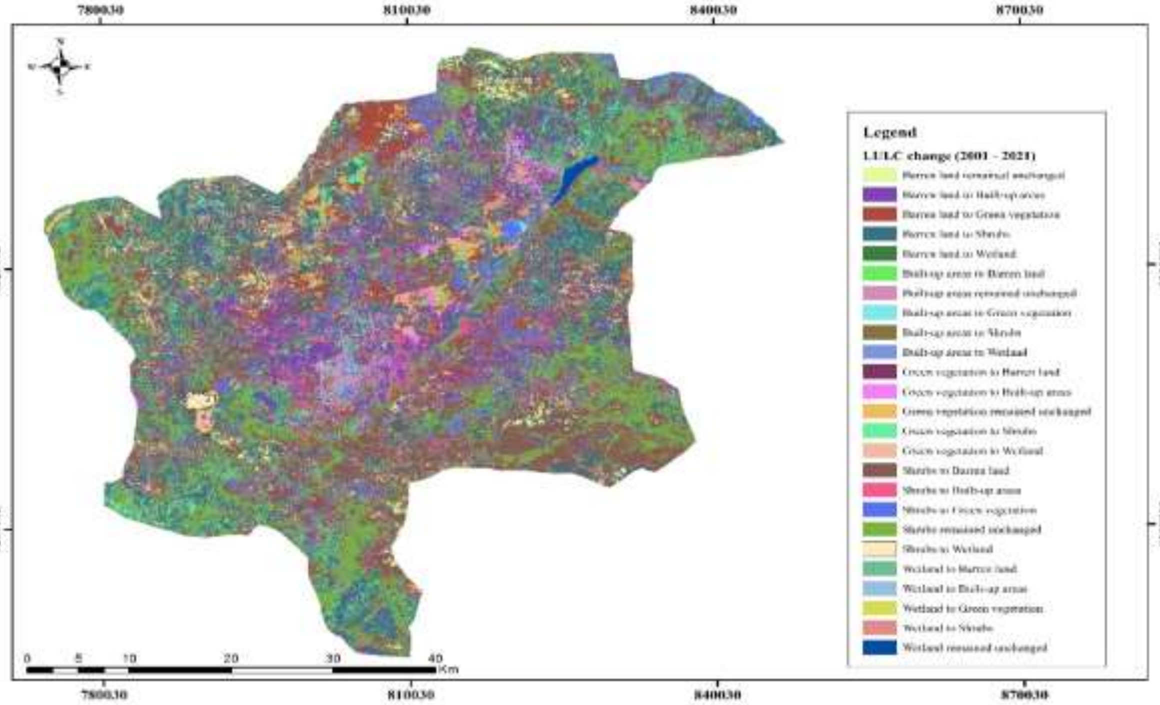
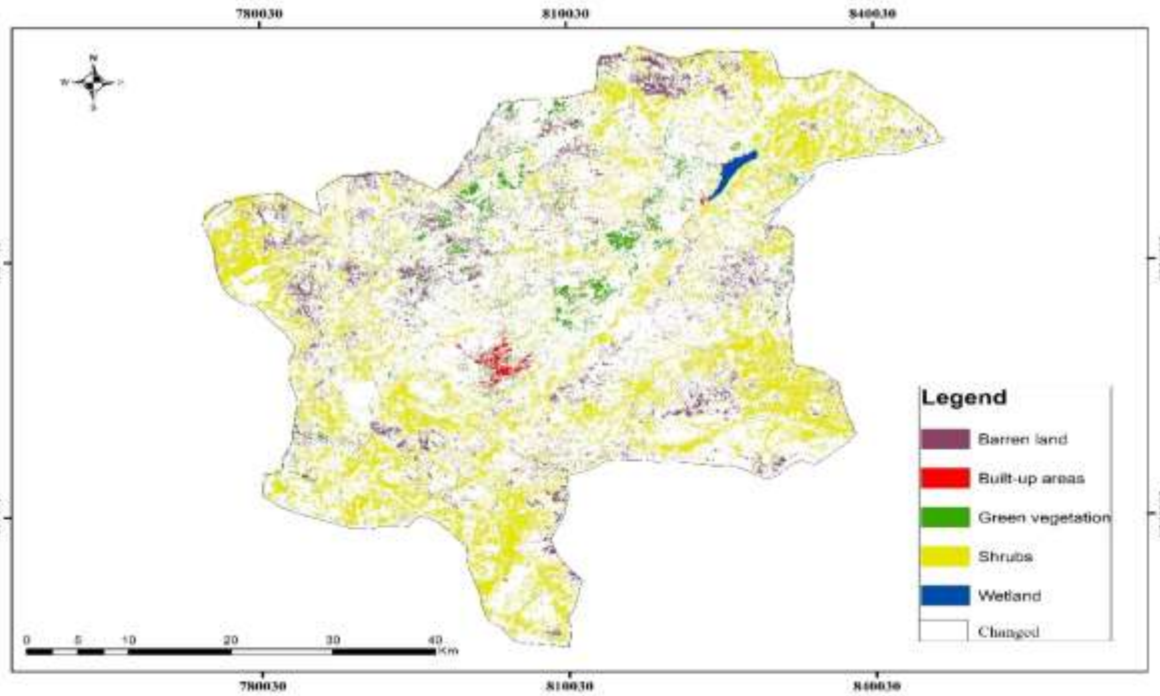


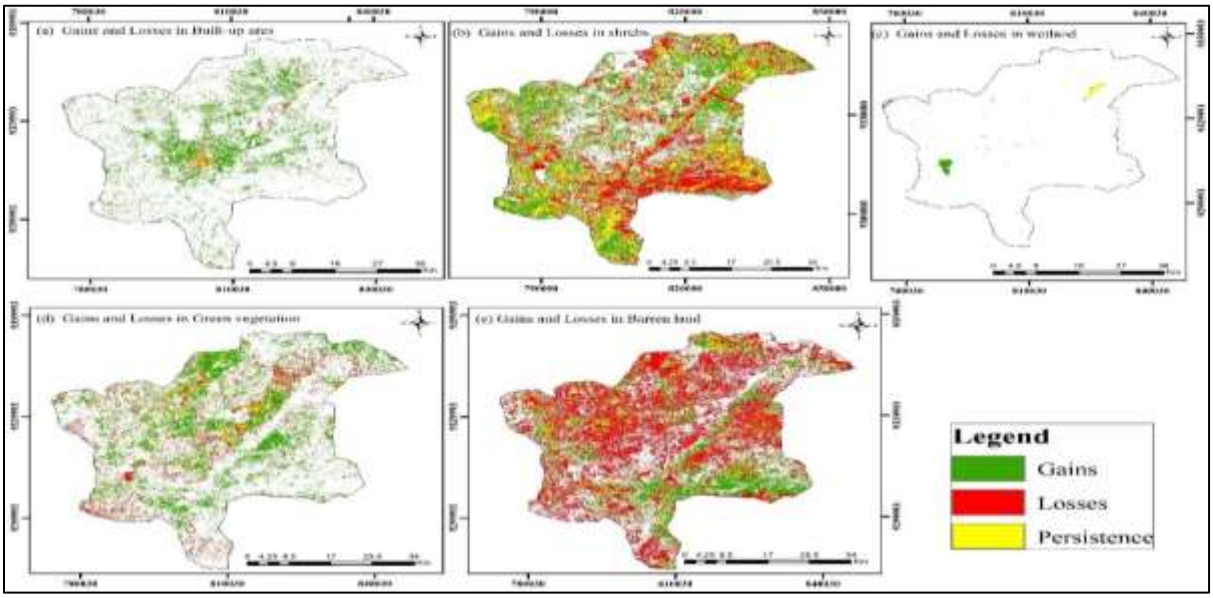
Figure 4. 8: Unchanged LULC Classes from 2001 to 2021



4.3.1 LULC Classes Gains, Losses and Persistence from 2001 to 2021

LULC class's gains, losses and persistence were analysed for the past twenty years to determine which LULC class gained from other classes, lost and remained unchanged for the whole period from 2001 to 2021. The green colour in the map (Figure 4.9) indicates the LULC types of a cell converted from another LULC class to that respective class type, which depicts gains of the respective class. The red colour shows certain types of classes that have been converted to other class types, which reveals that a respective class had lost to another LULC class, while yellow cells indicate those classes that did not change for the past 20 years.

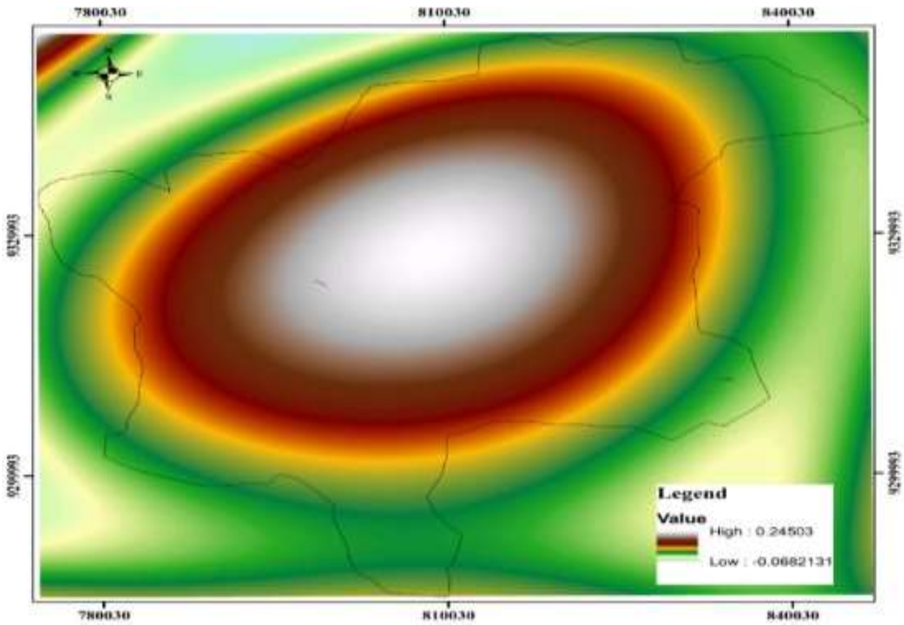
Figure 4. 9: LULC Gains, Losses, and Persistence from 2001 to 2021



4.4 Spatial Urbanization Trend in Dodoma City.

The spatial change trend was analysed for the interval of twenty years (2001-2021). This involved contribution of spatial change from all other classes to built-up areas classes in the study area. The findings demonstrated that transition of all other classes to built-up (urban) areas are mostly concentrated in the city centre, and radiate outward with a northeastern trend. This implies that in the future, most of these areas will be fully urbanized because of city expansion (figure 4.10).

Figure 4. 10: Spatial Change Trend in Dodoma City (2001-2021)



4.5 Accuracy Assessment for the Classified LULC Maps (2001, 2011, and 2021)

Accuracy assessment reports were generated to access how accurate LULC features are represented on the maps. Kappa Coefficient, Overall, producer and user accuracies were both produced to access the quality of the classified LULC maps (Congalton & Green, 2019). In the current study, the overall accuracy obtained was 88.33%, 87.3% and 98.75% for 2001, 2011 and 2021, respectively (Table 3.6), which indicates a good classification accuracy. However, the Kappa Index Coefficient was used to access the classification quality, in which 0.85, 0.83 and 0.98 were obtained for 2001, 2011 and 2021, respectively, indicating a higher level of agreement (Tadese et al., 2021).

Table 3. 6: Kappa Coefficients, Overall, Producer's and User's Accuracies for the LULC Maps (2001, 2011 and 2021)

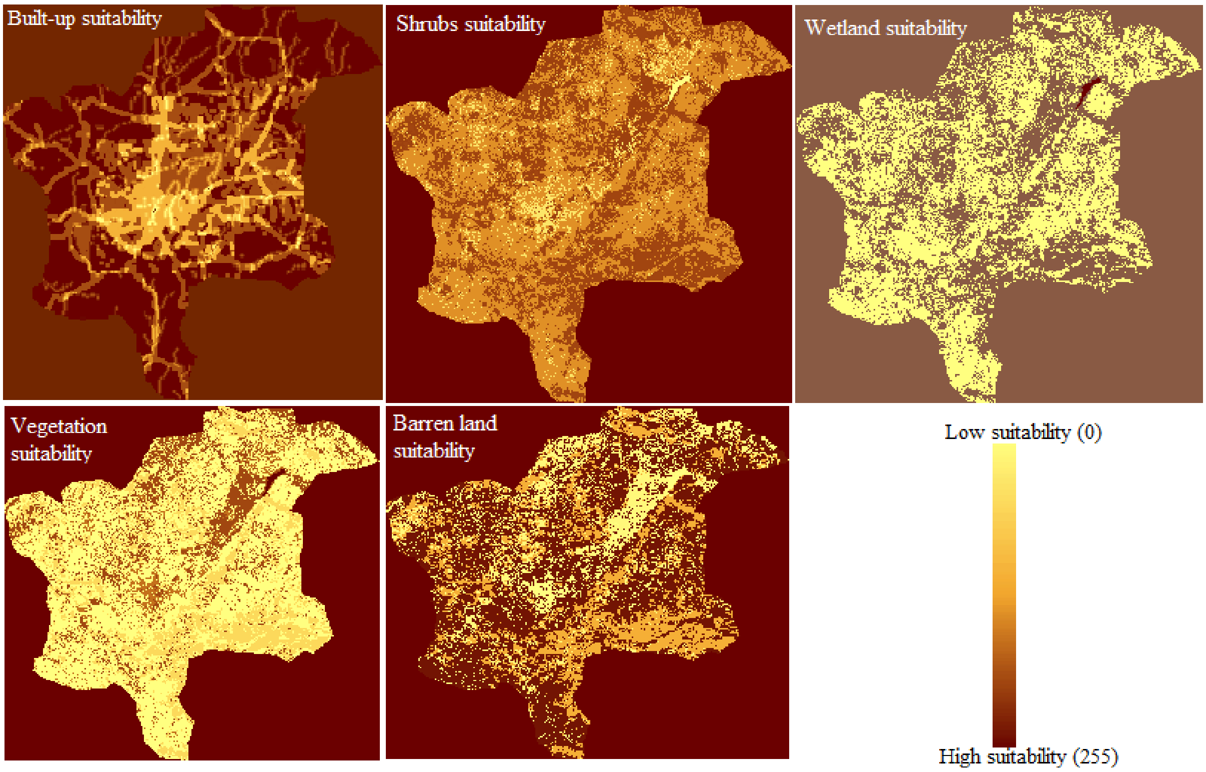
LULC	2001		2011		2021	
	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy	Producer's accuracy	User's accuracy
Wetland	100.00	100.00	89.00	91.90	93.75	100.00
Vegetation	100.00	88.89	90.00	85.78	100.00	100.00
Barren land	92.31	75.00	80.50	79.90	100.00	100.00
Shrubs	0.00	0.00	83.40	81.70	97.00	96.00
Built-up areas	100.00	100.00	85.70	82.00	100.00	93.33

Overall accuracy (%)	88.33	87.30	98.75
Kappa coefficient	0.85	0.83	0.98

4.6 Transitional Suitability Maps

Transitional suitability maps were prepared based on the number of LULC classes employed in this study. For the built-up area's class, the suitability map was generated by the weighted linear combination method in TerrSet software, while shrubs, wetlands, vegetation and barren land were harmonized and standardized from the transitional areas, generated from the Markov Model as applied in other studies (Keshtkar & Voigt, 2016; Kisamba & Li, 2022). Furthermore, these maps were standardized into a continuous scale of 0 to 255, indicating low suitability to high suitability, respectively, by the use of the fuzzy membership function tool embedded in Terrset software (figure 4.7).

Figure 4. 11: Transitional Suitability Maps Employed



4.7 Simulated LULC Map for 2021

A new simulated LULC map for 2021 was generated by the integrated CA-Markov technique, using the 2001 and 2011 observed LULC maps for validation of the model, before the actual prediction of the 2040 LULC map (Figure 4.12). This is normally applied to test the capacity of the model to accurately simulate the 2021 LULC map and assess its accuracy parameters, and upon certification the model is then applied for future LULC simulation (Pontius Jr & Schneider, 2001). In this process, the transition matrix areas and transitional probability files were generated. Thus, transitional matrix areas show the total areas expected to change in the future, while the transitional probability indicates the likelihood of a given class to change to other classes in the coming period or remain unchanged (Eastman, 2012) (Table 3.7).

Figure 4. 12: Simulated and Observed LULC Maps for the Year 2021

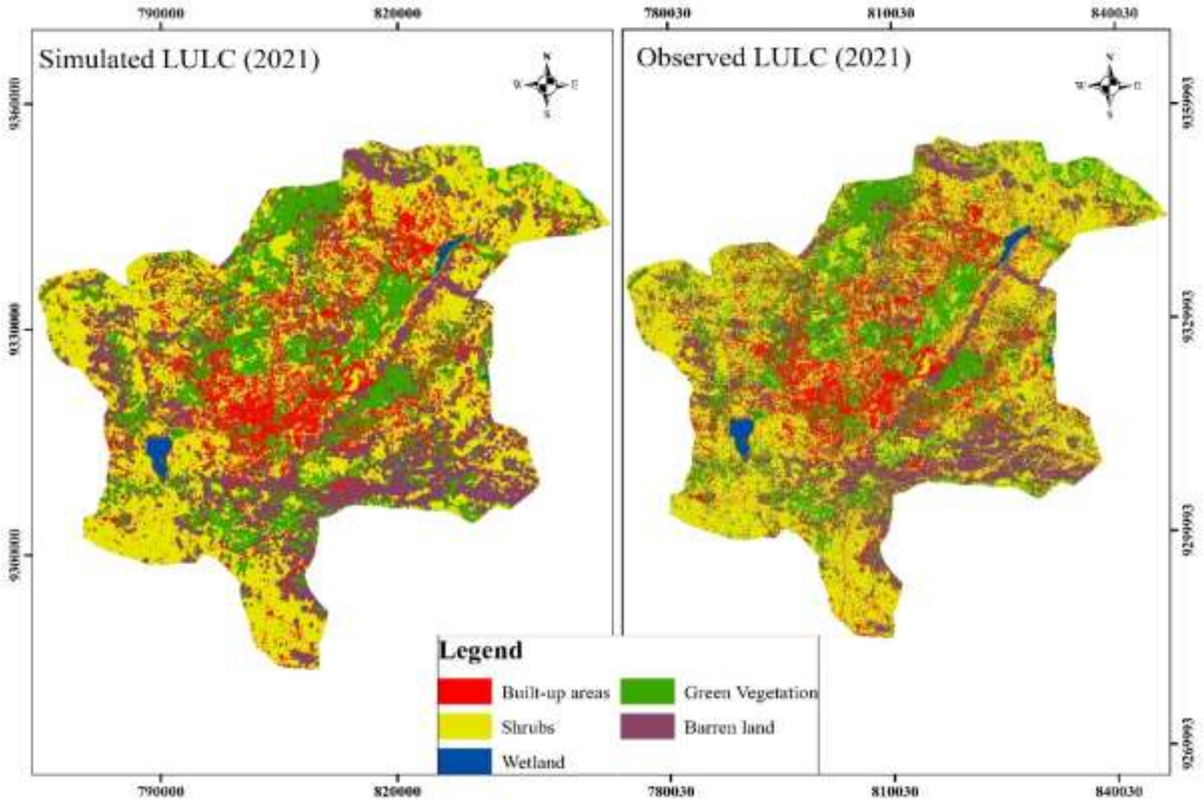


Table 3. 7: Transitional Probability Matrix of Change for the Simulated 2021 LULC Map Using 2001 and 2011 LULC Maps.

	Probability of Change to				
LULC Classes	**Built-up areas**	**Shrubs**	**Wetland**	**Vegetation**	**Barren land**
Built-up areas	0.4866	0.322	0	0.1887	0.0027
Shrubs	0.0206	0.504	0	0.1099	0.3655
Wetland	0.0501	0.0759	0.542	0.3133	0.0187
Vegetation	0.1396	0.6306	0	0.1948	0.035
Barren land	0.0694	0.6221	0	0.169	0.1396

4.8 Validation of the Simulated Model

To assess the validity of the LULC simulation models, various validation methods have been proposed, including the Chi-Square Test, Kappa Coefficient (k) and Cramer's V, quantity disagreement and allocation disagreement techniques, among others (Hyandye & Martz, 2017). In the current study, quantity disagreement and allocation disagreement techniques were used for model validation, in which the simulated and observed 2021 LULC maps were used before the simulation of the 2040 LULC map and assessment of the dynamics. Thus, modules embedded in TerrSet software were employed in the validation process and various parameters were generated including Kappa for no information (Kno), Kappa for location (Klocation), and Kappa standard (Kstandard), which were used to determine the model accuracy (Table 3.8).

Table 3. 8: Kappa Index Values of the Model Validation

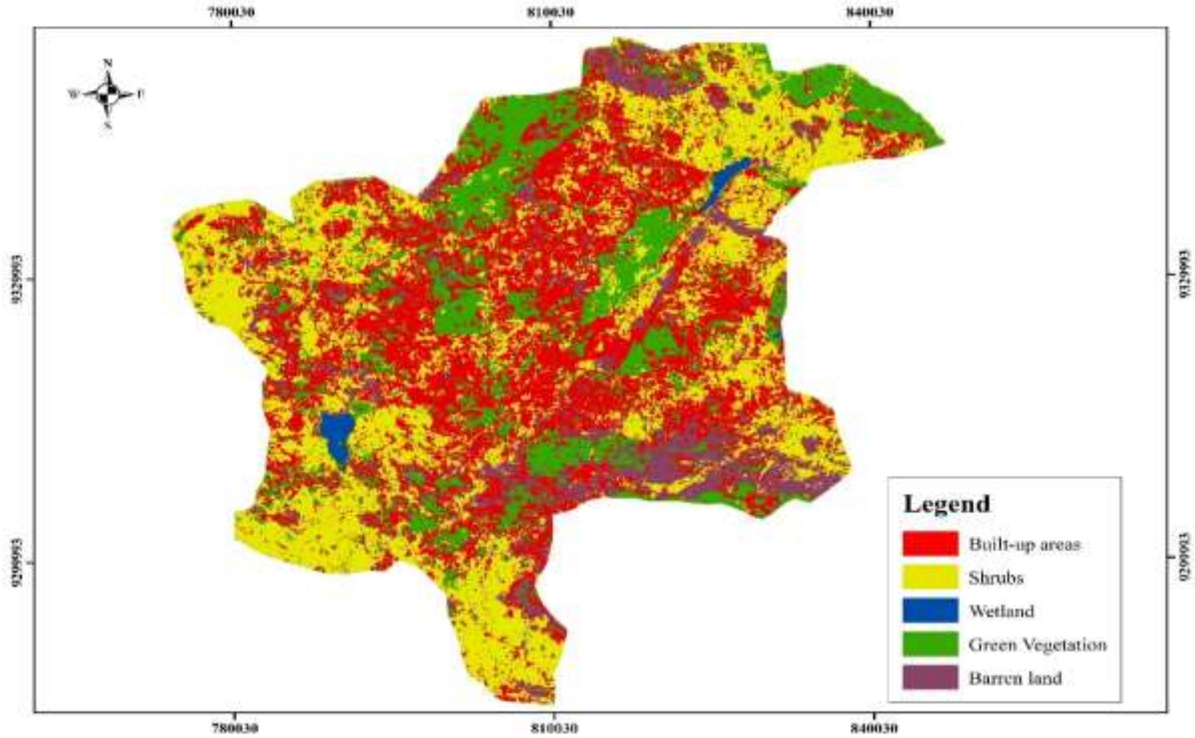
Model Parameters	Values
Kno	0.8123
Klocation	0.8962
Kstandard	0.7646

The analysis shows that Kappa Index values obtained indicate a perfect agreement between the observed and simulated 2021 LULC maps. Pontius Jr (2000), suggested that Kno is an important Kappa Index value that should be used in assessing the overall model accuracy, and Klocation for accuracy in identifying the location. Hence in the current study, the overall model indicated high accuracy of the simulation model.

4.9 Simulated 2040 LULC and its Dynamics

The visual representation of the simulated 2040 LULC map reveals a significant increase in built-up areas, as compared to other classes, showing that the city will continue to grow in the future. From the findings, this growth occurred within existing urban regions as a result of urban development, as well as in isolated urban areas that grew apart from existing urban areas. Furthermore, the findings indicate that shrubs, green vegetation and barren ground would decline in the coming years, because of increased urbanization and other construction activities (figure 4.13).

Figure 4. 13: Simulated 2040 LULC Map of Dodoma City.



Furthermore, the results of the pixel-based areal analysis show a positive increase of built- up areas by nearly 20.47%, while barren land is predicted to continue reducing by almost 8.3%, because of increased human intervention on these virgin areas. However, the results indicate that green vegetation and shrubs will significantly decrease by almost 21.45% and 9.19%, respectively (table 3.9) as a result of expected expansion of construction activities within the city. Nevertheless, wetlands are also expected to increase in the future, given that various intervention are undertaken to conserve these areas.

Table 3. 9: LULC Classes Areal Change for the Years 2021 and 2040

		LULC Classes 2040					**Total**
		Barren land	**Built-up areas**	**Green vegetation**	**Shrubs**	**Wetland**	
LULC Classes 2021	**Barren land**	15955.86	18493.18	74.21	9352.13	5739.60	**49614.98**
	Built-up areas	1383.79	20916.17	72.50	10992.69	4363.84	**37729.00**
	Green vegetation	2860.57	20804.02	145.88	10099.52	23327.22	**57237.21**

	Shrubs	7930.42	30303.34	107.91	57625.83	15930.83	**111898.33**
	Wetland	41.66	111.66	1444.00	108.04	137.44	**1842.80**
	Total	**28172.30**	**90628.36**	**1844.51**	**88178.21**	**49498.92**	**258322.31**

CHAPTER FIVE
SUMMARY, CONCLUSION AND POLICY RECOMMENDATION

5.1 Summary of the Findings

The current research work is solely focused on the examination of the spatial-temporal changes of urbanization for 2001, 2011 and 2021, in relation to the population growth of Dodoma City. The main objective of this study was attained through the determination of LULC classes for both respective years, examination of LULC changes and finally simulation of 2040 LULC, and expected changes assessed. Landsat satellite imageries were employed in the preparation of LULC maps for each respective year, using ENVI software and five LULC classes were generated, i.e. built-up areas, shrubs, wetlands, barren land and green vegetation, in which Arcmap software was employed in analysing and determining various areal changes of each respective class. However, the built-up class was used to assess the city's urbanization trend because of population growth. A hybrid of the CA-Markov Model embedded in TerrSet software, was employed to simulate the 2040 LULC classes, to examine future urbanization trends within the city. The findings revealed that, barren land and wetlands showed a significant decrease of almost 20.85% and 0.17%, respectively, while built-up areas, green vegetation and shrubs depicted a rise of 4.32%, 4.67% and 12.02%, respectively. However, from 2011 to 2021, the results indicated that built-up areas, vegetation and wetlands had a positive increase of about 8.87%, 7.57% and 0.5%, respectively, while barren land and shrubs had a decline of about 3.03% and 13.89%, respectively, due to various human interventions on land. The predicted LULC map of Dodoma City shows that the city will continue to urbanize, with a high increase of built-up areas by almost 20.47%, with the north-eastern trend, while showing an expected decrease in other classes.

5.2 Conclusion

According to the current study, Dodoma City experienced a positive urbanization trend from 2001 to 2021, but a significant increase was observed between 2011 and 2021, due to progressive population growth. Thus, it can be concluded that built-up areas are tremendously increasing in Dodoma City, thus showing increasing urbanization for the last 10 years, since the relocation of the government offices from Dar es Salaam to the city. LULC classes were rapidly changing because of human interventions on land, resulting in high decrease of natural vegetation and virgin land, as people infringed in search of areas for construction activities, especially in unsurveyed areas. From the LULC simulation of 2040, the results have revealed a continuous increase in urbanization for the next twenty years, with a significant decrease in other natural vegetation such as shrubs, green vegetation and virgin land, hence the city will experience steady growth. Furthermore, it is concluded that GIS and RS technologies play a great role in the assessment of urbanization, and they are more advantageous in terms of cost-effectiveness and are also less time-consuming, while giving high coverage and reliable results of past, current and future urbanization scenarios.

5.3 Policy Recommendation

Among the major elements shown in this study is the rapid increase of built-up areas, which is related to urbanization and city growth. This substantial rise is due to displacements and urban migration in pursuit of jobs, business opportunities and a better living, which has increased the number of residential houses and offices in Dodoma City over the last 20 years, thus modifying the land surface with time. This increase suggests that the government should increase proper land planning schemes in most unsurveyed parcels, particularly in the city's peripherals. Thus, the government and other stakeholders should take immediate and early measures of natural resource conservation programs, such as afforestation, grazing management and understanding of the natural landscape, climate and environment, to control and reduce human stress on the natural environment, biodiversity conservation as well as increase efforts on the *'Dodoma ya Kijani'* campaign.

REFERENCES

Abebe, G., Getachew, D., & Ewunetu, A. (2022). Analysing land use/land cover changes and its dynamics using remote sensing and GIS in Gubalafito district, Northeastern Ethiopia. *SN Applied Sciences*, *4*(1), 1-15.

AfDB. (2016). African Economic Outlook 2016: Sustainable Cities and Structural Transformation. In: 15th editi. Paris: African Development Bank, Organisation for Economics Co.

Ali, E. (2020). Geographic Information System (GIS): Definition, Development, Applications & Components. *Department of Geography, Ananda Chandra College. India*.

Alshari, E. A., & Gawali, B. W. (2021). Development of classification system for LULC using remote sensing and GIS. *Global Transitions Proceedings*, *2*(1), 8-17.

Arumugam, T., Yadav, R. L., & Kinattinkara, S. (2021). Assessment and Predicting of LULC by Kappa Analysis and CA Markov model using RS and GIS Techniques in Udham Singh Nagar District, India.

Baqa, M. F., Chen, F., Lu, L., Qureshi, S., Tariq, A., Wang, S., Jing, L., Hamza, S., & Li, Q. (2021). Monitoring and modeling the patterns and trends of urban growth using urban sprawl matrix and CA-Markov model: A case study of Karachi, Pakistan. *Land*, *10*(7), 700.

Boba, M. K. (2014). *Influence of urban expansion on institutional arrangements for management of urban open spaces; a case study of Dodoma capital city district* The University of Dodoma].

Campbell, J. B., & Wynne, R. H. (2011). *Introduction to remote sensing*. Guilford Press.

CCD. (2020). The Provision of Consultancy Services for Study and Design of Storm Water Drainage System and Preparation of Drainage & Sanitation Development Plan (DSDP) for Dodoma City for a period of 2020-2040. (1). www.http://dodomamc.go.tz/

Chen, X., Vierling, L., & Deering, D. (2005). A simple and effective radiometric correction method to improve landscape change detection across sensors and across time. *Remote Sensing of Environment*, *98*(1), 63-79.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and psychological measurement*, *20*(1), 37-46.

Congalton, R. G., & Green, K. (2019). *Assessing the accuracy of remotely sensed data: principles and practices*. CRC press.

Dahal, K. R., Benner, S., & Lindquist, E. (2018). Analyzing spatiotemporal patterns of urbanization in Treasure Valley, Idaho, USA. *Applied Spatial Analysis Policy*, *11*(2), 205-226.

Dinda, S., Chatterjee, N. D., & Ghosh, S. (2021). An integrated simulation approach to the assessment of urban growth pattern and loss in urban green space in Kolkata, India: A GIS-based analysis. *Ecological Indicators*, *121*, 107178.

Eastman, J. R. (2012). *IDRISI Selva Tutorial*. C. L.-C. Idrisi Production.

El-Hallaq, M. A., & Habboub, M. O. (2014). Using GIS for time series analysis of the Dead Sea from remotely sensing data.

Elmqvist, T., Andersson, E., Frantzeskaki, N., McPhearson, T., Olsson, P., Gaffney, O., Takeuchi, K., & Folke, C. (2019). Sustainability and resilience for transformation in the urban century. *Nature sustainability*, *2*(4), 267-273.

Foody, G. M. (2004). Thematic map comparison. *Photogrammetric Engineering & Remote Sensing*, *70*(5), 627-633.

García, M. (2010). The breakdown of the Spanish urban growth model: social and territorial effects of the global crisis. *International Journal of urban and regional research*, *34*(4), 967-980.

Ghalehteimouri, K. J., Shamsoddini, A., Mousavi, M. N., Ros, F. B. C., & Khedmatzadeh, A. (2022). Predicting spatial and decadal of land use and land cover change using integrated cellular automata Markov chain model based scenarios (2019–2049) Zarriné-Rūd River Basin in Iran. *Environmental Challenges*, *6*, 100399.

Hall, J., & Hossain, A. (2020). Mapping urbanization and evaluating its possible impacts on stream water quality in Chattanooga, Tennessee, using GIS and remote sensing. *Sustainability*, *12*(5), 1980.

Hamer, G. (2003). Solid waste treatment and disposal: effects on public health and environmental safety. *Biotechnology advances*, *22*(1-2), 71-79 %@ 0734-9750.

Han, J., Hayashi, Y., Cao, X., & Imura, H. (2009). Evaluating land-use change in rapidly urbanizing China: Case study of Shanghai. *Journal of Urban Planning and Development*, *135*(4), 166-171.

Hinich, M. J., & Munger, M. C. (2004). Spatial theory. In *The encyclopedia of public choice* (pp. 305-311). Springer.

Hotelling, H. (1929). Stability in competition'economic journal 39, 41-57. *Reprinted in Dean RD, Leahy WH and McKee DL (eds) Spatial economic theory (Free Press, New York)*, 103-118.

Hoyt, H. (1939). *The structure and growth of residential neighborhoods in American cities*. US Government Printing Office.

Hugo, G. (2015). Urban migration trends, challenges, responses and policy in the Asia–Pacific. *World Migration Report*.

Hyandye, C., Mandara, C. G., & Safari, J. (2015). GIS and logit regression model applications in land use/land cover change and distribution in Usangu catchment. *American Journal of Remote Sensing*, *3*(1), 6-16.

Hyandye, C., & Martz, L. W. (2017). A Markovian and cellular automata land-use change predictive model of the Usangu Catchment. *International Journal of Remote Sensing*, *38*(1), 64-81.

IPPMEDIA. (2016). Govt Shifts to Dodoma in 2 Months. http://www.ippmedia.com/en/news/govt-shifts-dodoma-2-months

Jeykumar, R., & Chandran, S. (2019). Impact of urbanization on climate change and geographical analysis of physical land use land cover variation using RS-GIS. *Global Nest Journal*, *21*(2), 141-152.

Jones, G. W. (1991). Urbanization Issues in the Asian-Pacific Region. *Asian-Pacific Economic Literature*, *5*(2), 5-33.

Kabanda, T. (2019). Land use/cover changes and prediction of Dodoma, Tanzania. *African Journal of Science, Technology, Innovation and Development*, *11*(1), 55-60 %@ 2042-1338.

Kafy, A.-A., Naim, M. N. H., Subramanyam, G., Ahmed, N. U., Al Rakib, A., Kona, M. A., & Sattar, G. S. (2021). Cellular Automata approach in dynamic modelling of land cover changes using RapidEye images in Dhaka, Bangladesh. *Environmental Challenges*, *4*, 100084.

Keshtkar, H., & Voigt, W. (2016). A spatiotemporal analysis of landscape change using an integrated Markov chain and cellular automata models. *Modeling Earth Systems and Environment*, *2*(1), 1-13.

Keys, P., Galaz, V., Dyer, M., Matthews, N., Folke, C., Nyström, M., & Cornell, S. (2019). Anthropocene risk. Nat. Sustain. 2, 667–673. In.

Khan, S., Qasim, S., & Ambreen, R. (2016). Spatio-temporal analysis of landuse/landcover change of district pishin using satellite imagery and GIS. *Journal of Geographic Information System*, *8*(3), 361-368.

Khanal, N., Uddin, K., Matin, M. A., & Tenneson, K. (2019). Automatic detection of spatiotemporal urban expansion patterns by fusing OSM and landsat data in Kathmandu. *Remote Sensing*, *11*(19), 2296.

Kiduanga, J. (2014). Managing Land for Developing Dodoma, the Capital City of Tanzania. Critical Analysis of the Role of Dodoma Municipal Council and Capital Development Authority. *Journal of Sustainable Development*, *7*(5), 178-186.

Kisamba, F. C., & Li, F. (2022). Analysis and modelling urban growth of Dodoma urban district in Tanzania using an integrated CA–Markov model. *GeoJournal*, 1-22.

Kukkonen, M., & Käyhkö, N. (2014). Spatio-temporal analysis of forest changes in contrasting land use regimes of Zanzibar, Tanzania. *Applied Geography*, *55*, 193-202.

Lancaster, T. (1979). Econometric methods for the duration of unemployment. *Econometrica: Journal of the Econometric Society*, 939-956.

Lerch, M. (2017). International migration and city growth. *Population Division Technical Paper*, *10*.

Liping, C., Yujun, S., & Saeed, S. (2018). Monitoring and predicting land use and land cover changes using remote sensing and GIS techniques—A case study of a hilly area, Jiangle, China. *PloS one*, *13*(7).

Ma, C., Zhang, G., Zhang, X., Zhao, Y., & Li, H. (2012). Application of Markov model in wetland change dynamics in Tianjin Coastal Area, China. *Procedia Environmental Sciences*, *13*, 252-262.

MacLachlan, A., Biggs, E., Roberts, G., & Boruff, B. (2017). Urban growth dynamics in Perth, Western Australia: using applied remote sensing for sustainable future planning. *Land*, *6*(1), 9.

Mahmoud, A. S., Kalantar, B., Al-Najjar, H. A., Moayedi, H., Halin, A. A., & Mansor, S. (2021). Object-Oriented Approach for Urbanization Growth by Using Remote Sensing and GIS Techniques: A Case Study in Hilla City, Babylon Governorate, Iraq. In *Geospatial Technology and Smart Cities* (pp. 39-57). Springer.

Makonyo, M., & Msabi, M. M. (2021). Potential landfill sites selection using GIS-based multi-criteria decision analysis in Dodoma capital city, central Tanzania. *GeoJournal*, 1-31. https://doi.org/https://doi.org/10.1007/s10708-021-10414-5

Mishra, V. N., Rai, P. K., & Mohan, K. (2014). Prediction of land use changes based on land change modeler (LCM) using remote sensing: a case study of Muzaffarpur (Bihar), India. *Journal of the Geographical Institute" Jovan Cvijic", SASA*, *64*(1), 111-127.

Mlambo, V. (2018). An overview of rural-urban migration in South Africa: its causes and implications. *Archives of Business Research*, *6*(4).

Mnyali, E. T., & Materu, S. F. (2021). Analysis of the Current and Future Land Use/Land Cover Changes in Peri-Urban Areas of Dar es Salaam City, Tanzania using Remote Sensing and GIS Techniques. *Tanzania Journal of Science*, *47*(5), 1622-1636.

Mohamed, A., & Worku, H. (2020). Simulating urban land use and cover dynamics using cellular automata and Markov chain approach in Addis Ababa and the surrounding. *Urban Climate*, *31*, 100545.

Mondal, B., Das, D. N., & Bhatta, B. (2017). Integrating cellular automata and Markov techniques to generate urban development potential surface: a study on Kolkata agglomeration. *Geocarto international*, *32*(4), 401-419.

Montgomery, M. R., Stren, R., Cohen, B., & Reed, H. E. (2013). *Cities transformed: Demographic change and its implications in the developing world*. Routledge.

Mosammam, H. M., Nia, J. T., Khani, H., Teymouri, A., & Kazemi, M. (2017). Monitoring land use change and measuring urban sprawl based on its spatial forms: The case of Qom city. *The Egyptian Journal of Remote Sensing and Space Science*, *20*(1), 103-116.

Msabi, & Makonyo, M. (2020). Flood susceptibility mapping using GIS and multi-criteria decision analysis: A case of Dodoma region, central Tanzania. *Remote Sensing Applications: Society and Environment*, 100445. https://doi.org/https://doi.org/10.1016/j.rsase.2020.100445

Msuya, I., Moshi, I., Levira, F. J. E., & ASIA, U. (2021). Land Pattern of Highly Urbanizing Cities: Change in Built-up Area, Population Density and Spatial Development of the Sprawling Dar es Salaam City. *12*(1_suppl), S165-S182.

Mubako, S., Nnko, H. J., Peter, K. H., & Msongaleli, B. (2022). Evaluating historical and predicted long-term land use/land-cover change in Dodoma Urban District, Tanzania: 1992–2029. *Physics and Chemistry of the Earth, Parts A/B/C*, *128*, 103205.

Mücher, C. A. (2009). *Geo-spatial modelling and monitoring of European landscapes and habitats using remote sensing and field surveys*. Wageningen University and Research.

Munthali, M., Mustak, S., Adeola, A., Botai, J., Singh, S., & Davis, N. (2020). Modelling land use and land cover dynamics of Dedza district of Malawi using hybrid Cellular Automata and Markov model. *Remote Sensing Applications: Society and Environment*, *17*, 100276.

Murayama, Y., Simwanda, M., & Ranagalage, M. (2021). Spatiotemporal Analysis of Urbanization Using GIS and Remote Sensing in Developing Countries. In (Vol. 13, pp. 3681): Multidisciplinary Digital Publishing Institute.

Ndzabandzaba, C. (2015). Data sharing for sustainable development in less developed and developing countries. *Glob. Sustain. Dev. Rep*.

Nourqolipour, R., Shariff, A. R. B. M., Balasundram, S. K., Ahmad, N. B., Sood, A. M., & Buyong, T. (2016). Predicting the effects of urban development on land transition and spatial patterns of land use in Western Peninsular Malaysia. *Applied Spatial Analysis Policy*, *9*(1), 1-19.

OECD. (2017). *Social Protection in East Africa: Harnessing the Future,* . P. OECD Publishing.

Oforo, V. (2017). UN Opens Offices in Dodoma. www.thecitizen.co.tz,

Olsson, G., & Gale, S. (1968). Spatial theory and human behavior.

Onilude, O. O., & Vaz, E. (2021). Urban sprawl and growth prediction for Lagos using GlobeLand30 data and cellular automata model. *Sci*, *3*(2), 23.

Pacifici, F., Longbotham, N., & Emery, W. (2014). The importance of physical quantities for the analysis of multitemporal and multiangular optical very high spatial resolution images. *IEEE Transactions on Geoscience Remote Sensing Applications: Society and Environment*, *52*(10), 6241-6256.

Pontius Jr, R. G. (2000). Comparison of categorical maps. *Photogramm. Eng. Remote Sens*, *66*, 1011-1016.

Pontius Jr, R. G., & Schneider, L. C. (2001). Land-cover change model validation by an ROC method for the Ipswich watershed, Massachusetts, USA. *Agriculture, ecosystems & environment*, *85*(1-3), 239-248.

Rahnama, M. R., & Society. (2021). Forecasting land-use changes in Mashhad Metropolitan area using Cellular Automata and Markov chain model for 2016-2030. *Sustainable Cities*, *64*, 102548.

Ranagalage, M., Ratnayake, S. S., Dissanayake, D., Kumar, L., Wickremasinghe, H., Vidanagama, J., Cho, H., Udagedara, S., Jha, K. K., & Simwanda, M. (2020). Spatiotemporal variation of urban heat islands for implementing nature-based solutions: A case study of Kurunegala, Sri Lanka. *ISPRS International Journal of Geo-Information*, *9*(7), 461.

Roy, B., & Kasemi, N. (2021). Monitoring urban growth dynamics using remote sensing and GIS techniques of Raiganj Urban Agglomeration, India. *The Egyptian Journal of Remote Sensing and Space Science*, *24*(2), 221-230.

Sahana, M., Hong, H., & Sajjad, H. (2018). Analyzing urban spatial patterns and trend of urban growth using urban sprawl matrix: A study on Kolkata urban agglomeration, India. *Science of the total environment*, *628*, 1557-1566.

Salamatnia, A., Jozi, S. A., Malmasi, S., Nezakati, R., & Zaeimdar, M. (2019). Assessment of the Temporal and Spatial Variations of Urban Development Using RS and GIS: A Case Study—Yasuj, Iran. *Journal of the Indian Society of Remote Sensing*, *47*(7), 1163-1172.

Serra, P., Pons, X., & Saurí, D. (2008). Land-cover and land-use change in a Mediterranean landscape: a spatial analysis of driving forces integrating biophysical and human factors. *Applied Geography*, *28*(3), 189-209.

Seto, K. C., Fragkias, M., Güneralp, B., & Reilly, M. K. (2011). A meta-analysis of global urban land expansion. *PloS one*, *6*(8), e23777.

Shah, A., Ali, K., & Nizami, S. (2021). Spatio-temporal analysis of urban sprawl in Islamabad, Pakistan during 1979–2019, using remote sensing. *GeoJournal*, 1-14.

Shamsi, S. F. (2010). Integrating linear programming and analytical hierarchical processing in raster-GIS to optimize land use pattern at watershed level. *Journal of Applied Sciences and Environmental Management*, *14*(2).

Shang, Y., & Liu, S. (2021). Spatial-Temporal Coupling Coordination Relationship between Urbanization and Green Development in the Coastal Cities of China. *Sustainability*, *13*(10), 5339.

Simwanda, M., Murayama, Y., & Ranagalage, M. (2020). Modeling the drivers of urban land use changes in Lusaka, Zambia using multi-criteria evaluation: An analytic network process approach. *Land Use Policy*, *92*, 104441.

Stow, D. A. (2017). Radiometric Correction of Remotely Sensed Data. In: San Diego: San Diego State University.

Tadese, S., Soromessa, T., & Bekele, T. (2021). Analysis of the current and future prediction of land use/land cover change using remote sensing and the CA-markov model in Majang forest biosphere reserves of Gambella, southwestern Ethiopia. *The Scientific World Journal*, *2021*.

Tewabe, D., & Fentahun, T. (2020). Assessing land use and land cover change detection using remote sensing in the Lake Tana Basin, Northwest Ethiopia. *Cogent Environmental Science*, *6*(1), 1778998.

UN. (2020). *15 fastest-growing cities in the world*. UN. https://www.un.org/en/development/desa/population/publications/database/index.asp

UNDESA. (2018). Revision of world urbanization prospects. *New York: United Nations Department of Economic Social Affairs*.

UNDESA, P. (2014). World urbanization prospects: the 2014 revision. *Report No. ST/ESA/SER. A/322*.

Vinayak, B., Lee, H. S., & Gedem, S. (2021). Prediction of land use and land cover changes in Mumbai City, India, using remote sensing data and a multilayer perceptron neural network-based markov chain model. *Sustainability*, *13*(2), 471.

Wang, S. W., Munkhnasan, L., & Lee, W.-K. (2021). Land use and land cover change detection and prediction in Bhutan's high altitude city of Thimphu, using cellular automata and Markov chain. *Environmental Challenges*, *2*, 100017.

Wei, G., Zhang, Z., Ouyang, X., Shen, Y., Jiang, S., Liu, B., & He, B.-J. (2021). Delineating the spatial-temporal variation of air pollution with urbanization in the Belt and Road Initiative area. *Environmental Impact Assessment Review*, *91*, 106646.

Xinhua, H. (2018). African News website. http://www.xinhuanet.com/english/2018-04/27/c_137139622.htm

Xu, P., Lin, M., & Jin, P. (2021). Spatio-temporal Dynamics of Urbanization in China Using DMSP/OLS Nighttime Light Data from 1992–2013. *Chinese Geographical Science*, *31*(1), 70-80.

Zhang, Z., Hu, B., Jiang, W., & Qiu, H. (2021). Identification and scenario prediction of degree of wetland damage in Guangxi based on the CA-Markov model. *Ecological Indicators*, *127*, 107764.

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