TOPIC: Urban growth monitoring using spatial landscape matrices.
ACKNOWLEDGEMENT

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<tr>
<td>ETM+</td>
<td>Enhanced Thematic Mapper Plus</td>
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<td>GDP</td>
<td>Gross Domestic Product</td>
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<td>GIS</td>
<td>Geographic Information Systems</td>
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<td>LULC</td>
<td>Land use/land cover change</td>
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<td>MLC</td>
<td>Maximum-Likelihood Classification</td>
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<td>Mean Patch Size</td>
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<td>Normalized Difference Vegetation Index</td>
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<td>TM</td>
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Abstract

With over 80% of global GDP created in cities, urbanization may contribute to long-term growth if properly managed. (The World Bank, 2021). In Uganda, the population living in urban areas are rising at a rate of 2.335% since 1990 to 2020. Cities must act fast to plan for expansion and provide the fundamental services, infrastructure, and affordable housing that their growing populations require. Urbanisation occurs at the expense of transformation of other landscapes hence the process of urbanization has a large influence on landscape and ecosystem function. For assessing policy alternatives for future growth and sustainable development of urban planning must be considered. Through mapping and analyzing land use/land cover transition in urban areas, as well as monitoring their environmental effects with the help of landscape metrics was the focus of this research. Landsat Images of 1990, 2000, 2010 and 2020 were used for this study, band ratios of NDVI, NDBI, NDWI were used for image enhancement to clearly identify the vegetated areas, built up areas and the areas that were covered with water, then a maximum likelihood classification technique was used to classify the images accordingly with an accuracy assessment of above 80% was accepted, the resulting classified images were then taken to FRAGSTATS for computation of landscape metrics. The metrics examined included class area, number of patches, total core area, core area percent of landscape, splitting Index, and landscape division index. It was discovered that the urban areas that converged between 1990 and 2020 contributed significantly to the fragmentation of predominantly the primarily vegetated regions of the research area, as well as the loss of the core portions of several habitats.
Chapter One: Introduction

1.1 Background.

Globally, 55% of the population lives in urban areas. By 2045, the number of people living in cities will increase by 1.5 times to 6 billion, adding 2 billion more urban residents, with more than 80% of global GDP generated in cities, urbanization can contribute to sustainable growth if managed well (The World Bank, 2021). In Uganda, 11.1% of the country’s population were living in urban areas in 1990 and by 2020, 25.0% of the country’s population was leaving in urban areas, these values are increasing at an average rate of 2.335% (Knoema, 2021). City leaders must move quickly to plan for growth and provide the basic services, infrastructure, and affordable housing their expanding populations need. The process of global urbanization is accelerating and has potentially large influences on landscape and ecosystem function in cities and surrounding areas (Li et al., 2010). The transformation of land covers from rural/natural ecosystems to built-up land that supports various types of human activity is one of the major consequences of urbanization. These changes have an impact on local geology, soil, water, flora and fauna and the human existence of the region's ecosystem services (Furberg, 2014a). For assessing policy alternatives for future growth and fostering sustainable urban planning, mapping and analyzing land use/land cover transition in urban areas, as well as monitoring their environmental effects, is critical.

For those striving toward a more sustainable developed future, urbanization presents multiple obstacles. As cities expand, internal difficulties will arise, their impact on the surrounding external natural environment upon which they depend is of critical importance (Lambin et al., 2001). Land use/land cover change (LULC) mapping and study of urban areas are critical for monitoring this "ecological footprint" and deciding policy strategies and/or solutions for future development and environmental protection. Thus, it is important for us to analyze urbanization as one of the major changes humanity does to the earth surface (Wentz et al., 2009).

The use of remote sensing and geographic information systems (GIS) technologies to capture and map urban LULC changes has been demonstrated in previous studies. e.g. (Ban et al., 2014, 2015; Qin et al., 2013; Yang, 2006) Tracking the environmental impact of these changes has often been undertaken with the help of landscape metrics (Botequilha Leitão & Ahern,
2002; Haines-Young et al., 1993; Hargis et al., 1998; Kamusoko & Aniya, 2007; Laboratory et al., 1988; Li et al., 2010; McGarigal & Marks, 1995; Monica G. Turner, 1990; Narumalani et al., 2004). For mitigation and planning purposes, there is a need for the creation of ecosystem status indicators based on GIS and remote sensing data (Revenga, 2005). Remote sensing specialists have perhaps focused on technological issues as their principal concern, rather than ecological problems (Aplin, 2005). Yet there exists a greater potential for use of remote sensing within landscape ecology but also draw attention to a traditional divide between the remote sensing and ecological science research communities (Newton et al., 2009).

Africa is projected to have the fastest urban growth rate in the world and by 2050, Africa’s cities will be home to an additional 950 million people, much of this growth is taking place in small and medium-sized towns (OECD & Club, 2020). The overall aim of this study is to examine the scale of urban growth and/or sprawl in the areas around the selected built up areas in Masaka district and their possible effects on the ecosystem utilizing landscape metrics and other environmental indicators. The analyses will be are dependent on classifications of optical satellite imagery (Landsat TM/ETM+) of 1990, 2000, 2010, and 2020. A method of supervised classification (a maximum-likelihood classification (MLC)) is to be used to retrieve class boundary.

This research intends to show how GIS techniques can be used to evaluate both the spatial-temporal dynamics of urban growth and its effects on the ecosystem in selected built-up areas in Masaka District using urban and environmental indicators derived from remote sensing data. The findings will be useful knowledge for urban and environmental planners in several different areas by comparing trends and impacts of urban development in different regions.
1.2 Problem Statement.
In reality, urbanization affects land use change through the transformation from rural – agricultural areas to urban – built-up areas since mostly the urban developments are built at the expense of other landscapes. Rapid land use/cover change and landscape fragmentation is occurring in many countries in central and southern Africa, as a result of colonial imbalances in land distribution, demographic pressure, agricultural expansion, government policies and environmental factors such as drought (Kamusoko & Aniya, 2007). The rapid land use/cover change, unprecedented in human history especially in developing tropical and subtropical countries, is continuously transforming landscapes, thereby threatening global sustainability and livelihood systems (Singh & Kumar, 2012). Hence threatening the achievement of the UN Sustainable development goals, 11 and 13 that intend to “Make cities and human settlements inclusive, safe, resilient and sustainable” and “Take urgent action to combat climate change and its impacts” respectively (United Nations, 2016).

One of the major concern of landscape fragmentation is due to the clearing of forests and woodlands, which constitute a fundamental carbon store as well as the source of food and fuel, and utility products (Nagendra et al., 2004). The use of environmental indicators and landscape matrices in conjunction with remote sensing and GIS techniques for estimation of potential environmental impact in urban regions is an underexplored area of research in this field (Furberg, 2014a). The current methods used by planners often ignore the concept of landscape matrices as used in ecology and environmental indicators to address the environmental degradation processes. Hence the need to protect the environment and devise means on how sustainable development can be achieved with the growing urbanization. This research therefore intends to assess the impacts of urbanization on the environment and the ecosystem at large using landscape matrices and environmental indicators and suggest means on which measures to take in order to achieve sustainable development.

1.3 Major Objective.
To assess urban growth, as well as its possible effect on the ecosystem, in the built-up areas of Masaka District in Uganda, using landscape metrics.
1.4 Specific Objectives.
1. To identify analyze the extents of urbanization that has happened on the selected built up areas of Masaka District and its surroundings for the last three decades
2. To analyze the different landscapes using landscape matrices and the possible effects on the preserving biological diversity for the last three decades.

1.5 Research Question.
When and where has urbanization occurred in the district over last three decades and what are the likely impacts of the urban expansion on the climate surrounding agriculture and nature?

1.6 Justification
This research helps the city planners to make informed plans that address both fields of technological and ecological aspects of environmental degradation and sustainable development of cities putting in consideration the indicators used in this study. Hence increasing on the chances of achieving the UN SDGS, 11 & 13. If this study is not taken into consideration, city planners will continue using models that ignore the preserving of the biodiversity to address environmental degradation processes thus not effectively combat the effects urbanization has on both the ecosystems and the environment.
1.7 Study Area.
Masaka District was used as a case study. Masaka District is located in the southern hemisphere. The district is bordered by Bukomansimbi District to the north-west, Kalungu District to the north, Kalangala District to the east and south, Rakai District to the south-west, and Lwengo District to the west (Masaka District, 2021).
Figure 1: A satellite image of Masaka District
Chapter Two: Literature Review

The process of global urbanization is accelerating and has potentially large influences on landscape and ecosystem function in cities and surrounding areas (Riley et al., 2005; J. J. Wu, 2008). Hence there is urgent demand for scientific research to provide ecological solutions for problems related to urbanization, degradation of freshwater, and movement of materials between ecosystems (Palmer et al., 2004). Changes in ecological conditions that result from these actions affect the quality of the urban and global environment and ultimately people’s health and well-being (Musacchio et al., 2005).

2.1 Landscape Ecology.

Forman and Godron (1986) defined landscape as a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout. The concept differs from the traditional ecosystem concept in focusing on groups of ecosystems and the interactions among them. Landscape ecology, if not ecology in general, is largely founded on the notion that environmental patterns strongly influence ecological processes (M. G. Turner, 1989). The habitats in which organisms live, for example, are spatially structured at a number of scales, and these patterns interact with organism perception and behavior to drive the higher-level processes of population dynamics and community structure. Anthropogenic activities (e.g., roads, development, and timber harvest) can disrupt the structural integrity of landscapes and is expected to impede, or in some cases facilitate, ecological flows (e.g., movement of organisms) across the landscape.

Land ecology is the study of the relationships between phenomena and processes in the landscape or geosphere including the communities of plants, animals and man (Haines-Young et al., 1993). Landscape ecology investigates landscape structure and changes in the landscape, these change express any modification occurring in the landscape over time (Gkyer, 2013).

Landscape, according to (Vink & Davidson, 1983), is the sphere in which a range of processes are active. Landscape ecology aims to focus on the way in which these processes interact, and provide a framework in which human impact on the environment can be understood.

A more technical definition of landscape ecology is given by (Forman & Godron, 1986) as the study of the structure, function and change in a heterogeneous land area composed of
interacting ecosystems. Landscape ecology considers the development and dynamics of spatial heterogeneity, spatial and temporal interactions and exchanges across heterogeneous landscapes, influences of spatial heterogeneity on biotic and abiotic processes and management of spatial heterogeneity (Haines-Young et al., 1993). Many of the rigors involved with earning a living from the land have been removed by modern technology. Too many have seen the landscape as merely a backdrop to our everyday lives instead of as a resource to be nurtured and maintained. In other areas traditional landscape patterns, which have been largely stable or only slowly changing for many generations, are now being rapidly altered (Haines-Young et al., 1993). It is unclear what the implications would be, but some argued that they may be deep, for instance in industrialized parts of the world, effects on the landscape are more indirect, but equally significant, and they are not just of local and regional significance, but may also impact upon the global system. Our current challenge is the pace and magnitude of these changes, which can make it impossible to adapt biologically, socially and economically.

Landscape ecology is a well-recognized ecological discipline dealing with the spatial distribution of organisms, patterns and processes (Farina, 2009). Landscape ecology uses numbers related to complexity studies including remote sensing, geographical information systems and geostatistical tools, these tools have been developed for landscape ecology studies (Farina, 2000). Landscape ecology investigates internal dynamics and interaction of landscapes. Landscape ecology focuses on spatial relationship of landscape elements and ecosystems, functional and structural features of the land mosaic and change that is emerged over time (Dramstad et al., 1989). Landscape ecology investigates the relationship between spatial pattern and ecological process, i.e. the causes and effects of spatial heterogeneity at various scales. (Turner et al., 2001).

Landscape ecology acknowledges that ecological units (systems) are arranged in space in response to topographic, temperature, moisture, and soil gradients (Yu & Ng, 2006). Disturbances, biotic interactions and human use of the land impose additional patterns. Spatial arrangement, in turn, affects many ecological processes, like organism movement patterns, disturbance distribution, and also the movement of matter or energy. Landscape ecology, focusing on spatial pattern and the ecological responses to this pattern, leads to a new set of
principles, distinct from the principles that govern ecosystem and population dynamics at finer scales (Turner et al., 2001).

The availability of remote sensed imagery has made it possible to study spatial patterns over large areas and its change through time, opening new horizons for landscape analysis (Turner et al., 2001).

Landscape ecology focuses on three characteristics of the landscape (Forman & Godron, 1986).

a) Structure: The spatial relationships among the distinctive ecosystems or elements.

b) Function: The interactions among the spatial features.

c) Change: The alteration in the structure and function of the ecological mosaic over time.

2.2 Landscape structure

While understanding landscape structure, connectivity and fragmentation must be known, and landscape structure helps in assessing landscape function and landscape change.

Landscape structure expresses the spatial pattern of landscape elements and the connections between the different ecosystems or landscape elements, it also assesses the relationship between ecosystems as measure, number, size and shape (Forman & Godron, 1986; Palmer et al., 2004).

Landscape structure has two qualities. These are composition and configuration (Farina, 2009).

i. Landscape composition: Attribute of composition is not spatial, and can't be measured. It defines the quality of the landscape patches, scattered in landscape. The composition is not a precise identification of the mosaic structure of the landscape. But it is a good indicator for living environment suitability of some species (appropriate patch type for species) (Farina 2000).

ii. Landscape configuration: Configuration refers to the spatial characteristics. It refers to spatial characteristics same as the spatial distribution of land cover (Farina 2000).
Landscape ecologists use four basic terms to define spatial structure (FISGRW, 1998)

- **Patch**: A nonlinear area (polygon) which is less abundant. It is different from the matrix.
- **Corridor**: A special type of patch which links other patches in the matrix. Typically, a corridor is linear or elongated in shape, such as a stream corridor.
- **Matrix**: the land cover that is dominant and interconnected over the majority of the land surface. Often the matrix is forest or agriculture, but theoretically it can be any land cover type.
- **Mosaic**: a collection of patches, none of which are dominant enough to be interconnected throughout the landscape.

The space in between the patches and corridors is what is called a landscape matrix, patches often work as habitats of many ecological species. Patch size and isolation are predicted to be the critical variables in determining the efficacy of these habitat patches in preserving biological diversity (J. F. Franklin & Lindenmayer, 2009). The size of both the patch and the matrix strongly affects the habitats and the species as they can distort or preserve these habitats if managed well. It is highlighted by (Prugh et al., 2008) that the resource management practices that maintain or improve the suitability of the matrix are fundamental to the conservation of biodiversity yet many conservation biologists have largely overlooked the

![Figure 2: Basic terms to define landscape ecology (FISGRW 1998)](image-url)
pivotal importance of the matrix and the habitat that it provides for enhanced biodiversity conservation (J. F. Franklin & Lindenmayer, 2009). Hence researchers need to move forward to devise means how the we can live in a sustainable ecosystem not at the expense of other species.

2.3 Landscape Matrices.

A landscape is defined as a heterogeneous land area composed of a cluster of interacting ecosystems that is repeated in similar form throughout (Forman & Godron, 1986).

Landscape metrics are important tools which are used to understand landscape structure and landscape changes, these metrics use numeric data that is related to landscape structure and this data is produced from satellite images and air photos (Gkyer, 2013). In addition, landscape metrics are used as geographic information systems compatible and allow doing objective reviews on landscape structure.

Landscape metrics describe the spatial structure of a landscape at a set point in time. They provide information about the contents of the mosaic, e.g. the proportion of each landscape type or category present in the study area, or the shape of the component landscape elements (André Botequilha & Jack, 2002). Landscape metrics help us to understand changes in landscape from different perspectives like visual, ecological, and cultural (Cushman et al., 2008).

Landscape metric tools were used to help landscape planning and management decisions in landscape ecology (Gkyer, 2013; Palmer et al., 2004). Landscape metrics were used to measure the landscape structure and the complexity of this structure, landscape metrics used for measuring and mosaic structure and related information can be obtained (Farina, 2000; J. Wu, 2004). Landscape metrics also help in calculation composition and configuration, which have two characteristics of landscape structure (Gkyer, 2013).

Different ways are possible to perceive landscape composition and configuration using landscape metrics. To perceive composition, metrics are used with regard to the importance of each patch type, its characteristics such as rate, richness (patch richness), regularity, dominance and diversity (patch number) with metrics related composition (Gkyer, 2013).
Its physical distribution of patches in mosaic structure with landscape configuration, metrics are size and shape, neighborhood (the distance to the nearest neighborhood) and distribution related configuration (Botequilha Leitão & Ahern, 2002).

Landscape metrics are used in conjunction with geographic information systems (GIS) (Gkyer, 2013). GIS has made a major contribution to the study of the landscape metrics (Haines-Young et al., 1993). GIS and related technologies are used for a long time in studies related to the ecology as it offers a lot of possibilities to the users (Monica G. Turner, 1990). To use landscape metrics and digital data adapted with GIS have been made to contribute to the landscape planning studies (Monica G. Turner, 1990). To quantify the Landscape metrics, computer programs have been developed such as Fragstats (Gkyer, 2013; Mcgarigal, 2015; McGarigal & Marks, 1995), and Patch Analyst (Elkie et al., 1999).

2.4 Landscape pattern analysis

Landscape pattern is generally referred to the spatial pattern of landscape, including types, numbers and spatial distribution and deployment of landscape unit (Jian et al., 2008).

Landscape pattern is the essential performance of heterogeneity as well as the ecology process result on different scale (Chen Wenbo et al.,2002,).

Landscape pattern analysis is used to detect and to describe observed structures in landscape features (most commonly land cover) as surrogates for specific ecological values (e.g., wildlife habitat, species richness, vegetation, etc.) or land use (Pasher et al., 2013; Monica G. Turner, 1990; Wagner & Fortin, 2005; Wu, 2004).

2.4.1. Classes of Landscape Pattern

Broadly considered, landscape pattern analysis involves four basic types of spatial data corresponding to different representations of spatial heterogeneity, although in practice these models of landscape structure are sometimes combined in various ways (Forman & Godron, 1986). These classes of landscape structure look rather different numerically, but they share a concern with the characterization of spatial heterogeneity

i. **Spatial point patterns**: These represent collections of entities where the geographic locations of these entities are of primary interest than any quantitative or qualitative attribute of the entity itself. An example is a map of all trees in a
forest stand, where the data consists of a list of trees referenced by their geographic locations. The goal of analysis with such data is to determine whether the points are more or less clustered.

ii. **Linear network patterns:** These represent collections of linear landscape elements that intersect to form a network. The goal of analysis with such data is to characterize the physical structure (e.g., network density, mesh size, network connectivity, and circuitry) of the network, and a variety of metrics have been developed for this purpose.

iii. **Surface patterns:** These represent quantitative measurements that vary continuously across the landscape. Here, the data can be conceptualized as representing a three-dimensional surface, where the measured value at each geographic location is represented say height of the surface. An example is a digital elevation model. The goal of analysis is to describe the spatial structure of the surface in a single metric.

iv. **Categorical map patterns:** These represent data in which the system property of interest is represented as a mosaic of discrete patches. Hence, this type of spatial pattern is also referred to as a patch mosaic. An example is a map of land cover types, where the data consists of polygons (vector format) or grid cells (raster format) classified into discrete land cover classes. The goal of analysis with such data is to characterize the composition and spatial configuration of the patch mosaic, and a plethora of metrics has been developed for this purpose (Gkyer, 2013).

### 2.4.2. Landscape Pattern Metrics.

A “landscape metric” is any scalar quantitative summary of landscape structure. Although landscape metrics can be computed for any of the classes of landscape pattern, the common usage of the term landscape metrics refers exclusively to indices developed for categorical map patterns (ELI 2003).

In this regard, landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics (Forman & Godron, 1986). In
addition, landscape metrics are focused on the characterization of the spatial properties of categorical map patterns represented at a particular scale.

Landscape metrics have been utilized in order to assess how much fragmentation has occurred at patch, class and landscape scales, this analysis does not only describe these patterns, but also to correlate them with the underlying ecological processes driving them (De Araujo Barbosa et al., 2015).

2.4.3. Levels of Landscape Metrics.

Patches form the basis (or building blocks) for categorical maps. In most applications, once patches have been established, the within-patch heterogeneity is ignored and patches are assigned a nominal class value to represent the composition of the patch. Landscape pattern metrics focus on the spatial character and distribution of patches (Kevin McGarigal, 2013).

i. **Patch-level metrics.** These are defined for individual patches, and characterize the spatial character and/or context (i.e., ecological neighborhood) of patches. The result is a single value for each patch (Kevin McGarigal, 2013).

ii. **Class-level metrics.** These are integrated over all the patches of a given type (class). These may be integrated by simple or area-weighted averaging. In addition, there are aggregate properties at the class level that result from the unique configuration of patches across the landscape. The result is a single value for each class (Kevin McGarigal, 2013).

iii. **Landscape-level metrics.** These are integrated over all patches and classes over the full extent of the landscape. Like class metrics, these may be integrated by a simple or area-weighted averaging, or may reflect aggregate properties of the entire patch mosaic. The result is a single value for the entire landscape (Kevin McGarigal, 2013).

FRAGSTATS divides metrics into 5 groups, including area and edge, shape, core area, contrast, and aggregation. These groups are available for all the levels of landscape matrices i.e. Patch level, Class level and Landscape level.

i. **Area and edge.** These metrics describe aspects of area for different levels. Example metrics: "Class area," "percentage of landscape (PLAND)", etc.
a. **Class area (CA)** and percentage of landscape (PLAND) are fundamental measures of landscape composition; specifically, how much of the landscape is comprised of a particular patch type. This is an important characteristic in a number of ecological applications. For example, an important byproduct of habitat fragmentation is habitat loss. In the study of forest fragmentation, therefore, it is important to know how much of the target patch type (habitat) exists within the landscape.

b. **Mean patch size (AREA_MN)** at the class level is a function of the number of patches in the class and total class area. Importantly, although mean patch size is derived from the number of patches, it does not convey any information about how many patches are present. A mean patch size of 10 ha could represent 1 or 100 patches and the difference could have profound ecological implications. Furthermore, mean patch size represents the average condition.

c. **Total edge (TE)** is an absolute measure of total edge length of a particular patch type (class level) or of all patch types (landscape level).

   ii. **Shape.** These metrics estimate characteristics of patch shape, e.g., how long, thick, thin, patches are. Example metrics include: Area–perimeter ratios, Contiguity indexes, etc. Shape is a difficult parameter to quantify concisely in a metric for the reasons discussed below. Generally speaking, the shape of a geometric object, such as a patch, is a function of its morphology. Thus, one might expect shape metrics to discriminate among patch morphologies.

       a. Perimeter-area ratio (PARA). A problem with this metric as a shape index is that it varies with the size of the patch. For example, holding shape constant, an increase in patch size will cause a decrease in the perimeter-area ratio

       b. Shape index (SHAPE) measures the complexity of patch shape compared to a standard shape (square) of the same size, and therefore alleviates the size dependency problem of PARA.

   iii. **Core area.** These metrics quantify aspects of the patch core area. A core is the area of a patch in which edge effects do not occur. Evaluation of patch core is crucial
for conservation efforts because many species, especially large predators, cannot survive without enough core area. Example metrics include: number of core areas, total core area, etc.

iv. **Contrast**. Contrast refers to the relative difference among patch types. For example, mature forest next to young forest might have a lower contrast edge than mature forest adjacent to open field, depending on how contrast is defined (Kevin McGarigal, 2013). Example metrics include: Total contrast edges, Edge densities, etc.

v. **Aggregation**. Aggregation metrics quantify the degree to which patch types are or are not aggregated. Example metrics include: Proximity indexes, Similarity indexes, etc.

### 2.5 Landscape function

Animals, plants, resources, mineral nutrients, and interactions among these elements all play a role in landscape function. The primary structural characteristics for landscape function are corridors, hedgerows, matrix and networks (Forman & Godron, 1986).

Corridors have four important functions which include;

- A habitat for certain type of species,
- Movement area for species,
- A barrier or filter area,
- A source of environmental and biotic effects.

All these functions involve flows of animals and plants; the last two functions also include flows of energy and mineral nutrients (Forman and Godron 1986).

Corridors serve as conduits and as filters for much of the movement of animals, plants, materials, and water across the landscape (Gkyer, 2013). Network and matrix characteristics affect transactions in contrasting ways, depending on whether the objects cross corridors or use corridors as conduits. Landscape functioning integrates flows both between adjacent ecosystems and across a landscape (Forman and Godron 1986).
In the landscape flows dependent on the orientation of the structure (Forman and Godron 1986). Connectivity is very important for landscape function. Sometimes landscapes have fragmented structure.

Habitat fragmentation severely threatens biodiversity and ecosystem functioning wherever humans dominated landscape. Land use planners play a significant role in determining whether and how landscapes and ecosystems are fragmented or maintain natural connectivity (ELI 2003).

2.6 Biodiversity and nature conservation

Biodiversity includes conservation of all species, the genetic variability which they contain and the ecological communities they form (McNeely et al., 1990).

Conservation of nature entails two separate but related objectives. The first of these objectives is the maintenance of the maximum degree of biodiversity. The second objective is the development, management and maintenance of ecological infrastructure through the management of protected areas (Haines-Young et al., 1993).

Maintenance of biodiversity is a ‘typical’ role of conservation, and is increasingly seen as the prime conservation function. The most significant causes of biodiversity loss are habitat loss and degradation, but pollution, the introduction of invasive species (and, in some processes, overharvesting) all contribute to the loss.

Landscape ecology can help maintain biodiversity through an understanding of the structure and function of landscapes, good nature-conservation management requires a basic understanding of ecological science at all levels, especially focusing on the landscape ecological aspects (Haines-Young et al., 1993). Species and community ecology can be effectively addressed at the local level. However, the ability to document information and develop models in large areas is crucial to an attempt to develop an understanding of ecological infrastructure (De Araujo Barbosa et al., 2015). Hence the use of the geographical information systems (GIS) and their power.

(Simmons et al., 1978) looked at landscapes in terms of their degree of ‘naturalness’, suggested the following categories of landscape type.
• **Natural.** Landscapes unaffected by human actions, with flora and fauna spontaneous.

• **Subnatural.** Landscapes which, if human activity were removed, would revert to a natural state, with largely spontaneous flora and fauna.

• **Semi-natural.** Landscapes drastically modified by human activity, with the vegetation formation different from potential natural vegetation, but with a considerable degree of natural elements left intact.

• **Agricultural.** Landscapes predominantly arranged by human activity that have no areas of naturalness left or with a great many ruderals and neophytic species.

2.7 Ecosystems

The world's economies depend on ecosystem-derived products and services such as food, water, building materials, climate control, and water purification. Human survival is dependent on biological processes continuing to offer a wide range of benefits. Yet, for much too long, sustainability agendas in both rich and poor countries have centered on how far humanity can benefit from ecosystems, with much too little consideration paid to the consequences of our actions (Liu et al., 2018). At present, we tend to manage ecosystems for any one dominant good or service such as fish, timber, or hydropower, without fully realizing the trade-offs we are making, but this traditional management approach has led us to the current decline in ecosystem condition, which we are experiencing, among other things, in terms of water shortages, species loss, declining fish catches, and the loss of key habitats like wetlands, coral reefs, and forests (Revenga, 2005). Yet it’s the poor, whose livelihoods often depend most directly on these ecosystem goods and services, suffer most when ecosystems are degraded. Hence, the leaders in developing and developed countries government, private sector, and civil society need timely and targeted environmental indicators to understand the value and use of ecosystem goods and services, to analyze threats, and when combined with socio-economic indicators, assess the trade-offs at stake (Haas & Ban, 2014).

Global and regional spatial indicators not only inform us about the current condition of, and pressures on, ecosystems, but also about the likely capacity of the ecosystem to continue to provide goods and services to future generations (Revenga, 2005). The growing emphasis on combining socioeconomic and biological data with remote sensing and GIS technologies will only help to advance our knowledge and capacity to handle environments more sustainably.
because the information obtained from the satellite is digital, it is possible to perform computer analyzes of land type classification and trends. GIS also enables the integration of physical, biological, and socio-economic data in order to examine the state and change of ecosystems and make possible connections between change and impacts.

2.8 Classification techniques
A number of classification methods are available in order to generate landcover/use maps from optical remote sensing data and these include (Furberg, 2014b):

- Algorithms based on parametric and nonparametric statistics
- Nonmetric methods,
- Supervised
- Unsupervised classification logic,
- Hard or fuzzy set classification logic,
- Per-pixel or object-oriented classification logic
- Hybrid approaches

None of them are absolutely superior to the others; all classifiers are subject to a three-way compromise between the spectral information content of the imagery, the method of making class decisions and the information classes that are desired (S. E. Franklin & Wulder, 2002). Hence the choice of classification method depends on physical characteristics and prior knowledge of the study area, the distribution of the remote sensing data and the nature of the classification problem itself (Furberg, 2014b). Supervised pixel-based classification using the maximum likelihood classifier (MLC) was chosen based on its compatibility for the study area, the extent of prior knowledge and remote sensing data accessible, as well as the experience and rate of confidence of other authors in using it to study LULC change in urban areas. Supervised classification presents a better alternative when there is a defined area to be studied and when medium resolution satellite data and prior knowledge of the site are available (Haas et al., 2015). More research, however, has shown that when combined with other methods and data inputs, the findings obtained from MLC can be greatly improved (Dawson et al., 2016; Furberg & Ban, 2012; Shalaby & Moghanm, 2015; Wellmann et al., 2020), and hence will be used with the indices.
2.9 Environmental Indicators

An indicator is something that provides a clue to a matter of larger significance or makes perceptible a trend or phenomenon that is not immediately detectable. As opposed to statistics or primary data, which are direct measures of different parameters, indicators represent an empirical model of reality, but not reality itself (Hammond et al., 1995).

Indicators are key tools to carry out assessments without the resources and expenses needed in detailed data collection efforts. Indicators can be developed using a limited amount of data, which can be aggregated or correlated to simplify and communicate complex phenomena (Revenga, 2005). In many situations, indicators are used as proxies to measure or explain a situation or a phenomenon. Indicators can provide useful information and communication tools which can be used to simplify complex issues, they can be represented in a graphic and easy to understand forms (i.e., maps, charts, trend lines).

The need for indicators should be driven by demand rather than data availability, however, in practice, data availability still determines and sets the boundaries for indicator development (Revenga, 2005). In general, indicators focused solely on data availability are ineffective at addressing particular questions or informing specific choices. A common mistake in developing indicators is that many times the process itself starts by asking the question of “what data do we have?” instead of “what data do we need to answer the particular question?” (Dawson et al., 2016). The availability of referenced spatial data has an impact on the applicability of remote sensing and GIS methodologies used.

Three indices are to be used in this study to generate the three indicators to consider in this study which will include vegetation changes; Normalized Difference Vegetation Index (NDVI), Build-up Index (NDBI) and Water Index (NDWI). These will be calculated on basis of the following equations.

- Normalized Difference Vegetation Index (NDVI):

\[
\text{NDVI} = \frac{(\text{NIR} - \text{Red})}{(\text{NIR} + \text{Red})}
\]

\[Equation \ i\]

Where NIR represents the Near-infrared band and R represents the red Band.
• Normalized Difference Built-up Index (NDBI): To retrieve urban land from the Landsat imagery, the NDBI index will be used in this study which is sensitive to the built-up areas. NDBI will be used to analyze the spectral characteristics of different land use/cover types.

\[ \text{NDBI} = \frac{(\text{SWIR} - \text{NIR})}{(\text{SWIR} + \text{NIR})} \]

*Equation ii*

where Band 4 and Band 5 represent the spectral bands of the Landsat TM images.

• Normalized Difference Water Index (NDWI):

\[ \text{NDWI} = \frac{(\text{Green} - \text{NIR})}{(\text{Green} + \text{NIR})} \]

*Equation iii*

where Band 4 and Band 5 represent the spectral bands of the Landsat TM images.

These three indicators will help in the realization of four major environment degradation processes:

• Deterioration of Vegetation Cover
• Urbanization process
• Wetlands Loss
Chapter Three: Methodology

3.1 Data Used.
The datasets used include both raster dataset and vector datasets, the raster datasets include Landsat images and these include Landsat 5, which was used for the dataset of 1990, Landsat 7 that was used for the datasets of 2000 and 2010, Landsat 8 that was used for the dataset of 2020, the district boundary shapefile was used as the vector dataset. The images considered were those with the least amount of cloud cover.

3.2 Methods used.

3.2.1 Band ratio.
Band Ratios are used to amplify the spectral differences between bands and to minimize the effects of topography, by dividing one spectral band by another generates an image that gives comparable band intensities. The Band Ratio image enhances the spectral differences between bands and can be helpful when trying to discriminate between land cover types (Allen et al., 2013). The ratios give unique information and indicate small reflection changes across surface materials which in a normal picture can often be hard to identify (San et al., 2004). Spectral indices are created by dividing one or a set of bands by the other bands. The band ratios that were used highlighted the different land cover types that act as environmental degradation indicators.

3.2.2 Supervised Classification.
The approach used is known as supervised classification which is based on a Machine learning algorithms or model, known as random forest that utilizes training data combined with image values to learn how to classify pixels. The model classifies satellite image pixels and assigns them land cover classes based on training data provided. Supervised classification relies on having sufficient pixels to train the classifier that have known class labels. The supervised classification’s core is the concept of segmenting the spectral domain into regions that can be associated with the ground cover classes of interest to a
particular application (Richards, 2013). Supervised classification with maximum likelihood technique was used to classify the images into classes that highlight indicators that are considered in this research.

**Collection of training data.**

Training data were collected as polygons that represent a land cover class based on a spectral signature identified on the satellite imagery. However, a training site would first be validated using more reliable data like using very high spatial resolution data such as Google Earth and planet.com imagery.

### 3.2.3 Production of Change maps.

Post classification change detection algorithm was used. Post classification is the comparison of independently classified maps to identify changes in the land cover over time. This method is the most widely used but the quality of the resulting change map entirely depends on the quality of maps being compared (Tewkesbury, Comber, Tate, Lamb, & Fisher, 2015).

### 3.2.4 Computation of Landscape Matrices.

Landscape metrics refers exclusively to numerical indices developed to quantify categorical map patterns (or patch mosaics) (Mcgarigal, 2015). The patch-based matrix technique will be used for the assessment of the landscape matrices, the landcover types will be grouped in patches. Under the patch mosaic perspective, landscape metrics are algorithms that quantify specific spatial characteristics of patches, classes of patches, or entire landscape mosaics, or the spatial context of individual cells within a patch mosaic, and a plethora of metrics have been developed for this purpose (Cushman et al., 2008; Mcgarigal, 2015). These metrics are divided into two main categories: those that measure the map's composition without reference to spatial attribute as well as those that quantify the map's spatial configuration and need spatial information to be calculated.

In this study, metrics indices were derived using FRAGSTATS Version 4.2.1 software which is a spatial pattern analysis program for quantifying landscape structure (K McGarigal et al., 2002).
Landsat 4-5 TM

Landsat 7 ETM

Landsat 8

District Shapefiles

1990

2000

2010

2020

Band Ratio

Clipping

NDVI

NDBI

NDWI


Bare Land: 1990, 2000, 2010, 2020

Is Classification Accuracy >80%

No

Yes

Computation of Landscape Matrices

Landscape Matrices That Show Different Ecological Processes
3.3 Data Acquisition

The United States Geological Survey (USGS) website provided access to a sequence of Landsat imagery from 1990 to 2020, with ten-year intervals. One Landsat-4/5 Thematic Mapper (TM) image dated 1990, two Landsat 7 ETM+ images of 2000 and 2010, and one Landsat 8 OLI image dated 2020 were chosen for this research.

<table>
<thead>
<tr>
<th>No.</th>
<th>Type of Data/sensor</th>
<th>Scale/Resolution</th>
<th>Path/Row</th>
<th>Date</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Landsat 4 (TM)</td>
<td>30m</td>
<td>172/060</td>
<td>22/12/1990</td>
</tr>
<tr>
<td>2</td>
<td>Landsat 7 ETM+</td>
<td>30m</td>
<td>172/060</td>
<td>12/02/2000</td>
</tr>
<tr>
<td>3</td>
<td>Landsat 7 ETM+</td>
<td>30m</td>
<td>172/060</td>
<td>30/11/2010</td>
</tr>
<tr>
<td>4</td>
<td>Landsat 8 OLI</td>
<td>30m</td>
<td>172/059</td>
<td>14/01/2020</td>
</tr>
</tbody>
</table>

3.4 Image Data Pre-Processing

This included operations that took place before the data was processed and analyzed. To correct the images for atmospheric disturbances such as path radiance, scattering, and sky irradiance, atmospheric correction using dark object removal was used. To create multiple color composites, the satellite images were stacked into different bands. To choose the region of interest, image clipping was used. NDVI, NDBI, NDWI and band composites image enhancement techniques were also utilized to improve the images’ visual interpretation for identifying distinct land cover classes.

3.5 Image Classification.

The Landsat photos were divided into five land cover classes; Wetlands, Primarily Vegetated, Built Up, Bare soils, and water based on the FAO classification scheme. To estimate the extents of these classes, supervised classification using the maximum likelihood classifier was done in the GIS environment. The supervised technique allows for the identification of pixels (training regions) that indicate recognized or identifiable pattern or land use aspects using additional sources such as ground truth data. The training sites were digitized using visual interpretation, which takes into account all types of information such as object size, shape, shadow effect, tone, color, texture, pattern, and association of distinct spectral covers.
3.6 Accuracy assessment

The ground truth data for the accuracy evaluation was generated by randomly selecting reference pictures (Google Earth images) from the relevant years. For each land cover map, accuracy was assessed by constructing confusion matrices based on test samples. The Kappa index of agreement was also utilized as a classification grading criterion. Kappa analysis is a discrete multivariate approach for assessing accuracy. The Kappa value (Kap) is calculated as

\[
Kap = \frac{N\sum_{i=1}^{r} x_{ii} \ - \ \sum_{i=1}^{r} (x_{i+} \times x_{+i})}{N^2 - \sum_{i=1}^{r} (x_{i+} \times x_{+i})}
\]

where \( r \) is the number of rows in the matrix, \( x_{ii} \) is the observation in row \( i \) and column \( i \), \( x_{i+} \) and \( x_{+i} \) are the marginal totals of row \( i \) and column \( i \), respectively and \( N \) is the total number of observations. The Kappa value is between -1 and 1. If the test samples are in perfect agreement (all the same between classification results and ground truthing results), values for the Kappa index (Kap) equal to 1.

3.7 Class Descriptors Table.

The class descriptors table allows for specifying a character description (i.e., patch type) for each numeric class value, specify whether to compute statistics for each class, and whether to designate each class as background. The class descriptors table is optional. If you do not provide this table, then the numeric class values are used in the output, all classes are enabled and none are treated as background except any class with the assigned background value.
3.8 Edge depth.

The Edge depth table displays the “depth-of-edge” values to use in determining what constitutes the core of a patch in the core area metrics and is only relevant if one or more core area metrics are selected. The edge depth entries must be a square matrix, should contain a record for each unique pairwise combination of patch types (classes) in the input landscape (any missing class must be missing in both the rows and columns and will be assigned a zero-edge depth for all edges involving that class), and all arguments should be separated by a comma. These are written in meters (m).

```
FSQ_TABLE
CLASS_LIST_LITERAL(Swamp, Open_Water, Green_V
CLASS_LIST_NUMERIC(2, 3, 4, 5, 6, 0)
0, 2, 5, 5, 12, 0
2, 0, 15, 10, 12, 0
2, 5, 0, 15, 10, 0
20, 15, 100, 0, 2, 0|
10, 10, 20, 2, 0, 0
0, 0, 0, 0, 0, 0
```
3.9 Edge contrast.
The Edge contrast table displays the “edge contrast” values to use in determining the magnitude of contrast for each edge type. The edge contrast entries must be a square matrix, should contain a record for each unique pairwise combination of patch types (classes) in the input landscape (any missing class must be missing in both the rows and columns and will be assigned an edge contrast weight of one (maximum)). Contrast weights must range from 0 (no contrast) to 1 (maximum contrast).

3.10 Similarity.
The Similarity table displays the “similarity” values to use in determining the similarity between each pairwise combination of patch types and is only relevant if the similarity index is selected. The similarity entries must be a square matrix, should contain a record for each unique pairwise combination of patch types (classes) in the input landscape (any missing class must be missing in both the rows and columns and will be assigned a zero similarity (minimum) for all comparisons involving that class), and all arguments should be separated by a comma. Similarity weights must range from 0 (minimum similarity) to 1 (maximum similarity).
### 3.11 FRAGSTAS important code descriptions.

*Table 2: FRAGSTATS Important Column Code Descriptions*

<table>
<thead>
<tr>
<th>Metric (acronym)</th>
<th>Range</th>
<th>Units</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Patch level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Core area (CORE)</td>
<td>CORE $\geq 0$,</td>
<td>Hectares</td>
<td>Represents the area in the patch greater than the specified depth-of-edge distance from the perimeter.</td>
</tr>
<tr>
<td>Number of Core Areas (NCORE)</td>
<td>NCORE $\geq 0$,</td>
<td>None</td>
<td>A disjunct core is a spatially contiguous (and therefore distinct) core area</td>
</tr>
<tr>
<td>Core Area Index (CAI)</td>
<td>$0 \leq \text{CAI} \leq 100$</td>
<td>Percent</td>
<td>Core area index is a relative index that quantifies core area as a percentage of patch area (i.e., the percentage of the patch that is comprised of core area).</td>
</tr>
<tr>
<td>Total Core Area (TCA)</td>
<td>TCA $\geq 0$,</td>
<td>Hectares</td>
<td>Total core area is defined the same as core area (CORE) at the patch level, but here core area is aggregated (summed) over all patches of the corresponding patch type.</td>
</tr>
<tr>
<td><strong>Class level</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Core Area Percentage of Landscape (CPLAND)</td>
<td>$0 \leq \text{CAI} \leq 100$</td>
<td>Percent</td>
<td>CPLAND equals the percentage the landscape comprised of core area of the corresponding patch type</td>
</tr>
<tr>
<td>Number of Disjunct Core Areas (NDCA)</td>
<td>$TCA \geq 0$, None</td>
<td>NDCA equals the sum of the number of disjunct core areas contained within each patch of the corresponding patch type; that is, the number of disjunct core areas contained within the landscape.</td>
<td></td>
</tr>
<tr>
<td>-------------------------------------</td>
<td>---------------------</td>
<td>----------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Disjunct Core Area Density (DCAD)</td>
<td>$DCAD \geq 0$, Number per 100 Hectares</td>
<td>Disjunct core area density expresses number of disjunct core areas on a per unit area basis that facilitates comparisons among landscapes of varying size.</td>
<td></td>
</tr>
<tr>
<td>Total Core Area (TCA)</td>
<td>$TCA \geq 0$, Hectares</td>
<td>Total core area is defined the same as core area (CORE) at the patch level, but here core area is aggregated (summed) over all patches</td>
<td></td>
</tr>
<tr>
<td>Number of Disjunct Core Areas (NDCA)</td>
<td>$NDCA \geq 0$, None</td>
<td>NDCA equals to the number of disjunct core areas contained within the landscape.</td>
<td></td>
</tr>
<tr>
<td><strong>Contrast Metrics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Edge Contrast Index (ECON)</td>
<td>$0 \leq ECON \geq 100$, Percent</td>
<td>This index is a relative measure of the amount of contrast along the patch perimeter</td>
<td></td>
</tr>
<tr>
<td>Contrast-Weighted Edge Density (CWED)</td>
<td>$CWED \geq 0$, Meters per hectare</td>
<td>Contrast-weighted edge density standardizes edge to a per unit area basis that facilitates comparison among landscapes of varying size</td>
<td></td>
</tr>
<tr>
<td>Metric</td>
<td>Definition</td>
<td>Evaluation Criteria</td>
<td>Notes</td>
</tr>
<tr>
<td>--------------------------------</td>
<td>-----------------------------------------------------------------------------------------------</td>
<td>-----------------------------------------------------------</td>
<td>-------------------------------------------------------------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Total Edge Contrast Index (TECI)</td>
<td>Total edge contrast index is similar to the edge contrast index at the patch level, only here it is applied to all edges of the corresponding patch type</td>
<td>$0 \leq \text{TECI} \geq 100$ Percent</td>
<td></td>
</tr>
<tr>
<td>Aggregation Metrics</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Similarity Index (SIMI)</td>
<td>SIMI = 0, if all the patches within the specified neighborhood have a zero similarity coefficient. SIMI increases as the neighborhood is increasingly occupied by patches with greater similarity coefficients and as those similar patches become closer and more contiguous and less fragmented in distribution.</td>
<td>$\text{SIMI} \geq 0$ None</td>
<td></td>
</tr>
<tr>
<td>Patch Density (PD)</td>
<td>PD equals the number of patches of the corresponding patch type divided by total landscape area it expresses number of patches on a per unit area basis that facilitates comparisons among landscapes of varying size</td>
<td>$\text{PD} \geq 0$ Number per 100 hectares constrained by cell size</td>
<td></td>
</tr>
<tr>
<td>Patch Cohesion Index (COHESION)</td>
<td>COHESION approaches 0 as the proportion of the landscape comprised of the focal class decreases and becomes increasingly subdivided and less physically connected. COHESION increases</td>
<td>$0 &lt; \text{COHESION} &lt; 100$ None</td>
<td></td>
</tr>
<tr>
<td>Index Name</td>
<td>Value Range/Formula</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>-------------------------</td>
<td>-----------------------------------------------------------------------------------</td>
<td>---------------------------------------------------------------------------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Splitting Index (SPLIT)</td>
<td>$1 \leq \text{SPLIT} \leq (\text{number of cells in the landscape area squared})$</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Split is based on the cumulative patch area distribution and is interpreted as the effective mesh number, or number of patches with a constant patch size when the corresponding patch type is subdivided into $S$ patches, where $S$ is the value of the splitting index.</td>
<td></td>
</tr>
<tr>
<td>Connectance Index</td>
<td>$0 &lt; \text{COHESION} &lt; 100$</td>
<td>Connectance is defined on the number of functional joinings between patches of the corresponding patch type, where each pair of patches is either connected or not based on a user-specified distance criterion.</td>
<td></td>
</tr>
<tr>
<td>Contagion Index (CONTAG)</td>
<td>$0 &lt; \text{CONTAG} &lt; 100$</td>
<td>Contagion is inversely related to edge density. When edge density is very low, for example, when a single class occupies a very large percentage of the landscape, contagion is high, and vice versa.</td>
<td></td>
</tr>
<tr>
<td>Aggregation Index (AI)</td>
<td>$0 &lt; \text{AI} &lt; 100$</td>
<td>Aggregation index is calculated from an adjacency matrix at the class level, AI increases as the landscape is increasingly monotonically as the proportion of the landscape comprised of the focal class increases until an asymptote is reached near the percolation threshold.</td>
<td></td>
</tr>
<tr>
<td>Metric</td>
<td>Formula</td>
<td>Description</td>
<td></td>
</tr>
<tr>
<td>---------------------------------</td>
<td>-------------</td>
<td>-----------------------------------------------------------------------------</td>
<td></td>
</tr>
<tr>
<td>Number of Patches (PA)</td>
<td>$PA \geq 1$</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>NP equals the number of patches in the landscape.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>aggregated and equals 100 when the landscape consists of a single patch.</td>
<td></td>
</tr>
<tr>
<td>Patch Density (PD)</td>
<td>$PD \geq 0$</td>
<td>Number per 100 hectares</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>Patch density has the same basic utility as number of patches as an index,</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>except that it expresses number of patches on a per unit area basis that</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>facilitates comparisons among landscapes of varying size.</td>
<td></td>
</tr>
<tr>
<td>Landscape Division Index (DIVISION)</td>
<td>$0 \leq DIVISION &lt; 1$</td>
<td>Proportion</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DIVISION = 0 when the landscape consists of a single patch.</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>DIVISION is achieving its maximum value when the landscape is maximally</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>subdivided; that is, when every cell is a separate patch.</td>
<td></td>
</tr>
<tr>
<td>Patch richness (PR)</td>
<td>$PR \geq 0$</td>
<td>None</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>PR measures the number of patch types present; it is not affected by the</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>relative abundance of each patch type or the spatial arrangement of patches</td>
<td></td>
</tr>
<tr>
<td>Patch Richness Density (PRD)</td>
<td>$PRD \geq 0$</td>
<td>Number per 100 hectares</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>PRD standardizes richness to a per area basis that facilitates comparison</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>among landscapes</td>
<td></td>
</tr>
<tr>
<td>Shannon's Diversity Index (SHDI)</td>
<td>$SHDI \geq 0$</td>
<td>Information</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>SHDI = 0 when there is one patch, and it increases with the increase in</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>patches.</td>
<td></td>
</tr>
</tbody>
</table>
Chapter Four: Results and Discussions

4.1 Urban Growth Change Detection.

A supervised maximum likelihood classification was performed on the four images for the years 1990, 2000, 2010, and 2020. Five different land use/Land cover classes were identified namely; Wetlands, Primarily Vegetated, Built Up, Bare soils, and water. Figure 3 shows the land use/land cover types of the built-up areas of Masaka during the study periods.
4.1.1. Accuracy assessment


Table 3: A Summary of Accuracy Assessment of classified Images

<table>
<thead>
<tr>
<th>Classified image</th>
<th>1990</th>
<th>2000</th>
<th>2010</th>
<th>2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Overall accuracy</td>
<td>83.4955</td>
<td>97.3684</td>
<td>85.33</td>
<td>95.122</td>
</tr>
<tr>
<td>Kappa statistic</td>
<td>0.8235</td>
<td>0.9671</td>
<td>0.8167</td>
<td>0.9407</td>
</tr>
</tbody>
</table>

Figure 3: Land Cover Maps of the Urbanized Areas of Masaka District in 1990, 2000, 2010, 2020
4.1.2. Statistics from the change Detection

**LAND COVER CHANGE (1990 - 2000)**

- Bare Land
- Built Up
- Primarily Vegetated
- Wetland
- Water

**REFERENCE CLASS**

**NEW CLASS**

**LAND COVER CHANGE (2000 - 2010)**

- Bare Land
- Built Up
- Primarily Vegetated
- Wetland
- Water

**REFERENCE CLASS**

**NEW CLASS**
Table 4: Table showing Changes in landscapes.

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Area (Sq KM)</td>
<td>%</td>
<td>Area (Sq KM)</td>
</tr>
<tr>
<td>Water</td>
<td>2213.986</td>
<td>10.47%</td>
<td>1347.6908</td>
</tr>
<tr>
<td>Wetland</td>
<td>5763.567</td>
<td>27.27%</td>
<td>4956.7628</td>
</tr>
<tr>
<td>Primarily Vegetated</td>
<td>7930.726</td>
<td>37.52%</td>
<td>7823.726</td>
</tr>
<tr>
<td>Built Up</td>
<td>3853.98</td>
<td>18.23%</td>
<td>5406.5668</td>
</tr>
<tr>
<td>Bare Land</td>
<td>1376.283</td>
<td>6.51%</td>
<td>1603.5998</td>
</tr>
<tr>
<td>Total</td>
<td>21138.542</td>
<td></td>
<td>21138.3462</td>
</tr>
</tbody>
</table>

The table above shows how different classes investigated have been changing over time, and it can be observed that among the greatly affected classes include the vegetated areas which most of the classes have been transformed to built up, for the water class, it disappeared during the time between the years 2000 – 2010, this can be attributed to many factors that include the wetlands growing over the water among others.
4.2. Landscape Matrices
Among the parameters considered for the analysis included Class area (CA), Number of Patches (NP), total core area (TCA), core area percent of landscape (CPLAND), Splitting Index (SPLIT) and Landscape Division Index (DIVISION)

4.2.1. Class area (CA)

*Table 5: A Table showing the Class area (CA).*

<table>
<thead>
<tr>
<th></th>
<th>CA</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>72.18%</td>
<td>70.20%</td>
<td>56.39%</td>
<td>44.40%</td>
<td></td>
</tr>
<tr>
<td>Built Up</td>
<td>12.39%</td>
<td>20.92%</td>
<td>33.41%</td>
<td>44.61%</td>
<td></td>
</tr>
<tr>
<td>Swamp</td>
<td>7.35%</td>
<td>7.10%</td>
<td>8.67%</td>
<td>9.43%</td>
<td></td>
</tr>
<tr>
<td>Water</td>
<td>6.83%</td>
<td>0.62%</td>
<td>0.00%</td>
<td>0.00%</td>
<td></td>
</tr>
<tr>
<td>Bare land</td>
<td>1.25%</td>
<td>1.16%</td>
<td>1.53%</td>
<td>1.56%</td>
<td></td>
</tr>
</tbody>
</table>

The class area shows how the different classes change, it can be observed that the class area (area of vegetated class) is reducing over the years hence this is having a negative effect on the habitats that are with in the vegetated places, and the class area for the built up is observed to be increasing within the landscape. for the swamp, its slowly increasing in area and this can be attributed to the
possibility of the wetlands taking over the open waters and also the fact that it was observed that
the built up had a very minimal effect on the class of wetland, for the water class, it was all covered
by the wetland between 2000 – 2010.

4.2.2. Number of Patches

Table 6: A Table showing the number of Patches in a particular class

<table>
<thead>
<tr>
<th>NP</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>7.58%</td>
<td>11.43%</td>
<td>23.33%</td>
<td>30.23%</td>
</tr>
<tr>
<td>Built Up</td>
<td>38.12%</td>
<td>68.38%</td>
<td>59.61%</td>
<td>45.10%</td>
</tr>
<tr>
<td>Swamp</td>
<td>21.53%</td>
<td>3.75%</td>
<td>3.24%</td>
<td>4.85%</td>
</tr>
<tr>
<td>Water</td>
<td>18.03%</td>
<td>5.54%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Bare land</td>
<td>14.75%</td>
<td>10.91%</td>
<td>13.82%</td>
<td>19.82%</td>
</tr>
</tbody>
</table>

The number of patches is a great sign of fragmentation, it is observed that the vegetated class
is having an increase in the number of patches hence there is fragmentation happening to this
class (this is not good as it reduces the core area for the habitat patches). The built up shows
an increase in the number of patches between 1990 and 2000, and a decrease between 2000 –
2020, this means that the number of patches are significantly getting aggregated, the swamp
also gets aggregated between 1990 – 2000, and a slight increase in the number of patched from 2000 – 2020.

### 4.2.3. Total core area (TCA)

*Table 7: A table showing the Total Core Areas*

<table>
<thead>
<tr>
<th>TCA</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>91.24%</td>
<td>75.35%</td>
<td>67.48%</td>
<td>44.40%</td>
</tr>
<tr>
<td>Built Up</td>
<td>0.09%</td>
<td>21.81%</td>
<td>24.36%</td>
<td>44.61%</td>
</tr>
<tr>
<td>Swamp</td>
<td>2.81%</td>
<td>2.74%</td>
<td>6.34%</td>
<td>9.43%</td>
</tr>
<tr>
<td>Water</td>
<td>4.28%</td>
<td>0.01%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Bare land</td>
<td>1.57%</td>
<td>0.08%</td>
<td>1.83%</td>
<td>1.56%</td>
</tr>
</tbody>
</table>

This is the total area of a patch minus the area covered by the edge depth, a decrease in the TCA in the vegetated class shows a sign of fragmentation and a great loss of connectivity, this makes it hard for the animals to move through different patches of the same class, for the built up, the class didn’t have any core area by 1990, and there has been a significant increase mostly between 2010 – 2020, this means more aggregation and better connectivity.
4.2.4. Core area percent of landscape (CPLAND)

<table>
<thead>
<tr>
<th>CPLAND</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>37.67%</td>
<td>36.64%</td>
<td>28.84%</td>
<td>22.93%</td>
</tr>
<tr>
<td>Built Up</td>
<td>0.04%</td>
<td>10.60%</td>
<td>11.48%</td>
<td>12.77%</td>
</tr>
<tr>
<td>Swamp</td>
<td>1.16%</td>
<td>1.33%</td>
<td>2.71%</td>
<td>3.34%</td>
</tr>
<tr>
<td>Water</td>
<td>1.77%</td>
<td>0.00%</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>Bare land</td>
<td>0.65%</td>
<td>0.04%</td>
<td>0.78%</td>
<td>0.80%</td>
</tr>
</tbody>
</table>

This is similar to the TCA, and shows the same conclusion but now this expressed as a percentage of the total landscape.

4.2.5. Splitting Index (SPLIT)

<table>
<thead>
<tr>
<th>SPLIT</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>8.2761</td>
<td>7.7194</td>
<td>89.1617</td>
<td>154.0679</td>
</tr>
<tr>
<td>Built Up</td>
<td>1603.811</td>
<td>348.9578</td>
<td>69.4483</td>
<td>29.0156</td>
</tr>
</tbody>
</table>

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This is the probability of a particular patch to split up. It is observed that for the vegetated class, its probability of getting split up gets on increasing from 1990 – 2020, this is not a good sign mostly if it deals with conserving the vegetated class, it means that its chance of getting
fragmented is raising which is contrary to the built up which is having its chances of getting split getting lower and lower with time, it getting more aggregated. The water class showed a higher chance of getting split up by the year 2000, and by 2010, it was no more, so more care needs to be taken on protecting the vegetated areas.

4.2.6. **Landscape Division Index (DIVISION)**

<table>
<thead>
<tr>
<th>DIVISION</th>
<th>Year 1990</th>
<th>Year 2000</th>
<th>Year 2010</th>
<th>Year 2020</th>
</tr>
</thead>
<tbody>
<tr>
<td>Vegetation</td>
<td>0.8792</td>
<td>0.8705</td>
<td>0.9888</td>
<td>0.9935</td>
</tr>
<tr>
<td>Built Up</td>
<td>0.9994</td>
<td>0.9971</td>
<td>0.9856</td>
<td>0.9655</td>
</tr>
<tr>
<td>Swamp</td>
<td>0.9999</td>
<td>0.9995</td>
<td>0.9989</td>
<td>0.9988</td>
</tr>
<tr>
<td>Water</td>
<td>0.9997</td>
<td>1</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Bare land</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>1</td>
</tr>
</tbody>
</table>

This is a probability that two animals placed at the different ends of a patch can actually meet, this can be seen that the vegetated class, the probability is getting higher throughout the study period, which is not the case to the built up areas where the probability is getting lower and lower.
Chapter Five: Conclusions and recommendations

5.1. Conclusion
The intent of this research was to get find out the impact of urbanization on the ecosystem with the use of GIS and landscape matrices, it was found that for the urban areas converged between 1990 and 2020 contributed greatly to the fragmentation of mostly the primarily vegetated areas of the study area, the core areas of different habitat has been lost.

5.2. Recommendations
Precise metrics of these spatial changes are required for long-term decision making regarding regional planning and the conservation of important native, core habitats
References.


