A spatially explicit approach for analysing the landscape pattern of urban vegetation using remotely sensed data and its impacts on urban surface temperature

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Specialization in Remote Sensing

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ABSTRACT
The landscape pattern of urban green spaces and vegetation plays a significant role in supplying essential benefits and ecological services including sequestering and storing carbon, purification of air and water, regulating climate and providing recreational opportunities. However, due to the negative impacts of land cover change and rapid rates of urbanization, vegetation in an urban landscape typically becomes isolated and highly heterogeneous in space and time, relative to non-urban landscapes or natural areas. This research aimed to develop a spatially explicit approach based on remotely sensed data to quantify and monitor vegetation fragmentation and landscape structure of urban vegetation over time and its related impacts on the urban thermal environment using Harare metropolitan city in Zimbabwe as a case study. Specifically, multi-temporal Sentinel 2, Landsat 8 and Aster data were used in achieving the above objectives.

Results based on the forest fragmentation model showed that the patch vegetation conditions, which represents the highest and severe vegetation fragmentation level, were dominant across the landscape, followed by edge, transition and perforated, whilst the core vegetation covered a small portion of the city. The decrease of large, connected and contiguous vegetation to a more scattered and fragmented vegetated patches was common across the city but more dominant in the heavily built-up areas of western, eastern and the southern parts of the city, indicating the significant impact of urban development. The small, isolated and scattered vegetation patches were associated with low positive and negative spatial autocorrelation of Local Indicators of Spatial Association (LISA) indices. On the other hand, the more homogeneous (clustered) vegetation was associated with high positive spatial autocorrelation in the northern part of Harare metropolitan city. Furthermore, the study showed that clustered, highly connected vegetation produces stronger cooling effects than dispersed, isolated and smaller patches of vegetation. Overall, spatial explicit approach and tools including the forest fragmentation model and LISA indices could play a significant role in landscape ecology with significant implications for conservation and restoration efforts based on the delineation of spatially explicit clusters of high or low vegetation cover, core or patch or edge vegetation conditions.

PREFACE

This study was carried out in the School of Agricultural, Earth and Environmental Sciences (SAEES, University of KwaZulu Natal, Pietermaritzburg, South Africa, from July 2016 to May 2020, under the supervision of Professor Onisimo Mutanga (School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, South Africa).

I declare that the work reported in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgments are made.

Pedzisai Kowe Signe [redacted]_______________Date:22/06/2020_______________

As the candidate's supervisors, certify the above statement and have approved this thesis for submission.

1. Professor Onisimo Mutanga Signed: [redacted] Date:22/06/2020________________

DECLARATION 1 –PLAGIARISM

I, **Pedzisai Kowe**, declare that:

1. The research reported in this thesis, except where otherwise indicated, is my original research.

2. This thesis has not been submitted for any degree or examination at any other institution.

3. This thesis does not contain other people's data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons.

4. This thesis does not contain other persons' writing, unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted:

a. Their words have been rewritten and the general information attributed to them has been referenced.
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5. This thesis does not contain text, graphics or tables copied and pasted from the Internet, unless specifically acknowledged, and the source being detailed in the thesis and in the references section.

Signed_____ [redacted] ________________

DECLARATION 2 –PUBLICATIONS AND MANUSCRIPTS

1.**Pedzisai Kowe**, Onisimo Mutanga, Timothy Dube, "Advancements in the remote sensing of vegetation fragmentation in urban areas and related landscape structure of urban green spaces", International Journal of Remote Sensing(Manuscript ID: TRES-REV-2020-0017), 2020, **Under revision**

2.**Pedzisai Kowe**, Onisimo Mutanga, John Odindi, Timothy Dube, "Exploring the spatial patterns of vegetation fragmentation using local spatial autocorrelation indices", Journal of Applied Remote Sensing, 13(2), 024523 (2019), doi: 0.1117/1.JRS.13.024523.

3.**Pedzisai Kowe**, Onisimo Mutanga, John Odindi, Timothy Dube, "A quantitative framework for analysing long term spatial clustering and vegetation fragmentation in an urban landscape using multi-temporal Landsat data", International Journal of Applied Earth Observation and Geoinformation**,** 2020**,** https://doi.org/10.1016/j.jag.2020.102057

4.Pedzisai Kowe, Onisimo Mutanga, John Odindi, Timothy Dube, "Effect of landscape pattern and spatial configuration of vegetation patches on urban warming and cooling in Harare metropolitan city, Zimbabwe", GISciences and Remote Sensing,2019, **Under revision**

5.Pedzisai Kowe, Onisimo Mutanga, John Odindi, Timothy Dube, "The spatial configuration and connectivity of urban vegetation and its impacts on seasonal land surface temperatures in Harare metropolitan city", Zimbabwe, GISciences and Remote Sensing**, 2020, Under revision**

DEDICATION

This thesis is dedicated to my family and my wonderful sons, Declan Musongwe Kowe and Brenden Musongwe Kowe.

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TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

CHAPTER 1: GENERAL OVERVIEW AND CONTEXTUALISATION

1.1 Socio-economic and biophysical importance of urban vegetation

Urban vegetation in the form of urban parks, trees, forests, grassland, shrubs and lawns at different spatial scales is critical for management and conservation purposes due to their important social, economic and ecological benefits (Geoghegan et al.1997, Gobster and Westphal 2004). Urban vegetation contributes significantly to sustainable development and enhancement of quality of life (de la Barrera et al. 2016, Goddard et al. 2010). In particular, the landscape pattern of urban vegetation substantially plays a major part in influencing the supply of essential ecological goods and services to city dwellers (Akbari et al. 2016, Bolund and Hunhammar 1999, Breuste et al.2013, De Groot et al. 2002, Dobbs et al. 2011, Dobbs et al. 2014, Haase et al. 2014, Maimaitiyiming et al.2014, Mitchell et al. 2018, Nowak et al. 2008, Xu et al. 2018, Zhang et al. 2015, Zhang et al. 2017).

Large patch sizes compared to small patch sizes of urban vegetation are considered to have more biodiversity conservation value (Arifin and Nakagoshi 2011). Carbon densities storage and sequestration are significantly related to the density and proportion of urban vegetation coverage in a landscape (Mitchell et al.2018). Relatively large patches of urban vegetation can sequester and increase more carbon storage (Lv et al.2018). Furthermore, urban vegetation directly intercepts and reduces air pollutants (Nowak et al. 2006). By providing cooling effects through evapotranspiration and shading, urban vegetation effectively reduces urban warming in cities, thereby mitigating urban heat islands (Buyantuyev and Wu 2010, Chen et al. 2014, Weng et al. 2004, Zhang et al. 2017).

Urban vegetation improves the health and well-being of urban dwellers (Nielsen and Hansen 2007, Richardson and Mitchell 2010, Tsai et al. 2016; 2018). Urban vegetation have the potential in reducing the impact of heat related mortality (Chen et al.2014). Urban green spaces are associated with more physical activity and quality of life (Tsai et al 2016; 2018) particularly to vulnerable groups, as well as the elderly and children (Korpela et al.2002). In addition, urban park spaces can be used as meeting points and places for recreation and relaxation by urban dwellers of different ethnic groups, thereby promoting social inclusion (Barbosa et al. 2007, Peters et al.2010). Nielsen and Hansen (2007) noted that stress levels are reduced in people with access to green areas. In areas with more urban vegetation in the United Kingdom (U.K), urban dwellers were observed to have reduced mental distresses in contrast to geographical locations with less coverage of urban vegetation (White et al. 2013). Economically, urban vegetation contributes to the assessment of environmental externalities (Jim and Chen 2007).

Furthermore, the proximity of urban green spaces have been shown to significantly influence housing prices by increasing property values (as measured by hedonic pricing) (Cho et al. 2008, Crompton 2005, Tyrväinen 1997).

1.2 Impact of urbanization on vegetation fragmentation and urban climate

Approximately 2–3% of the Earth's total surface area is urban (Lambin 2001, Liu 2014), and in recent times, urban areas have been given much research due to the rapid wave of urban expansion and urbanization taking place across the world (Liu et al.2016). Currently, most of the world's population is now residing in cities (United Nations 2014). Around 2050, it is predicted that about 66% of global population is going to be mainly concentrated in the cities of the developing world particularly in Asian (52%) and African cities (21%) where there is a rapid population growth (United Nations Population Division 2012, United Nations 2014).

In the last decades, rapid urban expansion and urbanization through the conversion of the natural areas into impervious surface has led to the destruction, habitat loss (forests, shrubland, grassland) and fragmentation of open and green spaces (Antrop 2000, Benedict and Mc Mahon 2002, Dallimer et al. 2011, Fuller and Gaston 2009, Güneralp and Seto 2013, Haddad et al. 2015, Honu et al. 2009, McDonald et al. 2008, McKinney 2008, Turrini and Knop 2015, Seto et. al. 2011; 2012). In rapidly growing cities, vegetation fragmentation and an overall reduction in green space are a threat to biodiversity and affect the important ecosystem services provided by vegetation patches and the value of urban habitats for conservation (Alberti 2010, Gardiner et al.2013). For instance, some studies have established that significant decline in avian species abundance and biodiversity are associated with loss of connectivity and vegetation fragmentation caused by urban expansion (Vallejo et al.2009, Manhães and Loures-Ribeiro 2005).

Loss and significant reduction in landscape connectivity of vegetation due to the increasing inter-patch distance or presence of barriers between vegetation patches in complex urban landscapes, may prevent the spread of the species, leading to a lower possibility of recolonization of those patches (Garden et al. 2010, Güneralp and Seto 2013, Vergnes et al. 2012). This also negatively affects the survival of species that depend much on core and intact vegetation (Laurance et al. 2002). Small vegetation patches with reduced patch size and longer perimeters relative to the core area are prone to greater ecological disturbance than large vegetation patches (Laurance et al.1997).

Another adverse impact of rapid expansion apart from vegetation fragmentation is the growing trend of the urban heat island (UHI) effect (Oke 1987, Voogt and Oke 2003). Over the years, the UHI phenomena has been extensively explored in various disciplines like urban climate, landscape ecology and urban planning (Arnfield 2003, Weng 2009). The UHI phenomena is known for raising land surface temperatures (LST) in cities than in the non-urban areas (Oke 1987, Voogt and Oke 2003). At night, for instance, the high surface temperatures and heat released from the impervious surfaces (concrete and asphalt), pavements and urban infrastructure increases the frequent occurrence and extent of heat waves and heat strokes. The negative impacts of the UHI phenomena also include higher emissions and concentration of air pollution (Lai and Cheng 2009, Sarrat et al. 2006) which consequently cause more deaths (Gosling et al.2009) and other heat-related health problems including cardiovascular diseases (Clarke 1972, Kovats and Kristie 2006, Whitman et al. 1997,). The intensified UHI phenomena can lead to huge demands for water and electricity use (Guhathakurta and Gober 2007) through air conditioning to cool buildings, among others (Arnold Jr and Gibbons 1996).

UHI and urban climate change mitigation efforts are critical issues to promote better favourable and healthier living conditions. Urban green spaces and vegetation are effective in mitigating the negative UHI effects by lowering sensible heat and the amount of radiation absorbed from the sun (Akbari and Kolokotsa 2016, Demuzere et al. 2014, Yu et al. 2018b, Weng et al. 2004). The cooling effects provided by urban vegetation depends on the spatial patterns (landscape composition and configuration) (Akbari and Kolokotsa 2016, Cao et al. 2010, Connors et al.2013, Dugord et al.2014, Maimaitiyiming et al. 2014, , Song et al. 2014, Yu et al. 2018a, Zhang et al. 2009, Zheng et al. 2014, Zhou et al. 2011). In light of this, landscape metrics developed from landscape ecology concepts are frequently used to investigate the impacts of spatial configuration and composition of vegetation patterns on surface temperatures in cities (Cao et al. 2010, Connors et al. 2013, Feyisa et al. 2014, Li et al. 2011, Li et al. 2012, Kong et al. 2014, Kong et al. 2014a, Kong et al.2014b, Maimaitiyiming et al. 2014, Ward et al.2016, Zhang et al. 2009, Zheng et al. 2014, Zhou et al. 2011).

However, it has been observed that landscape metrics have challenges of being interrelated with each other and not all landscape pattern indices can convey meaningful information on the thermal processes, energy flow and exchanges occurring in a city (Chen et al. 2016). In addition, landscape pattern indices uniquely represent the spatial objects and their spatial configurations as discrete patterns rather than as continuous surfaces resulting in a loss of vital information (Fan and Myint 2014). Linked to this is the fact that clustered and dispersed patterns of urban vegetation and other land cover categories cannot be uniquely captured by landscape metrics since they are computed and derived from discrete and categorical land cover maps that overlook other continuous variations in spatial objects (Fan and Myint 2014, Fan et al. 2015, McGarigal and Cushman 2005).

Spatial statistics methods like Getis Ord Gi* and Local Moran's I are spatially explicit and can effectively be utilized to address these challenges as they uniquely provide a continuous depiction and characterisation of the true spatial heterogeneity at a distinct geographical area (Fan et al. 2015, McGarigal and Cushman 2005, Myint et al. 2015). Local spatial statistics can be used to depict how the spatial structure or spatial arrangement of objects are distributed spatially whether they are clustered, dispersed or randomly distributed in a given space (Goodchild 1986). Fundamental to this issue is the development of effective and accurate analytical tools for quantification of landscape pattern of vegetation and its influence on the urban thermal environment.

1.3 Remote sensing of vegetation fragmentation and urban climate

As climate change and rapid urban expansion negatively affect natural landscapes, improved and robust methods for characterising the spatial structure of urban vegetation patches across a span of different spatial scales are critical in linking important ecological processes and patterns. The extent of vegetation fragmentation is such that only the smaller vegetation fragments are commonly found across the urban landscape (Fuller et al. 2010, Gaston et al. 2005). However, one of the major challenges facing landscape ecology at present is to quantify the spatial heterogeneity of urban vegetation fragmentation accurately and effectively.

Monitoring vegetation fragmentation requires consistent datasets and a robust methodological approach to provide accurate and timely information in a meaningful way to support urban planning and design. The advent of remote sensing and quantitative tools in landscape ecology is incredibly useful to landscape ecologists. This provides them with a relative task to compute categorical maps in the existing software packages (landscape fragmentation tool, FRAGSTATS or Patch Analyst) and generate a large number of landscape pattern indices, patch and fragmentation metrics statistics. Depending on the type of sensor used, there is now remote sensing imagery data of broad and wide span of spatial resolutions: from high/fine (<

10m) to medium/moderate (10m–250m) and low/coarse (250m–5km) spatial resolutions (Warner et al. 2009).

In urban areas, vegetation fragmentation has generally been mapped based on coarse-resolution data (Gong et al. 2013, Miller 2012, Paul and Nagendra 2015, Richards et al. 2017, Rogan et al. 2016, Vogelmann 1995). Coarse-resolution data generally have higher temporal resolution and cover large areas. However, coarse resolution products have challenges when applied to complex urban areas, as they cannot fully capture the fine scale, highly dynamic and spatial heterogeneity of vegetation fragmentation resulting in inadequate spatial information for management and conservation purposes. High-resolution images such as GeoEye, Worldview, QiuckBird, IKONOS, SPOT can capture detailed, more accurate and subtle vegetation cover changes. However, high resolution images are costly to acquire and inaccessible to many users, thereby limiting their wide use in landscape ecology and conservation science. However, coarse resolution data like Landsat can overcome these challenges. Landsat data, are relatively easier to acquire because of their free availability and broad spatial coverage. The temporal record of archived Landsat data series spans a period of over 40 years (Roy et al. 2008, Roy et al. 2014).

At the same time, the thermal infrared (TIR) data are critical in retrieving and deriving remotely sensed surface temperature information, helping to understand the dynamics of heat flow, energy exchange and thermal processes within and across the landscape. Thermal infrared remote sensing has many advantages as it provides spatially continuous, highly consistent and attractive data source of the Earth's surface at broader or multiple scales over meteorological ground measurements of air temperatures (Nastran et al. 2019). Various thermal infrared (TIR) image data from Advanced Very High Resolution Radiometer (AVHRR) (Streutker 2002), Moderate Resolution Imaging Spectroradiometer (MODIS) (Buyantuyev and Wu 2010, Chen et al. 2006, Pu et al. 2006, Wang et al. 2007), Landsat TM/ETM+(Li et al. 2011, Weng et al. 2004) and Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data (Liu and Weng 2008, Lu and Weng 2006), are widely utilised to examine the spatial variability patterns of urban surface temperature in urban heat island studies.

Despite these advances, there have been limited usage of thermal infrared data in examining urban ecosystems for landscape ecological research (Liu and Weng 2008). This is because TIR data is too coarse in spatial resolution that sometimes, spatial heterogeneity is obscured (Liu and Weng 2008). Incorporation of very high resolution imagery in heterogeneous urban landscapes allows discriminations of detailed information of urban vegetation and other urban land cover classes.

1.4. Challenges in quantifying vegetation fragmentation

The existing paradigm in ecological studies for analysing the landscape heterogeneity of vegetation patterns and vegetation fragmentation is to use the discrete methods called landscape metrics (McGarigal and Marks 1995). In this regard, landscape metrics derived from classified satellite images represents a landscape as a collection of discrete or categorical patches (relatively homogeneous patches of vegetation) (McGarigal and Marks 1995, Pearson 2002, Turner 1989, Turner and Gardner 1991). Discrete landscape pattern analysis applies well to landscape patterns that show distinct landscape structure and crisp boundaries (Barrell and Grant 2013). Furthermore, the discrete approach based on landscapes metrics achieve high accuracy in distinguishing crisp, homogenous natural areas than heterogonous landscapes (Southworth et al.2004).

However, landscape metrics do not explicitly show specific geographical areas where the different types of spatial patterns of vegetation fragmentation are occurring (Dadashpoor et al. 2019, Gong et al. 2013, Zhang et al.2 020). Furthermore, transition zones or within-patch patterns cannot be adequately captured using landscape metrics, consequently failing to detect fine or subtle changes that are critical in landscape ecology (Foody and Boyd 1999, Lambin 1997). The discrete representation of a landscape based on landscape metrics also ignore major gradients and oversimplify discontinuities in underlying environment when all pixels of remote sensing data are classified and categorized into homogenous units (DeFries et al.2000, Frazer and Wang 2011, Foody 2000, McGarigal et al.2009, Palmer et al.2002, Rocchini et al.2010). This is because some ecological process may consist of continuous gradients or mosaics of different elements. The highlighted challenges limit the accurate mapping of landscape heterogeneity of vegetation fragmentation in urban areas using existing landscape metrics.

Over the years, however, a number of continuous metrics and methods that detect and compute different aspects of a landscape such as tasselled cap transformation indices, vegetation indices, topographical wetness, surface roughness and texture in landscape ecology have been suggested (McGarigal and Cushman 2005, McGarigal et al. 2009). In addition, continuous indices including fractal measures, Fourier decomposition, wavelet measures and spatial autocorrelation indices are well suited to quantify the landscape patterns of vegetation patches in an urban area. Local spatial statistics techniques including the Getis-Ord Gi*, local Moran's I and local Geary's C can detect the existence of pockets of spatial association and distances beyond which no discernible association remains (Anselin 1995, Getis and Ord 1992, Getis and Ord 1996, Legendre and Legendre 1998, Ord and Getis 1995, Ord and Getis 2001, Sokal et al. 1998).

LISA indices can reveal significant clusters of homogeneous and heterogeneous areas (Nelson and Boots 2008, Sokal et al. 1998). Previous studies have utilised LISA indices methods to map terrestrial patterns obtained from earth observation data (Wulder and Boots 1998). Despite their potential, the utility of continuous models like LISA indices in characterising the spatial configurations of vegetation fragmentation in urban landscapes has not been largely explored. In the realm of urban ecology and conservation science, the potential of local spatial autocorrelation statistics could highlight new opportunities for the delineation of critical hot spot areas for conservation purposes.

1.5. Aim

The objective of this study was to develop spatial explicit methods for quantifying the landscape pattern of urban vegetation and its effects on urban surface temperature. To achieve this objective, we combined local spatial statistics, forest fragmentation model and landscape pattern metrics derived from multi-temporal Sentinel 2, Aster and Landsat series data.

1.6. The specific objectives

(i) To determine the spatial variability patterns and the long-term changes in vegetation fragmentation using forest fragmentation model, landscape metrics and LISA indices.

(ii) To develop spatial analytical tools to quantify summer and seasonal impacts of the spatial configuration and connectivity of vegetation patches on urban warming and cooling.

(iii) To examine the effects of landscape patterns and spatial configurations of urban vegetation on urban surface temperature based on sensitivity of spatial resolution of different satellite data.

1.7. The scope of this study in the context of landscape ecology

In both natural and human-dominated landscapes, reducing habitat fragmentation and increasing the connectivity of isolated patches is an important goal of landscape ecology to improve and link ecological interactions, processes and patterns (McGarigal and Marks 1995, Turner 1990; 2005, Turner et al. 2001, Uuemaa et al. 2009, Wu and Hobbs 2002, Wu 2008). Over the years, continuous methods have demonstrated their effectiveness in several landscape ecological application studies (Adeyeri et al. 2017, Fan and Myint 2014, Fan et al. 2015, McGarigal et al. 2009, Pearson 2002, Tran et al. 2017). The applications of continuous methods including local spatial association (LISA) indices may advance our understanding in characterizing spatial heterogeneity of vegetation fragmentation and landscape connectivity in urban landscapes and linking to the ecological processes and patterns.

This can be done by exploring different suites of discrete data (e.g. vegetation and non-vegetation, forest and non-forest) and continuous data and indices (e.g. vegetation indices, tasselled cap transformation indices and land surface temperature) derived from image data. A similar approach of utilizing LISA indices can be extended to investigate the role of the landscape patterns of urban vegetation on surface temperature, which could provide critical information on urban cooling and warming trends.

1.8. Description of the study area

This research work was conducted in the Harare metropolitan city which is situated in the northeastern part of Zimbabwe. Harare is Zimbabwe's largest, administrative, political capital city and the centre of industrial production, trade and commerce. The metropolitan city incorporates Chitungwiza, Epworth and Ruwa satellites or urban dormitory. Chitungwiza is a high-density town situated approximately 25 km south of Harare. Ruwa is situated 22 km south-east of Harare and Epworth 12km east of the centre. These satellite or urban dormitory settlements were developed close to the major urban towns in Zimbabwe in the 1970s mainly to capture the drift of the working population.

Harare metropolitan city's surface area extends over 980 km^2 and is situated at an elevation of approximately 1500m. The undulating hilly areas are mainly found in the north and northeast side where there is concentration of high-income people and low-density and spacious residential areas. The heavy built-up areas, low and middle income residential and industrial areas are dominant in the south, west and east part of the metropolitan city. The last national census showed that the population of Harare metropolitan city was approximately 2.1 million (ZIMSTAT 2012). Harare metropolitan city was selected as the study area because it has witnessed rapid urban expansion over the years driven by rapid population increase and rural-urban migration.

The rapid urbanization experienced in the city since the independence of the country in 1980 has caused the conversions of natural areas into different land cover and land use changes. This has raised sustainability concerns about the impact of rapid urbanization and urban sprawl on vegetation fragmentation, urban ecosystems, environmental quality, loss of biological diversity and urban heat island effects.

1.9. Thesis Outline

This research work is composed of five scientific research papers that have gone through or are going through peer review processes in geographic information science and earth observation or remote sensing journals. Two of the research papers have been published online, and three are under review. Each of these articles is presented as an individual chapter that can be considered autonomously, from the entire thesis. In that regard, this means that each of the stand-alone or individual chapters consists of its abstract and conclusion, which relate it to the subsequent chapter, hence the presence of duplications and overlaps of the various thesis sections and chapters. The overlaps, repetition is assumed to be of little consequence when considering that these are peer-reviewed scientific articles, which are stand-alone chapters that can be read separately, without losing the overall context. The reason was to maintain a seamless flow of ideas, principles underpinning the entirety of the current scientific setting with each article contributing towards addressing the overall goal of the study. In compiling this thesis, the format and content of these peer-reviewed articles were preserved. Ultimately, the entire thesis is made up of seven chapters. These chapters can be split into four sections: (i) general overview and contextualisation, (ii) spatial patterns of vegetation fragmentation, (iii) spatial configurations of vegetation and its impacts on the urban surface temperature (iv) summary and synthesis.

1.9.1 General overview and contextualization

1.9.1.1. Chapter One

This is an introductory chapter, which unveils the essence of the study. Specifically, in this chapter, the objectives, knowledge gaps, scope and outline of the thesis are provided. Furthermore, this chapter contextualizes and illustrates the significance of the methods that seek to combine the use of satellite remote sensing, and spatial statistical modelling techniques in understanding vegetation fragmentation in an urban landscape and related impacts of the spatial configuration of vegetation patterns on urban surface temperatures. Generally, this thesis includes two main parts. The first part proposes to employ the spatial explicit tools in evaluating urban vegetation fragmentation and the second part examines the landscape pattern and spatial configuration on urban warming and cooling.

1.9.2. Geographical distribution of remote sensing of vegetation fragmentation studies

1.9.2.1. Chapter Two

Chapter Two presents results of the systematic literature review over two decades of selected studies that utilized remote sensing to examine historic trends and recent advances in quantifying the landscape structure of vegetation fragmentation across cities and urban areas around the globe. In highlighting the overview and progress, the review explains the nature of remote sensing data products, focusing on aspects of key ecological themes covered, geographical scale, the spatial distribution of studies, type of ecosystems and habitat studied, as well as methodologies used in urban vegetation fragmentation studies. Finally, the review also highlights knowledge gaps, challenges and provides future suggestions for increased utilization of available datasets in urban vegetation fragmentation.

1.9. 3 Spatially explicit patterns of vegetation fragmentation

1.9.3.1. Chapter Three

Chapter Three examines the utility of spatial explicit methods of local spatial autocorrelation indices and forest fragmentation model in analysing vegetation fragmentation in Harare metropolitan city based on Sentinel 2 data. Accordingly, the results of integrating remote sensing data and local spatial statistics of the Getis-Ord Gi* and the local Moran's I uniquely captured distinct and the subtle spatial variation of vegetation fragmentation which are otherwise easily overlooked by traditional methods. This chapter was published in the Journal of Applied Remote Sensing (2019).

1.9.3.2. Chapter Four

Chapter Four provides the analysis of utility of discrete methods of landscape metrics and forest fragmentation model and local spatial statistics (Getis-Ord Gi* and the Local Moran's I) and Tasseled Cap Transformation (TCT) indices in analysing vegetation fragmentation in Harare metropolitan city based on long-term multi-temporal resolution Landsat data. The continuous indices proposed in this chapter promote the improvement in uniquely capturing the long-term spatial-temporal variability patterns of urban vegetation fragmentation, which is an important aspect of urban and landscape ecology. This chapter was published in the International Journal of Applied Earth Observation and Geoinformation (2020) Journal.

1.9.4. Impact of vegetation patterns on urban thermal environment

1.9.4.1. Chapter Five

Chapter Five explores the impact of landscape pattern and spatial configuration of vegetation patches on urban warming and cooling over Harare metropolitan city by using thermal infrared (TIR) remote sensing data of Aster and Landsat. Various landscape pattern indices and local spatial statistics of urban vegetation derived from satellite data were used to compute and analyse their impact on urban warming and cooling in a city. A spatial regression model was employed to minimize bias estimates caused by the spatial autocorrelation effects in the regression modelling of land surface temperatures. The performance of the Spatial Lag model was compared to Ordinary Least Squares regression (OLS). This chapter highlighted the importance of modelling spatial non-stationarity and optimizing spatial configurations of vegetation and its influence on urban surface temperature for specific location in mitigating urban heat island effects. This chapter is still under revision in the GIScience and Remote Sensing (2019) Journal.

1.9.4.2. Chapter Six

Chapter Six sets out by examining the seasonal (spring, winter, autumn and summer) variability patterns of land surface temperature on the spatial configuration and connectivity of urban vegetation using Landsat 8 data. The research findings in this study highlighted the great potential of optimizing the spatial configuration and connectivity of vegetation patches in reducing city surface temperatures with evidence supporting the positive impacts of planning highly connected, spatially clustered vegetation patches rather than scattered and dispersed ones in all seasons. This chapter is still under revision in the GIScience and Remote Sensing (2020).

1.9.5. Summary and synthesis of the thesis

1.9.5.1. Chapter Seven

Chapter Seven as the final chapter presents a synthesis of the conclusions deduced and insights drawn from the main results of the previous six chapters of this research work and provides a concise summary of the main achievements of this thesis. Consequently, this section highlights the direction and makes recommendations for further research studies by considering the mentioned limitations of this research work. Finally, at the end of the thesis all references used and cited in this study are provided as a single reference list.

2. REMOTE SENSING AND GEOGRAPHICAL DISTRIBUTION OF LANDSCAPE STRUCTURE OF URBAN GREEN SPACES AND VEGETATION FRAGMENTATION STUDIES

This chapter is based on
Pedzisai Kowe, Onisimo Mutanga and Timothy Dube, "Advancements in the remote sensing of vegetation fragmentation in urban areas and related landscape structure of urban green spaces," International Journal of Remote Sensing, 2020, under revision

Abstract
The recent global urban expansion has seen a massive decline and loss in the connectivity of urban vegetation. In urban areas, some vegetation patches have increasingly become isolated and less connected by a matrix composed of impervious surfaces and transportation networks like roads. Vegetation fragmentation is a global threat to the remaining urban green spaces and has an impact on biodiversity conservation, environmental quality and urban microclimates. So far, a lot of work has been done in mapping and monitoring urban green spaces, some using conventional methods and of late using remotely sensed data. However, not much is known and well documented on developments in researching the remote sensing of vegetation fragmentation in urban areas over the last two decades. Thus, the objective of this research work is to present a detailed and comprehensive synthesis on the progress of remote sensing in assessing and monitoring landscape structure of urban green spaces and vegetation fragmentation. Specifically, scientific literature from the year 2000 to 2020 was reviewed to provide state-of-the-art progress on the remote sensing of vegetation fragmentation in urban areas. Results indicate that between 2000 and 2020, there was a considerable increase in the number of scientific publications on vegetation fragmentation in urban landscapes. The discrete landscape pattern indices are the most widely used method. Comparatively, Landsat data was widely used due to its suitable spatial and temporal resolution, free availability and the presence of historical archival data that spans over 40 years. The most commonly used scale was local (a city and/or municipality) followed by regional (more than one municipality in one continent) and then global (several selected cities and urban areas across continents). Only two studies were conducted at the global level. Further, geographic bias was observed in most of the accessed vegetation fragmentation studies. The review showed that vegetation fragmentation studies are carried out mostly for cities in China, North America and Europe while cities in most parts of Africa, Asia, Eurasia, Oceania and South America have not been comprehensively studied. The study also showed that the majority of cities across the globe have experienced severe vegetation fragmentation over the years. This review underscores the relevance of scientific findings in urban spatial planning to minimize the loss of urban green spaces and to conserve and restore affected areas.

Key words
Urbanizing landscapes, urban ecology, landscape connectivity and configuration, satellite data, landscape metrics, vegetation fragmentation

2.1. Introduction

Urban vegetation is critical in the supply of essential ecological goods and services that make urban areas more liveable and sustainable especially for urban dwellers (Bolund and Hunhammar 1999, McPherson et al. 1997, McPherson and Rowntree 1993). In urban areas, green vegetation provides cooling effects through evapotranspiration and shading, effectively lowering air and surface temperatures, thereby mitigating against the urban warming (Akbari et al.2001, Chen et al. 2015, Hamada and Ohta 2010). Urban green spaces and vegetation significantly play an essential part in the local carbon cycles through the sequestration of greenhouse gases like carbon dioxide (CO_2) (Sun et al. 2019). Furthermore, the urban vegetation provides wildlife resources including nest and roosting sites for birds, mammals and insects and wildlife habitat resources. Larger green spaces have been found to support higher species richness (e.g. in birds and mammals) than small green spaces (Shanahan et al. 2014a, Marzluff 2005). Socio-economically, urban green spaces contribute towards the improvement of human health (Hartig et al. 1996, Nowak and Walton 2005, Parsons et al. 1998, Tsai et al. 2016).

The world's population is rapidly growing and is estimated to reach 10 billion by the year 2050, with 70% of this projected number is expected to dwell in cities (United Nations 2012). This will further exert more pressure on the remaining urban green spaces and other natural ecosystems, creating numerous environmental and socio-economic problems (Kim and Baik 2005, Zhao et al. 2006). Vegetation fragmentation due to rapid urbanization threatens biodiversity hotspots with a negative impact on native species dispersal (Bierwagen 2007), causing a general decline in species richness (Garden et al. 2007) and localized species extinctions (Schurr et al.2007). In general, the spatial configuration and composition (landscape structure or landscape pattern) of urban vegetation is critical in influencing the various benefits and multiple ecosystem services that are provided to urban inhabitants (Dobbs et al. 2014; 2017).

Previous studies have expressed the need for updated information on spatial and temporal variability of landscape patterns of vegetation in urban areas (Dobbs et al. 2014; 2017, Hall 2010, Haung et al. 2018, Kabisch and Haase 2013). Information on landscape patterns and vegetation fragmentation patterns can be used as proxy measure for habitat conditions and primary productivity status of ecosystems (Mairota et al 2013, Nagendra et al.2013) . Such spatial information is also useful to model parameters required in species and community distribution modelling (Lausch et al. 2016). This can aid in the conservation of biodiversity hotspots or rich zones and increase, maintain or restore landscape connectivity in urban areas. Of late, this has become important in urban planning for meeting urban greening targets and achieving sustainability in cities (Dobbs et al. 2017, Grimm et al. 2008).

Due to the scarcity of appropriate spatial and in-situ field data, the heterogeneous landscape of fragmented urban green spaces further complicates the retrieval of this information. Remote sensing has since become the core source of ecosystems and landscape ecology information for broad-scale applications (Forman 1995). Over the past two decades, the accessibility and advent of optical and active remote sensing or earth observation data of various spectral, radiometric, spatial and temporal resolutions have increased significantly and constituted a very useful data source for urban landscape studies. This data has become important in mapping the landscape patterns of urban green spaces including the shape complexity, patch size, connectivity, density and aggregation as well as associated changes over time (Dobbs et al. 2014; 2019, Leitão and Ahern 2002, Luck and Wu 2002, Patino and Duque 2013, Qian et al. 2015, Turner et al. 2007, Uuemaa et al. 2013).

Despite these great strides, an overview of mapping vegetation fragmentation in urban areas using remote sensing data has not been documented. Although Frohn (1998) provided a systematic review of the application of remote sensing in landscape ecology, the review largely concentrated on the quantification of landscape pattern metrics. In light of this, this research work provides a systematic review and progress of remote sensing applications in mapping and monitoring the spatial structure of urban green spaces and vegetation fragmentation in cities and urban areas across the globe. The study highlights key research strides and further identifies knowledge gaps and draws conclusions as well as recommendations on possible future research directions in this field of study. To achieve this objective, the study first provides the conceptual framework and definition of key terms on urban green spaces and vegetation fragmentation.

2.1.2. Conceptual framework, key concepts and definitions

2.1.2. 1. Urban green spaces and vegetation

In this study, urban green space or urban vegetation refers to the wide range of habitat types (forest, woodland, shrubs or shrubland as well as grassland, garden city, urban parks and street trees) at different spatial scales (Aronson et al. 2017,Cilliers et al. 2013, Kabisch and Haase 2013). It therefore encompasses both natural or man-made urban green spaces and vegetation found in cities, built-up or urban areas (Kabisch and Haase 2013, Kong et al. 2010).

2.1.2.2. Urban vegetation fragmentation

One major distinction among definitions is to treat fragmentation (forest, vegetation and landscape) as both a process and pattern (Alig et al. 2000). Urban vegetation fragmentation can be described as the change in spatial or landscape composition and configuration of vegetation patterns through the process of urbanization (Tsai et al. 2016). It is commonly associated with the reduction of large patch sizes and areas of core, interior vegetation and habitat found in the built-up areas. Vegetation fragmentation partitions large patch sizes and contiguous vegetation into smaller, isolated vegetation patches and habitat edges due to expansion of human settlements, impervious surfaces and transportation networks like roads and the highways (Fernández and Simonetti 2013, McKinney 2008). Jaeger (2000) extended Forman's (1995a) concept of fragmentation and identified six fragmentation processes (perforation, incision, dissection, dissipation, shrinkage and attrition) in human-modified landscapes. The fragmentation phases or processes may occur simultaneously contributing to change within a landscape. Using the general model of landscape fragmentation proposed by Jaeger (2000), it can be applied to identify and understand the types of fragmentation phases or processes that have affected or likely to occur on existing vegetation patches in a landscape.

2.2. Methodology

We analysed scientific literature published in selected major scientific databases like international peer-reviewed journals. Literature was retrieved from key scientific engines such as the Scopus, Springer, Science Direct, ISI Web of Knowledge, WILEY and Google Scholar as well as from additional cross referencing. Only journal research articles published between 2000 and 2020 were retrieved by documenting the progress with the goal of highlighting recent research trends on the application of remote sensing data in vegetation fragmentation in urban areas from this time period as the baseline. Unpublished scientific literature, editorials, conference proceedings, book chapters or reviews and letters refereeing previous research articles were not included. To refine our search, a variety of key words and combinations were used to gather relevant literature in the major scientific databases. Key words and some terms were used and later combined including: "urban", "town", "cities", "metropolitan", "suburban", "earth observation", "satellite data", "remote sensing", "fragmentation", "spatial configuration", "spatial composition", "Fragstats", "patch metrics", "class metrics", "landscape metrics", "landscape indexes", "landscape indices", "landscape structure", "landscape pattern", "green spaces", "forests'', "street trees'', "green infrastructure", "parks", "vegetation", "shrubland", "grassland", woodland", "habitat" among others.

This approach allowed us to highlight and document (1) the satellite data or image data type (e.g.‘ALOS’,‘RapidEye’,‘MODIS’,‘Sentinel’,‘WORLDVIEW’,‘MERIS’,‘SPOT’,‘AVHRR’, ‘IKONOS’, ‘ASTER’, ‘LIDAR’ and ‘RADAR’), (2) the spatial resolution of the imagery (1m, 4m, 10m, 15m, 30m, 100m), (3) the type of application and analysis of remote sensing data (e.g. urban vegetation structure, vegetation fragmentation, connectivity, patch, class and landscape level) (4) the scale of analysis and application (i.e. metropolitan area, city, urban, town, suburban) and (5) the relevant theme or themes covered in the research article by focusing on how the spatial-temporal variability aspects of landscape structure of urban green spaces and vegetation fragmentation were studied.

We further defined some exclusion criteria, as follows: (i) removing studies that did not use remote sensing applications, nor where landscape structure of urban green spaces and vegetation fragmentation studies did not involve urban areas; (ii) this approach was applied to retrieve only relevant scientific papers and studies that had direct applications of vegetation fragmentation in urban areas. There are however, few limitations. This study cannot be considered exhaustive due to challenges of accessing relevant scientific literature written in other languages. Since we collected and used scientific articles published in the English language, we consider it to cover the largest parts of the available literature.

2.3. Results

2.3.1 General trend in the number of publications

In total, 103 research articles that incorporated remote sensing technology in examining vegetation fragmentation within the urban area during 2000–2020 period were retrieved and deemed relevant for the analysis. The literature review showed that more than two-thirds of studies examining vegetation fragmentation in urban studies were published between 2009 and 2020 (Figure 2.1). Not many studies were published between 2000 and 2008 (Figure 2.1). Results in Table 2.1 shows that most scientific papers preferred and targeted publishing in journals that specialize in urban and landscape ecology (e.g. Urban Ecosystems, Landscape and Urban planning, Ecological Indicators, Landscape Research, Landscape and Ecological Engineering, Landscape Ecology, Urban Forestry and Urban Greening, etc) along with conservation sciences and applications (Ocean and Coastal Management and Forest Ecology and Management). These scientific journals have common objectives of publishing scientific research papers that advances conservation research and management. Few and selected individual scientific papers were published in GIScience and Earth Observation journals (Table.2.1)

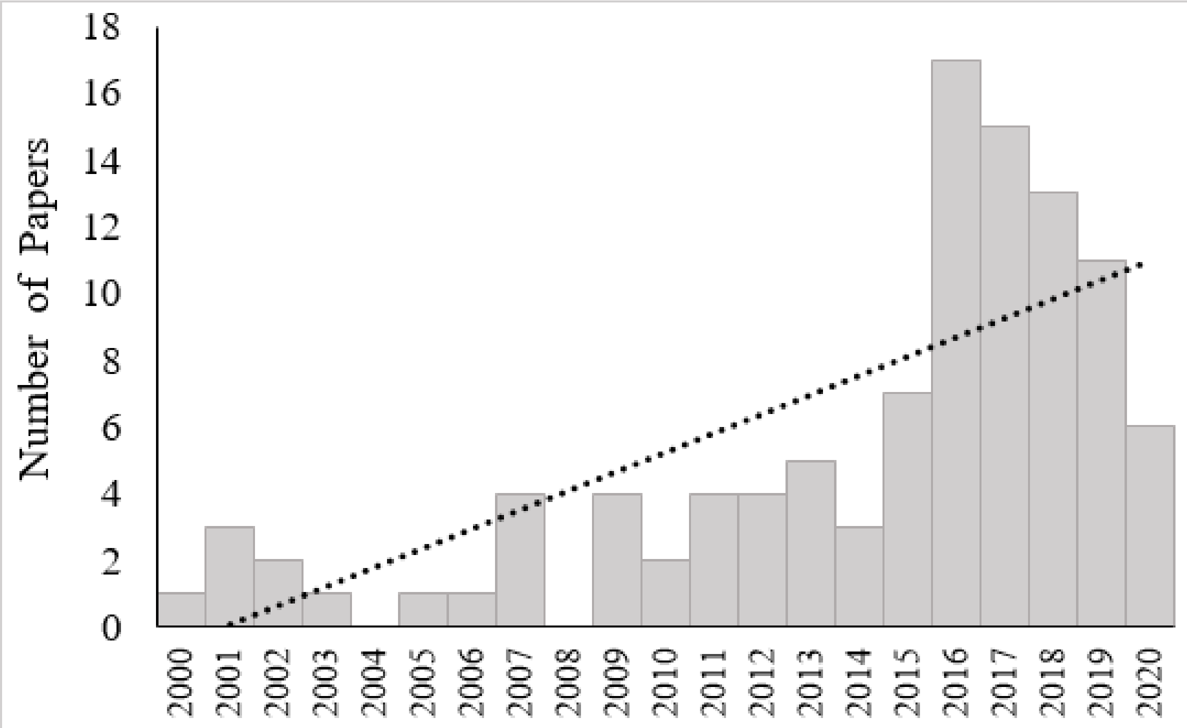


Figure 2.1. Number of published papers during 2000–2020 period on the remote sensing of vegetation fragmentation within urban areas.

2.3.2 Geographic location of urban vegetation fragmentation studies

Literature review established that the spatial distribution of the published scientific papers that focused on remote sensing of vegetation fragmentation studies in urban areas is geographically biased (Figure 2.2). Overall, it was observed that most of the studies were conducted in cities of China, the United States of America (USA) and European countries (Figure 2.2). In Asia, two-thirds of the most publications were derived from China. Except China, cities in other developing parts of Africa, South America and Oceania are understudied as they had a very limited number of vegetation fragmentation studies. This is a major concern because, urban vegetation is under threat due to impacts of land cover transformations and conversions caused by rapid urban expansion in these geographical regions. Furthermore, the higher rates of predicted urban growth and urbanization tend to occur in huge proportions in biodiversity hotspots and in areas that are relatively rich in greater natural primary production (McDonald et al. 2013, Seto et al. 2012).

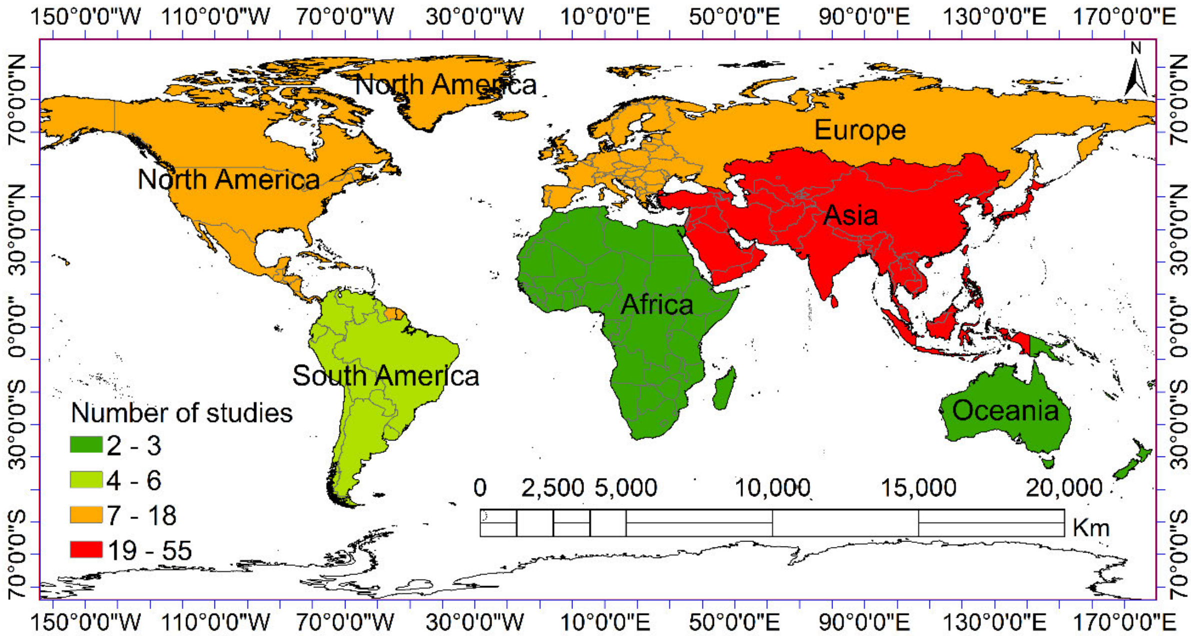


Figure 2.2.The geographical location and spatial variability patterns of the number of papers investigating vegetation fragmentation within urban areas during 2000–2020 period.

2.3.4. Remote sensing utilization patterns in vegetation fragmentation

Despite the significant advantages of the high temporal resolution (e.g.1–2 revisits/day) and large coverage, no research article was found that used freely available Advanced Very High Resolution Radiometer (AVHRR), Medium Resolution Imaging Spectrometer (MERIS) and Moderate Resolution Imaging Spectroradiometer (MODIS) datasets. This raises the concern and the feasibility of obtaining free, cloud free images and land cover maps (forest, vegetation, grassland, habitat) generated from low spatial resolution data (250m–1000m) that typically have low land cover classification accuracy, particularly in heterogeneous urban areas. Consequently, comparison of these maps to derive patch, class and landscape level metrics to inform spatial-temporal variability of vegetation fragmentation in large geographic regions (e.g. mega cities and metropolitan areas) is challenging.

The review showed that studies analysing vegetation fragmentation in urban areas have relied primarily on medium and coarse (≥30m resolution) series of Landsat data (Table 2.1) of different time period, accounting for 97% of studies. For instance, in North America, Landsat satellite imagery data was used to study vegetation fragmentation in cities and urban areas such as Minneapolis and St.Paul metropolitan area in the United States of America (USA) (Ward et al.2007), North-western Ontario, Canada (Gluck and Rempel 1996) and York in Canada (Puric-Mladenovic et al. 2000) (Table 2.1). Over the years, in the USA, some of these studies (Tsai et al. 2016;2018) have often used the free availability of the growing national datasets for instance the National Land Cover Database (NLCD) and Global Land Cover Characterization (GLCC) which are derived from Landsat satellite images (Wickham et al. 2010). Similar trends exist in Asian cities including Shenzhen in China (Gong et al. 2013), Dehli in India (Paul and Nagendra 2015), Karachi in Pakistan (Qureshi et al. 2010) where Landsat data were commonly used (Table 2.1). Landsat images are widely used in vegetation fragmentation studies in urban landscapes because they cover large geographic areas and provide a rich archive of long historical range of data.

Few studies that include Guneroglu et al.(2013), Qian et al.(2015a) and Zhou et al.(2018) used high resolution satellite imagery such as the ALOS, SPOT High Resolution Visible (HRV), IKONOS and QuickBird. Zhou et al. (2018) used ALOS and SPOT satellite imagery data to examine vegetation fragmentation in selected Chinese cities. The utilization of few high resolution image data (0.5 m to 10 m) in these studies indicates that highly detailed spatial information derived from high resolution data has not been extensively used in urban ecology for vegetation fragmentation studies. The highly detailed spatial information, landscape pattern indices and fragmentation metrics derived from high resolution data could be critical in providing more accurate detection of vegetation fragmentation. High resolution satellite data are also critical in detecting small urban vegetation fragments including stepping stones, narrow corridors, individual street trees and linear patches of vegetation at fine spatial scales (Boyle et al.2014, Fisher et al.2016, Gillespie et al.2008).

We found few scientific papers employing a combination of more than two different remote sensing data. Such combination of satellite data was used in Delhi in India (Paul and Nagendra 2015), Hanoi, Vietnam (Uy and Nakagoshi 2007), Santa Barbara, California in the USA (Alonzo et al. 2016), Bangalore, India (Nagendra et al.2012), Trabzon and Rize cities in Turkey (Guneroglu et al.2013), Mashad, Iran (Rafiee et al.2009) and in nine major cities in China (Zhou et al. 2018). The combination and use of multiple different sources of remote sensing data are essential in urban ecology to evaluate whether different image resolution significantly influences land cover classification accuracy in general and fragmentation metrics of vegetation patches in particular. Acquiring and combining various image datasets is also important in detecting rapid temporal change as vegetation fragmentation in urban areas can occur quickly.

Despite the advantage of providing highly detailed vertical structural information of vegetation, more flexibility in timing and mode as compared to optical satellite data, only four studies from our sample including Alonzo et al.(2016), Baines et al.(2020), Casalegno et al.(2017) and Mitchell et al.(2016) used structural and active remote sensing data. This shows that there is still a paucity of active remote sensing studies that can take advantage of the vertical structure and landscape connectivity of urban vegetation. The landscape connectivity and vertical structure of vegetation are important aspects in urban areas since in most cases they are made up of very large numbers of quite small, heterogeneous and isolated vegetation and habitat patches. Furthermore, the vertical structure of urban vegetation is important in understanding the patterns of habitat condition and quality which are critical for facilitating the movement of organisms in a landscape (Ashcroft et al. 2014, Hinsley et al. 2009).

Most studies on landscape connectivity of urban vegetation have widely used data derived from optical data. However, Casalegno et al. (2017) demonstrated that overreliance on optical 2D data such as Normalized Difference Vegetation Index (NDVI) can result in disproportionate estimates of landscape connectivity of urban vegetation. The 2D (NDVI) derived metrics exhibited a less fragmented vegetation pattern than 3D structure obtained from waveform Light Detection and Ranging (LIDAR) data (Casalegno et al.2017). Based on LIDAR data, Mitchell et al. (2016) showed that the vertical structure of urban vegetation in Brisbane, Australia at 1-km^2 and 1ha spatial scales increased where patches of urban vegetation were spatially clumped. Based on these results, it therefore implies that managing urban green spaces for biodiversity should not mainly concentrate on the amount of tree, green spaces or vegetation cover (2D) existing, but also on identifying the vertical complexity of vegetation. Urban green spaces with such structural complexity support multiple taxa (Threlfall et al.2016).

The high costs of acquiring structural remote sensing data like LIDAR and Radio Detection and Ranging (RADAR) (Selkowitz et al. 2012, Wolter et al. 2009) are a hindrance in providing citywide, regional or global coverage for broad scales analysis of vegetation fragmentation. There are limited image archives for LIDAR in contrast to traditional sensors like Landsat. This makes it difficult for most researchers to carry out the full coverage of cities and extensive metropolitan areas and frequent change analysis of urban vegetation structure.

Still there is lack of robust techniques that can accurately map the 3D structure of urban vegetation and capture the spatial heterogeneity of urban vegetation at fine spatial scales and grain size (Casalegno et al. 2017). In addition, active remote sensing data like LIDAR presents limitations in automating, processing and interpolating point clouds into raster layers, which are time-consuming and prone to misclassification (Zhou 2013) and requires significant input from remote sensing experts.

Table 2.1. List of selected papers investigation the landscape structure of urban green spaces and vegetation fragmentation in urban areas

Title of the paper	Location (City and country)	Region/Continent	Satellite data type	Published date and name of the journal Paper	Methods
Assessing the drivers shaping global patterns of urban vegetation landscape structure	100 cities around the globe located on six continents	World	Landsat 5 TM satellite imagery (2006 to 2011).	Dobbs et al. 2017 *Science of the Total Environment*	Landscape metrics
Impacts of population density and wealth on the quantity and structure of urban green space in tropical Southeast Asia	111 urban areas that included (32) cities in Indonesia, (27) cities in Thailand, (17) cities in the Philippines, (16) cities in Malaysia, (13) cities in Vietnam, (3) cities in Myanmar (1) city in Cambodia, Singapore,and Lao	South east Asian cities	Landsat satellite imagery(2012)	(Richards et al. 2017) *Landscape and Urban Planning*	Landscape metrics (PLAND, Aggregation Index)
Forest fragmentation in Massachusetts, USA: a town-level assessment using Morphological spatial pattern analysis and affinity propagation	Selected of towns across Massachusetts (Auburn, Lancaster Charlemont, Methuen, Marshfield, Hinsdale), United States (USA)	North America	Landsat 5 Thematic Mapper imagery (2000)	(Rogan *et al.* 2016) *GIScience and Remote Sensing*	Morphological Spatial Pattern Analysis (MSPA)
Fragmentation of Florida scrub in an urban landscape	Pinellas County, United States (USA)	North America	Landsat images (1999)	(Hall *et al.* 2002) *Urban Ecosystems*	Landscape metrics
Land development pressure on peri-urban forests: a case study in the Regional Municipality of York	York, Canada	North America	The MSS image (1975), Two TM (Thematic Mapper) scene of 1985 and the Landsat Thematic Mapper (1988). All images were resampled to 25 m resolution	(Puric-Mladenovic et al. 2000) *The Forestry Chronicle*	landscape indices
Land cover transition and fragmentation of River Ogba catchment in Benin City, Nigeria	Benin City, Nigeria	Africa	The Landsat TM image of January 6, 1988, ETM+ of January 28, 2002 and Landsat OLI image of December 28, 2016.	(Enaruvbe and Atafo 2018) *Sustainable Cities and Society*	Number of patches, largest patch index, area-weighted shape index and mean Euclidean nearest neighbour

Urban Vegetative Cover Fragmentation in the U.S.: Associations with Physical Activity and *Body mass index* (BMI)	U.S. metropolitan statistical areas greater than 1 million in population, United States (USA)	North America	National Land Cover Database 2006 derived from a 30-m resolution Landsat data	(Tsai *et al.*, 2016) *American Journal of Preventive Medicine*	Percentage of green land cover, patch area, patch density, edge density, edge contrast index, Euclidean distance, and patch cohesion index
Relationships between Characteristics of Urban Green Land Cover and Mental Health in U.S. Metropolitan Areas	U.S. metropolitan statistical areas greater than 1 million in population, United States (USA)	North America	National Land Cover Database (NLCD) of 2011, derived from a 30-m resolution Landsat data	(Tsai *et al.*, 2018) *International journal of environmental research and public health*	landscape indices
The Impacts of Atlanta's Urban Sprawl on Forest Cover and Fragmentation	Atlanta metro region, United States(USA)	North America	Landsat MSS data (1974 and 1985) based have a spatial resolution of 60-m pixels and the Landsat TM and ETM data 1991, 2001, and 2005 layers have 30-m resolution	(Miller, 2012) *Applied Geography*	Number and area of forest fragments
Quantifying and describing urbanizing landscapes in the Northeast United States.	Marlborough, Connectict, United States(USA)	North America	Landsat (1985 and 1999)	(Civco et al. 2002) *Photogrammetric Engineering and Remote Sensing*	The forest fragmentation model
Vegetation change and fragmentation in the mega city of Delhi: Mapping 25 years of change	Delhi,India	Asia	Three Landsat satellite image (1980.19986 and 1999) and 2010 IRS LISS	S Paul, H Nagendra (2015) *Applied Geography*	The Landscape Fragmentation tool (LFT)
Graying, greening and fragmentation in the rapidly expanding Indian city of Bangalore	Bangalore, India	Asia	Two satellite images, a Landsat ETM+November 2000 and a May 2007 IRS LISS 3 image	(Nagendra *et al.* 2012) *Landscape and Urban Planning*	The mean proximity index
Landscape ecological assessment of green space fragmentation in Hong Kong	Hong Kong, Hong Kong	Asia	Orthophoto maps and land use digital maps	(Tian *et al.* 2011) *Urban Forestry & Urban Greening*	landscape metrics
Assessing spatio-temporal changes in forest cover and fragmentation under urban expansion in Nanjing, eastern China, from long-term Landsat observations (1987–2017)	Nanjing, China	Asia	Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper Plus (ETM), and Landsat 8 Operational Land Imager (OLI) scenes from 1987 to 2017 except images for 1996, 2004, 2008,	(Zhang et al. 2020) *Landscape and Urban Planning*	Morphological spatial pattern analysis (MSPA)

Post-Soviet forest fragmentation and loss in the Green Belt around Moscow, Russia (1991–2001): a remote sensing perspective	Moscow, Russia	Europe	Landsat TM (1991 and 2001)	(Boentje and Blinnikov 2007) *Landscape and Urban Planning*	landscape metrics (mean patch size, Edge density, mean shape index and mean nearest neighbour
Impact of rapid urban expansion on green space structure	Kuala Lumpur (Malaysia), Metro Manila (Philippines) and Jakarta (Indonesia)	Asia	Landsat-5 Thematic Mapper satellite imagery of 1988 and 1999 for Kuala Lumpur,Jakarta and Metro Manila and Landsat-8 Enhanced Thematic Mapper 30 m resolution images for 2014 covering the three cities	(Nor *et al.* 2017) *Ecological Indicators*	Landscape metrics
Determining socioeconomic drivers of urban forest fragmentation with historical remote sensing images	Shenzhen, China	Asia	Nine sets of Landsat (1973,1979,1986,1991,1995,1998, 2000,2003, and 2005)	(Gong et al., 2013) *Landscape and urban planning*	Landscape metrics
Analysis on dynamic development of landscape fragmentation for urban forest in fast-urbanization regions	Huizhou, China	Asia	Landsat TM/ETM+ satellite images (1990, 2000 and 2010)	(Yang et al. 2016),*Journal of South China Agricultural University*	Landscape metrics
Assessing the Fragmentation of the Green Infrastructure in Romanian Cities Using Fractal Models and Numerical Taxonomy	14 cities Romanian	Europe	The Urban Atlas is providing pan-European comparable land use and land cover data	(Petrişor *et al.* 2016) *Procedia Environmental Sciences*	Fractal Models, Numerical Taxonomy and landscape metrics
Urban green infrastructure and urban forests: A case study of the Metropolitan Area of Milan	Metropolitan Area of Milan	Europe	European Programme CORINE (Coordination of Information on the Environment Land Cover, (CLC) land use for the years 1954, 1980, 1999, 2007, and 2012	(Sanesi et al. 2017) *Landscape Research*	Landscape metrics (Mean patch size (ha)Patch density (n/Km2), Nearest distance (m)% patch > 15 ha)
Ecological connectivity in the three-dimensional urban green volume using waveform airborne LIDAR	Towns of Milton Keynes, Luton, and Bedford, southern England, United Kingdom	Europe	Waveform LIDAR and hyperspectral data (4 m spatial resolution)	(Casalegno *et al.* 2017) *Scientific reports*	Landscape proportion Small patch density Largest patch index Connectivity Index Landscape division index
Green corridors and fragmentation in South Eastern Black Sea coastal landscape	Trabzon and Rize, Turkey	Europe	High resolution Ikonos and Quickbird	(Guneroglu *et al.* 2013)	CA (Class Area), PL (Class Percent of Landscape), NumP (Number of Patch), LPI(Largest Patch Index), MPS (Mean Patch

				Ocean and coastal management	Size), AWMSI (Area Weighted Mean Shape Index), AWMPFD (Area Weighted Mean Patch Fractal Dimension) and PD (Patch Density)
Forest and the city: A multivariate analysis of peri-urban forest land cover patterns in 283 European metropolitan areas	283 metropolitan areas in Europe	Europe	High-resolution land-use maps (2006–2010).Input data sources include Earth Observation panchromatic images with a spatial resolution of 2.5m;multispectral data	(Salvati *et al.* 2017) *Ecological Indicators*	85 landscape and class metrics
Landscape structure influences urban vegetation vertical structure	Brisbane, Australia	Australia	light detection and ranging (LiDAR) data of 2009	(Mitchell et al. (2016)) *Urban ecosystems*	Mean patch size, Mean edge/area ratio, proportion of tree cover (%), Clumpiness metric/spatial aggregation.
Exploring temporal dynamics of urban ecosystem services in Latin America: The case of Bogota (Colombia) and Santiago (Chile	The city of Bogota (Colombia) and Santiago (Chile)	Latin America	Landsat 5 TM data of 1985 multispectral pixel, 120 m thermal pixel (Band 6)	(Dobbs et al. 2018) *Ecological Indicators*	landscape metrics
Forest fragmentation and landscape connectivity change associated with road network extension and city expansion: A case study in the Lancang River Valley	Lincang City, southwest Yunnan Province, China	Asia	Landsat TM images of (February 17, 1991) and (December 11, 2006)	(Liu *et al.*, 2014) *Ecological Indicators*	Number of patches (NP),percentage of landscape (PLAND),largest patch index (LPI),mean shape index (SHAPE),mean fractal dimension (FRAC),division index (DIVISION) Connectivity analysis, integral index of connectivity
Changes in the landscape pattern of the La Mesa Watershed – The last ecological frontier of Metro Manila, Philippines	Metro Manila, Philippines	Asia	Landsat images in 1988, 2002, and 2016	(Estoque *et al*, 2018) *Forest Ecology and Management*	Percentage of Landscape (PLAND),Patch Density, Mean Patch Area, Area-Weighted Mean Fractal Dimension Index, Mean Euclidean Nearest Neighbour Distance, Contagion, Landscape Shape Index, Shannon’s Diversity Index

2.3.5 Scale of application

The spatial scale and unit of analysis remains one of the key issues in urban ecology for understanding spatial heterogeneity (Gustafson 1998). The literature review showed that remote sensing applications for vegetation fragmentation studies in urban areas have been conducted at various spatial scales. The spatial scale of analysis varied from residential or suburb, city to a metropolitan area. However, the most common spatial scale was local (a city and/or municipality), which was the metropolitan area in a single country. For instance, at the individual level of a city, landscape patterns of urban vegetation and vegetation fragmentation were quantified for cities such as Shanghai (Li and Liu 2016), Jinan (Kong and Nakagoshi 2006), Shenzhen (Gong et al. 2013, You 2016), Hong Kong (Tian et al. 2011) all in China, Santiago in Chile (de la Darrera et al.2016) and Hanoi, Vietnam (Uy and Nakagoshi 2007) based on various satellite images. This shows that although vegetation fragmentation research is receiving much attention around the world, it is much concentrated in larger urban areas at the level of individual cities.

Few studies included more than one city in a single country for cross-city comparison purposes. These include a study by Casalegno et al. (2017) for towns that included Milton Keynes, Luton, and Bedford in southern England, Guneroglu et al. (2013) for Trabzon and Rize cities in Turkey, Petrişor et al.(2016) for 14 Romanian Cities and Zhou et al. (2018) for nine Chinese cities of Beijing, Shanghai, Nanjing, Hangzhou, Tianjin, Tangshan, Suzhou, Wuxi and Changzhou. The systematic cross-city comparison analysis helped to reveal similarities, differences or distinct vegetation fragmentation in multiple cities. Guneroglu et al.(2013) indicated that the level of vegetation fragmentation was higher in Trabzon city due to a higher urbanization when compared to another city, Rize city in Turkey that had larger green cover patches.

There are a few studies of vegetation fragmentation conducted at a regional scale. This comprises a group of cities typically comprising a group of cities of varying demographic and economic conditions in one continent for example, South east Asia cities or European cities. These studies include Dobbs et al. (2018), Nor et al. (2017), Kabisch and Haase (2013), Richards et al. (2017), , Salvati et al.(2017) and Tsai et al.(2016; 2018). In Asia, Richards et al.(2017) examined the landscape pattern of urban vegetation of 111 Southeast Asian cities based on Landsat images. Again in Asia, Nor et al. (2017) studied the landscape structure of urban green space for Kuala Lumpur in Malaysia, Manila in the Philippines and Jakarta in

Indonesia. In Europe, Kabisch and Haase (2013) analysed the changes of the spatial configuration patterns of urban vegetation in 202 European cities while Salvati et al.(2017) examined the landscape structure of urban forest in 283 European metropolitan cities. In the USA, Tsai et al.(2016) studied the fragmentation of urban vegetation in the USA metropolitan areas that had a population size exceeding one million people. The relatively few studies at regional scale especially in Africa and South America geographical regions highlights the challenge of comparing vegetation fragmentation between cities that have considerable differences in their political, climatic and socio-economic conditions. Furthermore, cities from tropical regions, especially of Africa and South America, are usually excluded in these studies because of poor quality of satellite imagery related to cloud cover.

The spatiotemporal pattern of vegetation fragmentation across cities of different continents at a global scale remains elusive. To date, studies of vegetation fragmentation at global and large spatial scale using remote sensing data covering several selected cities and urban areas across continents (transnational continents) are still limited except in Dobbs et al (2017) and Liu et al (2016). Dobbs et al.(2017) studied the landscape pattern of urban vegetation using Landsat images of 100 cities around the world (i.e. Africa, America, Australasia and Europe) that were selected from cities and urban areas with a population size of more than 100.000 inhabitants. Furthermore, Liu et al. (2016) studied the dynamics of habitat loss (e.g.forest, grassland etc) and fragmentation using both remote sensing image datasets and historical maps based on a pool of only 16 large cities around the globe. This shows that the vegetation fragmentation studies in urban areas at a global scale are not comprehensive and conclusive as not all cities are studied. Most cities are not represented due to the challenges of comparing cities with wide differences in climate, demographics, economies, political backgrounds, ages, sizes and urban form (Dobbs et al. 2017).

Furthermore, at a global scale, cities in the geographical regions of South America and Africa are usually omitted because of cloud cover challenges whereas the studied cities of Europe and North America are selected because of better quality satellite data (Dobbs et al. 2017, Richards et al. 2017). For a broad range of cities, city boundaries are also difficult to acquire at large scale (Dobbs et al.2017, Schneider and Woodcock 2008). The limited number of urban vegetation fragmentation studies at global scale also highlights the challenge of computing and processing large image datasets which are labour-intensive and time-consuming given lack of appropriate processing tools.

2.3.6. Major research topics and study themes

The remote sensing of vegetation fragmentation in urban areas over the last decades, can be categorized into two major research areas: (1) spatio-temporal change dynamics and (2), the drivers of urban vegetation fragmentation.

2.3.6.1 Spatial and temporal change dynamics

The approach generally used for analysing spatial-temporal variability patterns of vegetation fragmentation can be outlined in the following stages (i) multitemporal remote sensing data acquisition, (ii) image and land cover classification to retrieve forest, vegetation and land cover maps, (iii) overall land classification accuracy assessment of classified data, and (iv) calculation of a suite of landscape indices and fragmentation metrics (largest patch area, shape complexity, contagion, aggregation) at patch, class and at landscape level. Remote sensing data like Landsat's temporal resolution of 16 days provide a rich context for long term and multi-temporal vegetation fragmentation change detection studies at local, regional, continental or global scales.

Using multi-temporal classified Landsat data, forest types and stands were used to quantify fragmentation statistics and monitor spatial-temporal change in York, Canada (Puric-Mladenovic et al. 2000). The research findings of the study showed that between 1975 and 1988, forest cover declined by 7%. Furthermore, the forest cover had been fragmented into smaller patches as mean patch size of forest cover declined by 56–87% for several areas (Puric-Mladenovic et al. 2000). Civco et al.(2002) quantified change in forest fragmentation in Marlborough, Connecticut in the USA between 1985 and 1999 based on landscape metrics derived from time series Landsat data. Besides a 7% decline in total forest cover, there was also a rapid forest fragmentation, which caused a rise of 89% in the number of forest patches between 1985 and 1999 period (Civco et al.2002).

In Europe, Lofman and Kouki (2003) analysed temporal changes in the landscape structure of private forest holdings in Nurmes, Finland. The study revealed a more fragmented pattern of private forest holdings between 1941 and 1997. In Asia, studies that used multi-temporal remote sensing data to document an increase in vegetation fragmentation over time included cities like Mashad, Iran (Rafiee et al. 2009), Bangalore in India (Nagendra et al. 2012) Manila, Philippines (Estoque et al. 2018), Jinan, China (Kong and Nakagoshi 2006), Nanjing, China (Zhang et al.2020) and Shenzhen, China (Gong et al. 2013).

Not all research papers provided information about where (urban core, urban fringe or periphery) in the cities, urban vegetation were most fragmented. However, those that show, indicate that urban vegetation was lowly fragmented, slightly changed or remained largely unchanged in urban core or city centres (Li et al. 2011, Paul and Nagendra 2015, Xu et al. 2011, Zhou and Wang 2011). The most dramatic changes of spatial structure in vegetation peaked on the urban fringe or urban periphery (Nielsen et al. 2017) coinciding with urban expansion (Miller 2012, Paul and Nagendra 2015). For instance, cities in Latin American have been found to have a pattern similar to the cities found in the United States of America, where most of the changes in the spatial and temporal variability patterns of urban vegetation occur mainly at the fringe and near urban cores (Schneider and Woodcock 2008).

2.3.6.2 Driving forces of vegetation fragmentation in urban areas

Remote sensing imagery data combined with biophysical (elevation, slope, rainfall, climate) and socioeconomic data of road density, distance to urban centres, per capita, Gross Domestic Product (GDP), education level, neighbourhood age, immigration status, unemployment rate, income and population size are widely employed to account for vegetation fragmentation dynamics in urban areas (Dobbs et al. 2017, Gong et al. 2013, Liu et al. 2016). Gong et al.(2013) used Landsat data from 1973 to 2005, combined remote sensing data with physical and socioeconomic drivers to characterize urban forest fragmentation rates in Shenzhen in the southern coastal China. The study revealed that 75.9% of socio-economic factors were largely responsible for the vegetation fragmentation dynamics in the city (Gong et al. 2013).

The review of literature also showed that cities with higher population densities (a surrogate measure for the degree of urbanization) tended to have more fragmented green spaces, and smaller vegetation patches that have greater edge effects (Dobbs et al 2014, Dobbs et al.2017, Huang et al. 2018, Richards et al. 2017). The highly fragmented nature of vegetation in Chinese cities has been associated with high population density. As a result, there will be fewer spaces for large and contiguous urban vegetation to thrive due to the encroachment into existing natural vegetated areas. This pattern has been observed in most European cities (Fuller and Gaston 2009). In agreement with the observation from previous studies, findings of drivers of landscape structure patterns of vegetation at a global scale of one hundred cities using satellite images for 1990 and 2000 show that vegetation fragmentation in urban areas is positively related to population growth and size of the economy (Dobbs et al. 2017).

High-income and rich cities have more urban green spaces than poor and low-income cities (Huang et al. 2018, Richards et al. 2017). Unequal social and economic development within cities is associated with more fragmented urban vegetation (Dobbs et al. 2017). The combination of satellite imagery data with biophysical and socio-economic data have also revealed the adverse impacts of urban sprawl on urban vegetation and natural habitats, causing significant vegetation fragmentation in some cities in the USA (Li et al. 2010). Examples of these cities are Atlanta in Georgia (Miller 2012) and Maryland in the USA (Irwin and Bockstael 2007). In Sheffield, the United Kingdom, the influence of the total length of the road network on the coverage of urban vegetation was established (Davies et al. 2008). In Asia, Huang et al. (2018) established a similar result where high road density is responsible for vegetation fragmentation in some cities, resulting in less urban green space coverage area. Besides the socio-economic factors, biophysical and climatic factors are also important. For instance, higher terrain roughness was observed to have a positive influence on the extent of tree canopy in Cincinnati, in the USA (Berland et al. 2015). By including biophysical and climatic factors, a negative relationship between higher precipitation and lower temperature was found to be responsible for the greater urban vegetation coverage in some megacities relative to other large cities (Huang et al. 2017).

2.3.7 Methodologies used in computing landscape structure of urban green space and vegetation fragmentation

About 98% of the research papers used landscape metrics indices to analyse the landscape patterns of urban vegetation and fragmentation at a local, regional and global scale. Landscape metrics are quantified and retrieved from the pixel and objected based image classification of remotely sensed data into a mosaic of discretely delineated homogenous areas of vegetation and habitat classes (grassland, forest) (McGarigal and Marks 1995, McGarigal et al.2002, O'neill et al. 1995, Riitters et al.1995). In linking ecological patterns and process (i.e. vegetation fragmentation), some of the landscape metrics provide important insights on the spatial configuration of urban vegetation and vegetation fragmentation in both space and time.

At a global scale, Dobbs et al. (2017) showed that percentage of land covered by urban green space (PLAND) differed considerably, ranging from 10% to 50%. Furthermore, the mean patch size of vegetation varied from 0.3 ha to 2 ha (Dobbs et al. 2017). At a regional scale, Richards et al. 2017 indicated that the PLAND in cities of Southeast Asia varied considerably. Tacloban in the Philippines was the greenest city in the pool of 111 Southeast Asian cities with 79%

green coverage (Richards et al. 2017). Mandalay in Myanmar was found to be the city with the lowest green vegetation coverage of 17% (Richards et al. 2017). In Asia, Zhou et al (2018) also noted that urban green spaces in nine Chinese cities were dispersed and highly fragmented, with a high number of patches. The vegetation patches were smaller than 0.1 ha. Huang et al.(2018) indicated that urban green spaces in most Chinese cities are more fragmented because of higher patch density (PD) but to some extent are less isolated (Huang et al 2018, Zhou et al.2018).

However, other studies combined landscape metrics derived from classified remotely sensed data with gradient analysis (Hepcan 2013, Jiao et al. 2017, Kong and Nakagoshi 2006, Luck and Wu 2002, Paul and Nagendra 2015). Spatio-temporal gradient analysis are computed to determine the changes of ecological processes along a distance gradient from the city centre to urban fringes (McDonnell et al.1997, McDonnell and Hahs 2008). Based on the gradient analysis, it has been observed that the fragmentation of vegetation generally increased with the distance to the urban core due to the urban growth and sprawl (Gao and Yu 2014).

Moving window techniques for vegetation fragmentation analysis like the Landscape Fragmentation Tool, the forest fragmentation model and the Morphological Spatial Pattern Analysis (MSPA) program have not been widely applied in quantifying vegetation fragmentation in urban areas, save for a few studies. The Landscape Fragmentation Tool, when compared to image convolution method, can accurately represent fragmentation (Vogt et al.2007). The Landscape Fragmentation Tool quantifies varying categories of fragmentation: core, inner edge, outer edge and patch. The Landscape Fragmentation Tool was used to examine vegetation fragmentation in the city of Delhi in India (Paul and Nagendra 2015). However , the Landscape Fragmentation Tool is different from widely used landscape metric indices. It cannot handle different edge widths. It assumes that all edges between land cover (forest, vegetation) types are the same.

The forest fragmentation model, although widely used in a natural forest, has not been widely applied in urban landscapes except in Civco et al. (2002) and Kowe et al. (2019; 2020). Unlike the widely used landscape metrics, the forest fragmentation model, does not require an arbitrary specification of Euclidian or edge distance to spatially explicitly delineate a core area within a patch of forest or vegetation. Furthermore, it explicitly quantifies the relative amount of a landscape covered by vegetation patches or habitat within a certain window size (eg.5x5 pixels, 9x9 pixels, 27x27 pixels and 81x81 pixels). Depending on selected window size, the forest fragmentation model works well both at class and landscape level to map the categories (interior, perforated, edge, transitional, patch) and extent of vegetation fragmentation. However, the quantification of spatial patterns of vegetation patches based on forest fragmentation model is sensitive to scale (i.e. the window size) (Dong et al. 2014, Riitters et al. 2000; 2002, Riitters and Wickham 2012).

The MSPA is suitable for mapping connectivity between core forest or vegetation patches and differentiate interior and exterior forest or vegetation edges in space and time (Soille and Vogt 2009, Vogt et al.2007). MSPA has previously been applied in examining forest fragmentation, structural connectivity of habitats in natural, vegetated and urban areas (Saura et al. 2011, Tannier et al. 2012, Wickham et al. 2010, Zhang et al.2020). Recently in Nanjing, in eastern China, Zhang et al.(2020) analysed the link between forest fragmentation and urban expansion from time series Landsat data acquired between 1987–2017. Rogan et al.(2016) used MSPA for forest fragmentation in town level assessments in Massachusetts in the United States of America.

Results of the use of MSPA show that it can be used not only to quantify habitat loss related to vegetation fragmentation but also the spatial connectivity of vegetation in a landscape. The spatial connectivity of urban green spaces can act as corridors and habitats (forests, grasslands, shrubland, woodlands) that help in conserving biodiversity in urban areas. Edges or boundaries of vegetation patches are mapped accurately and easily and delineated using the MSPA. In ecology, edges or boundaries of forest or vegetation patches are critical in providing transition zones between different elements of landscapes (Cadenasso et al.2003, Forman 1995). However, the computation of landscape patterns of vegetation patches using MSPA is sensitive to scale.

2.4. Discussion

2.4.1 Remote sensing data and spatial resolution issues

In general, urban areas are highly heterogeneous and the spatial resolutions may be larger than many of the vegetation patches being mapped as the results depend much on the pixel size of remote sensing data (Moilanen and Hanski 1998). While medium resolution images like Landsat data are very effective and useful in mapping broader patterns of vegetation fragmentation, they may fail to capture fine-grained change patterns (Qian et al.2015b).

Smaller patches of urban vegetation are often misclassified and underestimated because of mixed pixels from remote sensing products derived from low and medium resolution data (Boyle et al. 2014, Qian et al. 2015). Turner (1990) indicated that much information is often degraded when image data are resampled to coarser resolution data in comparison to the grain size of features.

Compared to high resolution data, coarse resolution remote data do not accurately detect the sharp edges of irregular patches (Karl and Maurer 2010, Roth et al.2015). This is a serious issue considering that the large proportion of urban vegetation and green spaces in urban landscape is complex, irregular and highly fragmented. Over the years, high spatial resolution data e.g. QuickBird and IKONOS (4m) (Qian et al. 2015a, Wang et al. 2018) have been increasingly explored and could be used to accurately map the landscape patterns and spatial-temporal dynamics of vegetation coverage at fine and highly detailed spatial scales (Gillespie et al. 2008).

It has been observed that there is significant difference in quantitative information of landscape pattern indices, patch and fragmentation metrics derived from medium resolution images compared with those from high resolution data (Buyantuyev et al. 2010, Feng and Liu 2015, Shen et al. 2004, Turner et al. 2001). Zhou et al.(2018) compared moderate Landsat data and ALOS and SPOT image data in quantifying the changes in spatio-temporal patterns of urban green spaces in nine major Chinese cities. High resolution image data of ALOS and SPOT were able to detect changes of small vegetation patches whilst medium resolution data (Landsat) failed to detect those changes (Zhou et al.2018).

Unlike the freely available Landsat data, the high spatial resolution imagery remains expensive, with a price of approximately US$3,000–5,000 for 10 km^2 (Gillespie et al. 2008). The high prohibitive access costs of commercial high resolution imagery data, make it costly to generate consistent high resolution maps across several cities or urban areas (Forkuor and Cofie 2011). Image files of high spatial resolution data tend to be large and cumbersome to store, manipulate and process. Data fusion and merging of medium and high remote sensing data with highly detailed LIDAR could be cost-effective in mapping large cities and urban areas (Chen et al. 2012,Hudak et al. 2002).

2.4.2. General trends and research gaps in published literature

The relatively small amount of vegetation fragmentation studies done in cities and urban areas of Africa and Latin America is likely due to financial resource constraints, language barriers, inadequate infrastructure, as well as lack of quantitative and ecological training (Griffiths and Dos Santos 2012). Furthermore, urban vegetation are not considered highly valuable in poor and less developed countries (Cilliers 2009). Although some studies (Huang et al. 2018, Irwin and Bockstael 2007) have addressed the impacts of rapid urban expansion and urban sprawl on vegetation fragmentation (especially forest), how alternative urban form patterns (i.e. compact or clustered and dispersed or haphazard) contribute to urban green fragmentation is, however, not known and has not been adequately addressed. Huang et al.(2018) demonstrated that the urban morphological patterns had much influence on the landscape patterns of urban vegetation in 262 Chinese cities. Cities that had high road density had less proportion of urban green space coverage and vegetation was more fragmented (Huang et al.2018).

2.4.3 Limitations, challenges and recommendations

This study was based on research articles written in English. This could be one of the reasons for the uneven geographical distribution of research articles that focused on vegetation fragmentation conducted in certain cities, urban areas and geographical regions. Furthermore, a review of the literature showed a geographic bias of concentration of studies in cities of the developed world. To reduce the geographic biased distribution of urban vegetation fragmentation studies, a broader international literature that incorporates scientific research articles written and published in languages other than English is necessary. Ideally, vegetation fragmentation studies should cover a broad range of geographic regions to provide relevant and comprehensive information that support effective conservation of urban vegetation.

Research that is more scientific is required to advance knowledge on vegetation fragmentation studies in cities and urban areas of Africa and South America as they face some of the greatest threats to its remnant vegetation patches and biodiversity hotspots (Güneralp and Seto 2013). The understudied cities in parts of Africa and Latin America provide an opportunity to do comparative research of vegetation fragmentation due to considerable differences in political, climate and social-economic characteristics. More efforts should be directed to further promote and facilitate interdisciplinary research, improve the training of local ecologists and conservation scientists. The availability of cloud platforms like Google Earth Engine that have high performance makes it possible to compute and process large datasets more efficiently. It also provides opportunity to study and analyse vegetation fragmentation at large spatial scales.

There are increasing free and open-source software solutions such as Fragstats software (McGarigal et al. 2002), R (R Development Core Team 2013), Landscape Fragmentation Tool (Vogt et al. 2007), the forest fragmentation model, Morphological Spatial Pattern Analysis, QGIS, Geographic Resources Analysis Support System (GRASS) that are on the rise and more relevant in landscape ecology studies. These quantitative methods and programs could play an important in urban ecology by accurately retrieving meaningful ecological information about the landscape structure and urban vegetation fragmentation. Open access and availability of freely available remote sensing data like Sentinel-2 imagery data as well as high resolution, unmanned aerial vehicles could play a significant role in vegetation fragmentation studies especially in cities of developing countries where financial constraints do not permit wide city-scale studies but only at a restricted scale.

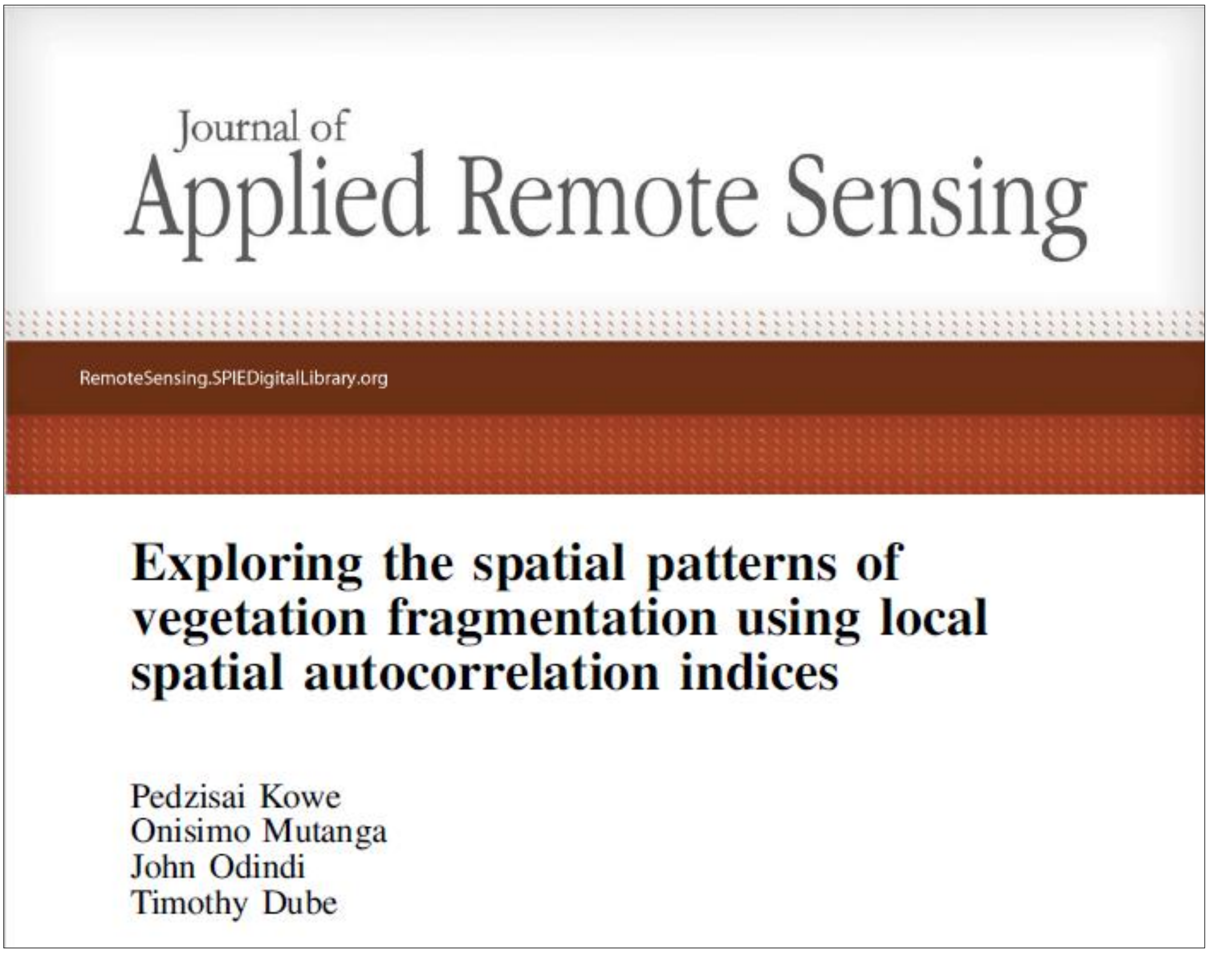
2.5. Conclusion

A systematic review of remote sensing of vegetation fragmentation in urban areas at varying spatial scales is important for conservation purposes. The increasing number of scientific papers, methods and applications related to remote sensing of vegetation fragmentation in urban areas highlights a growing research interest in this topic for conservation and biodiversity studies. Despite this, the use of these remote sensing datasets has yet to be explored in some parts of the world especially in cities of Latin America and Africa. Urban green spaces and vegetation are extremely important for various essential ecosystems services that they provide to urban dwellers. It is reasonable that increased landscape connectivity of urban green spaces that reduces vegetation fragmentation is important in maintaining biodiversity conservation in urban areas.

CHAPTER THREE AND FOUR

SPATIAL PATTERNS OF VEGETATION FRAGMENTATION

3.SPATIAL PATTERNS OF VEGETATION FRAGMENTATION USING SPATIALLY EXPLICIT METHODS



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Exploring the spatial patterns of vegetation fragmentation using local spatial autocorrelation indices

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Abstract
The spatial heterogeneity of urban vegetation obtained from discrete approaches is sensitive to image classification errors. There is also substantial loss of continuous and quantitative information when remotely sensed data is subjectively categorized into homogenous patches, ignoring important environmental variations in a landscape. Although there is an increasing ecological need to use continuous methods to understand the spatial heterogeneity and vegetation fragmentation, they remain unexplored. Since local indicators of spatial association (LISA) can capture important spatial patterns of clustering and dispersion at a local scale, they can capture important ecological patterns and process of vegetation fragmentation. This work examines the utility of LISA, which allows exploration of local patterns in spatial data in identifying high (hot spots) and low (cold spots) spatial clusters of vegetation patches and fragmentation patterns in Harare metropolitan city in Zimbabwe. The LISA indices of Getis Ord Gi* and local Moran's I were computed both on continuous NDVI and discrete land cover data of vegetation and non-vegetation of Sentinel 2016 and 2018. Local spatial clustering patterns were identified with Z-score values that indicated the significance of each statistic. High positive Z-scores were located in the large core, undisturbed, and homogeneous vegetation. Negative Z-scores were located in more dispersed and highly fragmented vegetation. The results suggest that there are a strong tendencies for large core, undisturbed, and homogeneous vegetation patches to be spatially clustered and for small, isolated and sparse vegetation patches to be dispersed. The highly fragmented vegetation patches were located in the heavily urbanized part of the city. In general, the results of this research work underline the relevance of the spatially explicit method of LISA as an important tool for providing spatial information in uniquely capturing local spatial clustering and dispersion of urban vegetation patches. This can be used to develop policies that support effective conservation and restoration strategies.

Keywords: Urban; Vegetation fragmentation; Harare; Local spatial autocorrelation indices; Spatial clustering.

3.1 Introduction

Until recently, urbanization was viewed as an insignificant driver of vegetation fragmentation. Urbanization causes significant reduction of large core and interior vegetation or habitats into smaller and isolated patches (Armsworth et al. 2004, Butler et al. 2004, Liu et al. 2016, Saunders et al.2002). Urban vegetation fragmentation consequently endangers the sustainability of ecological goods and ecosystem services. Specifically, it can negatively affect ecosystem health, biodiversity, water and environmental quality and microclimates (Noss and Csuti 1994, Riemann et al. 2004, Saunders et al 1991). Monitoring of vegetation fragmentation is therefore important for habitat and biodiversity conservation and management. Understanding spatial configuration patterns (e.g. shape, density and size) of vegetation fragmentation is also important to minimize ecological disturbances, degradation and protecting the remaining urban vegetation patches and green spaces.

Satellite remote sensing is useful in landscape ecology as it provides a relatively easy and robust way to generate land cover classifications. It is also valuable in generating several vegetation and land cover maps and fragmentation metric statistics and indices. In light of this, landscape metrics derived from classified satellite images that heavily rely on discrete land cover and categorical maps have been widely used in ecological studies (McGarigal and Marks 1995, Turner 1989, Turner and Gardner 1991). Remote sensing data and combined with landscape pattern analysis is an essential component in computing the landscape structure that can be associated with underlying ecological patterns and processes. However, linking important ecological patterns heavily depends on accurately characterizing spatial heterogeneity in a way that is relevant and meaningful.

Traditional landscape pattern analysis represents a landscape as a collection of discrete or categorical patches (relatively homogeneous patches of vegetation). Discrete landscape pattern analysis applies well to landscape patterns that show distinct landscape structure and unambiguous boundaries (Barrell and Grant 2013) and natural vegetation where boundaries between vegetation patches are crisp (McGarigal et al.2009). However, discrete landscape pattern indices derived from classified remote sensing images can lead to a considerable loss of important ecological information (McGarigal et al.2009). This is particularly caused by degradation of continuous spatial heterogeneity of ecological information within and among patch variability of spatial objects (Foody 2000, Frazier and Wang 2011,Palmer et al.2002, Rocchini et al.2010). In heterogeneous urban landscapes and in other human-dominated landscapes, environmental attributes are sometimes inherently continuous, landscape pattern indices may therefore poorly represent the true continuous spatial heterogeneity of the landscape (McGarigal and Cushman 2005, McGarigal et al. 2009).

The spatial heterogeneity of urban vegetation obtained from discrete cover classes is also sensitive to classification errors due to the complexity of urban landscapes. Vegetation patches are particularly difficult to delineate in urban landscape because of mixed pixels, where two or several classes are present within a single pixel area. Spatial statistics and methods that capture continuous rather than discrete spatial variation are receiving increased attention. McGarigal and Cushman (2005) developed a gradient model by introducing surface metrics that quantify and represent a continuous heterogeneity of the landscape to address the challenges of discrete methods. Other continuous indices including fractal measures, Fourier decomposition, wavelet measures (Cushman et al. 2010, McGarigal and Cushman 2005, McGarigal et al.2009) and spatial autocorrelation indices (Cliff and Ord 1973; 1981, Goodchild 1986, Moran 1948) have been developed and offer considerable scope for continuous analysis of spatial heterogeneity and landscape patterns.

Continuous indices of Local Indicators of Spatial Association or Autocorrelation (LISA) including Getis-Ord Gi*, local Moran's I and local Geary's C can depict pockets of spatial association in geographical space. Also, they help to reveal distances beyond which no discernible association remains (Anselin 1995, Getis and Ord 1992, Getis and Ord 1996, Ord and Getis 1995, Ord and Getis 2001, Sokal et al.1998). Furthermore, LISA is effective in revealing geographical areas with significant clusters of similar values called hot spots and dissimilar values known as cold spots (Nelson and Boots 2008, Sokal et al.1998). Hot spots are spatially explicit, in that they are detected at geographic locations and are separated by regions of lower density of some phenomenon (Azzalini and Torelli 2007).

LISA indices make use of both the differences between pixel values and the spatial arrangement of the data (Read and Lam 2002). In landscape ecology, LISA indices can be used to examine the spatial patterns of vegetation fragmentation without prior knowledge of landscape structure and spatial scale and involving discrete land cover classifications to generate categorical maps (Southworth et al.2004). One of the advantages of LISA indices over other spatial indices used in landscape ecology such as dominance contagion and interspersion is that it can be applied directly to unclassified images without reliance on patch definitions or boundaries (Lam et al. 2002). In urban areas, LISA indices have great potential in determining whether vegetation is dispersed, clustered or randomly distributed across the landscape. Such determinations are important in risk assessment and urban green conservation and management. Furthermore, this has a huge potential to offer many insights into ecological patterns and processes at a particular scale or across a range of scale (Tobin 2004, Turner 1990, Turner et al. 2003).

Some studies have shown interest in utilizing LISA indices for quantifying the spatial variability patterns of forest and landscape fragmentation and land cover change (Fan and Myint 2014, Levin 2009, Pearson 2002, Roberts et al. 2000, Southworth et al. 2004). Julian et al. (2009) for instance used LISA indices based on LiDAR imagery data to identify small seasonal wetlands, often masked under forest canopies. Such vital information would have not been easily detected solely from a discrete based landscape pattern approach. Pearson (2002) used LISA indices to examine the spatial structural variability of northern Australian savannah landscape. The landscape appeared to be intact using the traditional classification techniques but was, in fact, experiencing a decline in species diversity. Barrell and Grant (2013) used LISA indices to detect distinct and significant spatial and temporal dynamics patterns of seagrass and landscape structure at multiple spatial scales within a region of continuous spatial cover in Atlantic Canada.

Myint (2012) analysed the role of spatial configurations of green spaces on air temperature using Local Moran's I and Getis-Ord Gi* derived from Landsat data of 30m spatial resolution. Local Moran's 1 accurately and effectively revealed the true heterogeneity and continuous representation of the landscape by characterizing dispersed and clustered land cover type configurations. Southworth et al.(2004) used LISA indices based on an NDVI data to track changes and spatial patterns of forest fragmentation in western Honduras. The large forest patch appeared homogeneous when studied using a discrete landscape metrics but LISA indices were able to provide subtle changes of forest fragmentation that took place inside the large forest patch within the core of the protected mountain forest.

Unlike discrete measures, LISA indices remain largely unexplored for understanding vegetation fragmentation patterns in urban landscapes. The objective of this research work was to examine the capability and utility of local spatial autocorrelation indices as an analytical tool for identifying spatial clusters of high (homogenous) and low (heterogeneous) vegetation patches and fragmentation patterns. The homogeneous vegetation or hotspots will have a high probability of being connected, thus favouring the persistence of animal species due to the maintenance of metapopulational dynamics. The heterogeneous clusters of vegetation patches or cold spots have a high probability of being at risk due to their isolation, attributed to anthropogenic influences and urbanization.

3.2 Materials and Methods

3.2.1. Study area

This research work was conducted in Harare metropolitan city. It is found in the northeast of Zimbabwe. Harare metropolitan city is situated at 17.83° South latitude and 31.05° East longitude (Figure 3.1). The city has an surface area covering about 980.6 square kilometres. Mukuvisi and Manyame are the major rivers that flow across the southwestern part of the city of the city. The topography within the city varies from approximately 1400m to approximately 1500m in the southern and northern parts, respectively. The city tends to undulates in the north due to the presence of hilly and rocky areas, while it flatters in the south because of low lying surface. The city's climate supports the growth of natural vegetation of open woodland and grassland. The Harare metropolitan city encompasses Harare urban and rural, satellite towns of Epworth and Ruwa to the east and Chitungwiza to the south (ZIMSTAT 2012).

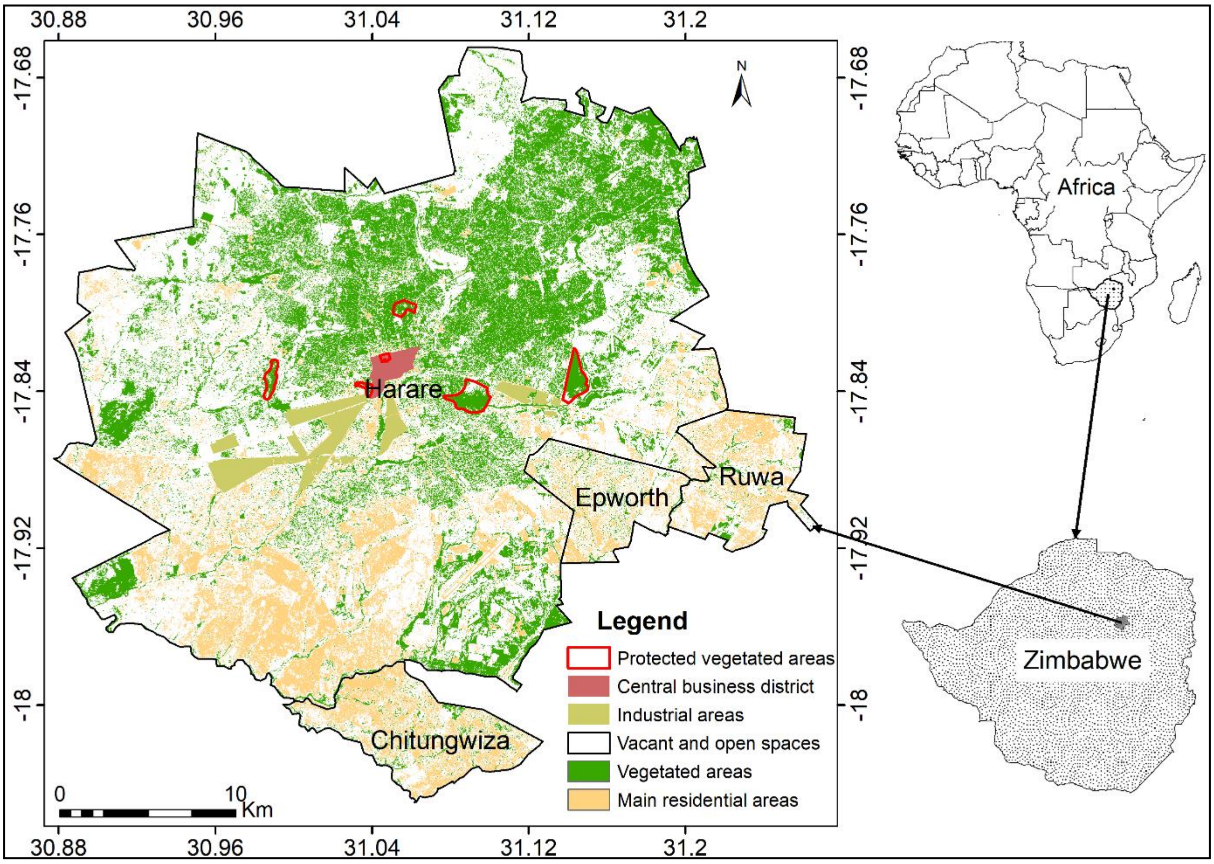

Figure 3.1. Geographical location of the study area, Harare metropolitan city in Zimbabwe.

Densely built-up and heavy concentration of high-density residential areas are found in the western, southern and eastern part of Harare. The low density residential areas and housing developments are predominant in the northern portion. The city has protected forest and vegetation, botanical gardens and parks in the northern part, despite being a highly built-up and urbanized city. These include Haka Game Park, Mukuvisi Woodlands, Harare Kopje, Harare botanical gardens and areas surrounding the Harare National Heroes Acre.

3.2.2 Satellite Data

Sentinel 2 satellite data of October 14, 2016 and October 14, 2018 were utilized to obtain detailed urban vegetation. The images were acquired during the dry season, hence dense and sparse vegetation cover, bare soils, water and urban areas were evident. There are many data sources of higher resolution satellites images, including IKONOS, WorldView, GeoEye, SPOT 5, QuickBird and OrbView. Although, such higher resolution imagery data are excellent data sources for mapping small vegetation patches and highly heterogeneous urban areas, they are, however, very costly (Gillespie et al. 2008, Levin et al.2009). Freely available medium resolution satellite data with relatively broad swath width like Sentinel 2 are capable of providing spatial details compatible with urban mapping.

3.2.3 Land cover classification and accuracy assessment

The Sentinel 2 optical bands of blue (490nm), green (560 nm), red (665nm), and near infrared (842 nm) bands with a 10m spatial resolution were the selected wavelength bands employed in the image classification of the study area. In the preliminary stage before classifying the images, we used a decorrelation stretch to enhance the image for more effective visualization. We also used textural, shape, colour, grain and spatial relationships between image pixels in addition to generating spectral signatures information for accurate identification, mapping and separability of vegetation and other land cover classes. True and false colour band combinations images were also used to improve image interpretation. Initially, training sample sites were drawn as polygons in the image and assigned to a specific land cover class of bareland, built-up, vegetation, water and grassland. Based on the selected training sample sites, a Support Vector Machine (SVM) classifier algorithm in ENVI 5.3 software was then used to classify the images. SVM is a powerful supervised classification and machine learning algorithm that is known to outperform most of the conventional classifiers and pattern recognition methods such as artificial neural networks (Huang et al. 2002). SVM is also known to generate highly accurate results in heterogeneous landscapes and effectively deals with mixed pixels (Huang et al. 2002).

An independent accuracy assessment of the classified Sentinel 2 images of 2016 and 2018 was done to validate the land cover classification results. It was performed using an independent set of ground verification points that were not used as inputs in the supervised image classification. This was done by randomly selecting a large set of 707 random points corresponding to the five land cover classes (bareland, built-up, vegetation, water and grassland) using recent Google Earth high resolution satellite images of study area. Google Earth imagery has frequently been used as reference data for land cover classification validation because of the high geometric precision and fine spatial resolution (Potere 2008). The overall accuracy of the error matrix (confusion matrix) was computed by dividing the total number of correctly classified pixels (sum along the major diagonal) by the total number of validation plots, known as percentage correct (Congalton and Green 1999). Kappa coefficients were calculated to quantify the overall and categorical accuracies (Congalton et al.1983). Land cover map derived from image classification was later reclassified to vegetation and non-vegetation map for further analysis.

3.2.4 Moving window analysis of vegetation fragmentation

The forest fragmentation model outlined in Riitters et al.(2000; 2002) was computed to depict the degree of vegetation fragmentation components (core/interior, perforation, edge, patch, transitional) based on the vegetation and non-vegetation data (vegetation =1 and non-vegetation =0) of 2016 and 2018. This was implemented in QGIS using the SAGA GIS Fragmentation (standard) PLUGIN tool. Whereas previous studies like Riitters et al. (2000; 2002) recommended 5 x 5 pixels for 30m spatial resolution (Landsat data), a moving spatial window size of 3 x 3 pixels was deemed appropriate for maintaining a fair and appropriate representation of the core or interior vegetation patches in Sentinel 2 data. The forest fragmentation model has previously been used to analyse the forest, vegetation and landscape fragmentation based on land cover, forest and vegetation maps of remote sensing products (Li et al. 2010, Wickham et al. 2007). It has been found to be an effective alternative in characterizing vegetation fragmentation at diverse scales (Hurd et al. 2001, Riitters et al. 2000 ; 2002,Wade et al. 2003).

3.2.5 Local Indicators of spatial autocorrelation (LISA)

3.2.5.1 Getis-Ord Gi*

The Hot Spot Analysis (Getis-Ord Gi*) tool in ArcGIS 10.5 software was used to calculate Getis Ord Gi* statistic to identify homogeneous (hot spots) and heterogeneous (cold spots) locations of vegetation patterns. This was done using the vegetation and non-vegetation map as input data. The Getis-Ord Gi* statistic measures the intensity of clustering of high or low values in spatial or geographical data relative to its neighbouring values (Getis and Ord 1992). The Getis-Ord Gi* generate statistically significant Z-scores (standard deviations) when values in bin's sum are different than expected, and that differences are too large to be the result of random chance. A Z-score above 1.96 or below −1.96 means that there is a statistically significant hot spot or a statistically significant cold spot at a significance level of $p < 0.05$ (95% confidence interval). A Z-score near zero indicates no apparent spatial clustering. The standard formula for Getis-Ord Gi* statistic is

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{\mathrm{ij}}(d)x_j - W_i^*\bar{x}}{s\left[W_i^*(n-W_i^*)/(n-1)^{1/2}\right]} \qquad \text{Equation (3.1)}$$

Where $W_i^* = \sum_{j=1}^{n} w_{ij}(d)$, $\bar{x}$ and s are mean and standard deviation, respectively. ω_{ij} is a binary weighting matrix for the adjacent spaces.

3.2.5.2. Local Moran's I

The utility of local Moran’s I was examined using a continuous data of Normalized Difference Vegetation Index (NDVI), representing the amount of vegetation coverage. The NDVI which was derived from Sentinel 2, is effective in measuring green vegetation cover because of the strong absorption in the red band (Band 4) and strong reflection in the near infrared band (Band 8) of remote sensing image data (Tucker 1979). The NDVI as a continuous measure could perform particularly well for this purpose in medium to low vegetation cover areas (Xu et al.2012), such as in Harare metropolitan city. We assumed that LISA indices like the local Moran’s I computed on a continuous measure of NDVI could provide additional information as important indicators of landscape pattern particularly the clustering and fragmentation of urban vegetation.

The local Moran’s I is distinct from the Getis statistic in that it computes covariances instead of the sums. Homogenous or clustered spatial objects and geographical areas are indicated by the local Moran’s I that is significantly higher than the mean. On the other hand, the dispersed or heterogeneous patterns and geographical locations are indicated by a significantly low values of local Moran's I (Fan and Myint 2014). The local Moran's I was computed in ENVI 5.3. Following the methodology of Myint et al.(2015), the obtained values of local Moran's I were normalized to the range of −1 to 1. In this case, the local Moran's I values of -1 represented heterogeneous patterns, values of 1 represented clustered patterns and values of 0 indicated random patterns. The standard equation for calculating local Moran's I is

$$I_i(d) = \frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})^2} \sum_j w_{ij}\ (d)\left(x_j\ - \bar{x}\right) \qquad \text{Equation (3.2)}$$

Where xi is the variate value at location I and $\bar{x}$ is the average value of all the pixels in the geographical area. Figure 3.2 illustrates the methodology and the processing steps presented in this study.

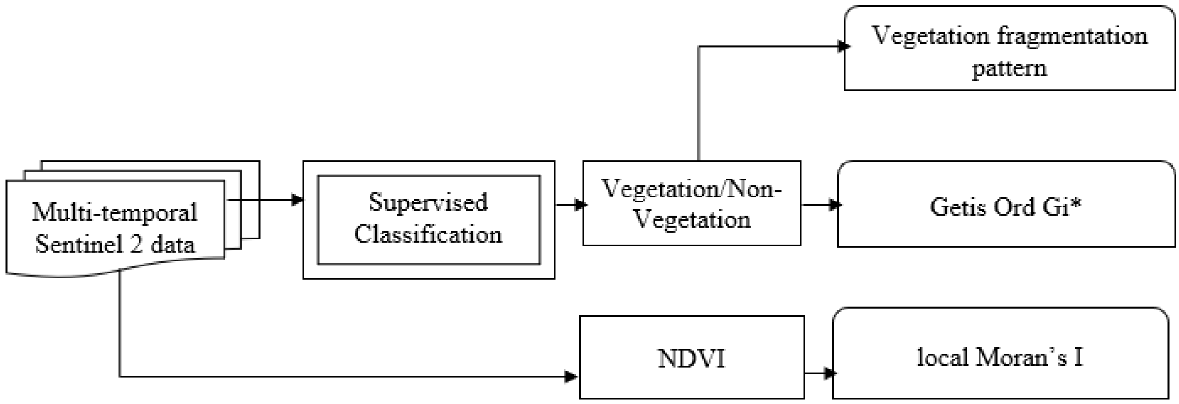

Figure 3.2. Flowchart of the methodology and the processing steps presented in this study.

3.3. Results

3.3.1. Accuracy of land cover classification

The land cover classification of the Sentinel 2 of 2016 and 2018 images had a high overall accuracy. The overall accuracy of classified image of 2016 was 85.7% with overall Kappa Coefficient of 0.79. The overall classification accuracy of classified image of 2018 was 87% and the overall Kappa Coefficient of 0.80 respectively. This is above the 85% and 80% classification accuracy thresholds recommended by Thomlinson et al.(1999) and Omran (2012) respectively.

3.3.2 Spatial distribution patterns of vegetation fragmentation

Table 3.1 shows the moving window spatial analysis results of vegetation fragmentation based on the forest fragmentation model. The patch category of vegetation pattern, which represents the highest level of vegetation fragmentation, was the dominant pattern across the landscape in both 2016 and 2018. The patch category of vegetation pattern had many smaller and isolated vegetation patches as indicated in Figure 3.3. Most of the patch vegetation patterns were mainly concentrated in the southern, eastern and western part of the Harare. On the other hand, the core vegetation which represents undisturbed, lowly fragmented vegetation patterns covered a small portion of the city as they were dominant in the northern part of Harare.

The perforated pattern, which represents the moderate level of vegetation fragmentation showed a slight increase between 2016 and 2018, indicating spatial intrusion of vegetation clearing within core vegetated areas. Perforated pattern was dominant in the northern part of the city. Edge and transitional patterns also showed a slight increase between 2016 and 2018 (Table 3.1). Transitional patterns were mainly located between edge and patch vegetation patterns. Edge and transition fragmented vegetation patterns were also dominant in the northern part of the Harare.

Table 3.1 Moving window analysis results of vegetation fragmentation

	2016		2018	
Fragmentation type/pattern	Total area (ha)	(%)	Total area (ha)	(%)
Core	982	(1 %)	1738	(1.7 %
Perforated	3201	(3.3 %)	3950.	(4.0%)
Edge	7543	(7.7 %)	10372	(10.6%)
Transitional	6976	(7.1 %)	7114.	(7.2%)
Patch	16280	(16.6 %)	15920	(16.2%)
Non vegetation	63075	(64.3%)	58968	(60.1%)

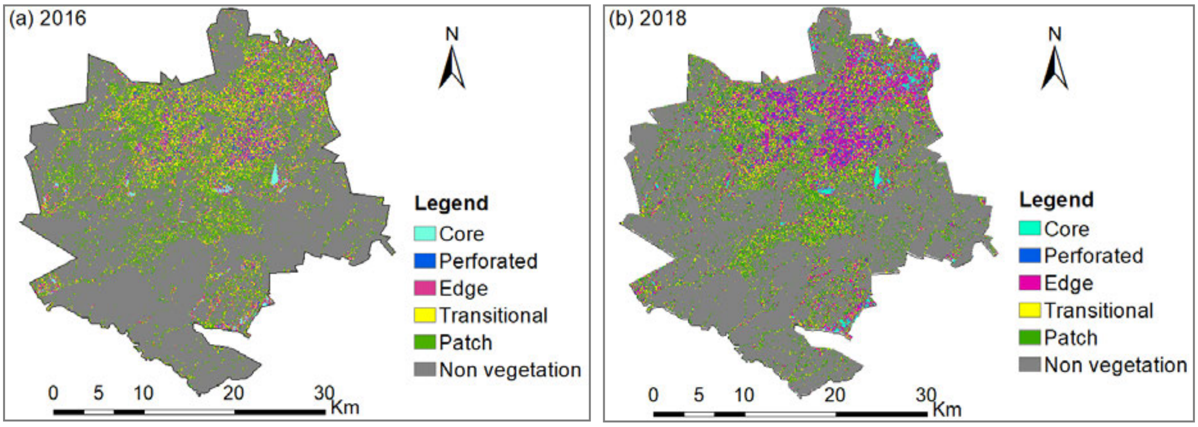

Figure 3.3. The spatial distribution of vegetation fragmentation patterns in Harare metropolitan city in (a) 2016 and (b) 2018 based on the forest fragmentation model.

3.3.3. Local indicators of spatial autocorrelation (LISA)

3.3.3.1 Detecting cold spots and hot spots

The results of the Hot Spot Analysis (Getis-Ord Gi*) are indicated in Table 3.2. Significant hot spots and cold spots of vegetation patches are indicated with statistical confidence levels ranging from 90% ($p< 0.10$), 95% ($p< 0.05$) to 99% ($p < 0.01$). A high Z-score and small p-value indicates a significant hot spot. On the other hand, a low negative Z-score and a small p-value indicates a significant cold spot. Table 3.2 shows that between 2016 and 2018, there was a slight decrease in statistically significant hotspots (99% confidence levels) and an increase in cold spots (99% confidence levels). Statistically significant hotspots have significantly high positive Z-score (>+1.96 and > +2.58) values as indicated in Figure 3.4. High positive Z-score values above 1.96 were mainly concentrated in northern part of Harare metropolitan city, a less urbanized but more vegetated area of large and contiguous vegetation patches.

Table 3.2 Hot Spot Analysis (Getis-Ord Gi*) results in 2016 and 2018

	2016 Area(ha)	2018 Area(ha)	Z-score	P-value (Probability)
Cold spot	1539	2786	< -2.58	p< 0.01 (99%)
Cold spot	871	1309	< -1.96	p< 0.05 (95%)
Cold spot	4599	4470	< -1.65	p< 0.10 (90%)
Not Significant	78068	77571		
Hot spot	345	526	> +1.65	p< 0.10 (90%)
Hot spot	857	879	> +1.96	p< 0.05 (95%)
Hot spot	11777	10521	> +2.58	p< 0.01 (99%)

On the hand, statistically significant cold spots have negative Z-scores (< -1.96 and < -2.58). Statistically significant negative Z-scores of Getis-Ord Gi***** were mainly concentrated in highly fragmented vegetation patches in the southern, eastern and western part of Harare. Generally, the southern, eastern and western side of Harare has many isolated and sparse vegetation (Figure 3.4). The southern, eastern and western side of Harare, is more densely urbanized than the northern part of the city. In areas where Getis-Ord Gi* values were significantly different from the surroundings, they were considered as neither hot spots nor cold spots. These were identified as not significant in the Hot Spot Analysis because they were non-vegetation.

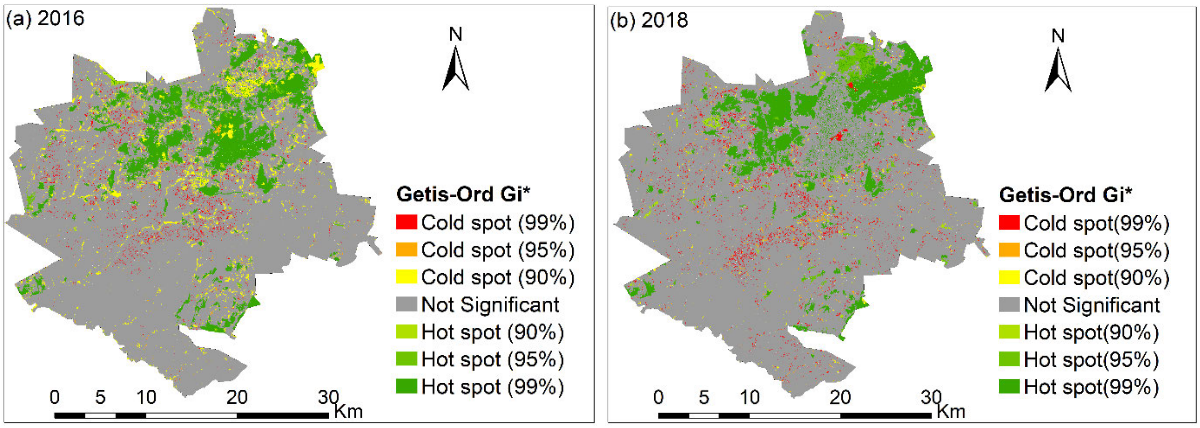

Figure 3.4. Getis-Ord Gi* in (a) 2016 and (b) 2018 with categories corresponding to regions of different statistical confidence (99%, 95% and 90%).

Overall, the findings of Hot Spot Analysis indicated the strong tendency for undisturbed and homogeneous vegetation patches to be spatially clustered. The results also suggest that in areas experiencing high vegetation fragmentation levels, small, isolated and sparse vegetation patches do not spatially cluster but disperse.

3.3.3.2. Detecting high and low clustering patterns of vegetation based on Local Moran's I

The results in Figure 3.5 indicated the presence of spatial clustering pattern and patchiness of high and low vegetated areas respectively. The local Moran's I was significantly different ($p < 0.05$) in 2016 and 2018, with mean value of 0.37 in 2016 and decreased to 0.13 in 2018. In both 2016 and 2018, the northern part of Harare metropolitan city was characterized by high positive values of local Moran's I, indicating the concentration of clustered vegetation patterns due to the presence of high, dense and contiguous vegetation patches as indicated in Figure 3.5 (a) and (b).

The western, eastern and the southern part of the city was characterized by low positive and negative values of local Moran's I. Low positive values of local Moran's I indicate low spatial clustering. The negative values of local Moran's I suggest clustering of dissimilar values (Anselin 1995). Close visual interpretation of Figure 3.5 (a) and (b) indicate patchiness and greater spatial heterogeneity of vegetation patches in western, eastern and the southern part of the city.

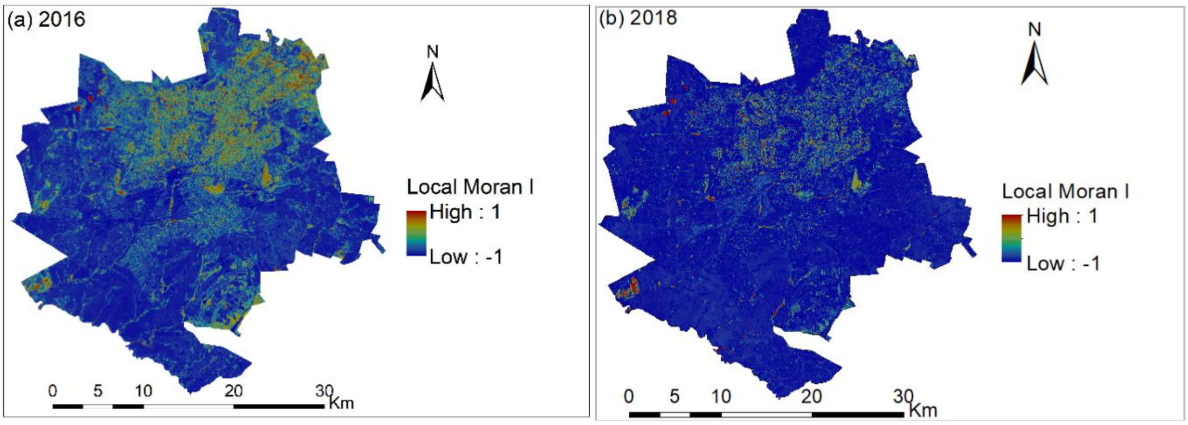

Figure 3.5. Local Moran's I in (a) 2016 and (b) 2018. High positive values of local Moran's I represent a clustered pattern and low positive and negative values represent a dispersed pattern of vegetation.

3.3.3.3. The relationships between NDVI and local Moran's I

Figure 3.6 illustrates the relationship between vegetation cover (NDVI) and local Moran's I in both 2016 and 2018. In both years, the local Moran's I was positively correlated with vegetation cover. The Pearson correlation coefficient between local Moran's I and NDVI was ($r = 0.44$, $p<0.05$) in 2016 and ($r= 0.35$, $p<0.05$) in 2018. The relationship between vegetation cover and local Moran's I highlight the importance of continuous vegetation cover data in landscape pattern analysis of vegetation fragmentation. It implies that vegetation patches tend to cluster when vegetation cover is large and contiguous and vice versa than when it is small, isolated and scattered.

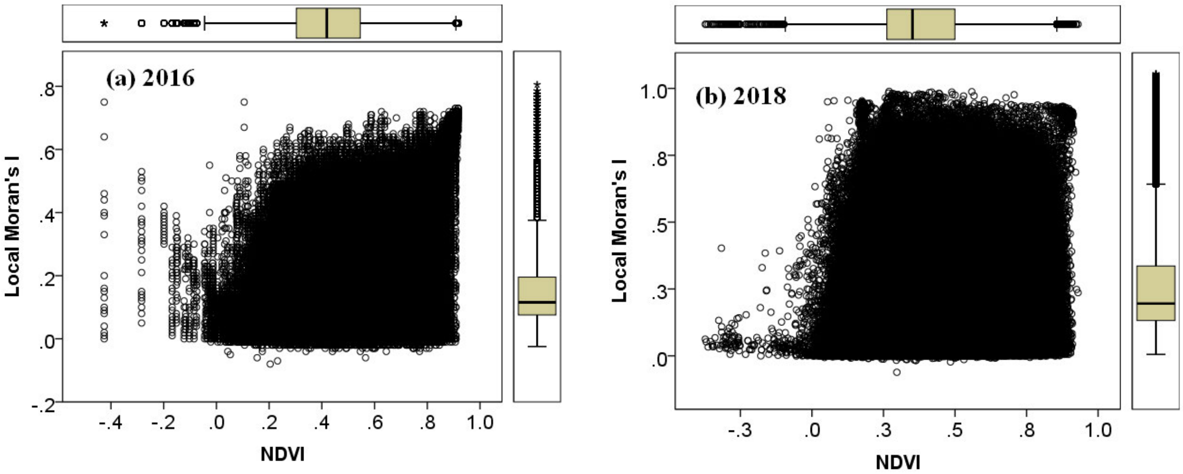

Figure 3.6. Scatter plots representing the relationships between vegetation cover (NDVI) and local Moran's I in (a) 2016 and (b) 2018

3.4 Discussion

The land cover classification of the Sentinel 2 imagery showed high overall accuracy. The reasonably high overall accuracy assessment results confirm the observations by Yu et al.(2013) that indicate effectiveness of advanced and robust machine learning algorithms like the support vector machine (SVM) in improving land cover classification accuracy. These findings have important implications when analysing vegetation fragmentation, especially in the case of heterogeneous and complex urban landscapes where smaller and isolated vegetation patches are critical for the movement of individuals and populations of a variety of species.

Vegetation fragmentation pattern in Harare metropolitan city presents a similar trend as evidenced in some cities in developing and developed countries, where most of the changes result in a decrease of the core vegetation and increase in the patch vegetation areas. Paul and Nagendra (2015) found that there was increased fragmentation of green space in the city of Delhi, India between 1986 and 1999 as indicated by the decrease in the core vegetation and increase in the patch vegetation areas. The city core experienced significant vegetation fragmentation over time caused by infrastructural expansion, while peri-urban part of the city witnessed a decline in vegetation fragmentation.

Paul and Nagendra (2015) showed that areas under the patch category, representing isolated and small patches of vegetation, increased from 72.92 km^2 in the year 1986 to 83.03 km^2 in the year 1999. This trend was partially reversed in 2010 due to afforestation. Further, the increasing trend in vegetation fragmentation in Delhi, India also indicated that edges increased from 94.31 km^2 in 1986 to 106.51 km^2 in 1999 and then reduced to 93.97 km^2 in 2010 (Paul and Nagendra 2015). Furthermore, studies by Dobbs et al. (2018) in the South American cities of Bogota (Colombia) and Santiago (Chile) is in line with earlier work of Schneider and Woodcock (2008) which showed that most of the changes in green spaces and vegetation fragmentation occurred at the fringe and near city cores in the United States. Nagendra and Gopal (2010) found out that fragmentation of green spaces in the city core, for instance in the case of Bangalore in India are possibly linked to the clearing of vegetation in connecting corridors including roads.

Local spatial statistical methods of the Getis-Ord Gi* and local Moran's I indices used in this research provided comparable results in revealing spatially explicit areas of clustered and dispersed vegetation patches. The results corroborate studies by Coulston and Riitters (2003) in identifying distinct clusters of fragmented forests representing extreme indicator values in the southeastern United States. The observed spatial patterns of vegetation fragmentation in the study area are likely the result of the impact of both social economic and biophysical factors across the landscape. However, previous research associated negative spatial autocorrelation with high fragmented vegetation patches (Pausas 2006) and disturbances (Biswas et al.2017). For instance, the negative spatial clustering (cold spots) is concentrated in areas where the vegetation distribution is strongly affected by human activities of high densification of built-up areas in the southern, eastern and western part of Harare.

The small, isolated and scattered vegetation patches are common in the western, eastern and southern side of Harare, in geographical locations mainly affected by anthropogenic disturbance. During urbanization, large areas of natural vegetation and habitat are converted into impervious surfaces causing core and interior vegetation and habitat loss (Liu et al.2016). Jiao et al.(2017) indicated that urbanization had a significant influence on the spatial and temporal fragmentation of urban green space in Wuhan metropolitan area in China. In Delhi, India, Paul and Nagendra (2015) found that vegetation was highly fragmented in peri-urban areas caused by rapid urban expansion. Biswas et al.(2017) found that disturbance increases negative spatial autocorrelation, which was more pronounced in the clear-cut than uncut sites in the boreal forest of Alberta, Canada. Swetnam et al.(2015) found that the negatively valued Z-scores of Getis Ord Gi*and the local Moran's I characterized clustering within the disturbed (fire exclusion, high-severity wildfire, logging) areas in semi-arid forests of the southwestern USA.

Conversely, high and positive spatial autocorrelation and clustering are associated with low and non-fragmented vegetation patches (Pausas 2006). The strong and positive spatial clustering as revealed by local Moran's I can be attributed to minimum human interference and degradation of the vegetation. In our study, high positive spatial clustering is concentrated in the large and contiguous vegetation patches in the northern part of the city. Vegetation patches in the northern part of the city are mainly found in public and state-protected large parks, reserves and monuments that are well managed by various state and national government departments. These include Haka Game Park (Cleveland dam vegetation), Mukuvisi Woodlands, Harare Kopje, Harare botanical gardens and the vegetation surrounding the Harare National Heroes Acre monument.

Our results revealed a moderately positive relationship between NDVI and local spatial autocorrelation statistic of local Moran's I. However, in other studies, significantly higher positive correlations coefficients were found between local spatial statistics indices and percent tree cover. In the agricultural landscape of Albury-Wodonga area, located on the New South Wales in Australia, Levin et al. (2009) found that the Local indicator spatial autocorrelation statistics of Getis-Ord Gi*, Local Moran's I and Geary C had strong positive correlation with percent tree cover. Getis-Ord Gi* had high correlation of (r =0.98), Local Moran's I had also high correlation coefficient of (r =0.95) and local Geary C had a correlation coefficient (r =0.85). It is important to highlight that percent tree cover is highly positively correlated with NDVI (Levin et al.2009). High positive correlations of LISA indices and vegetation cover (percent tree cover or NDVI) are expected in highly vegetated areas unlike in modified urban landscape with low and medium coverage of vegetation patches.

Ecological green networks and corridors, which form continuous connections between habitats or urban green spaces including grasslands, woodlands, street trees, gardens have been widely used to reduce the negative impact of fragmentation (Benedict and McMahon 2006, Hess and

Fischer 2001, Noss 1991, Tian et al. 2011, Tian et al. 2012). Establishing connected green networks and corridors in the highly fragmented vegetation areas of southern, eastern and western parts of the Harare metropolitan city could help mitigate or reverse the impacts of vegetation fragmentation.

Connected green networks and corridors of urban green spaces provide enhanced landscape connectivity compared to dispersed and isolated vegetation areas (Jim and Chen 2003). This enables natural populations of species and threatened habitats to survive, facilitating the interaction and movement of fauna (Hale et al. 2012,Noss 1991, Jim and Chen 2003, Nor et al. 2017, Rouquette et al. 2013, Saunders and Hobbs 1991,Tian et al. 2011, Tian et al. 2012,). For example, the 40-meter-wide Long Island Motor Parkway in New York City has been associated with an increase of gene flow populations (Munshi-South 2012). Greenways have also been recommended as an effective strategy in reducing fragmentation and connecting urban vegetation. Examples include greenways in Georgia in the United States of America (Dawson 1995), in Canadian cites (Taylor 1995) and urban greening in Singapore (Fábos and Ryan 2004).

3.5. Conclusion

The spatial explicit tools of the moving window analysis of forest fragmentation model and continuous indices of LISA employed in this study showed great promise in effectively identifying the clustered or dispersed vegetation patches and quantifying the level of vegetation fragmentation in a landscape. For example, the moving window analysis results have demonstrated that vegetation fragmentation varied between 2016 and 2018, with 3.3% perforated in 2016 and 4.0% in 2018. Furthermore, spatial variations trends were also observed for other vegetation fragmentation types or patterns (core, patch, transitional and edge). The LISA index of Getis-Ord Gi* findings revealed significant hot spots and cold spots of vegetation patches in the study area. In future, it is important to demonstrate how the proposed spatial explicit analytical tools can be linked with land transformations such as urbanization, land cover changes and land degradation analysis. The findings of this study could be used to inform policies that support the effective conservation and habitat planning, contributing to the restoration programmes and strategies that provide decision support for the management.

4. LONG TERM SPATIAL CLUSTERING AND VEGETATION FRAGMENTATION IN AN URBAN LANDSCAPE USING MULTI-TEMPORAL LANDSAT DATA

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A quantitative framework for analysing long term spatial clustering and vegetation fragmentation in an urban landscape using multi-temporal landsat data

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Abstract

Rapid urbanization threatens urban green spaces and vegetation, demonstrated by a decrease in connectivity and higher levels of fragmentation. Understanding historic spatial and temporal patterns of such fragmentation is important for habitat and biological conservation, ecosystem management and urban planning. Despite their potential value, Local Indicators of Spatial Autocorrelation (LISA) measures have not been sufficiently exploited in monitoring the spatial and temporal variability in spatial clustering and fragmentation of vegetation patterns in urban areas. LISA indices are an important local spatial statistics measures that identifies the presence of outliers, zones of similarity (hot spots) and of dissimilarity (cold spots) at proximate locations, hence could be used to explicitly capture spatial patterns that are clustered, dispersed or random. Landscape metrics, the forest fragmentation model and LISA indices were used to examine the temporal variability in clustering and fragmentation patterns of vegetation patches in Harare metropolitan city using Landsat series data for 1994, 2001 and 2017. The analysis and use of landscape metrics showed an increase in the fragmentation of vegetation patches between 1994 to 2017 as shown by the decrease in mean patch size, an increase in the number of patches, edge density and shape complexity of vegetation patches. The study further demonstrates the utility of LISA indices in identifying key hot spot and cold spots. Comparatively, the highly vegetated northern side of Harare was characterised by significantly high positive spatial autocorrelation of vegetation patches. Conversely, the more dispersed vegetation patches were found in the highly and densely urbanized western, eastern and southern side of Harare. This suggests that with increasing vegetation fragmentation, small and isolated vegetation patches do not spatially cluster but are dispersed geographically. The research findings of the study underline the potential of LISA measures as a valuable spatially explicit method for the assessment of spatial clustering and fragmentation of urban vegetation patterns.

Keywords:

Urban vegetation; fragmentation; LISA; spatial clustering; Harare; Landsat

4.1. Introduction

Urban vegetation and green spaces have important socio-economic and ecological values in the urban sustainability and for enhancing the well-being of urban dwellers. For instance, urban parks, street trees, woodlands, forests, grasslands, playgrounds and green belts provide essential services such as aesthetics, recreation and carbon assimilation (Nowak and Crane 2002). Vegetation cover in urban environments also help to reduce urban surface temperatures, purify air and water, sequestrate carbon dioxide, regulates the water cycle and storm water drainage. Furthermore, urban vegetation contains diverse plant and animal species, thus acting as biodiversity hubs (Zapparoli 1997).

However, most urban vegetation and green spaces are increasingly threatened by rapid urbanization and other competing land uses within urban landscapes. One of the major impacts of urbanization is the fragmentation of vegetation, natural habitat (forests, woodlands, grasslands and open spaces) into smaller, more isolated with increased edge effects causing habitat loss (Alberti 2005, Andersson 2006, Güneralp and Seto 2013,Liu et al. 2016a, McKinney 2002; 2006, Nagamitsu et al. 2014, Nor et al. 2017, Saunders et al. 1991, Swenson and Franklin 2000). The growing amount and an increase in the extent of vegetation fragmentation will adversely increase the costs of species conservation and restoration due to loss of movement corridors and connectivity.

Most studies of habitat, vegetation and landscape fragmentation have only been primarily applied to natural or rural landscapes and were previously related to metapopulations and the dynamics of special animals (Davidson 1998, Li et al. 2009, Tian et al. 2011). In particular, understanding vegetation fragmentation in urban landscapes has mainly concentrated on its impacts on birds (Nichol et al. 2010) and arthropods (Gibb and Hochuli 2002). The landscape patterns of impervious, land cover features and urban vegetation patches have been widely studied in United States of America (Connors et al.2013, Fan et al. 2015, Zhou et al. 2011, Zheng et al. 2014) and Chinese cities (Kong et al. 2014, Li et al. 2012, Maimaitiyiming et al. 2014) for the purposes of understanding its impact on surface temperatures in urban areas. Results show that clustered, clumped and aggregated vegetation patches are effective in lowering surface temperatures and therefore enhancing more local cooling effects than dispersed and fragmented vegetation patches (Fan et al. 2015, Kong et al. 2014, Li et al. 2012, Maimaitiyiming et al. 2014).

However, the phenomenon of urban vegetation fragmentation (Jiao et al. 2017, Paul and Nagendra 2015, Tian et al.2011) has recently attracted attention due to the growing concerns of habitat and biodiversity loss as well as the need for ecosystem management and urban planning. Quantification of the landscape structure and urban vegetation fragmentation patterns is required to provide ecological baseline information for understanding how urbanization is linked to the supply of essential ecological services and goods (Mitchell et al. 2013) and to facilitate the development of sustainable cities (Grimm et al. 2008). Remotely sensed imagery data provide a comprehensive temporal and synoptic way to map and monitor changes in fragmentation patterns (Vogelmann 1995). Due to the advantages of global availability, repetitive data acquisition and long-term consistency, remotely sensed image data like Landsat have become invaluable in landscape ecology studies (Gomez et al.2016). Consequently, landscape metrics that heavily rely on discrete land cover and categorical maps (McGarigal and Marks 1995, O'Neill et al. 1988, Turner 1989, Turner and Gardner 1991) derived from classified satellite images are widely used. The use of landscape metrics, in particular, provide the ability to quantify both the spatial composition and configurations of vegetation patches and vegetation fragmentation (McGarigal and Marks 1995).

However, concerns have recently emerged on the challenges of landscape metrics in accurately representing spatial heterogeneity in landscape ecology (McGarigal and Cushman 2005). This is because landscape metrics are calculated using discrete categorical and land cover maps derived from classified images, without considering all other gradual variations in the landscape (Fan and Myint 2014, McGarigal and Cushman 2005). Discrete categorical and thematic land cover maps are associated with misclassification errors that undermines the reliability of landscape pattern indices (Fan and Myint 2014, Turner et al. 2001). Consequently, urban planners and conservation scientist are faced with the task of developing appropriate, cost-effective monitoring and assessment tools that provide comprehensive patterns of vegetation fragmentation change. In the context of conservation science, the possibilities associated with local spatial autocorrelation statistics could present new opportunities for the discrimination of important conservation areas (Cliff and Ord 1973, Goodchild 1986).

Local measures of spatial autocorrelation focus on identifying distinct spatial clusters and detailed local variations patterns in a geographical space and are therefore useful for revealing spatial relationships, which might otherwise be undetected (Anselin 1995, Wulder and Boots

1998). These include Local Indicators of Spatial Association (LISA) measures like Anselin local Moran's I, Getis and Ord Gi* and local Geary's C (Anselin 1995, Getis and Ord 1996, Ord and Getis 1995, Ord and Getis 2001, Sokal et al. 1998). In particular, LISA may assist conservation decisions by identifying homogeneous and heterogeneous clusters of vegetation patches. This is due to the potential of LISA in identifying hot spots and cold spots. Hot spots are spatially explicit in that they are detected at specific geographic locations (Nelson and Boots 2008). Since hot spots are locations and regions of high density that are separated by regions of the lower density of some phenomenon (Azzalini and Torelli 2007), it is easy to visualize locations of vegetation abundance and scarcity. LISA statistics could also be used to convey and uncover emergent trends of changing landscape structure of urban vegetation whether the spatial pattern expressed is clustered, dispersed or random. Such information can help urban planners to design well-connected greenways and corridors for better conservation and urban green infrastructure planning.

The utility of continuous representation of landscape structure is illustrated in several studies (Julian et al. 2009, Pearson 2002, Read and Lam 2002, Qi and Wu 1996, Seixas 2000, Southworth et al. 2004). LISA statistics have previously been utilised to quantify spatial variability patterns of land cover, forest, vegetation and landscape fragmentation change (Fan and Myint 2014, Levin 2009, Gao and Li 2011,Pearson 2002, Roberts et al. 2000, Southworth et al. 2004,). Barrell and Grant (2013) used LISA indices to detect distinct and significant spatial and temporal dynamics patterns and landscape structure of seagrass at multiple spatial scales. The study was conducted within a region of apparently continuous spatial cover in Atlantic Canada. Unlike landscape pattern and geostatistical methods, LISA indices were able to detect distinct boundaries particularly in turbid waters and between areas of high and low seagrass cover. LeDrew et al. (2004) demonstrated the value of Getis statistic in analysing multi-image change in the spatial structure of a coral reef in Fiji and in the Bunaken regions in North Sulawesi, Indonesia based on SPOT imagery.

Generally, continuous methods like LISA have largely been applied to understand the landscape structure of natural vegetation (Levin 2009,Pearson 2002, Southworth et al. 2004) and the landscape patterns of urban vegetation and landscape fragmentation in the cities of the developed world (Fan and Myint 2014). Whereas LISA approaches hold much promise for analysing landscape patterns of urban vegetation fragmentation, this area remains little explored in much of the cities of the developing world of Africa (Banzhaf et al. 2013, Dobbs et al. 2017, Luck et al. 2009). Hence our research objectives were two-fold (1) to develop a methodological framework that use a multi-temporal Landsat data to characterize variability to better understand spatial configurations of vegetation fragmentation, and (2), to develop continuous indices in comparison with traditional discrete landscape metrics in examining their ability to understand spatial clustering, connectivity and vegetation fragmentation patterns between 1994–2017 in Harare metropolitan city in Zimbabwe.

4.2 Materials and Methods

4.2.1 Study area

Harare metropolitan city is situated in the northeastern part of Zimbabwe approximately on 17.83° latitude and 31.05°longitude (Figure 4.1). The city encompasses Harare urban and rural as well as satellite towns of Epworth and Ruwa to the east and Chitungwiza to the south (ZIMSTAT 2012). The population of Harare in the year 2012 was 2.1 million (ZIMSTAT, 2012). The city covers approximately 980.6km^2. Two major rivers, Mukuvisi and Manyame flow across the southwestern part of the city. The topography within the city varies from approximately 1400m to 1500m in the southern and northern parts, respectively. It undulates in the north because of the presence of the hilly and rocky areas and flatters in the south. The city falls within the subtropical highland climate, which is mild and cool, with relatively longer sunshine hours and a mean annual rainfall of 800-1000 mm. It experiences warm summers (with an average temperature of 26°C) and cold winters (with an average temperature of 10°C). The city's climate supports the growth of natural vegetation of open woodland and grassland. Primarily by roads and large residential lots, commercially built-up areas and small agricultural fields (grassland and herbaceous land cover) boarder the wooded forest areas.

The western, southern and eastern portions of the city are largely composed of urban and built up areas, with the dominance of high-density residential areas while the northern portion is largely vegetated with predominance of low-density residential areas. Harare, despite being a highly built-up and urbanized city, it has protected forest and vegetated areas. Haka Game Park, Mukuvisi Woodlands, Harare Kopje, Harare botanical gardens and the vegetation surrounding the Harare National Heroes Acre monument are state protected. Harare metropolitan city was selected for this study because it is in a constant state of change due to rapid urban expansion and other land cover transformations, typical of most urban areas in Zimbabwe. The rapid urbanization in rapidly developing cities like Harare, Zimbabwe (Wania et al. 2014, Mushore et al. 2017) may accelerate patterns of vegetation fragmentation.

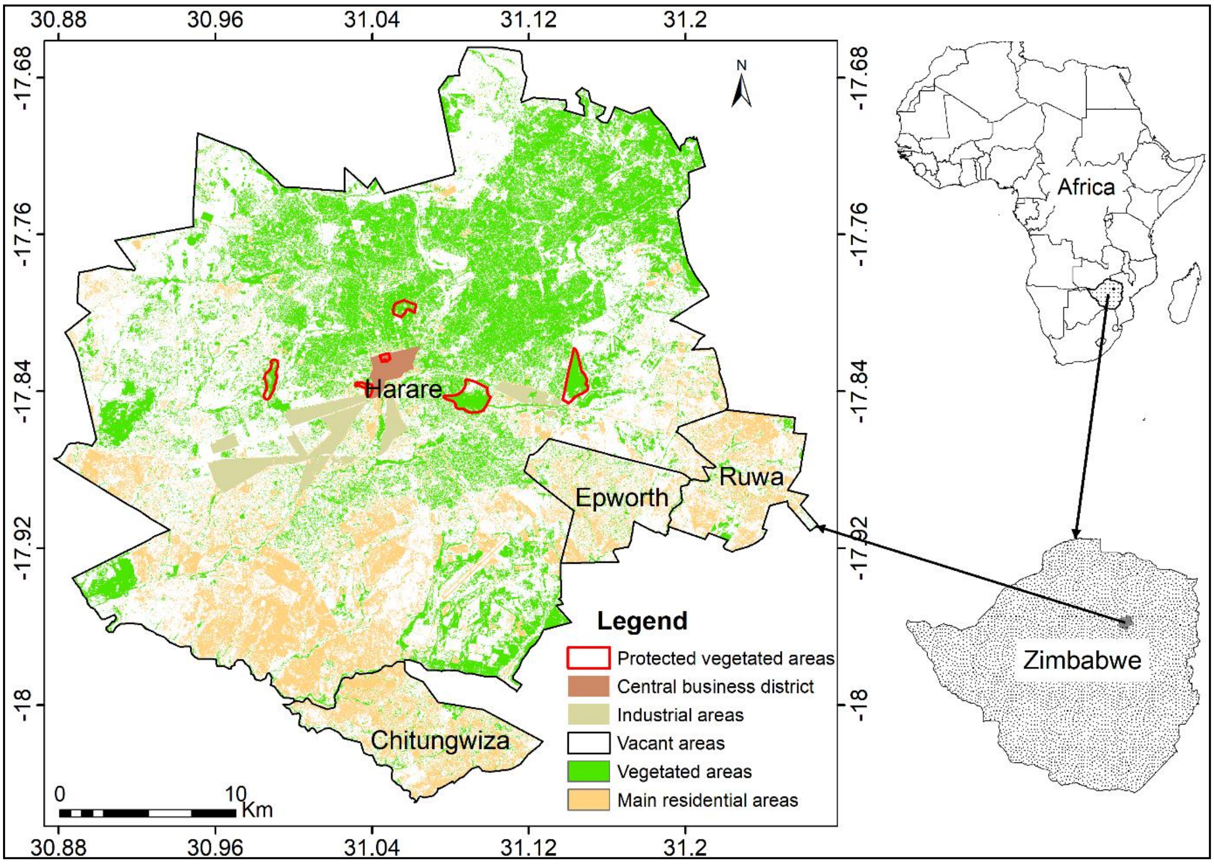


Figure 4.1. The geographical location of the study area, Harare metropolitan city.

4.2.2. Multi-temporal satellite data

The freely available Landsat satellite image data were utilised in this research work. The images were obtained and downloaded from the Earth Explorer's United States Geological Survey website (http://earthexplorer.usgs.gov/). Landsat satellite image data were chosen because of the wide use in urban landscape studies (Van de Voorde et al. 2008, Zhu et al. 2012). The Landsat 5 Thematic Mapper (TM), Landsat 7 Enhanced Thematic Mapper (ETM +) and Landsat 8 Operational Land Imager (OLI) acquired on the 8 October 1994, 19 October 2001 and 23 October 2017, respectively were used. The satellite image data utilised in this research work are presented in Table 4.1.

Table 4.1 Satellite image data

Satellite data	Sensor	Spatial Resolution(m)	Date of Acquisition
Landsat 5	Thematic Mapper	30	08 October 1994
Landsat 7	Enhanced Thematic Mapper Plus	30	19 October 2001
Landsat 8	Operational Land Imager	30	23 October 2017

The period (1994–2017) was appropriate to understand comprehensive and long-term fragmentation of urban green spaces due to rapid urban expansion with significant changes in the spatial patterns and extensive loss of green spaces that have occurred over the last two decades. More importantly the selected three satellite datasets and years chosen reflects different periods of urbanization in the city In the mid 1990s, the city was still compact and growing by occupying agricultural rural areas adjacent to the existing built areas. In the early 2000 low-density suburban developments appeared and urbanization extended in all directions. In recent times, urban growth occurs by infilling vacant or bareland and new urban developments dispersed in the urban fringe and peri-urban areas.

Further, the Landsat satellite data were acquired in dry and summer season because they were cloud free and with more stable atmospheric factors. All images were selected within October (dry and summer season) for stability and consistency in vegetation phenological condition. In Harare in particular and Zimbabwe in general, October is the warmest month and during this period, the differentiation between vegetation cover and bare ground is evident. In particular, vegetation coverage versus non-vegetation patches of bareland, vacant land, open spaces, water and urban areas are clearly identified and separated during this time. The acquired Landsat imagery data were used to extract two types of data (1) vegetation distribution based on Normalised Difference Vegetation Index (NDVI) and (2) vegetation and non-vegetation data derived from land cover classifications both acquired at a 30 m spatial resolution.

4.2.3. Normalised Difference Vegetation Index

The Normalised Difference Vegetation Index (NDVI) was quantified using the Near Infrared (NIR) and visible Red (R) bands from the Landsat image data. NDVI is an established index for estimating vegetation greenness and quantity (Tucker 1979). The values of NDVI varies between -1 and 1. The negative values of NDVI generally indicate presence of water while 0 values indicate presence of non-green vegetation. The large positive values of NDVI generally signal the increasing proportion and fraction of green vegetation coverage, with values usually varying from 0.5 for sparse vegetative coverage to 0.7 for dense vegetative coverage (Tucker 1979).

4.2.4. Vegetation and non-vegetation data

To derive the vegetation and non-vegetation data, the supervised image classification approach was performed to classify the three Landsat images. In the preliminary stage before classifying the images, we used a decorrelation stretch to enhance the image for more effective visualization. We also used textural, shape, colour, grain and spatial relationships between image pixels in addition to generating spectral signatures information for accurate identification, mapping and separability of vegetation and other land cover classes. True and false colour band combinations images were also used to improve image interpretation. Training sample sites were drawn as polygons in the image and assigned to a particular class of bareland, built-up area, vegetation, water and grassland. Based on the selected training sample sites, a Support Vector Machine (SVM) classifier algorithm in ENVI 5.3 software was then used to classify the images. An independent accuracy assessment of the three classified Landsat images was done to validate the land cover classification results using independent set of ground verification points.

The classification accuracy assessment was obtained using selected random points within each land cover class by cross-referencing with the Google Earth imagery of the study area. Google Earth imagery has recently become popular as reference data for land cover classification validation due to its high geometric precision and fine spatial resolution (Potere 2008). The overall accuracy of the error matrix was computed by dividing the total number of correctly classified pixels (sum along the major diagonal) by the total number of validation plots, known as percentage correct (Congalton and Green 2002). Kappa coefficients were calculated to quantify the overall and categorical accuracies (Congalton 1991). The land cover map derived from image classification was later reclassified to vegetation and non-vegetation map for further analysis.

4.2.3 Discrete approaches

4.2.3.1 Vegetation fragmentation using landscape metrics

A binary vegetation and non-vegetation data of 1994, 2001 and 2017 were computed to determine the landscape configuration patterns (e.g. size, density, shape complexity) of vegetation fragmentation. The selected landscape metrics included the number of patches (NP), Mean Patch Size (MPS), Patch size coefficient of variation (PSCV), Area Weighted Mean Shape Index (AWMSI), Area Weighted Mean Patch Fractal Dimension Index (AWMPFDI), Mean Perimeter Area Ratio (MPAR) and Edge Density (ED). Low fractal dimension is associated with clustered patterns while a high fractal dimension indicates a more fragmented pattern (Read and Lam 2002). The selected landscape metrics were quantified in Fragstats 4.2, widely used pattern analysis software (McGarigal and Marks 1995, McGarigal et al.2002).

4.2.3.2 Vegetation fragmentation using the forest fragmentation model

The forest fragmentation model outlined in Riitters et al. (2000; 2002) was used to generate maps depicting vegetation fragmentation patterns (core/interior, perforated, edge, and patch, transitional). The vegetation fragmentation was calculated based on a land cover map of vegetation and non-vegetated data (vegetation=1 and non vegetated= 0) using SAGA Fragmentation (Standard) module in QGIS. The forest fragmentation model has proven to be an effective alternative in characterizing fragmentation (forest, vegetation, landscape) at diverse spatial scales (Dong et al. 2014, Hurd et al. 2001, Riitters et al. 2002, Wade et al. 2003). The calculation of the forest fragmentation model is based on: forest/vegetation area density (P_f) and forest/vegetation connectivity (P_{ff}) within a specified "spatial window size" or sliding scale. The two indicators, forest/vegetation area density (P_f) and forest /vegetation connectivity (P_{ff}) of the forest fragmentation model are computed using the following formulas;

$$P_f = \frac{N_f}{N_w} \quad \text{Equation (4.1)}$$

$$P_{ff} = \frac{D_{ff}}{D_f} \quad \text{Equation (4.2)}$$

where Pf is the proportion of vegetation or density pixels in a certain spatial window size (e.g., 3×3, 5×5, 7×7, 9×9), and is computed by dividing vegetation pixels (NF) in a certain spatial window by the total number of pixels (NW) (Dong et al. 2014). (P_{ff}) is the forest/vegetation connectivity is computed by dividing the pixel pair number that includes at least one vegetation pixel (Dff) by the pixel pair number that includes two vegetation pixels in cardinal directions (D_f) (Dong et al.2014). After deriving the vegetation area density (P_f) and vegetation connectivity index (P_{ff}), each subject vegetation pixel centered within the moving window was classified into fragmentation categories (core or interior, perforated, transitional, edge and patch) defined in the forest fragmentation model. The outcome of the moving window analysis of the forest fragmentation model is threshold and scale dependent (Riitters et al. 2000; 2002). With smaller spatial window sizes, a greater percentage of vegetation in the landscape is classified as core or interior than other types and larger window sizes tend to overestimate edge and patches patterns. To maintain a fair representation of core or interior vegetation, a moving window size of 5 by 5 pixels was used as recommended by Riitters et al. (2000; 2002) in analysing the vegetation fragmentation for Landsat's 30m spatial resolution imagery.

4.2.4 Continuous approaches

Two measures of LISA that included the local Moran’s I index (Anselin 1995) and the Getis–Ord Gi* index (Getis and Ord 1992) were computed to map the spatial heterogeneity of vegetation fragmentation and spatial clustering of vegetation. Tasseled Cap Transformation indices of greenness (Tasseled Cap Greenness), brightness (Tasseled Cap Brightness), wetness (Tasseled Cap Wetness) and Tasseled Cap Angle (TCA) derived from Landsat data were also computed for subsequent analysis and comparisons with LISA indices.

4.2.4.1 Getis-Ord Gi*

The utility of Getis-Ord Gi* statistic (Getis and Ord 1992, Getis and Ord 1996, Ord and Getis 1995) was computed on land cover data of vegetation and non-vegetation using the Hot Spot Analysis Tool in Environmental Systems Research Institute (ESRI)'s ArcGIS 10.5 Toolbox. The Getis-Ord Gi* tells whether locations with high or low attribute values tend to cluster and form a hot spot or cold spot. The Getis-Ord Gi* statistic generates Z-scores (standard deviations) and P-values (statistical probabilities) that indicate whether attribute values are statistically clustered. A Z-score (standard deviation) above 1.96 or below −1.96 indicates that there is a statistically significant hot spot or cold spot at a significance level of $p < 0.05$. The larger the Z-score, the more intense the spatial clustering of values (hot spot) i.e. higher Gi* statistic. A low and statistically significant z-score signal the spatial clustering of low values (cold spot) i.e. lower Gi* statistic. A Z-score near zero indicates no apparent spatial clustering. The standard formula for Getis-Ord Gi* statistic is

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{\mathrm{ij}}(d)x_j - W_i^* \bar{x}}{s\left[W_i^*(n-W_i^*)/(n-1)^{1/2}\right]} \quad \text{Equation (4.3)}$$

Where $W_i^* = \sum_{j=1}^{n} w_{ij}\,(d)$, $\bar{x}$ and s are mean and standard deviation respectively.Where ω_{ij} is a binary weighting matrix for the adjacent spaces. The Queens Case Contiguity method was used to define neighbourhood size in space.

4.2.4.2 Computing low and high spatial clustering of vegetation patterns

The utility of local Moran’s I (Anselin 1995) was applied to the continuous vegetation index data (NDVI image) in ENVI image processing software. The local Moran’s I (Anselin 1995) is different from the Getis statistic (Getis and Ord 1992). It computes the covariances, instead of the sums (Fan and Myint 2014). Following the methodology proposed by Fan and Myint (2014), the derived local Moran’s I values were standardized and normalized to the value range of −1 to 1. Positive values of local Moran’s I generally indicates a spatial clustering of similar values around an individual location. On the other hand, the negative values of local Moran's I implies spatial clustering of dissimilar values and high variability between neighbouring pixels around an individual location. Significantly low values of local Moran's I indicates a dispersed pattern or locations (Fan and Myint 2014). The standard formula for local Moran's I is

$$I_i(d) = \frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})^2} \sum_j w_{ij} \ (d)(x_j - \bar{x}) \dots\dots\dots\dots\dots\dots\dots\dots\dots \text{Equation (4.4)}$$

Where xi represents the variate value at geographical location I and $\bar{x}$ denotes the average value of all the pixels in the geographical location.

4.2.4.3 Tasseled Cap transformation indices

Following Gómez et al. (2011), the Tasselled Cap indices were used in this study to analyse landscape change of vegetation using time series Landsat data. For each image, the Tasseled Cap (TCT) transformation was computed into three orthogonal indices of Tasseled Cap Greenness (TCG), Tasseled Cap Brightness (TCB) and Tasseled Cap Wetness (TCW) (Crist and Cicone 1984, Crist and Kauth 1986, Huang et al. 2002, Kauth and Thomas 1976). TCG, TCB and TCW components were calculated using coefficients as in Crist and Kauth (1986) to transform Landsat 5 TM imagery. The procedures of Huang et.al.(2002) were used for calculating the Tasseled Cap coefficients for Landsat 7 ETM+. We used the Tasseled Cap coefficients provided by Baig and Zhang et.al.(2014) for computing Tasseled Cap Transformation (TCT) indices of Landsat 8 data. Landsat Tasseled Cap Transformation (TCT) indices have been demonstrated to be reliable, effective and powerful in a wide spectrum of environments and landscapes (Healey et al. 2005) and widely used in agriculture, forest and landscape ecology (Jin and Sader 2005) and disturbance mapping projects because of its ability to highlight relevant vegetation changes.

4.2.4.4 Tasseled Cap Angle (TCA)

The TCA (Powell et al.2010) is determined as the angle formed by Tasseled Cap brightness and Tasseled Cap greenness in the vegetation plane. It was computed using the derived TCG and TCB images for each date. The formula for computing Tasseled Cap Angle is;

TCA=arctan (Tasseled Cap greenness /Tasseled Cap brightness)……………… (Equation 4.5)

TCA has extensively been utilised as surrogate measure to compute the proportion of vegetation to non-vegetation within Landsat pixel data (Gómez et al. 2011, Powell et al. 2010).

Higher positive values of TCA are found in geographical areas that are densely occupied by vegetation (greenness) compared to bare soil or clear-cuts with less dense vegetation characterised by negative values (brightness) (Cohen et al. 1998, White et al. 2011). The derivation of TCA image was based on time series of Landsat images (i.e. years). Analysing the comparative changes of Tasseled Cap Angle does not require calibration (Gómez et al.2011). This is because either increase or decrease in the fraction of vegetation to non-vegetation results in a consequent change of TCA values (Gómez et al.2011). Figure 4.2 shows a flow chart on all major steps undertaken in this study.

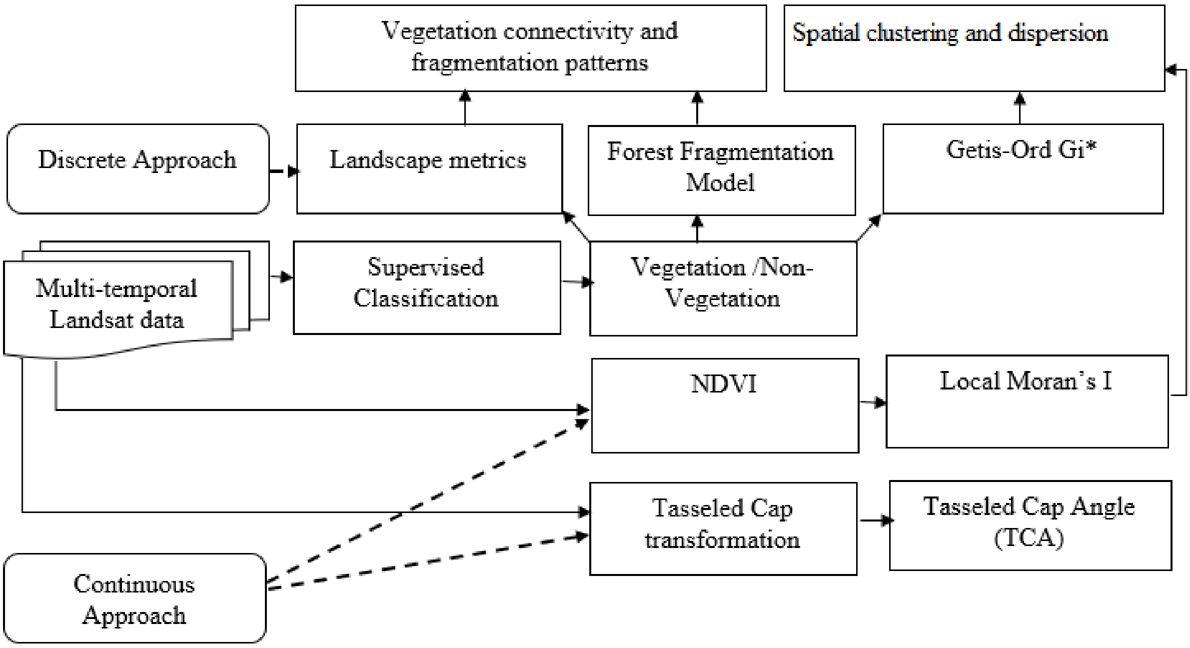


Figure 4.2. A flow chart on major steps undertaken in this study.

4.3 Results

4.3.1. Land cover classification accuracy assessment

The classification accuracy assessment of vegetation and non-vegetation maps generated from the three classified Landsat data was high. To some degree, this can be accredited to the simple classification scheme of using few land cover classes and the effectiveness of the use of support vector machine classification algorithm in the image classification. The overall classification accuracy was 97.65 % in 1994, 97.55 % in 2001 and then 97.14 % in 2017. The Kappa Coefficient was 0.96 for the three temporal periods.

4.3.2 Link between vegetation change and fragmentation

The spatial distribution and variability patterns of vegetation in the city show that it is mainly concentrated in the northern part of Harare (Figure 4.3). Between 1994 and 2017, a significant decline in vegetation cover was observed. Table 4.2 shows that in 1994, the amount of vegetation cover was approximately 27,190.8 (ha), declined to 26575.5 (ha) in 2001 then decreased to 19582.7 (ha) in 2017.

Table 4.2. Temporal vegetation cover change

Year	Vegetation (ha)	Non-vegetation (ha)
1994	27190.8	70871.5
2001	26575.5	71486.8
2017	19582.7	78481.0

Figure 4.3 shows the locations where fragmentation patterns have increased at the expenses of core natural vegetation cover. The western, eastern and the southern side of Harare experienced a decrease in the size of vegetation cover, indicating heavy disturbances to the existence of large vegetation patches (Figure 4.3).

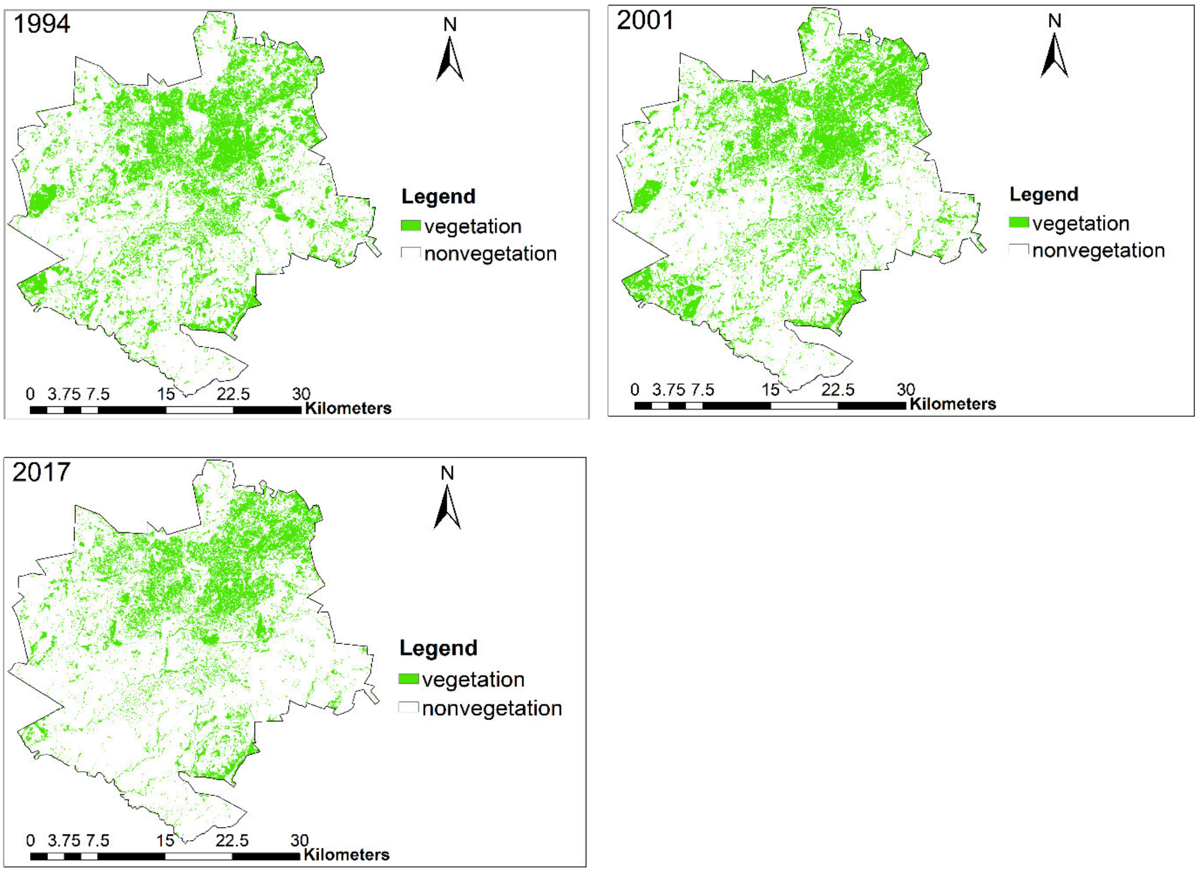


Figure 4.3. The spatial variability patterns of vegetation and non-vegetated areas in the Harare metropolitan city in 1994, 2001 and 2017.

The increasing trend of vegetation fragmentation is illustrated in Figure 4.4 where large, connected and more spatially clustered vegetation patches gradually became more scattered, dispersed and fragmented over time.

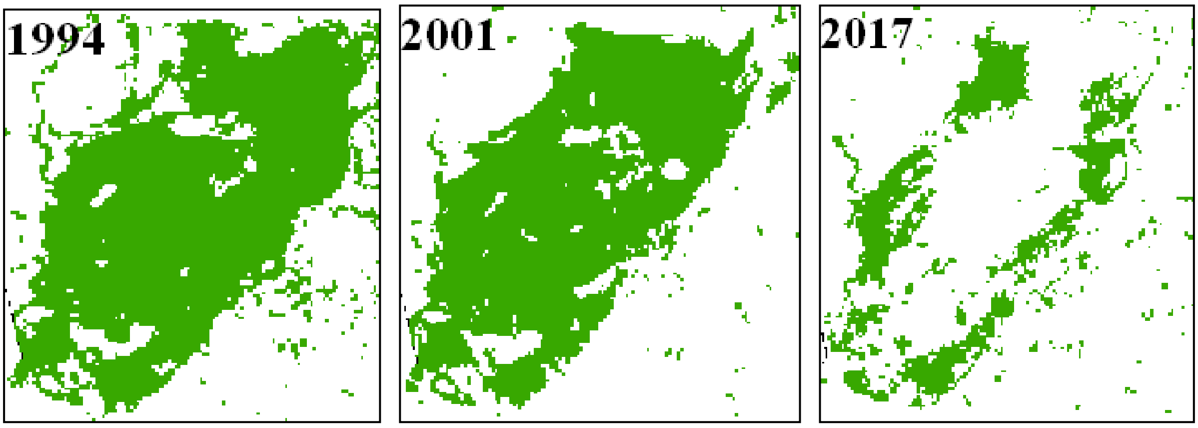


Figure 4.4 shows an example of a transition from the large, connected and contiguous vegetation to a more scattered and fragmented state in a selected portion west of the city. Green and white areas indicate vegetation and non-vegetation, respectively.

4.3.3 Temporal vegetation fragmentation analysis using landscape metrics

Table 4.3 shows the results of vegetation fragmentation analysis using landscape metrics. There was a clear trend of increasing fragmentation of vegetation during the period 1994–2017. Between 1994 and 2017, Harare metropolitan city experienced an increase in the of Number of Patches (NP), Mean Perimeter Area Ratio (MPAR) as well as a decrease in Mean Patch Size (MPS).Table 4.3 indicates that the number of patches of vegetation was approximately 6441 ha in 1994, increased to 6537 ha in 2001 and then increased to 7705 ha in 2017. The mean patch size of vegetation patches was 4.2 ha in 1994, slightly decreased to 4.0 ha in 2001 and further declined to 2.5 ha in 2017. Patch Size Coefficient of Variation (PSCV) increased between 1994 and 2001, reflecting a higher relative variability in size of vegetation patches within the study area. However, PSCV in 2001 was higher than in 1994 and 2017. Edge density indicated an increasing trend between 1994 and 2017. Table 4.3 indicates that the edge density of vegetation was approximately 109.5 (m/ha) in 1994, slightly increased to 111.9 (m/ha) in 2001 then increased to 117.8 (m/ha) in 2017.

Both AWMSI and AWMPFDI increased between 1994 and 2017 (Table 4.3). AWMSI was approximately 15.3 in 1994, increased to 22.8 in 2001 and further increased to an index of 23.5 in 2017. AWMPFDI showed a similar increasing trend as it was 1.27 in 1994, slightly increased to 1.29 in 2001 and then to 1.30 in 2017 (Table 4.3). AWMSI and AWMPFDI values above 1 indicates irregular and complex shapes of patches of land cover categories like vegetation (McGarigal and Marks 2002).

Table 4.3 Temporal vegetation fragmentation analysis using landscape metrics

Landscape Metrics	**1994**	**2001**	**2017**
Number of patches	6441	6537	7705
Mean Patch Size (ha)	4.2	4.0	2.5
Patch size coefficient of variation (%)	2369.3	3738.8	3560.9
Area-weighted mean shape index	15.33	22.8	23.5
Area weighted mean fractal dimension index	1.27	1.29	1.30
Mean Perimeter Area Ratio	967.9	964.1	1010.2
Edge density (m/ha)	109.5	111.9	117.8

4.3.4 Moving window vegetation fragmentation patterns

Table 4.4 shows the vegetation fragmentation statistics derived from the quantification of the forest fragmentation model. The core vegetation component slightly increased from 1994 to 2001. However, between 2001 and 2017, there was decreasing trend of core vegetation. It was 3709 ha in 2001 and declined to approximately 699 ha in 2017 suggesting the study area was losing a relatively higher percentage of core and interior vegetation patches as it becomes more fragmented. Lowly fragmented and undisturbed core vegetation areas connect the highest number of large and dense vegetation areas with lower inter-patch distances. Between 1994 and 2017, edge and transitional vegetation component indicated a decreasing trend (Table 4.4).

Table 4.4. Vegetation fragmentation using forest fragmentation model

Fragmentation pattern	1994	2001	2017
Core	3609.18	3709.8	699.48
Perforated	3129.75	2902.68	4602.96
Edge	14328.9	14289.93	8660.34
Transitional	8615.97	7860.51	7212.15
Patch	18475.65	17802.18	17449.02
Non vegetation	49902.84	51497.19	59439.69

Figure 4.5 shows that the core vegetation areas were mainly dominant in the northern side of Harare. The patch category, which represents the highest level of vegetation fragmentation and proportion of poorly and less connected vegetation, dominated the landscape over the 1994–2017 period as shown in Figure 4.5. Patch vegetation fragmentation patterns have many small, scattered and isolated vegetation patches. These are heavily concentrated in the southern, eastern and western side of the city. Perforated vegetation conditions show a relatively decreasing trend between 1994 and 2001 but increased in 2017.

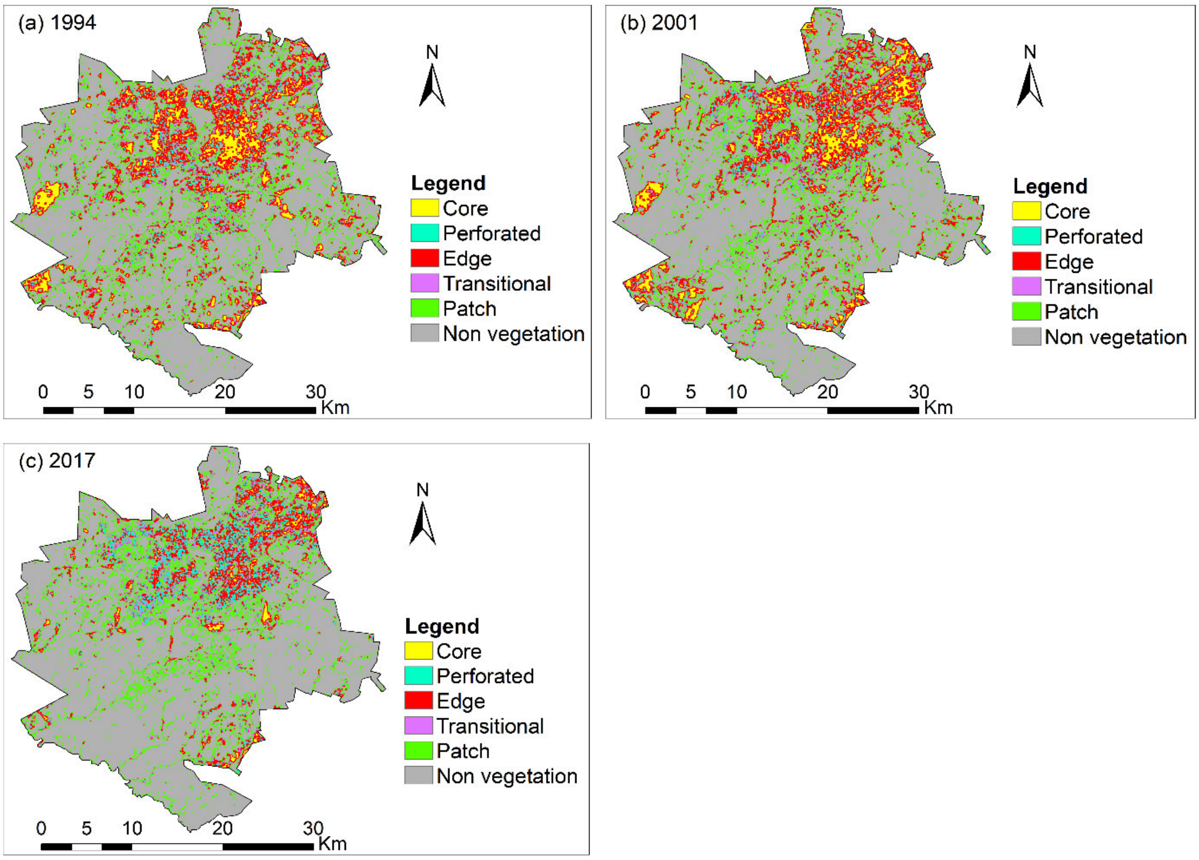


Figure 4.5. The spatial distribution patterns of vegetation fragmentation in Harare metropolitan city in (a)1994, (b) 2001 and (c) 2017 based on the forest fragmentation model.

4.3.5. The spatial patterns of vegetation connectivity

The vegetation connectivity index derived from the forest fragmentation model showed that most vegetation in the study area is not highly connected across the landscape. Vegetation connectivity between 1994 and 2017, indicated a general decreasing pattern, reflecting the increasing patch isolation of the corresponding vegetation patches. Figure 4.6 shows that areas with less connected vegetation are found in the western, southern and eastern part of Harare. These are illustrated with lower vegetation connectivity ranges (<0%−30%). Less connected vegetation (<0 %−30%) represent the highly fragmented nature of smaller vegetation patches, isolated and scattered across the landscape (Figure 4.6). Therefore, it is reasonable to assume that a decrease in vegetation cover and density inevitably leads to fragmentation and less connectivity. Areas with moderate to high-connected vegetation are located in the highly vegetated northern part of Harare. Moderately and highly connected vegetation have ranges of 50%–70% and above 70% respectively. Higher vegetation connectivity (i.e. less isolation of vegetation patches) have a greater proportion of high, contiguous and mean patch area reflecting shorter distances between vegetation patches.

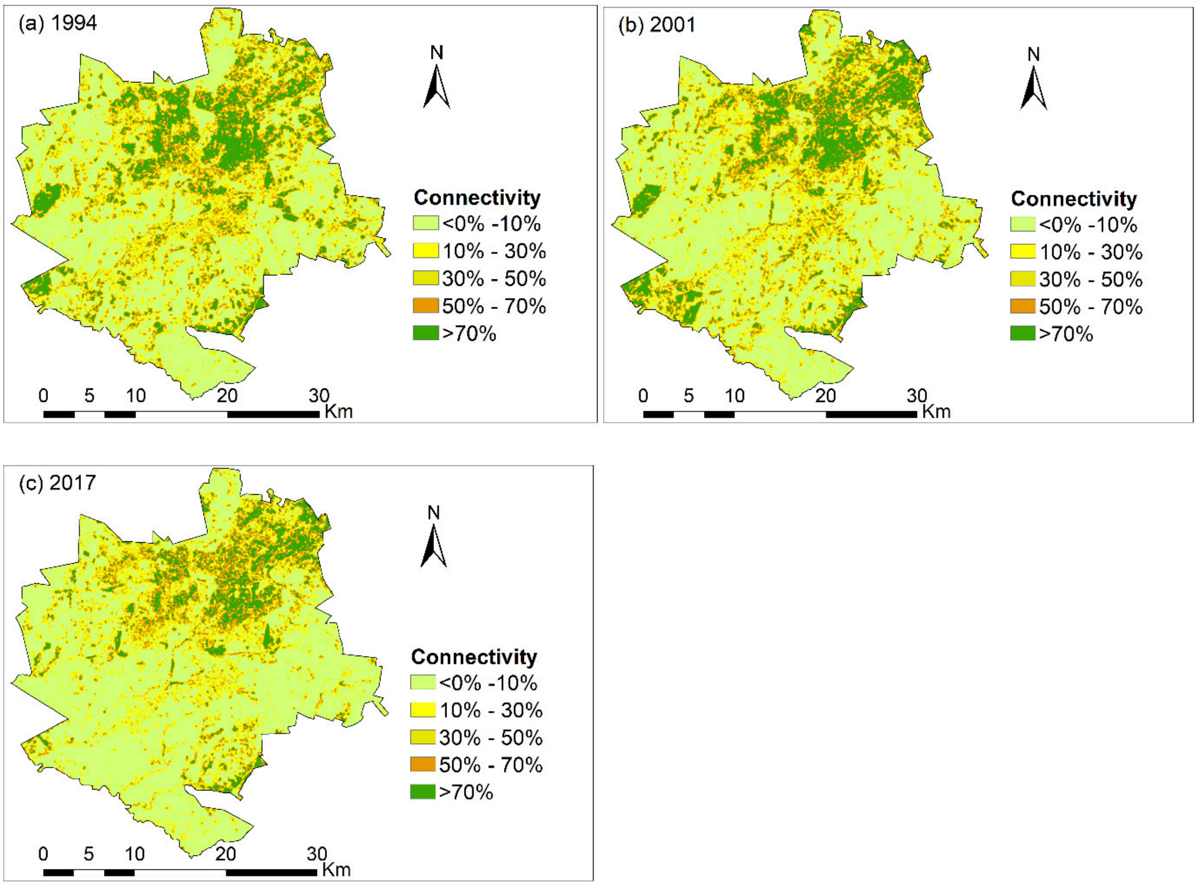


Figure 4.6 The spatial variability patterns of vegetation connectivity in 1994, 2001 and 2017.

4.3.6. Temporal variability of Getis Ord Gi*

The results of the Hot Spot Analysis (Getis-Ord Gi*) are shown in Table 4.5. Significant hot spots and cold spots of vegetation patches are indicated with statistical confidence levels ranging from 90% ($p < 0.10$), 95% ($p < 0.05$) and 99 % ($p < 0.01$). Table 4.5 shows that between 1994 and 2017, there were a slight decrease in the statistically significant hotspots and an increase in cold spots. The Getis Ord Gi* showed that the spatial clustering of vegetation ranged from being dispersed (negative values) to highly clustered (positive values) (Figure 4.7). The statistically significant hotspots were mainly concentrated in northern part of Harare metropolitan city, a more vegetated area of large and contiguous vegetation patches (Figure 4.7).

The statistically significant negative Z-scores of Getis-Ord Gi* were mainly concentrated in the western, eastern and the southern side of Harare (Figure 4.7). Generally, the southern, eastern and western side of the city has many isolated and sparse vegetation with highly fragmented vegetation patches (Figure 4.7). Furthermore, it is more densely urbanized than the vegetated northern part of the city. In areas where Getis-Ord Gi* values were significantly different from the surroundings, they were considered as neither hot spots nor cold spots. They were indicated as not significant because they were non-vegetation.

Table 4.5 Hot Spot Analysis (Getis-Ord Gi*)

Cluster type	1994 Area(ha)	2001 Area(ha)	2017 Area(ha)	Z-score	P-value (Probability)
Cold spot	2563.11	2417.85	2786.91	< -2.58	p< 0.01 (99%)
Cold spot	6922.58	1210.3	1309.87	< -1.96	p< 0.05 (95%)
Cold spot	690.068	1155.53	882.384	< -1.65	p< 0.10 (90%)
Not Significant	68694.6	78102.5	74964.3		
Hot spot	1451.33	298.467	526.142	> +1.65	p< 0.10 (90%)
Hot spot	1834.7	2672.51	879.644	> +1.96	p< 0.05 (95%)
Hot spot	15893.5	12168.7	16705	> +2.58	p< 0.01 (99%)

Overall, the findings of Hot Spot Analysis indicated the strong tendency for undisturbed and homogeneous vegetation patches to be spatially clustered. The results also suggest that in areas with high vegetation fragmentation patterns there are many small, isolated and sparse vegetation patches.

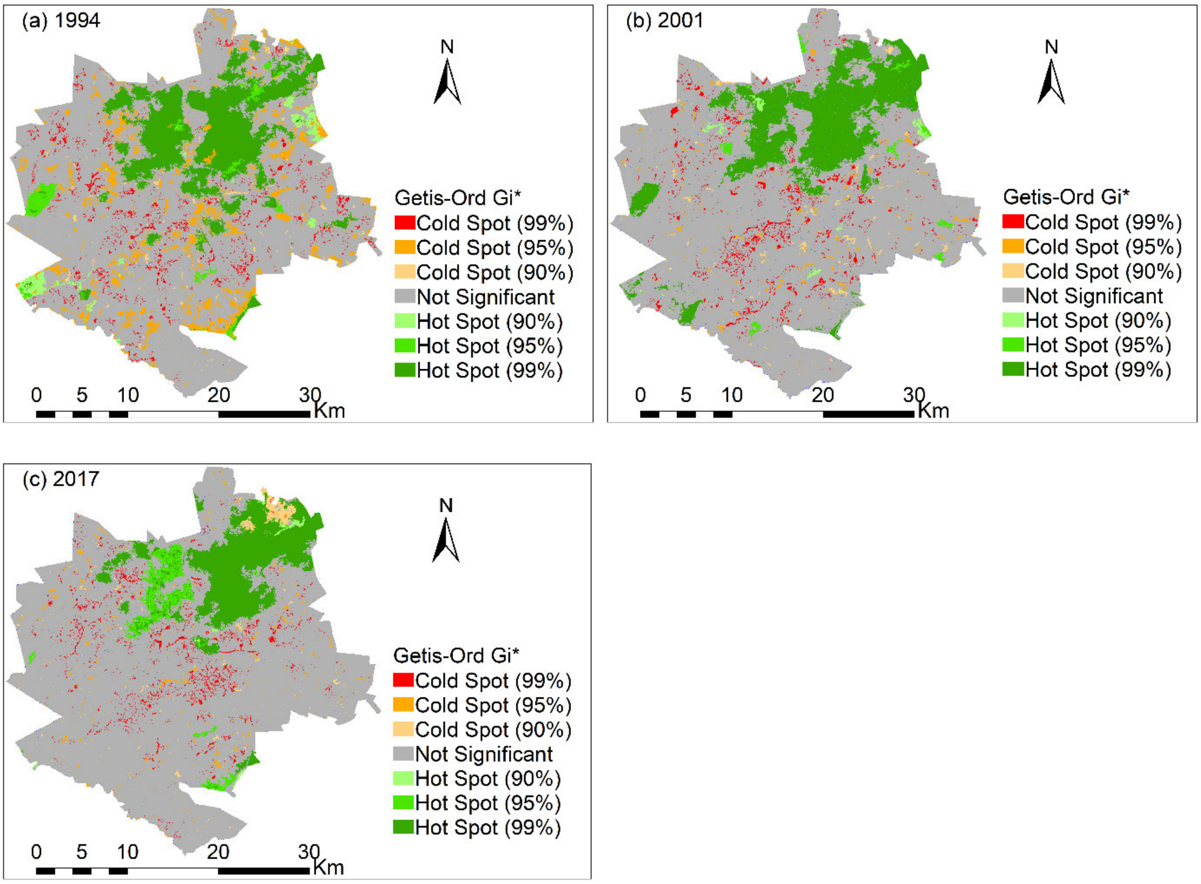


Figure 4.7 Getis-Ord Gi* in (a)1994, (b) 2001 and (c) 2017 with categories corresponding to regions of different statistical confidence (99%, 95% and 90%). Hot spots correspond to vegetation patches of large, contiguous or non-fragmented and lowly fragmented vegetation patterns. Cold spots correspond to vegetation patches of small, isolated, sparse or highly fragmented vegetation patterns.

4.3.7. Temporal variability of local Moran's 1

The results of local Moran's I were significantly different ($p < 0.05$) for the period 1994-2017. The mean values of local Moran's I were (0.39, $p < 0.05$) in 1994, (0.34, $p < 0.05$) in 2001 and (0.23, $p < 0.05$) in 2017. The results suggest a slight general decrease in spatial clustering of large and dense vegetation to small and scattered vegetation patches. The trend of decreasing local Moran's I dominated the entire landscape but notably in the western, eastern and the southern part of the city, which is occupied by dense built-up and residential areas. For this reason, lower positive and negative values of local Moran's I were detected in the western, eastern and the southern part of Harare, indicating low spatial clustering due to the presence of small and isolated vegetation patches. Areas with high positive values of local Moran's I were located in the highly vegetated northern part of Harare. High and positive values of local Moran's I implied the high spatial clustering of large and homogeneous dense vegetation as shown in Figure 4.8.

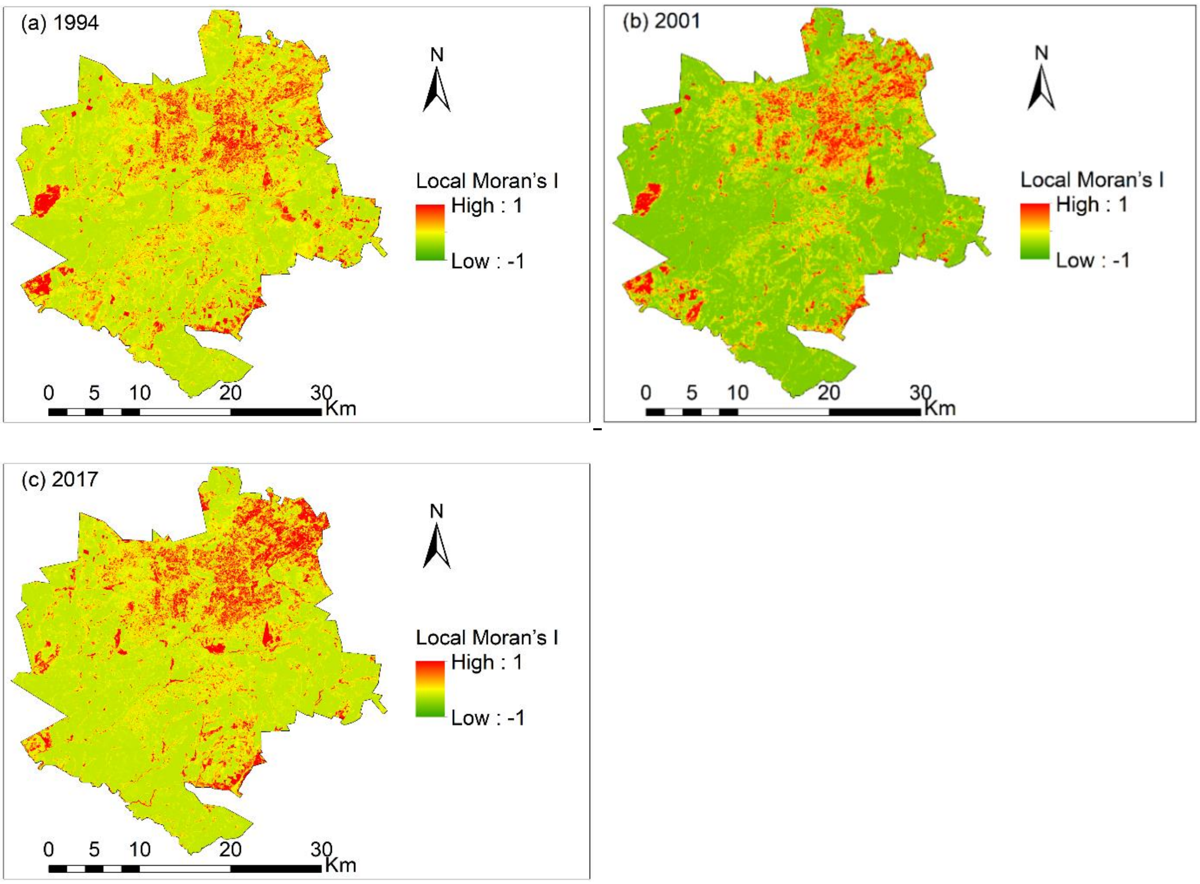


Figure 4.8. Local Moran's I in (a) 1994, (b) 2001 and (c) 2017. High positive values of local Moran's I represent highly clustered pattern and low positive and negative values represent highly dispersed patterns of vegetation.

4.3.8. Temporal variability of Tasseled Cap Angle (TCA)

Table 4.6 shows that the mean values of the TCA had a consistent decreasing trend between 1994 and 2017. The proportion of vegetation to non-vegetation was high in 1994 than in subsequent years. Change detection of TCA between (1994–2017) period indicated that vegetation in the landscape was constantly changing, not maintaining a significant amount of vegetation to non-vegetation.

Table 4.6. Descriptive statistics of TCA

	1994	2001	2017
Mean	189.56	164.38	160.44
Standard deviation	83.65	101.54	128.89
Skewness	0.43	0.85	0.91
Maximum	762.73	505.81	728.29
Minimum	-634.60	-454.11	-678.14

Of noteworthy is the dynamic change of the high positive TCA values indicative of a dense and high proportion of vegetation and of negative TCA values for non-vegetated areas. TCA was significantly lower in non-vegetation areas (negative TCA values) than in vegetated areas (positive TCA values). Based on the standard deviation and skewness, the lowest dispersion in TCA values occurred in 1994. In fact, both the standard deviation and skewness showed an increasing trend over the years (2001-2017), which could be an indication of increasing vegetation heterogeneity.

4.3.9. Comparative analysis of vegetation connectivity and continuous spectral indices

The relationships between selected Landsat derived spectral indices and vegetation connectivity are shown in Table 4.7. Tasselled Cap Brightness (TCB) was negatively related to historic vegetation connectivity between 1994 and 2017. This means that low vegetation connectivity is associated with high Tasselled Cap Brightness (TCB) and vice versa. Tasselled Cap Brightness (TCB) is particularly sensitive to an alteration in non vegetation areas (bareland, rocky outcrops and soil brightness).

The Landsat derived spectral indices of Tasselled Cap Greenness (TCG), Tasselled Cap Wetness (TCW), the Tasseled Cap Angle (TCA), NDVI (Normalized Difference Vegetation Index), Local Moran's I were moderately and highly positively related with vegetation connectivity for all three image dates. The comparative analysis of vegetation connectivity and continuous indices implies that connectivity of vegetation patches tend to increase when greenness (expressed by Tasselled Cap Greenness), vegetation cover (expressed by NDVI) is high and clustered (expressed by Local Moran's I), having a high proportion of vegetation to non-vegetation (expressed by TCA).

Table 4.7. Correlation coefficients between vegetation connectivity, local Moran 1 and Landsat spectral indices in 1994, 2001 and 2017 and Landsat spectral indices

Year		Vegetation Connectivity	TCG	TCB	TCW	TCA	Local Moran's I	NDVI
1994	Vegetation Connectivity	**1**	.623**	-.349**	.576**	.726**	.774**	.707**
	TCG	.623**	**1**	-.215**	.363**	.463**	.494**	.447**
	TCB	-.349**	-.215**	**1**	-.219**	-.249**	-.263**	-.252**
	TCW	.576**	.363**	-219**	**1**	.422**	.452**	.417**
	TCA	.726**	.463**	-249**	.422**	**1**	.621**	.520**
	Local Moran's I	.774**	.494**	-263**	.452**	.621**	**1**	.558**
	NDVI	.707**	.447**	-252**	.417**	.520**	.558**	**1**
2001	Vegetation Connectivity	**1**	.675**	-.296**	.561**	.699**	.655**	.604**
	TCG	.675**	**1**	.183**	.383**	.505**	.481**	.381**
	TCB	-.296**	.183**	**1**	.171**	-192**	-.168**	.172**
	TCW	.561**	.383**	.171**	**1**	.396**	.372**	.311**
	TCA	.699**	.505**	-.192**	.396**	**1**	.489**	.390**
	Local Moran's I	.655**	.481**	-.168**	.372**	.489**	**1**	.363**
	NDVI	.604**	.381**	.172**	.311**	.390**	.363**	**1**
2017	Vegetation Connectivity	**1**	.593**	-.333**	.555**	.723**	.600**	.548**
	TCG	.593**	**1**	.179**	.332**	.464**	.394**	.295**
	TCB	-.333**	.179**	**1**	.203**	217**	-.192**	-.160**
	TCW	.555**	.332**	.203**	**1**	.405**	.339**	.267**
	TCA	.723**	.464**	.217**	.405**	**1**	.472**	.370**
	Local Moran's I	.600**	.394**	-.192**	.339**	.472**	**1**	.291**
	NDVI	.548**	.295**	.160**	.267**	.370**	.291**	**1**

Note: TCA (Tasseled Cap Angle); TCW (Tasseled Cap Wetness); TCG (Tasseled Cap Greenness); TCB (Tasseled Cap Brightness); NDVI (Normalized Difference Vegetation Index), local Moran's I. ** Correlation is significant at the 0.01 level (2-tailed).

4.4. Discussion

This study analysed the long-term vegetation fragmentation and spatial clustering in an urban landscape based on the utility of discrete and continuous representation of landscape structure. The historical freely available Landsat satellite data enabled the study of vegetation fragmentation change in Harare metropolitan city dating from 1994 to 2017. The results of landscape metrics and forest fragmentation model demonstrate that the reduction in the core vegetation cover decreases the size of the fragments or patches, as well as increasing the isolation and the number of small vegetation patches. The results of LISA showed that the vegetation in study area was more spatially clustered before 1994. In later years, especially in 2017, gradually large and connected vegetation patches became more scattered and fragmented. Although there was a general increase in vegetation fragmentation between the 1994–2017, those changes were not uniform with some areas showing distinct patterns.

In our study, the two LISA indices of Getis-Ord Gi* and Local Moran's I indicated where the more homogeneous (clustered) and heterogeneous (fragmented) areas occur spatially and indicate the location of occurrence within the landscape. Both Getis-Ord Gi* and Local Moran's I statistics showed that the homogeneous (clustered) vegetation had high positive spatial autocorrelation. Conversely, small, isolated and scattered vegetation patches had low positive and negative spatial autocorrelation. LISA was able to show explicitly areas associated with specific vegetation clusters. The significant spatial clusters of vegetation (hot spots) and the highest proportion of undisturbed stable core vegetation were located in state protected and large parks in the northern part of Harare metropolitan city. The findings demonstrated the role of public institutions, various state and government departments in maintaining large patches of green cover in the core areas as observed in other urban areas including Melbourne (Dobbs et al. 2013) and Bangalore (Nagendra et al. 2012). Public green spaces, vegetation in state protected large parks and various institutions like Harare City Council, Forestry Commission (Ministry of Environment), The National Museums and Monuments of Zimbabwe (NMMZ), Environmental Management Agents (EMA), Zimbabwe Parks and Wildlife Management Authority (Zimparks).

On the other hand, highly fragmented and heterogeneous patterns of small, isolated and scattered vegetation patches detected as cold spots in LISA indices were mainly concentrated in the highly and densely built-up western, eastern and southern side of Harare. Over the years, there has been a pattern of increased urban sprawl in Harare with open spaces and natural vegetation being rapidly converted into built-up areas. The world has also witnessed accelerated and high urbanization during the last decades (Liu et al. 2016b), significantly causing habitat loss and vegetation fragmentation (Swenson and Franklin 2000). During urbanization, large areas of contiguous and natural habitat are converted into built-up and impervious surfaces causing habitat (forest, woodland, grassland) loss and fragmentation of the large core and interior vegetation into smaller patches (Liu et al. 2016a, Nor et al. 2017).

It has been shown in several studies that rapid urban expansion and urbanization leads to decrease in patch fragment sizes and increase in the number of patches and a high amount of edge habitats (Gong et al. 2013, Grimm et al. 2008, Hall et al. 2002, Hepcan 2013, Jiao et al. 2017, Liu et al. 2014, Nagendra et al.2012, Paul and Nagendra 2015, Wang and Wang 2009, Tian et al. 2011). In Delhi, India's capital city, Paul and Nagendra (2015) observed that vegetation was highly fragmented with an increase in the patch and edge area because of rapid urban growth. More vegetation fragmentation was severe in the periphery and the peri-urban areas. The least fragmented vegetation were found in large parks in the urban core of the city (Paul and Nagendra 2015). The increasing vegetation fragmentation has been recognised not only in the cities of the developing regions but also in the developed world including USA and Europe. In the USA, Hill (1985) examined the forest fragmentation in central New York and Rogan et al. (2016) assessed the forest fragmentation in Massachusetts towns. Petrişor et al. (2016) documented fragmentation of the urban green spaces in Romanian cities. In Europe, widespread urbanisation, land-use change, intensification and other developments have resulted in the loss and fragmentation of its green spaces (Mazza et al. 2011). In Asia, Tian et al.(2011) examined green space fragmentation in Hong Kong. However, vegetation in less developed regions is often more isolated and fragmented because urbanization and economic growth are regarded as a higher priority than maintaining urban vegetation (Grimm et al. 2008).

Moving window models of connectivity and fragmentation are valuable in computing patterns and degree of vegetation fragmentation at specific geographical locations within the landscape. Using the moving window forest fragmentation model, categories and levels of vegetation fragmentation are visually and well represented and easily understood. Unlike landscape metrics that do not spatially and explicitly show where and how the degree of vegetation fragmentation varies across space, the forest fragmentation model as demonstrated in this study can spatially show the degree to which that vegetation is fragmented. Furthermore, unlike other connectivity methods, the connectivity index (P_{ff}) of vegetation derived from forest fragmentation model has an added advantage that it does not require specification of an arbitrary edge and Euclidian distance to define a core area within a vegetation patch. It explicitly quantify the proportion of a landscape occupied by vegetation patches. Dense and intact vegetation will have high vegetation connectivity percentages, while the isolated and lower density of vegetation represents low vegetation connectivity percentages.

The forest fragmentation model has important implications and significance to conservation efforts. Using the forest fragmentation model, one strategy that can be used to identify large regions for conservation might be based on the dynamics of the core, interior, edge or perforated vegetation conditions. However, the forest fragmentation model has been observed to be sensitive to scale (Dong et al. 2014, Millington et al. 2003,Riitters and Wickham 2012). Usually, the large spatial window size in forest fragmentation model tends to reduce the amount of core or interior vegetation areas. It is important therefore for ecologists, environmental managers and decision makers to use and apply the forest fragmentation model at an appropriate scale depending on the policy under consideration.

Our results revealed a significant positive relationship between Landsat derived indices (Local Moran's I, Tasselled Cap Greenness, Tasselled Cap Wetness, The Tasseled Cap Angle and Normalized Difference Vegetation Index) and vegetation connectivity, highlighting that the spatial connectivity of vegetation patches tend to be higher and connected when the proportion of vegetation cover is large and contiguous. This confirms the hypothesis that vegetation patch connectivity increases as patch isolation decreases and vice versa (D'Eon et al. 2002). In ecological studies, vegetation connectivity is important for understanding species or community diversity and composition and how species are exposed to threats from predators or invasive species.

Unlike traditional techniques that could have confounded additional interpretation of change in vegetation patterns, tasselled cap transformation components like TCA are uncorrelated and contain enhanced biophysical information (Masek et al.2008). The Tasseled Cap derived indices used in this study captured important insights relating to both positive and negative changes in the fraction of vegetation to non-vegetation between 1994 and 2017. Areas that were more densely occupied by vegetation had higher and positive values of TCA than geographical locations with less dense vegetation as indicated with negative values of the TCA. The TCA highlighted that between 1994–2017, vegetation was highly dynamic, significantly not maintaining a high amount of vegetation to non-vegetation. Overall, the combination of Landsat spectral indices (TCA, TCW, TCG, TCB, NDVI and local Moran's I) and its relationship with vegetation connectivity showed that vegetation cover was becoming more disperse and less connected after 1994.

4.4.1 Implications for the study of vegetation fragmentation and landscape ecology

One of the challenges in the study of spatial and temporal dynamics of vegetation fragmentation is to provide an accurate and effective characterization of spatial heterogeneity in a detailed and meaningful way to link important ecological patterns and processes (Gustafson 1998). This study took a spatial explicit approach in analysing the long term quantification of vegetation fragmentation patterns in the urban landscape. This was done by combining landscape metrics, forest fragmentation model, LISA indices and Tasselled Cap indices derived from time series Landsat data of continuous NDVI and discrete vegetation and non-vegetation data.

Discrete landscape metrics derived from land cover and image classifications are extensively used in linking landscape pattern and ecological processes occurring in a landscape (McGarigal and Marks 1995, O’Neill et al. 1988, Turner and Gardner 1991). They provide useful quantitative and ecological information on aspects of landscape pattern including patch size variability, patch shape complexity, density, aggregation, isolation and connectivity (Southworth et al. 2004). However, discrete landscape metrics indices were developed to understand crisp and homogenous landscapes, for instance, the European and North American and agriculture landscapes (Southworth et al. 2004).

Furthermore, it has been repeatedly reported that many landscape metrics widely used in landscape ecology are highly correlated with each other (Uuemaa et al. 2009). Discrete landscape metrics have challenges in uniquely representing and capturing gradual and continuous variation in landscape for example in land cover change as significant information is lost (DeFries et al. 2000, McGarigal et al. 2009). Furthermore, discrete or categorical landscape metrics are conceptually simple. Landscape metrics can accurately map broadly vegetated and unvegetated areas in natural landscapes. However, they have challenges in detecting critical transition zones or within-patch variability patterns (Southworth et al. 2004) particularly in urban areas. Vegetation in the urban landscape is highly heterogeneous in space and time (Fahrig 2003). Thus, quantitative approaches such as those based on landscape fragmentation theories (Fahrig 2003), that map landscape patterns of urban vegetation as rather static or homogenous unit may fail to identify relevant long term spatio-temporal patterns affecting ecological processes.

The advantage of local spatial autocorrelation indices over other approaches of quantifying landscape structure is that it allows environmental variation to be distinctly represented in a pixel across the image. This is because LISA statistics uniquely utilise both the differences between pixel values and spatial arrangement of the image data (Read and Lam 2002). As demonstrated in this study, LISA statistics can effectively utilize unclassified raw data like remotely sensed NDVI. The advantage of using the continuous raw data is that it eliminates the subjective land cover classification process and a lot of uncertainty related to the discrete categorization and representation of landscape, especially in heterogeneous urban areas because of mixed pixels challenges.

Southworth et al.(2004) demonstrated that local indicators of spatial associations (LISA) indices derived from NDVI data could capture subtle changes and natural spatial variability of forest patterns in mountainous Celaque National Park in western Honduras. This is in sharp contrast to widely used landscape metrics that often overlook fine-scale and detailed spatial heterogeneity through categorical map delineation into subjective homogenous areas leading to significant uncertainties and errors (Fan et al.2015, Southworth et al.2004). LISA indices are generally parametric and provide additional information as they are calculated for each pixel in the input image data unlike landscape metrics that tend to use less information (Southworth et al. 2004). In our study, LISA statistics of Anselin local Moran’s I and Getis-Ord Gi* provided a spatial explicit detection of homogeneous and heterogeneous of vegetation patterns. From a conservation and restoration perspective, the homogeneous and connected vegetation patches have a high probability of favouring the persistence of animal species due to the maintenance of metapopulation dynamics. On the other hand, the heterogeneous vegetation patches have high probability of being at risk due to their low connectivity and small patch size mainly affected by the immense impact of rapid urban expansion.

4.5. Conclusions

This study quantified long-term spatial clustering and vegetation fragmentation analysis in Harare metropolitan city in Zimbabwe and there was evidence that the vegetation cover was coalescing into fewer, isolated and smaller vegetation patches. Continuous methods like LISA indices provide much detail in image data representing the subtle, within-class variability variation and continuous heterogeneity of vegetation fragmentation across the landscape. LISA indices may complement the information found in traditional discrete landscape metrics in evaluating vegetation fragmentation. Combining the continuous and discrete models of landscape structure of landscape pattern indices, forest fragmentation model, local indicators of spatial associations (LISA) and Landsat Tasseled Cap Transformation (TCT), promotes future work in improving greater understanding of land transformation patterns and processes is an important theme of landscape ecology.

CHAPTERS FIVE AND SIX

LANDSCAPE PATTERN AND SPATIAL CONFIGURATIONS OF VEGETATION AND ITS IMPACTS ON THE URBAN SURFACE TEMPERATURES

5.LINKING LANDSCAPE PATTERN AND SPATIAL CONFIGURATION OF URBAN VEGETATION WITH URBAN WARMING AND COOLING

This chapter is based on:

Pedzisai Kowe, Onisimo Mutanga, John Odindi, Timothy Dube, "Effect of landscape pattern and spatial configuration of vegetation patches on urban warming and cooling in Harare metropolitan city," GIScience and Remote Sensing**, Under revision**

Abstract

The spatial configuration of urban vegetation in a landscape has socio-economic and ecological implications in the provision of essential ecosystem services and goods, human adaptation to climate change, increasing or reducing urban surface temperatures. Until recently, the role of spatial configuration of urban vegetation to enhance or mitigate urban heat island has received little consideration in urban thermal assessments. This study examines the role of spatial configuration and landscape pattern of vegetation on urban warming and cooling in Harare metropolitan city, Zimbabwe. The study used Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) data acquired on 03 September 2010, Landsat 8 acquired on 28 October 2013 and 23 October 2017 and Sentinel 2 acquired on 24 October 2017 to derive detailed information on vegetation patches, landscape metrics and land surface temperature (LST°C). The spatial configuration of urban vegetation patterns was analysed using landscape metrics in Fragstats program. Pearson correlation coefficient was applied to examine the relationship between spatial configurations of vegetation patches and land surface temperature. A local spatial statistic, Getis Ord Gi* was used to characterize the spatial clustering and dispersion of urban vegetation patches. Results of the Getis Ord Gi* showed that clustered or aggregated vegetation patterns reduces land surface temperatures more effectively than dispersed and fragmented patterns of vegetation. The size, density, shape complexity and cohesion of vegetation patches conferred different levels of cooling but Patch Cohesion Index had the strongest negative relationship with LST (°C) at three spatial resolutions of 10m (Sentinel 2), 15m (ASTER) and 30m (Landsat 8). The relationship between LST (°C) and spatial configuration of landscape metrics was better captured and estimated by the Spatial Lag Regression model than the Ordinary Least Squares regression. Specifically, the Spatial Lag Regression model showed higher R^2 values and log-likelihood, lower Schwarz criteria and Akaike Information Criterion. The overall information provided important insights on the influence of large, well connected, less fragmented urban vegetation patches in the contribution of maximum and higher cooling effects, which is critical for urban planning and design approaches for mitigating increasing surface temperatures in cities.

Keywords:

Urban warming and cooling; Getis Ord Gi* ; Land surface temperature; vegetation; Landscape metrics; Harare

5.1 Introduction

With increasing urbanization, climate change and global warming, urban heat island (UHI) effects (Oke 1982, Voogt and Oke 2003) are growing in magnitude across space and time (Gabriel and Endlicher 2011, Gill et al.2007, Wang and Akbari 2016). Urban heat island effects causes higher surface temperatures and increases the number of warm nights in cities than in less developed, rural and surrounding areas (Oke 1982). Urban warmth and high surface temperatures can reduce annual energy consumption in cold climates (Svensson and Eliasson 2002), but the reverse is true in warm and tropical cities where summer air conditioning demand loads far outweigh potential savings in energy use for heating during winter (Santamouris et al. 2001). Intensified UHI can lead to increased demands for water consumption (Guhathakurta and Gober 2007), degraded water quality (Arnold Jr and Gibbons 1996) and higher levels of air pollutants (Lai and Cheng 2009). UHI worsens the thermal comfort conditions, heat-related health problems and welfare of urban dwellers (Tomlinson et al. 2011). The urban heat island impacts are severe in summer season, when heat released from the urban infrastructure at night increases the duration and intensity of heat waves (Tomlinson et al. 2011).

Urban green spaces (UGSs) and vegetation cover including urban parks, street trees, lawns, woodlands, forests, grasslands, playgrounds and green belts play a significant part in the urban climate discourse (Dobbs et al. 2014, Gill et al. 2007) in mitigating the impacts of the UHI phenomena. For instance, in the city of Nanjing in China, Kong et al.(2014) observed a significant decrease of land surface temperature (LST) by 0.83°C following a 10% increase in forest cover. Urban trees and green spaces through evapotranspiration and shading reduce surface temperatures, which may subsequently lower demand for energy required to cool buildings during the hot season. The positive influence of urban vegetation in alleviating urban warming has already been established through in situ field measurements, thermal remote sensing of land surface temperature (LST) and computer modelling (Farhadi et al. 2019, Lai et al. 2019). Over the past ten years, substantial scholarly work have studied the spatial patterns of urban vegetation cover on UHI phenomenon (Akbari and Kolokotsa 2016, Aram et al. 2019).

However, current knowledge of the effects of urban vegetation on LST is not comprehensive as it ignores the possible influence of landscape pattern and the spatial configuration of vegetation patches such as edge density, shape complexity, size, aggregation, connectivity and fragmentation on their cooling effect (Masoudi et al. 2019). The results of a few number of previous research work indicate that the landscape pattern and the spatial configuration of urban vegetation patches have significant impacts on LST and can be used to lower the urban surface temperatures (Asgarian et al. 2015, Bao et al. 2016, Chen et al. 2014, Connors et al. 2013, Estoque et al. 2017, Huang and Cadenasso 2016, Kong et al. 2014, Li et al. 2012; 2016; 2017, Maimaitiyiming et al. 2014, Zhang et al. 2009, Zhibin et al. 2015, Zhou et al.2011). A set of landscape metrics have often been employed to quantify the landscape pattern or the spatial configuration including patch size, shape complexity, edge density, diversity, and connectivity metrics (Connors et al. 2013, Kong et al. 2014, Li et al. 2017, Peng 2016). For instance, urban green spaces and vegetation with more irregular and complex shapes were previously demonstrated to produce higher cooling effects (Asgarian et al.2015, Chen et al. 2014, Estoque et al.2017, Li et al.2012, Zhang et al.2009, Zhou et al. 2011). Other research work have demonstrated that the patch size of urban green space is responsible for higher cooling effects in a city (Feyisa et al. 2014, Hamada et al.2013).

Despite the fact that the spatial configuration is strongly influenced by underlying ecological processes and patterns, however not all landscape metrics that exhibit landscape configuration properties are responsible for the energy flow, exchanges and thermal processes in urban thermal environment (Chen et al.2016). In addition, most landscape metrics create serious redundancy challenges in interpreting their role in urban thermal studies because they are highly correlated with each other (Song et al.2014, Uuemaa et al.2013). There are still some uncertainties and inconsistencies regarding the effects of other spatial configuration patterns such as connectivity and aggregation of vegetation patches on the resultant cooling and warming of the urban environment. For instance, the positive effects of spatial patterns of connectivity and aggregation of urban vegetation have been observed in some studies (Asgarian et al.2015, Chen et al.2014, Estoque et al.2017, Zhibin et al.2015). On the other hand, some studies (Bao et al. 2016, Chen et al. 2014a, Li et al. 2012; 2013, Zhou et al. 2011) have reported that landscape connectivity of vegetation is responsible for raising high surface temperatures. Therefore, appropriate selection of landscape metrics that uniquely capture heat exchanges and thermal processes in an urban area is important in exploring the impact of landscape configuration on LST (Chen et al. 2016).

Since most of these landscape metrics indiscriminately categorize land cover category into homogenous units, they do not entirely capture the dispersed and clustered patterns of spatial objects and overlook other natural variations in a landscape (Fan and Myint 2014, McGarigal and Cushman 2005, McGarigal et al. 2009, Myint et al. 2015). Consequently, most UHI studies do not consider spatial configurations of spatial objects and land cover features as continuous surfaces but rather as discrete spatial variation resulting in loss of vital information (Myint et al. 2015). The ultimate result has been that effects of spatial autocorrelation of LST are not taken into account in most existing UHI studies (Chen et al. 2006, Li et al. 2011, Zhou et al. 2011) when conducting bivariate and multiple correlation and regression analysis between LST and landscape indices.

To address the limitations associated with discrete landscape metrics, an alternative and effective approach is to use continuous methods of local spatial statistics, otherwise called Local Indicator of Spatial Association (LISA) indices. Previous studies have indicated that the local Moran's I index is very effective in characterizing the impact of clustered and dispersed spatial configurations and composition patterns of vegetation cover (Fan et al. 2015), impervious surface area (Wu et al. 2019) and other land cover categories (Myint et al. 2015, Zheng et al 2014) on surface temperatures. Compared with local Moran's I index, the utility of Getis-Ord Gi* has largely been ignored and not explored in examining the spatial configurations of clustered and dispersed vegetation on UHI studies. Only recent applications of Getis-Ord Gi* statistics in UHI studies, have analysed the LST pattern change through time to assess the impacts of land use and land cover dynamics and urbanization on UHI effects (Tran et al. 2017) and to identify the high concentration of the LST visually across an urban landscape (Adeyeri et al. 2017, Tran et al. 2017).

Furthermore, the response or sensitivity of landscape metrics at different spatial resolution on LST relative to the spatial heterogeneity of urban vegetation has not been extensively explored. Previous studies have mainly examined these relationships at a single scale as derived from remote sensing and other data sources. The issue of spatial resolution is relevant in urban thermal studies as landscape metrics have been shown to be susceptible to scale of the observation or analysis (Turner et al. 1989, Wu et al. 2000, Wu et al. 2002) as well as their relationships with land surface temperature (Kong et al. 2014, Li et al. 2013, Song et al. 2014). The spatial configurations and landscape patterns of urban vegetation have landscape planning and urban heat island implications at different spatial resolution and scales. The land surface temperature is significantly influenced by the energy flows and heat exchange between patches in diverse landscape (Adams and Smith 2014). Various spatial resolution and scales could influence the distribution of energy flows, heat exchanges in the landscape, thus resulting in diverse thermal effects and processes (Berger et al. 2017, Chen et al. 2017, Forman 1995, Turner 2005, Zhou et al. 2014).

However, to date, the spatial configuration studies of land cover patterns of urban green vegetation on LST have largely been performed mainly in cities of the United States of America (Buyantuyev and Wu 2010, Maimaitiyiming et al. 2014, Myint 2012, Myint et al. 2013 and 2015) and China (Kong et al. 2014, Li et al. 2012, Zhang et al. 2009, Zhang et al.2013). Cities from Africa are largely ignored. The conclusions and implications for urban heat island mitigation drawn from these undertakings may not be conclusive and comprehensive mainly due to limitations of the geographical locations, different climate conditions and patterns of urban and economic growth levels. Given this background, the objective of this study was to examine how landscape pattern and the spatial configuration of urban vegetation significantly enhance or mitigate the urban warming in the Harare metropolitan city, Zimbabwe. The study further examined the effects and sensitivity of different spatial resolutions on the relationship between land surface temperature and the spatial configuration of vegetation using spatial regression models.

5.2 Materials and Methods

5.2.1 Study area

This research work was conducted in Harare metropolitan city, which is situated in the northeastern part of Zimbabwe. It is found at 17.83° latitude and 31.05°longitude (Figure 5.1). The city has an area of approximately 980.6 square kilometres. The Harare metropolitan city encompasses Harare urban and rural, satellite towns of Epworth and Ruwa to the east and Chitungwiza to the south (ZIMSTAT 2012). Harare is Zimbabwe's economic hub, administrative capital and the largest city. The population of Harare in the year 2012 was 2.1 million (ZIMSTAT 2012). Harare metropolitan city is characterized by mainly low lying areas in the southern part and is generally hilly in the northern part. The city falls within the subtropical highland climate, which is mild and cool with relatively longer sunshine hours. It experiences warm summers (with an average temperature of 26°C) and cold winters (with an average temperature of 10°C).

The western, southern and eastern parts portion of the Harare metropolitan city is largely composed of urban and built-up areas with the dominance of high-density residential areas. The northern portion is largely vegetated with predominance of low-density residential areas.

Despite being a highly built-up and urbanized city, there are protected forest and vegetated areas in Harare, which include Haka Game Park (Cleveland dam vegetation), Mukuvisi Woodlands, Harare Kopje, Harare botanical gardens and the vegetation surrounding the Harare National Heroes Acre.

Harare metropolitan city was selected for this study because it has witnessed a rapid urban expansion wave during the last decades (Kamusoko et al. 2013) and the trend is expected to continue (Mushore et al.2017) mostly replacing open spaces and surrounding natural habitats (grassland and remnant forests). Such rapid urban expansion is responsible for the loss of vegetation and consequently generates high urban surface temperatures leading to urban heat island effects.

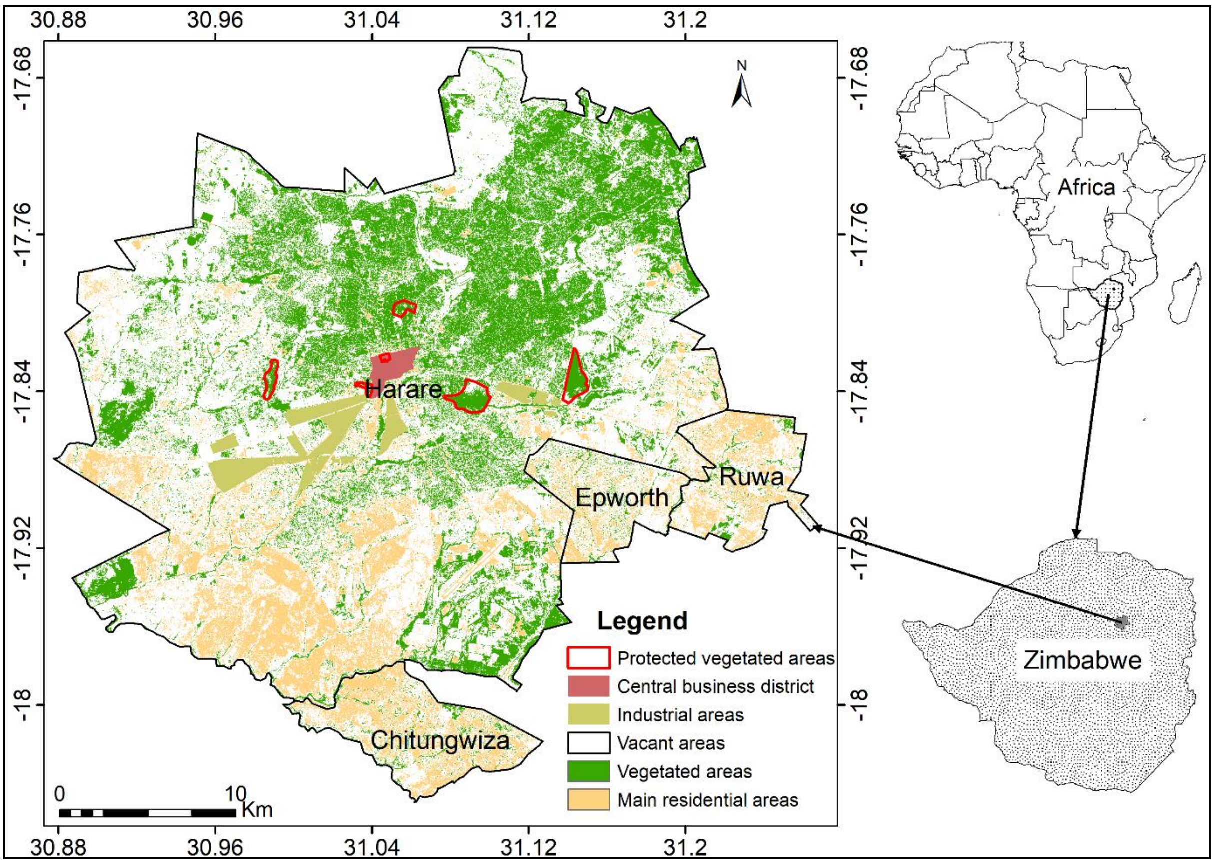


Figure 5.1. The geographical location of the study area, Harare metropolitan city in Zimbabwe.

5.2.2. Satellite data

The data used in this study consist of four satellite images, an Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER), a Sentinel 2 Multispectral Instrument (MSI) and two Landsat 8 data carrying both the Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) (Table 5.1). The satellite imagery data were freely downloaded from Earth Explorer United States Geological Survey website (http://earthexplorer.usgs.gov/). The satellite data were in a dry season because the images were cloud free and with more stable atmospheric factors. Only ASTER imagery was acquired in September rather than in October due to cloud coverage challenges. Dates of image acquisition were paired closely to help ensure consistency in vegetation phenology, comparison of land cover classification and in accurately distinguishing vegetation and non vegetation coverages.

The acquired satellite datasets were used to derive detailed vegetation areas, landscape metrics and summer daytime land surface temperature (LST). It is one of the most widely used indicator of surface-energy balance (Voogt and Oke 2003) which is sensitive to surface characteristics. Land surface temperature data and information derived from the thermal infrared imagery have been instrumental in capturing urban heat island effects (Weng et al 2004). In general, thermal image data have coarser spatial resolution than shorter wavelength bands, which can be shortcoming in urban landscape studies in general and UHI studies in particular because of the requirement of spatially detailed data. For example, the spatial resolution of ASTER and Landsat 8's thermal bands are 90m and 100m respectively, despite both image data having resolutions of 15m and 30 for other multispectral bands, respectively. While airborne sensors like Airborne Topographic Laser System (ATLAS) and Airborne Hyperspectral Scanner (AHS) can offer a greater and finer spatial and thermal resolution, however, airborne data have a disadvantage of small spatial coverage at a cost to most end users compared to freely available moderate resolution sensor data.

Similarly, high resolution satellite data were not used in this study as these are also costly and not accessible for most users and most of them do not have thermal bands. Although low and coarse resolution data like Moderate Resolution Imaging Spectroradiometer (MODIS) on the Terra and Aqua satellites and Advanced Very High Resolution Radiometer (AVHRR) are readily available, they have limitations in accurately depicting detailed land cover in complex urban areas because of challenges of mixed pixels. Low-resolution satellite images like MODIS and AVHRR are useful only for coarse-scale urban landscape mapping.

Table 5.1 Satellite image data

Satellite data	Spatial resolution (m)	Date of Acquisition
ASTER	15m(VNIR) and 90m (TIR)	09 September 2010
Landsat 8	30m(VNIR) and 100m (TIR)	28 October 2013
Sentinel 2	10m (VNIR)	24 October 2017
Landsat 8	30m(VNIR) and 100m (TIR)	23 October 2017

Visible and Near Infrared (VNIR), and the Thermal Infrared (TIR)

5.2.3 Urban green areas and vegetation extraction

The acquired satellite data were classified into five land cover classes (vegetation, grassland, built-up, water, and bareland) based on the supervised image classification approach. The powerful Support vector machine learning algorithm in the ENVI 5.3 software image processing software was used to classify the images. Later, the classified land cover map was reclassified into a binary vegetation and non-vegetation map for subsequent landscape analysis. A value of one and zero was assigned to vegetation and non-vegetation pixels, respectively.

A land cover accuracy assessment was performed based on ground reference data derived from Google imagery of 2010 (ASTER), 2013 (Landsat 8) and 2017 (Sentinel 2 and Landsat 8). The overall accuracy of the error matrix was computed by dividing the total number of correctly classified pixels (sum along the major diagonal) by the total number of validation plots, known as percentage correct (Congalton and Green 1999). A non-parametric Kappa test was used to compute the land cover classification accuracy as it accounts for all the elements in the confusion matrix rather than the diagonal elements. The Kappa coefficient was calculated following the procedure given by Congalton and Green (1999).

5.2.4 Spatial configuration analysis of urban green vegetation

Since most landscape metrics are often correlated with one another and they should be relatively independent of each other with minimal redundancy, we only selected a suite of landscape metrics based on their widespread use in landscape analysis, their easy interpretation and their relevance as indicators of ecosystem functioning (McGarigal et al. 2002, Wu 2004, Riitters et al. 1995). After computing several landscape metrics, only five landscape metrics indices including Edge density (ED), Mean Patch Size (MPS), Area Weighted Mean Shape Index (AWMSI), Area Weighted Mean Patch Fractal Dimension (AWMPFD) and Patch Cohesion Index (Table 5.2) were employed in this research work. The landscape metrics were quantified based on the binary vegetation and non-vegetation data in the FRAGSTATS 4.2 software (McGarigal et al. 2002).

The selected and computed landscape metrics indices accounted for divergent and important dimensions of the landscape patterns and configurations of size, density, shape, isolation and connectivity of urban vegetation patches. A lower Mean Patch Size values are usually associated with a more fragmented land cover pattern in a landscape. AWMSI and AWMPFDI are simple measures of patch shape complexity. The higher the values of AWMSI and

AWMPFDI, the more complex and irregular the patch shape of a land cover category. The Patch Cohesion Index assesses the contiguity of the shape and the percentage of physically connected patches. Patch Cohesion index (COHESION) varies between 0–100%. Patch Cohesion Index is higher when there are more physically connected pattern of patches in a landscape and vice versa (McGarigal et al. 2002). A more detailed description of each landscape metric can be found in (McGarigal et al. 2002).

Table 5.2: Description of landscape metrics used in the study area.

Landscape metrics	Description
Mean Patch Size/Area	The average mean surface of patches
Area-Weighted Mean Shape Index	A larger value of SHAPE_AM means the area is more complex and irregular in shape
Area-Weighted Mean Fractal Dimension Index	Fractal dimension: ratio of perimeter per unit area. Increases as patches become more irregular
Patch Cohesion Index	Increases as the patches of the corresponding patch type become less connected.
Edge Density	Total length of all edge segments in the landscape (green space) per hectare (m/ha)

5.2.5. Computing land surface temperature

To compute the land surface temperature, the digital number (DN) of the thermal bands were first converted to spectral radiance (w/m^2/sr/µm) or Top of Atmosphere (TOA) reflectance based on the radiometric rescaling coefficients (Chander and Markham 2003, Chander et al. 2009). Next, the derived spectral radiance was then converted to brightness temperature (i.e. blackbody temperature) in Kelvin at the sensor by applying the inverse of the Planck radiance function using the following formula;

$$T_B = \frac{K_2}{\ln(\left(\frac{K_1}{L_\lambda}\right)+1)} \quad \text{...(5.1)}$$

where T_B is the at-sensor brightness temperature in degrees Kelvin. L_λ is spectral radiance in Wm^{-2}sr^{-1}mm^{-1}. K_1 and K_2 are calibration constant 1 and 2 respectively. For Landsat 8 Band 10, K_1 value is 774.89 and K_2 value is 1321.08 respectively. For Aster band 13, K_1 value is 866.46 and K_2 value is 1350.06 respectively. The next step was to compute the land surface emissivity **(ε)** following the procedures of Sobrino et al. (2004).

The land surface emissivity **(ε)** values ranges between 0.97 and 0.99. The land surface emissivity **(ε)** was assigned to be 0.97 at NDVI < 0.2 and 0.99 at NDVI > 0.5 using the Normalized Difference Vegetation Index (NDVI) (Tucker 1979) thresholds method proposed by Sobrino et al. (2004). When $0.2 \leq NDVI \leq 0.5$, the emissivity was calculated by the following formula;

$$\varepsilon = 0.004 * P_v + 0.986 \qquad (5.2)$$

where P_v is the Proportion of Vegetation (Carlson and Ripley 1997, Sobrino et al. 2004). The Proportion of Vegetation (Pv) of each pixel was determined from the NDVI using the following equation (Carlson and Ripley 1997)

$$P_v = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \qquad (5.3)$$

where $NDVI_{min}$ is the minimum NDVI value (0.2) where pixels are considered as bareland or bare soil (non-vegetated areas) and $NDVI_{max}$ is the maximum NDVI value (0.5) where pixels are considered as healthy vegetation and dense vegetation. The Normalized Difference Vegetation Index (NDVI) (Tucker 1979) which is spectral index of green vegetation cover was derived from Aster and Landsat 8 satellite data by using the following equation:

$$NDVI = \left(\frac{NIR - R}{NIR + R}\right) \qquad (5.4)$$

Where R and NIR are the red and infrared bands respectively as derived from image data.

Lastly, the emissivity-corrected LST was computed using the following equation (Weng et al. 2004, Sobrino et al. 2004).

$$\mathrm{LST} = \left[\frac{T_B}{1 + (\lambda \sigma T_B/(hc)) \ln \varepsilon}\right] - 273.15 \qquad (5.5)$$

where LST = land surface temperature, T_B = at-satellite brightness temperature, λ = wavelength of emitted radiance (λ = 10.8 µm for Landsat TIRS Band 10), σ is Boltzmann constant (1.38×10^{-23}J/K),h=Planck's constant (6.626×10^{-34}Js), c=velocity of light (2.998×10^{-8}m/s). The retrieved LST values were later converted from Kelvin temperature to degrees Celsius (°C) by subtracting 273.15 from the derived pixel values. An absolute zero, 0 °C equals 273.15 Kelvin (K).

5.2.6 Spatial clustering and dispersion of vegetation based on Getis-Ord Gi*

Based on NDVI data (Tucker 1979), Getis-Ord Gi* (Getis and Ord 1992, Ord and Getis 1995) was calculated in ENVI image processing program to depict the spatial clustering and dispersion of vegetation patterns. This method identifies the presence of hot spots (clustered patterns) and cold spots (dispersed patterns) within its neighbouring features over an entire geographical area. The Getis-Ord Gi* statistic was calculated according to following formula;

$$G_i^*(d) = \frac{\sum_{j=1}^{n} w_{\text{ij}}(d)x_j - W_i^* \bar{x}}{s\left[W_i^*(n - W_i^*)/(n-1)^{1/2}\right]} \quad \text{(5.6)}$$

$\bar{x}$ and s denotes mean and standard deviation, respectively.

Basically, Wij is calculated based on the conceptualized spatial relationship and in reference to *d*. Therefore, it is often written as wij (d). Following the methodology of Myint et al. (2015), Getis-Ord Gi* values were standardised and normalized to the value range of −1 to 1. Positive values of Getis-Ord Gi* statistic represent highly clustered and homogeneous patterns that are, on average, greater than the mean. Getis-Ord Gi* of negative values represent highly dispersed and heterogeneous patterns that are less than the mean. Getis-Ord Gi* values of zero indicate random patterns suggesting no apparent spatial clustering. Getis-Ord Gi* statistic has previously been used in rainfall modelling (Liu et al.2019), heat vulnerability assessment (Wolf and McGregor 2013), urban criminal analysis (Craglia et al. 2000), roads incident management (Songchitruksa and Zeng 2010), as well as in agriculture (Chopin and Blazy 2013, Rud et al. 2013).

5.2.7 Statistical analysis

The normal distribution of each dataset was tested using the Kolmogorov–Smirnov test. The Kolmogorov–Smirnov test (K–S test/ KS test) verified that all significant indicators were normally distributed, meeting the basic requirements of Pearson's correlation analysis. Therefore, the Pearson’s product-moment correlation coefficient was used to examine the correlation between LST and the selected landscape metrics of vegetation after it was discovered that the data were normally distributed based on Kolmogorov–Smirnov test.. LST was the dependent variable in our analysis and landscape metrics of Edge density (ED), Mean Patch Size (MPS), Area Weighted Mean Shape Index (AWMSI), Area Weighted Mean Patch Fractal Dimension (AWMPFD) and Patch Cohesion Index were the independent variables. A negative correlation means that the landscape pattern component can reduce LST and a positive correlation means it can increase and enhance LST. The landscape metrics of vegetation derived from ASTER image and Landsat 8 were related to the LST of the same images respectively. Since Sentinel 2 does not have thermal bands, the landscape metrics of vegetation derived from Sentinel 2 of 2017 were compared to the LST acquired from Landsat 8 Thermal Infrared Sensor (TIRS) of 2017.

5.2.8. Computation of spatial autocorrelation

This section will introduce the concepts of spatial regression analysis and Moran's I index (Cliff and Ord 1981, Legendre and Fortin 1989, Moran 1950). The Moran's I index was used to measure the spatial autocorrelation of LST for the ASTER acquired on 09 September 2010 , the Sentinel 2 acquired on 24 October 2017 and on the Landsat 8 acquired on 23 October 2017. Moran's I, is widely used to capture the degree of spatial concentration or dispersion for the variables over an entire geographical space, which is defined as follows;

$$Moran's\ I = \frac{n \quad \sum_i \sum_j w_{ij}(d)(x_i - \bar{x})(x_j - \bar{x})}{\sum_i \sum_j w_{ij} \qquad \sum_i (x_{i-} \bar{x})^2} \quad \text{..................................(5.7)}$$

i and j depict the various locations, xi and xj denotes the values of the variable x of geographical location i and j respectively, $\bar{x}$ is the mean value of the variable and w_{ij} represents a spatial weight matrix for measuring spatial proximity (connectivity) between i and j geographical areas or locations. The Moran's 1 is standardized to values ranging from −1 to 1, hence positive values of Moran's I points to significant spatial autocorrelation (0 to ≥ 1) and a tendency of more spatial clustering. On the other hand, the negative values of Moran's I values points a tendency of spatial dispersion (0 to ≥ -1). On other hand, a zero signal the absence of spatial autocorrelation in a geographical space.

The Moran's I was conducted using a queen contiguity matrix in defining the neighbouring size of LST. The queen contiguity weights criterion is recommended in practice in order to deal with potential inaccuracies in the polygon file (such as rounding errors) (Anselin 2003, Anselin 2006). After discovering significant spatial autocorrelation, we, therefore, conducted Lagrange Multiplier test. This was performed in the Geoda software package (Anselin 2003, Anselin 2006) to determine the more appropriate spatial autoregression models specifications: either the spatial lag or spatial error that integrate spatial autocorrelation. One of the critical outcomes of this study is that the inclusion of any of the spatial autoregression model (spatial lag or spatial error) into examining the correlation between LST and spatial configuration patterns of urban vegetation significantly results in a decrease in the Akaike Information Criterion (AIC), when comparing the OLS and spatial lag models.

5.2.9 OLS and SLM models analysis

Two regression models, the Ordinary Least Squares (OLS) (Model 1) and a Spatial Lag model SLM (Model 2) were developed to estimate the mean LSTas the dependent variable. The selected landscape indices of Mean Patch Size, Area Weighted Mean Patch Fractal Dimension Index, Area Weighted Mean Shape Index and Edge Density were independent variables at 10m, 15m and 30m spatial resolution. The Ordinary Least Squares (OLS) is described as:

$$y = X\beta + \epsilon \qquad (5.8)$$

where *y* denotes the dependent variable, *X* is the matrix of explanatory variables without an intercept term; *β* is a vector of slopes; and *ε* is a vector of random error terms. Since most geographical variables are spatially autocorrelated, spatial regression models (Spatial Lag Model, Spatial Error Model) are more suitable than Ordinary Least Squares (OLS) models for analysing the relationships between dependent and independent variable (Song et al. 2014). In particular spatial regression models have stronger explanatory power and lower spatial autocorrelations of residuals compared with Ordinary Least Squares (OLS) (Song et al. 2014).. Therefore, spatial regression models including the spatial lag model (SLM) are often used. The SLM is expressed as follows

$$y = \rho \mathrm{Wy} + X\beta + \epsilon \qquad (5.9)$$

where ρ is a spatial autocorrelation parameter; and *Wy* is the spatial weight matrix.

The OLS and SLM regression models were compared to evaluate their performance and their goodness fit in explaining the relationship between LST and explanatory variables of landscape metrics. The fitness of the OLS and SLM models were compared using four parameters including R^2, log likelihood, Akaike Information Criterion (AIC) and Schwarz criteria. The higher the R^2 value and the log likelihood of the model, the higher the model fitness. On the other hand, the lower the AIC and Schwarz criteria indicates a better model fit. The analysis was conducted in the GeoDa software. Figure 5.2 illustrates the research methodology undertaken in this study.

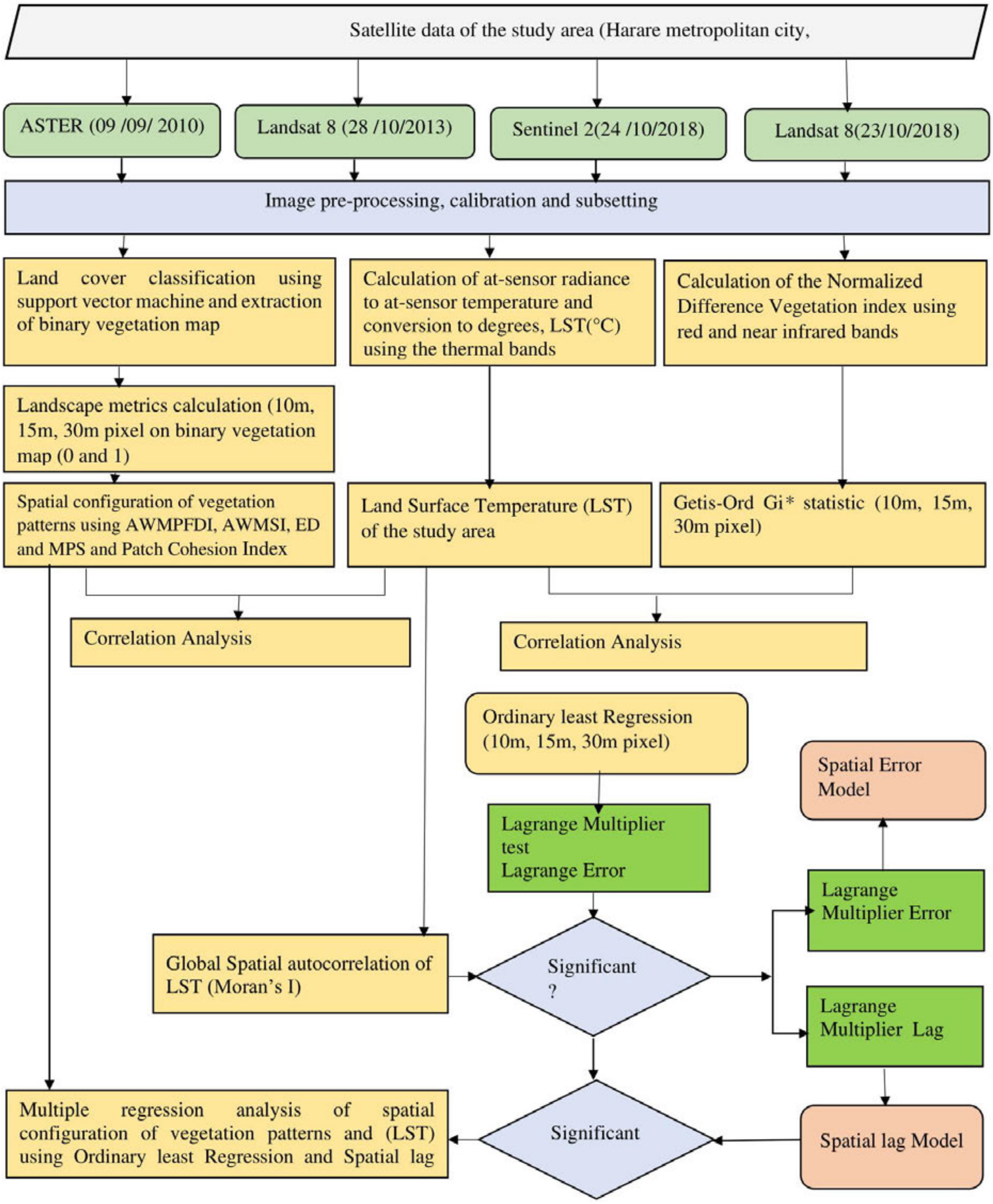


Figure 5.2. Flowchart of the research methodology and the steps presented in this study.

5.3 Results

5.3.1 Land cover classification accuracy

The land cover classification for Harare metropolitan city based on the four satellite imagery datasets had a high overall accuracy, which to some degree could be ascribed to the simple land cover classification scheme used. The overall accuracy was 96.12% in 2010, 96.13 % in 2013. It was 97.14% and 97.32% for Landsat 8 acquired on 23 October 2017 and Sentinel 2 data acquired on 24 October 2017 respectively. On the other hand, the Kappa coefficient was 0.95 for ASTER data acquired on 09 September 2010 and Landsat 8 acquired on 28 October 2013, 0.96 for both Landsat 8 acquired on 23 October 2017 and Sentinel 2 data acquired on 24 October 2017 respectively. This is more than 85%, the minimum level of mapping accuracy generally required for most land cover studies that use remote sensing data products (Anderson et al.1976).

A significant proportion of vegetation is mainly concentrated in the northern part of the city whilst small, scattered vegetation is dominant in the southern, western and eastern part of Harare. In 2010, the total area of vegetation comprised 28432.7 hectares (ha) and non-vegetation was 69625.7 ha. In 2013, the total area of vegetation was approximately 25377.2 ha and non-vegetation was around 72687.24 ha. The total area of vegetation was 19582.6 ha and non-vegetation was 78480.9 ha on Landsat 8 acquired on 23 October 2017. On the other, the total area of vegetation was 25958.6 ha and non-vegetation was 72126.2ha on Sentinel 2 acquired on 24 October 2017.

5.3.2 Spatial variability pattern of LST

The descriptive statistics of LST (°C) derived from Aster and Landsat data in 2010, 2013 and 2017 are shown in Table 5.3. In 2010, the LST) derived from ASTER data ranged from 18.89°C to 45.50°C (Table 5.3). On the other hand, LST derived from Landsat data of 2013 varied from 22.93°C to 51.05°C. In 2017, LST varied from 23.81°C to 48.5 °C. The mean LST was 35.93°C in 2010, increased to 36.71°C in 2013 and then 38.26°C in 2017 indicating the increasing warming trend in the study area. In 2010, 2013 and 2017, the significantly low values of LST dominated the northern side of the city suggesting the presence of dense vegetation and a cooler region (Figure 5.3).

Table 5.3. Descriptive statistics of LST

Acquisition date	*Min (°C)	*Max (°C)	Mean (°C)	*SD
09/09/2010 (ASTER)	18.89	45.50	35.93	2.96
28/10/2013 (Landsat data)	22.93	51.05	36.71	3.58
23/10/2017 (Landsat data)	23.81	48.5	38.26	2.89

*Min-Minimum, *Max (Maximum), SD* (Standard Deviation).

On the other hand, significantly high values of LST dominate the sparsely vegetated western, southern and eastern part of Harare indicating a warmer region. The western, southern and eastern side of Harare is a highly urbanised area with a heavy concentration of industries and residential areas, indicating the impact of impervious surfaces in raising higher land surface temperature.

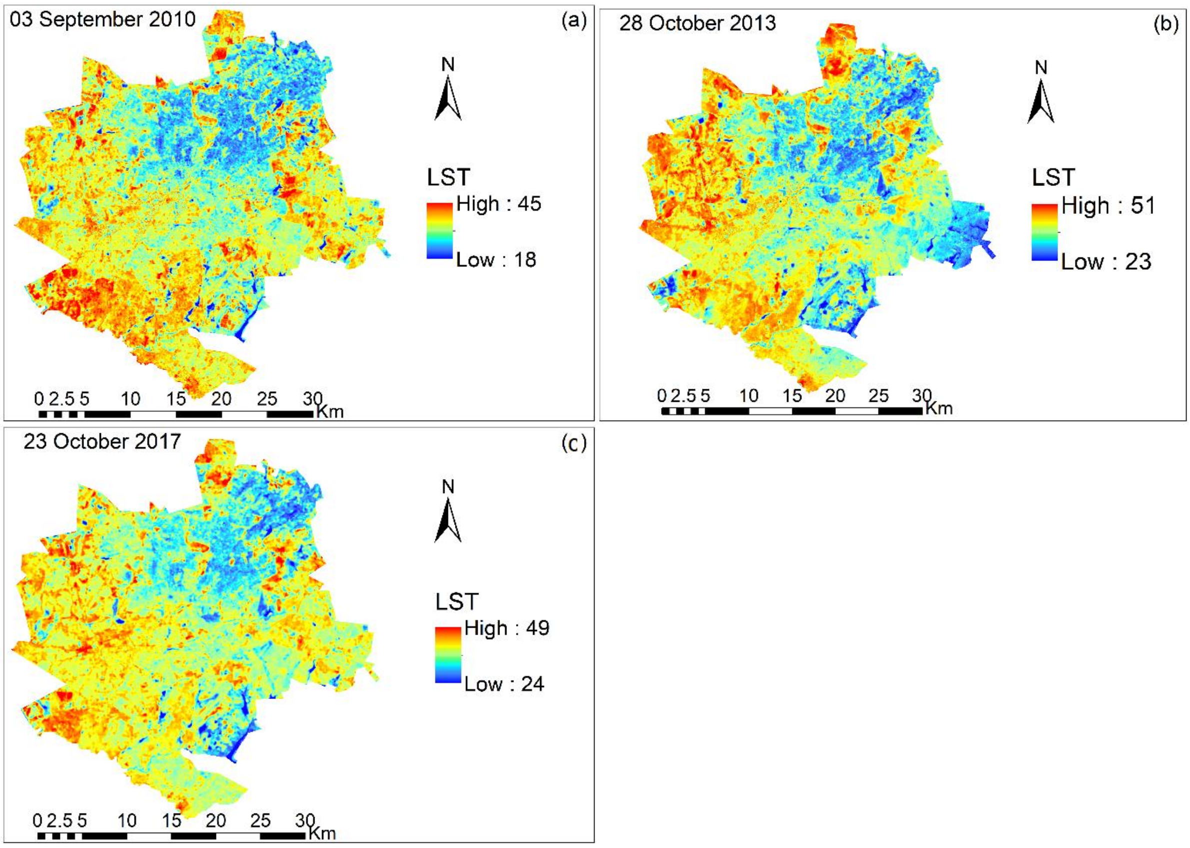


Figure 5.3. The spatial distribution of (a) LST derived from Aster data acquired on 09 September 2010 (b) 28 October 2013 and (c) 23 October 2017. Low values of LST are heavily concentrated in the northern side of the city and significantly high values of LST in the sparsely vegetated western, southern and eastern side of the city.

5.3.3. The correlation between LST and Getis-Ord Gi* of vegetation

The Pearson correlation coefficients indicated a relatively moderate to a strong negative linear correlation between LSTand Getis-Ord Gi*.The relationships between the Getis-Ord Gi* and LSTwas ($r = -0.67$, $p< 0.05$) on Aster data of 2010, ($r = - 0.60$, $p< 0.05$) on Landsat data of 2013, ($r = - 0.60$, $p< 0.05$) on Sentinel 2 data of 2017 and ($r = - 0.64$, $p< 0.05$) on Landsat data of 2017. This suggests that the spatial clustering of vegetation has strong impact in decreasing LST and correlate strongly with cooler surface temperatures.

The spatial clustering of vegetation based on Getis Ord Gi* ranged from being dispersed (negative values), random (zero) and to highly clustered (positive values) as indicated in Figure 5.4. The statistically significant high attribute values of Getis Ord Gi* were heavily concentrated in the northern part of Harare, indicating that LST was low in geographical locations with high and positive clustering of vegetation (Figure 5.4). Conversely, LST was high in areas with low, negative clustering and dispersed vegetation patches in the western, southern, and eastern side of Harare (Figure 5.4). Therefore, high LST closely correlate under dispersed and isolated vegetation patches.

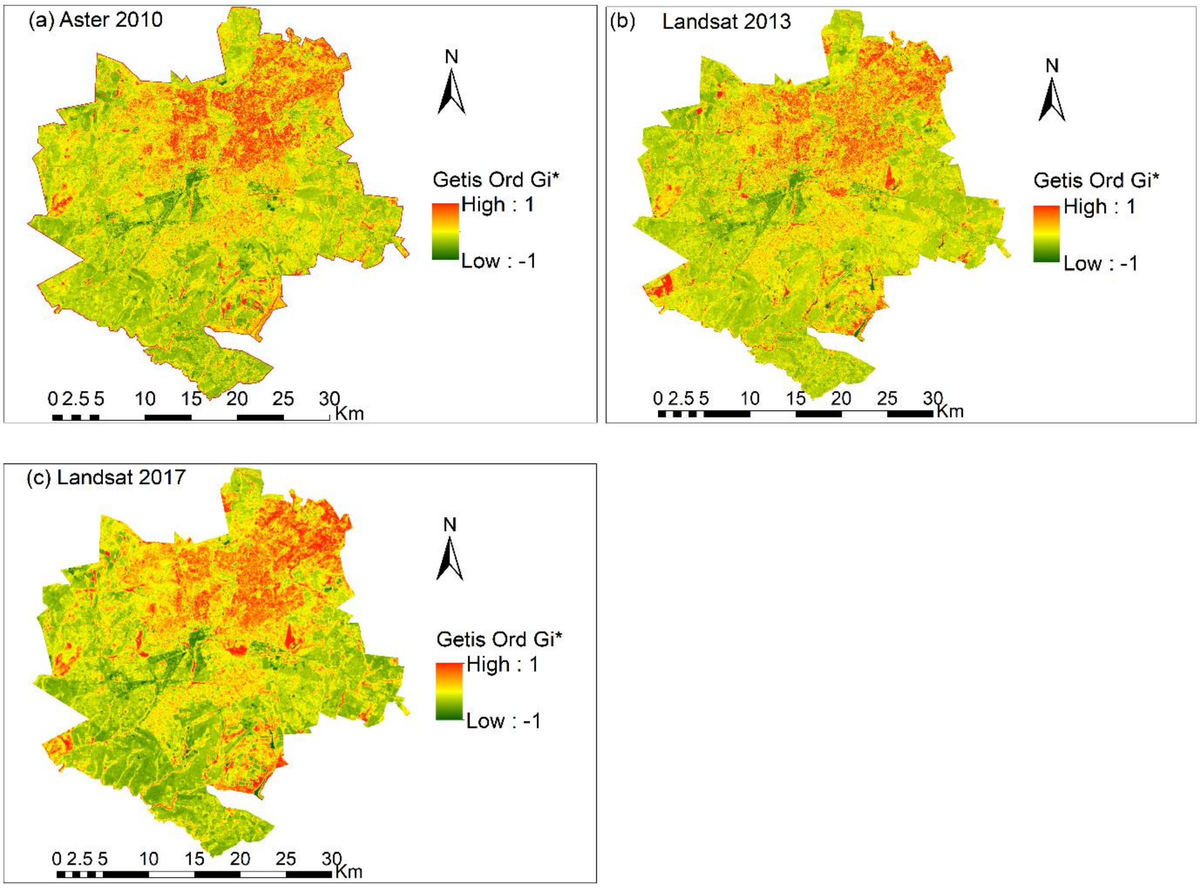


Figure 5.4. Getis-Ord Gi* derived from (a) Aster data of 2010 (b) Landsat data of 2013 and (c) Landsat data of 2017. High positive values of Getis-Ord Gi*represent a highly clustered pattern and low and negative values represent highly dispersed patterns of vegetation.

5.3.4 The relationship between landscapes metrics of vegetation and LST

The patch size, density, shape complexity and connectivity of vegetation have an important influence on LST. Table 5.4 indicates that the landscape metrics of urban vegetation patterns had consistently negative relationships with LST ($p<0.05$), but the magnitude of the correlation varied by spatial resolution at 10m (Sentinel 2), 15m (ASTER) and 30m (Landsat 8). The AWMPFDI, AWMSI, Edge Density and Mean Patch Size of landscape metrics were less correlated with LST at 30m of Landsat 8 imagery data acquired on 28 October 2013 and 23 October 2017 than at 10m (Sentinel 2) and 15m (ASTER) spatial resolution. This suggests that the negative correlations between LST and landscape metrics of AWMPFDI, AWMSI, Edge Density and Mean Patch size were stronger at finer spatial resolution.

Table 5.4: Pearson's correlation coefficients (R-values) showing the degree of associations between LST (°C) and landscape metrics

	COHESION	MPS	ED	AWMSI	WMPFDI
09/09/2010 ASTER (15m)	-0.65	-0.26	-0.32	-0.37	-0.32
28/10/2013 (Landsat data) (30m)	-0.68	-0.16	-0.21	-0.07	-0.09
23/10/2017 (Landsat data) (30m)	-0.69	-0.15	-.0.24	-0.08	-0.11
24/010/2017 (Sentinel 2) (10m)	-0.61	-0.40	-0.37	-0.49	-0.34

MPS- Mean Patch Size, AWMPFDI- Area Weighted Mean Patch Fractal Dimension Index, AWMSI- Area Weighted Mean Shape Index, ED- Edge Density, COHESION -Patch cohesion index.

Although all the landscape metrics had a significant negative correlation with LST, , Patch Cohesion index (COHESION) had the most consistently strong correlation with LSTacross all three spatial resolutions (10m, 15m and 30m) ($p<0.05$). Table 5.4 shows that the Patch Cohesion index had relatively higher and stronger correlation at 30m spatial resolution ($r=-0.69$, $p<0.05$) in 2017 data and ($r=-0.68$, $p<0.05$) in 2013 for Landsat 8 than at 10m ($r=-0.61$, $p<0.05$) for Sentinel 2 data acquired in 2017 and 15m ($r=-0.65$, $p<0.05$) for ASTER data of 2010 as indicated in (Table 5.4). This suggests that the relationship between LSTand Patch Cohesion index increase with subsequent decrease of spatial resolution. Besides, the results of the Patch Cohesion index may indicate that highly connected and less isolated vegetation patterns do have strong cooling effect and impact in decreasing LST. Higher vegetation connectivity (i.e. less isolation of vegetation patches) are associated with a greater proportion of high, contiguous vegetation patterns, reflecting shorter distances between the vegetation patches and may contribute to lower and minimum LST values (e.g. 18°C, 22 and 23°C) as indicated in Figure 5.5. These are illustrated with higher vegetation connectivity ranges (<50%-70%).

On the other hand, lower vegetation connectivity (higher degree of isolation of vegetation patches) contribute to higher and maximum LST values (e.g. 45°C, 48°C and 51°C) as illustrated in Figure 5.5. Areas with less connected vegetation are found in the western, southern and eastern side of the Harare. These are illustrated with lower vegetation connectivity ranges (<0%-30%). Less connected vegetation (<0%-30%) represent the highly fragmented nature of vegetation patches that are smaller, isolated and scattered across the landscape.

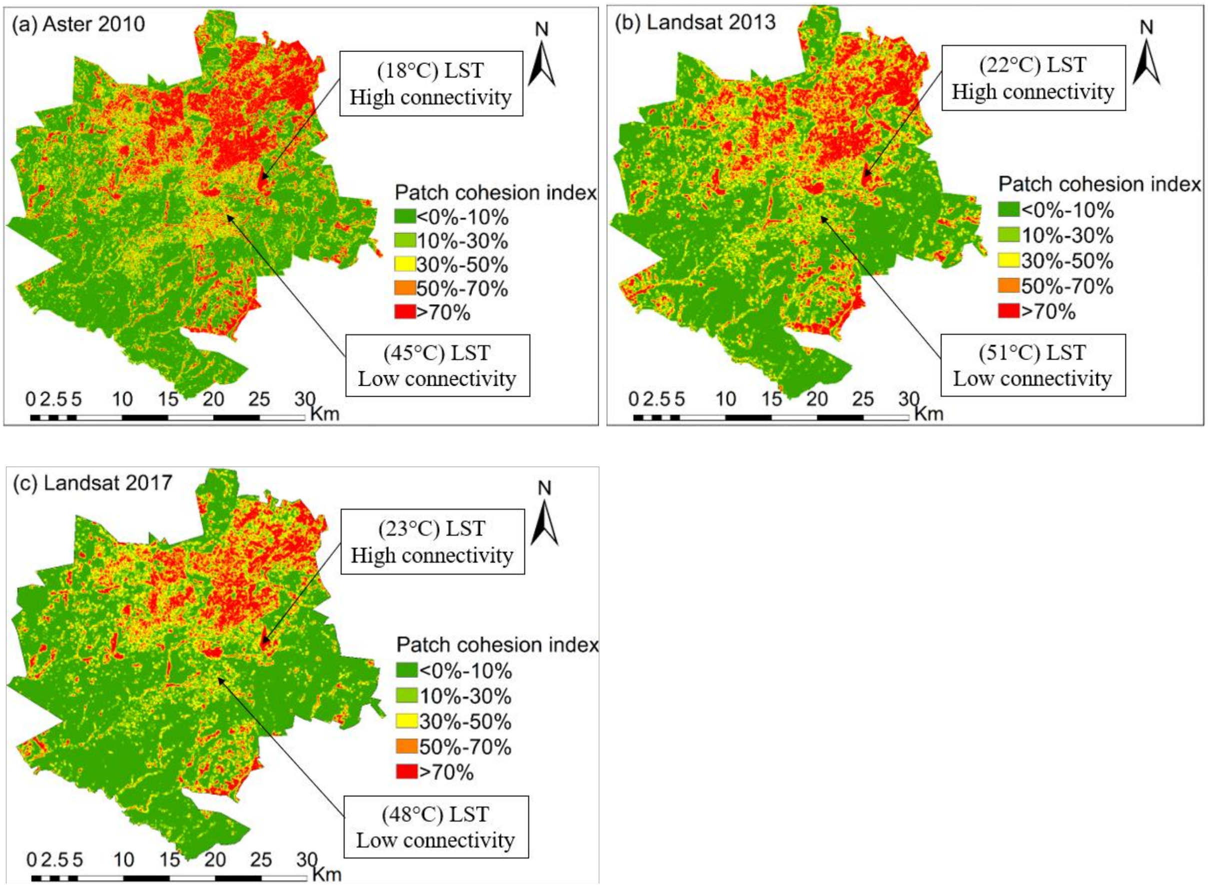


Figure 5.5. Patch cohesion index derived from (a) Aster data of 2010 (b) Landsat data of 2013 and (c) Landsat data of 2017 illustrating that high vegetation connectivity corresponds to lower LST and vice versa.

5.3.5 Spatial autocorrelation of LST

Significant spatial autocorrelation of LST was detected which indicated that similar LST (°C) values were closely clustered together in the study area. Table 5.5 indicates that the value of Moran's I was 0.21 ($p<0.001$) for Sentinel 2 data of 2017, 0.18 ($p<0.001$) for Aster data of 2010 and 0.27 ($p<0.001$) for Landsat 8 of 2017 data which meant that there was less than a 0.1% chance that the observed spatial clustering pattern in the study was due to random chance. Due to the significant spatial autocorrelation of LST found in the study area, it implied that the results of the Ordinary Least Squares model regression model would have been biased without the adoption of a spatial regression model. When applied to spatial data with spatial dependence (e.g LST), OLS regression models are known for violating the independent observations and uncorrelated error assumptions of classical statistical approaches.

5.3.6 Comparisons of OLS and SLM regression models

Table 5.5 shows the results of Model 1 (Ordinary Least Squares regression) and Model 2 (Spatial Lag regression) that examined the relationships between mean LST and spatial configurations of vegetation based on landscape metrics as independent variables at different spatial resolutions. The three different spatial resolutions were based on 10m spatial resolution (Sentinel 2) acquired on 24 October 2017, 15m spatial resolution (ASTER) acquired on 09 September 2010 and 30m spatial resolution (Landsat 8) acquired on 23 October 2017. The Landsat acquired on 28 October 2013 was not considered. The Model 1(OLS) explained about 11% (R^2 = 0.1058) for Sentinel 2 (10m), 13% (R^2 = 0. 1304) for Aster data (15m) and 53% (R^2 = 0.5285) for Landsat 8 data (30m) of the variance in the relationship between landscape metrics and mean LST .

On the other hand, Model 2 (SLM) explained 51% (R^2 = 0.5076) for Sentinel 2 (10m), 52% (R^2 = 0.5153) for Aster data (15m) and 64% (R^2 = 0.6353) for Landsat 8 data (30m) of the variance in the relationship between mean LST and spatial configuration of vegetation. This indicates that more than 50% of the variations in mean LST were estimated and explained by the selected landscape metrics in SLM model. In both models, the values of R^2 increased with subsequent decrease of the spatial resolution.

Table 5.5. Results of Ordinary Least Squares (OLS) and Spatial lag regression model (SLM) analysis

	Models					
	Model 1: OLS			Model 2: SLM		
Parameter	Sentinel 2 (10m)	ASTER (15m)	Landsat 8 (30m)	Sentinel 2 (10m)	ASTER (15m)	Landsat 8 (30m)
R-squared (R^2)	0.11	0.13	0.53	0.51	0.52	0.64
LL	-110805	-58143.7	-26092.2	-98932.8	-51344.8	-24594.7
AIC	221621	116299	52196.4	197880	102704	49203.4
SC	221674	116348	52241.2	197941	102761	49255.7
Moran's I	0.21	0.18	0.27			

LL-log likelihood; AIC-Akaike Information Criterion; and SC-Schwarz criterion,

Besides the higher R^2 values, the results demonstrated in the SLM (Model 2) were characterized by higher log likelihood than those in OLS model. Both AIC and Schwarz criteria were smaller in SLM model than in OLS model. Based on the four parameters used, the comparison of these two models suggests that the SLM was superior and performs better than OLS model for investigating the spatial configurations of vegetation on land surface temperature.

5.4. Discussion

This study examined the effect of landscape pattern and spatial configuration of vegetation on land surface temperature in Harare metropolitan city. The research findings demonstrated that the effect of spatial configuration of vegetation on LST significantly vary with a particular landscape metrics used. The results of Pearson's correlation coefficient of LST with landscape metrics suggest that highly connected (Patch cohesion index), irregularly shaped vegetation patterns (AWMSI and AWMPFD), patch size (MPS) and green space edge (edge density) conditions significantly reduce LST. This corroborates previous studies that show that the landscape metrics of vegetation were significantly correlated with land surface temperature (Kong et al. 2014a, Maimaitiyiming et al. 2014, Li et al. 2012, Zhang et al. 2009, Zhou et al. 2011). This is largely because different landscape patterns and spatial configurations such as the patch shape, mean patch size, connectivity and edge density can influence the energy fluxes, heat flow and thermal exchanges between vegetation and its nearby locations, triggering different warming and cooling effects.

A negative correlation between land surface temperature and the shape complexity and mean patch size of the patches of vegetation was found in Beijing, China (Li et al. 2012). Several studies (Asgarian et al.2015, Bao et al. 2016, Kong et al. 2014, Li et al.2012, Zhang et al. 2009, Zhou et al.2011) also found that green spaces with more complex shapes could produce higher cooling effects. In our study, the negative correlation between the surface temperature and shape complexity were relatively higher on AWMSI than AWMPFD. This is not surprising as in computing the average shape complexity, the larger patches are weighted more heavily in the AWMSI than smaller patches (McGarigal et al.2002). The negative correlations between edge density of vegetation patches with LST were observed in the Mediterranean cities of Europe (Nastran et al. 2019), Aksu city in China (Maimaitiyiming et al. 2014) and in Baltimore in USA (Zhou et al. 2011). Zhou et al (2011) noted that LST decreased with subsequent increase in the fraction of urban vegetation and edge density.

The green vegetation patches are large, more complex and contiguous in the northern part of Harare. On the other hand, vegetation patches are fragmented and dispersed in the western, southern and eastern side of Harare. A previous investigation by Mushore et al. (2017) reported higher LST in the sparsely vegetated western, southern and eastern side of the city. Due to high thermal load, small green spaces are unlikely to deliver significant cooling effects (Bao et al. 2016). Conversely, the densely vegetated northern part of Harare had consistently lower LST . Large, contiguous vegetation patches greatly offset the warming effects, are more heat tolerant and have been found in previous studies to produce stronger cooling effects than that of several smaller and isolated vegetation patterns (Li et al. 2012, Maimaitiyiming et al. 2014, Zhang et al. 2009). Dugord et al (2014) also reported that larger and aggregated forest patches significantly reduced surface temperature in Berlin in Germany.

Based on a Getis-Ord Gi*, our results corroborates with previous studies that indicate that clustered patterns of urban vegetation lower surface temperature more effectively (Fan et al. 2015, Peng et al. 2016) than more fragmented (dispersed) patterns of urban vegetation that raise LST as indicated in Li et al. (2012) and Zhang et al.(2009). Clustered patches of vegetation may increase latent heat exchanges through evapotranspiration, thereby lowering the sensible heat emitted from the earth surface. Furthermore, clustered vegetation patches may provide more shade onto the ground by absorbing solar radiation, significantly reducing LST.

4.1. Effect of spatial resolution on LST and landscape metrics relationship

The effect and magnitude of landscape metrics of vegetation on LST was significantly affected by the different spatial resolution of the satellite image data, which confirms the previous findings (Li et al. 2013). Except of Patch Cohesion index, the correlation coefficients of LST with landscape metrics of AWMPFDI, AWMSI, Edge Density and Mean Patch size declined significantly with the decrease of spatial resolution becoming stronger at finer spatial resolution of 10m (Sentinel 2) and 15m (ASTER) than at 30m (Landsat 8). Finer rather than low satellite imagery data are known to effectively extract and retrieve number of small, isolated vegetation patches in urban areas. This also explains a non-significant and low correlation coefficient between LST and landscape metrics of AWMPFDI, AWMSI, ED, Edge Density and Mean Patch size at 30m Landsat 8 imagery data.

On the other hand, several reasons can be attributed for the higher negative correlation between LST and Patch Cohesion index at 30m ($r=-0.69$) than at 15m ($r=-0.65$) and 10m ($r=-0.61$) resolutions. One of the reasons is that, Patch cohesion index is susceptible to the aggregation and clumping of the focal class or patch type (McGarigal et al. 2002). Patch cohesion index tends to increase in its spatial distribution as focal class patch type becomes more clumped or aggregated consequently creating a more and highly connected patch (Gustafson 1998). Hence, Patch Cohesion index tends to be biased towards larger patches than smaller patches. In low and coarse image data such as the 30m (Landsat 8), small patch sizes of vegetation easily detected from the fine and high resolution image data may be identified as single large vegetation patch. Patch cohesion index has been previously found to exhibit less fragmentation levels at coarse spatial resolutions (Saura 2004).

4.2. The choice of OLS and SLM models

LST is spatially autocorrelated because of land surface heat fluxes (Song et al. 2014). Moran I showed that there was significant effects of spatial autocorrelation of land surface temperature in the study area. This implied that the results of the OLS regression model would have been biased without controlling spatial autocorrelation effects, which are often influenced by nearby locations. Significant spatial autocorrelation of spatial data such as land surface temperature and its relationship with spatial configurations of vegetation have high possibility of violating the basic assumption of independence among spatial data that is required by widely used parametric statistical tests. Conventional Pearson correlation and Ordinary least squares regression analysis do not consider spatial autocorrelation.

To solve the biases associated with spatial dependence, spatial regression models are often employed. This is because spatial regression methods provide more reliable and robust prediction of spatial autocorrelation effects in spatial datasets. The comparison of OLS and SLM models showed that all the parameters such as R^2, log likelihood, AIC and Schwarz criteria were better estimated in the SLM model than in OLS model. These results confirm previous research findings studies that emphasize the utility of spatial regression methods (Li et al. 2012, Song et al. 2014) which are necessary when examining the relationships between mean land surface temperate and spatial configurations of vegetation.

In both SLM and OLS, our results indicated that Landsat 8 had better model parameter estimations and significant reduced statistical bias than the Aster and Sentinel images on the effects of landscape patterns of urban vegetation on LST. However, this must be interpreted with caution as coarse Landsat 8 data could overestimate the mitigation impacts of landscape patterns of urban vegetation on the UHI effect. The spatial resolution of Landsat data may not be highly detailed enough to predict the landscape patterns of urban vegetation on LST. This is because small urban green patches are not easily extracted and recognizable in low and medium resolution image data such as the 30m resolution Landsat data, thus leading to underestimation of the amount of urban greenspace (Li et al. 2013, Townsend et al. 2009). Many small urban vegetation patches identified from the fine resolution imagery (Sentinel and Aster) may be mapped as one single large vegetation patch when using coarse Landsat imagery suggesting that clumped or aggregated urban vegetation is better than fragmented vegetation in decreasing LST. Although the objective of this research was not to identify a single optimal spatial scale or resolution for mapping and examining the spatial configurations patterns of urban vegetation on LST, our results could be expanded. The use of satellite data with higher spatial resolution such as QuickBird, IKONOS, SPOT and World View can be employed to gain more reliable parameter estimates and finding the optimal scale and resolutions at which the contribution of landscape patterns of urban vegetation on LST to model fitting is maximum and that of spatial autocorrelation is minimum.

5.5. Conclusions and Recommendations

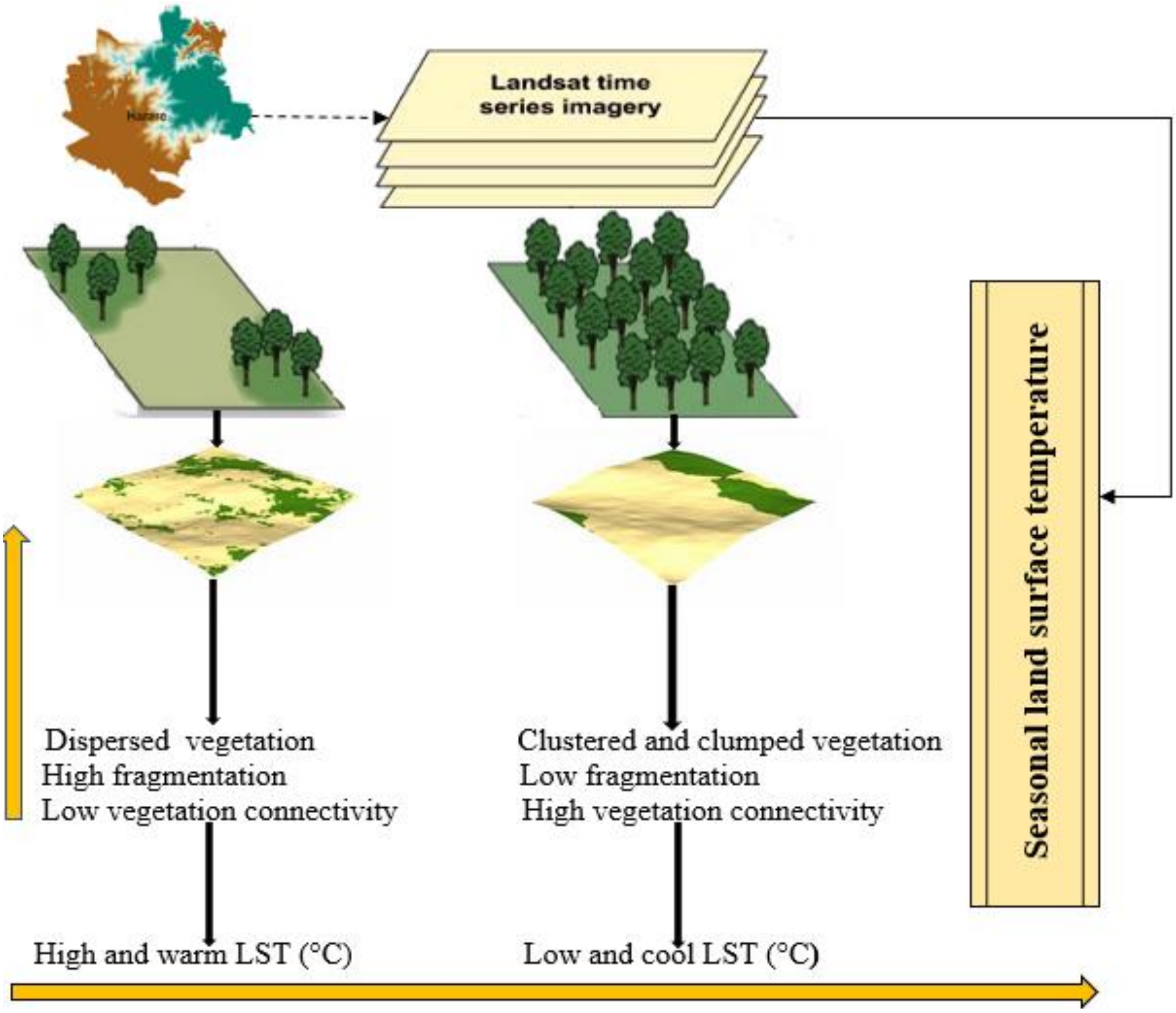
Understanding the landscape pattern and configuration of green spaces is important in climate adaptation and mitigation of the UHI effects in rapidly growing cities and sprawling metropolitan regions. Due to continuing fragmentation of green spaces in urban areas, urban planners should optimize the landscape patterns and the spatial configurations of urban landscapes by aggregating or clustering vegetation. Clustered or clumped vegetation could be effective in mitigating urban warming effect and maximizing cooling effects. In general, this study demonstrated that the Getis Ord Gi* and landscape metrics can convey meaningful information on the spatial configuration of vegetation and its effects on different levels of warming and cooling in a landscape. The effects of finer spatial resolution generally had better correlation coefficients of spatial configurations of urban vegetation with land surface temperature providing important indications of specific spatial resolutions at which maximum warming and cooling effects are achieved. Spatial regression methods are effective in dealing with spatial dependency and provide robust and reliable prediction of the relationship between spatial configuration of urban vegetation and LST at specific locations in alleviating urban heat island effects.

6.SEASONAL LAND SURFACE TEMPERATURE AND ITS IMPACTS ON ECOLOGICAL, SPATIAL CONFIGURATION AND CONNECTIVITY OF URBAN VEGETATION PATTERNS

This chapter is based on:

Pedzisai Kowe, Onisimo Mutanga, John Odindi, Timothy Dube, "Seasonal land surface temperature and its impacts on ecological, spatial configuration and connectivity of urban vegetation patterns in Harare metropolitan city, Zimbabwe," GIScience and Remote Sensing, under revision

GRAPHICAL ABSTRACT



Abstract
The urban heat island (UHI) effect is a growing social-economic and ecological challenge affecting among others, urban climate, public health and urban energy demand. Several studies have highlighted the value of urban green ecology in mitigating the negative effects arising from UHI effects. Whereas the effects of UHI are hugely influenced by seasonal climatic variability and vegetation density, the implication of seasonal spatial configurations (clustered or dispersed) and connectivity of vegetation have been largely ignored in the UHI literature. In this study, we combined landscape metrics, spatial statistics and land surface temperature (LST) to quantify the spatial configuration and connectivity of vegetation and its impact on seasonal surface temperature in Harare metropolitan city, Zimbabwe. To represent the four different seasons (spring, winter, autumn and summer), remotely sensed Landsat 8 data (optical and thermal) were acquired between May 2015 to October 2018. The data were used to retrieve urban green spaces, LST and the Patch Cohesion Index (%), a landscape connectivity metric to determine the city's vegetation connectivity. The spatial configuration patterns (dispersed or clustered) of vegetation were determined using a continuous local spatial autocorrelation index of local Moran's I. Results showed that UHI intensities were higher during warmer and summer months, lower during the cooler spring, winter and autumns months. Local Moran's I of urban vegetation showed a strong negative correlation with LST in all seasons, implying that less fragmented but clumped or clustered vegetation were more efficient in assimilating and reducing urban heat than dispersed patterns. In addition, the negative correlations of Patch Cohesion Index (%) with LST in all seasons implied that highly connected vegetation patterns are more beneficial in decreasing LST throughout the year. These findings provide valuable insight into how the spatial configuration and connectivity of urban vegetation affect urban thermal environment across different seasons. The study offers an opportunity for informed and effective urban planning and design, useful in urban socio-ecological sustainability and climate mitigation.

Keywords:
Connectivity; Patch Cohesion Index; Seasonal; urban vegetation; land surface temperature; Harare,

6.1 Introduction

The rapid urban expansion across the world has led to increasing surface temperatures due to conversion of natural vegetated areas to impervious surfaces (Mallick et al.2008). As the landscape becomes urbanised, it fragments an area's natural landscape, reduces its diversity and abundance and affects is spatial configuration (i.e. shape complexity, density, aggregation and cohesion). Hence, urbanization leads to isolation of vegetation cover and green spaces, limiting connectivity of urban greenery. Buildings and impervious surfaces such as buildings, roads and pavements have a high thermal conductivity that significantly increases the heat storage capacity of cities. Such change leads to significantly warmer and higher temperatures than a surrounding rural area, creating an urban heat island effect (UHI)(Oke 1982,Voogt and Oke 2003).

The UHI phenomenon affect the daily lives of urban dwellers and sustainability of cities. The UHI effects degrades air quality by elevating the emissions of air pollutants and greenhouse gases such as sulphur dioxide (SO_2), nitrogen oxide (NO_x), volatile organic compounds (VOC_s) and carbon dioxide (CO_2) whose formation further accelerate surface temperature and heat waves (Akbari et al. 2001, Fischer et al. 2007). Furthermore, UHI may compromise human health and comfort, trigger heat-related diseases and premature deaths (Anderson and Bell 2010, Jenerette et al. 2007). UHI also increases electricity consumption (Battista et al.2016) and decreases water quality (Heaviside et al.2017, Hester and Bauman 2013). Urban vegetation and green spaces have been found to be effective in mitigating UHI effects especially during warmer seasons (Chen et al. 2012, Hamada and Ohta 2010, Shashua-Bar and Hoffman 2000, Santamouris 2001, Taha 1997). In this regard, previous studies have extensively established an inverse correlation between land surface temperature (LST) and the amount of vegetation cover based on vegetation indices such as Normalized Difference Vegetation Index (NDVI) (Carlson et al.1994,Voogt and Oke 2003). Such studies have also shown that vegetation varies with seasons as determined by the onset of growth, maturity, senescence and full dormancy phenological cycles (Zhang et al. 2003, Zhang et al. 2015). Such dynamics affect the energy fluxes and balance of ecosystems on the landscape, in turn influencing thermal variability within an urban landscape.

Although the effects of spatial composition of vegetation on urban land surface temperature are well established (Chen et al. 2016, Connors et al. 2013, Kong et al. 2014, Li et al. 2017, Peng et al.2016), previous studies were only limited to the summer season. Hence, there is paucity of studies in the literature on how the seasonal effect of spatial configuration of vegetation affects surface temperatures in African cities. In fact, studies of the UHI phenomenon in African cities have been mainly conducted in few cities and urban areas including eThekwini municipality in South Africa (Odindi et al.2015), Harare in Zimbabwe (Mushore et al.2018) and Ibadan in Nigeria (Abegunde and Adedeji 2015). Simwanda et al. (2019) recently carried a comparative analysis of UHI in four rapidly growing African cities of Lagos (Nigeria), Nairobi (Kenya), Addis Ababa (Ethiopia) and Lusaka (Zambia). However, the study did not consider the influence of spatial configuration of vegetation on surface temperature but focused on the effects of urban growth and land use and land cover changes on UHI.

Landscape metrics have particularly been widely utilized in linking surface temperature to spatial configuration (Cao et al. 2010, Connors et al. 2013, Kong et al. 2014, Li et al. 2011; 2012; 2016; 2017, Peng et al. 2016, Zhang et al. 2009, Zhou et al. 2011). Linking landscape metrics to urban thermal responses of vegetation cover is useful in capturing the impact of spatial configuration of land surface temperature through its effects on heat and energy exchange and flows in a landscape (Connors et al. 2013, Chen et al. 2016, Kong et al. 2014, Li et al. 2017 and Peng et al. 2016). For example, Zhibin et al. (2015) found an inverse relationship between Largest Patch Index (LPI) of green space and LST. Similarly, green spaces and vegetation with more complex shapes have been found to significantly produce higher cooling effects (Bao et al. 2016, Li et al. 2012, Li et al. 2013, Zhang et al. 2009, Zhou et al. 2011).

Although discrete landscape metrics can convey important information on material energy flows in a landscape, not all landscape metrics can be related to heat energy exchanges and flows in a city (Chen et al.2016). Many landscape metrics are highly correlated with each other, consequently producing redundant information, thus making it difficult to make useful strategies for urban heat mitigation (Song et al. 2014, Uuemaa et al. 2013, Li and Wu 2004). Furthermore, previous research that focused on the role of landscape connectivity of vegetation in regulating surface temperatures are still limited (Zhou et al. 2011). To date, studies on the role of landscape connectivity of vegetation have mainly examined the impact of structural connectivity on biodiversity (Pascual-Hortal and Saura 2006), that include immigration rates and dispersal success (Goodwin 2000).

Furthermore, the influence of spatial clustering of urban vegetation on seasonal surface temperature remains largely unexplored. Spatial clustering is often computed using a continuous local spatial statistics methods like the widely used Local Moran's I (Anselin 1995), Getis-Ord Gi* statistic (Getis and Ord 1992, Getis and Ord 1996, Ord and Getis 1995), local Geary's C and Moran's I (Moran 1950). Local spatial statistics also referred to as Local Indicator of Spatial Association (LISA) can identify whether objects in a landscape are clustered, dispersed or randomly distributed (Cuzick and Edwards 1990). The Local Moran's I can effectively capture the spatial clustered and dispersed patterns of land cover characteristics (Fan and Myint 2014). In this study, we combined local Moran's I and Patch Cohesion index to understand how spatial configuration and connectivity of urban vegetation affect urban thermal characteristics across different seasons in Harare metropolitan city in Zimbabwe. Such information is useful for informing strategies to optimise ecological functioning, regulate energy use, facilitate sustainable urban development and mitigate effects UHI and climate change.

6.2. Materials and Methods

6.2.1 Study area

This research work was carried out in Harare metropolitan city (Latitude 17.83° and Longitude 31.05°), the political capital and the major centre of industrial production, trade and commerce (Figure 6.1) in Zimbabwe. The city has a surface area of about 980.6 square kilometres and about 2.1 million people as per the 2012 population census (ZIMSTAT 2012). Harare metropolitan city has a flat topography in the southern part and a hilly topography in the northern part. The city falls within the subtropical highland climate, which is typically mild and cool with relatively longer sunshine hours. It experiences warm and hot summers (average temperature of 26°C) and cold winters (average temperature of 10°C). Generally, there are four distinct seasons in the city (1) Spring or transitional season from April to May (2), a cool, dry winter season from June to July (3), a warm and dry season from August to October and (4) a wet summer season from November to March.

The city's landscape is heterogeneous and composed of various land cover types. It is surrounded by rural agricultural land, forests, wetlands, grasslands, industrial and residential areas (Figure 6.1). Harare metropolitan city has witnessed rapid urban expansion over the last decades (Kamusoko et al.2013) and the trend is expected to continue (Mushore et al. 2017).

Such rapid urbanization will inevitably generate UHI effecting, negatively affecting the environmental quality.

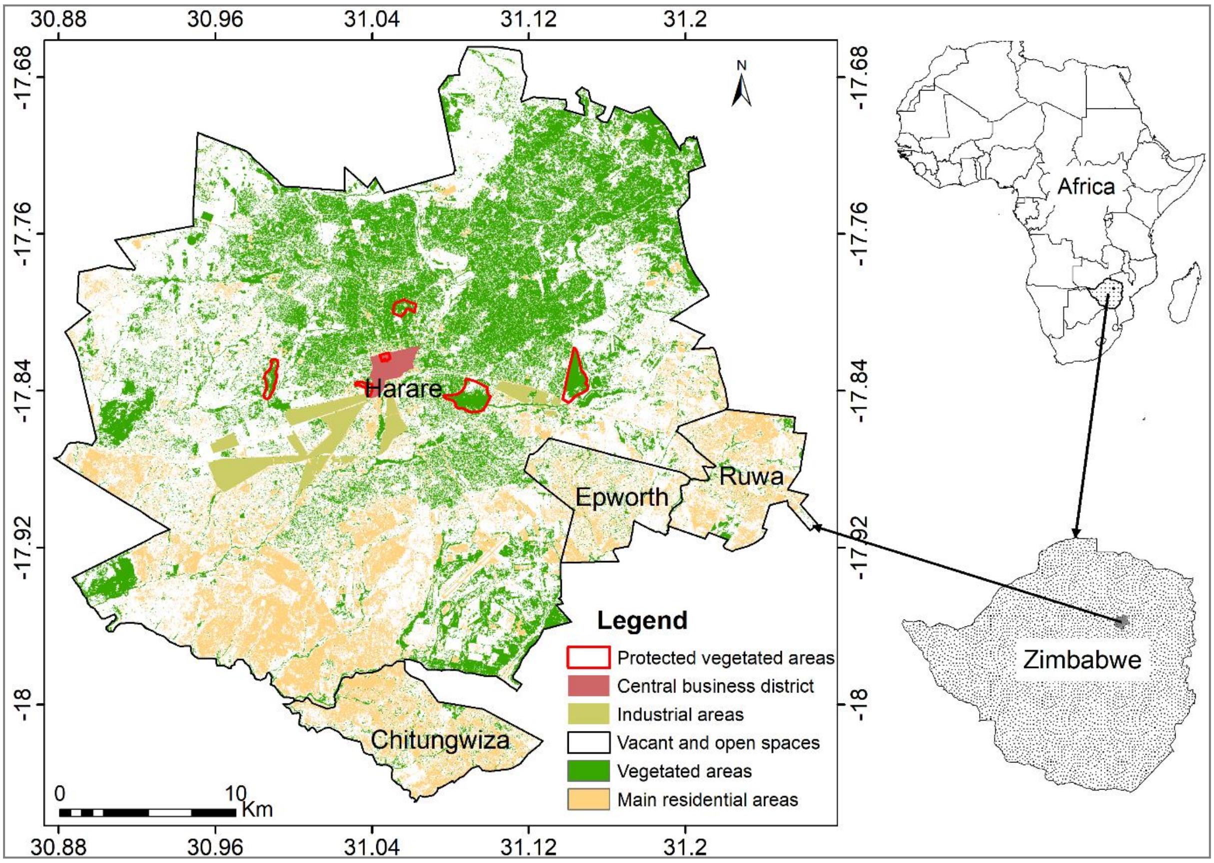


Figure 6.1. The geographical location of the study area, Harare metropolitan city.

6.2.2 Satellite data acquisition

The Landsat 8 Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS) thermal bands of 2018 were used to obtain the city's detailed urban vegetation cover and land surface temperature. Landsat 8 optical bands are the visible, near infrared, short-wavelength infrared and cirrus bands, which have a spatial resolution of 30m. The Landsat's Thermal Infrared Sensor (TIRS) has two channels at 100 m (10.6–11.19mm; 11.5–12.51mm). Although Landsat sensor data are generally coarse for identification of individual features at fine scale, they are the most widely used data source for retrieving urban vegetation and land surface temperature (LST) for urban studies. Landsat data have high spatial resolution relative to other widely available thermal bands of sensors like 1km Advanced Very-High-Resolution Radiometer (AVHRR) and Moderate Resolution Imaging Spectroradiometer (MODIS). It has better temporal resolution than the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) thermal data. The available Landsat satellite cloud-free images were downloaded from the United States Geological Survey (USGS) website (http://earthexplorer.usgs.gov/).

Generally, the amount of cloud cover in Harare is high between December and April, therefore, the image data selected for this study were from May (spring, mild and cool), June (winter, cold and dry), August- September (cool and dry), October (hot and dry) to November (hot and wet). These correspond to spring, winter, autumn and summer seasons, respectively (Table 6.1). We chose and used images of 2018 because there were more seasonal Landsat images available than in other calendar years. The non-availability of suitable images between December and April 2018 because of either cloud cover was not considered a major problem for the study as representative seasons were available.

Table 6.1. Details of Landsat 8 (OLI/TIRS) satellite data acquisition

	Acquisition date	Season	Season conditions
Landsat 8	19 May 2018	Spring	Mild and cool
Landsat 8	20 June 2018	Winter	Cold and Dry
Landsat 8	23 August 2018	Autumn	Cool and dry
Landsat 8	24 September 2018	Autumn	Cool and dry
Landsat 8	26 October 2018	Summer	Hot and dry
Landsat 8	11 November 2018	Summer	Hot and wet (Rainy)

6.2.3 Computing and retrieving land surface temperature

Land surface temperature was computed from imagery captured between May 2018 to November 2018 using Landsat's thermal band (Band 10). The normal approach of computing land surface temperature from Landsat thermal data involves the conversion of the thermal band's Digital Number(DN) values into spectral radiance associated with band 10 according to radiometric rescaling coefficients (i.e., calibration coefficients) (Chander and Markham 2003) using the following equation (6.1).

$$L_{(\lambda)} = \frac{\left(LMAX_{(\lambda)} - LMIN_{(\lambda)}\right)}{\left(Q_{calmax} - Q_{calmin}\right)} \text{ x } \left(Q_{cal} - Q_{calmin}\right) + LMIN_{(\lambda)} \quad \text{……………(6.1)}$$

Where $L_{(\lambda)}$ is the spectral radiance at the sensor's aperture in W/(m^{2}srμm)
Q_{cal} is the quantized calibrated pixel value [DN]
Q_calmix is the minimum quantized calibrated pixel value corresponding to $LMIN_{(\lambda)}$ [DN]
Q_calmax is the maximum quantized calibrated pixel value corresponding to $LMAX_{(\lambda)}$[DN]
$LMIN_{(\lambda)}$ the spectral at-sensor radiance scaled to Q_calmix in W/(m^{2}srμm) and
$LMAX_{(\lambda)}$ the spectral at-sensor radiance scaled to Q_calmax in W/(m^{2}srμm)

The derived spectral radiance values were then converted to at-sensor or satellite brightness temperatures (Chander et al. 2009). Converting at-sensor's spectral radiance to brightness temperature is achieved by computing the inverse of the Planck radiance function for temperature, with an assumption that surface emissivity is equal to that of a black body (i.e. spectral emissivity is 1). The Planck's Law is implemented using the following formula;

$$T_B = \frac{K_2}{\ln\left(\left(\frac{K_1}{L_\lambda}\right)+1\right)} \quad \text{(6.2)}$$

where T_B is the at-sensor brightness temperature in degrees Kelvin. L_λ is spectral radiance in $Wm^{-2}sr^{-1}mm^{-1}$. The at-sensor temperature uses the pre-launch calibration constants K_1 and K_2. K_1 and K_2 are calibration constant 1 and 2 respectively. For Landsat 8 band 10, K_1 and K_2 values are 774.89 and 1321.08, respectively. The at-satellite brightness temperatures was scaled to retrieve land surface temperature values by computing land surface emissivity (ε) following the method developed by Sobrino et al.(2004;2008) expressed as;

$$(\varepsilon) = \varepsilon_v P_v + \varepsilon_s (1 - P_v) + d\varepsilon \quad \text{(6.3)}$$

Where

ε_s = soil emissivity

ε_v = vegetation emissivity,

d_ε = geometrical distribution of natural surfaces (Guha et al.2018). In heterogeneous or complex surfaces, the value of $d\varepsilon$ (Equation 6.4) may be 2% and ***F*** is a shape factor whose mean is 0.55 (Guha et al. 2018; Sobrino et al.2004)

$$d\varepsilon = (1 - \varepsilon_s)(1 - P_v) F\varepsilon_v \quad \text{(6.4)}$$

Pv is the Proportion of vegetation or fractional vegetation cover. The *Pv* is derived from the Normalized Difference Vegetation Index (NDVI) (Tucker 1979) using a method developed by Sobrino et al. (2004; 2008) and Carlson and Ripley (1997). Pv is computed from NDVI values following the approach of Carlson and Ripley (1997);

$$Pv = \left(\frac{NDVI - NDVI_{min}}{NDVI_{max} - NDVI_{min}}\right)^2 \quad \text{(6.5)}$$

Where ($NDVI_{min}$) is the minimum NDVI value (0.2) where pixels are considered as bare soil (non-vegetated areas) and ($NDVI_{\max}$) is the maximum NDVI value (0.5) where pixels are considered as dense vegetation according to Sobrino et al.(2004; 2008). Emissivity **(ε)** values ranges between 0.97 and 0.99. A constant emissivity value of 0.99 is considered when ($NDVI > NDVI_v$), i.e. $NDVI > 0.5$ for fully vegetated pixels in the land surface (PV=1). An emissivity value of 0.97 is assumed when $NDVI < 0.2$ for bare soil (Sobrino et al.2004; 2008).

On the other hand, when NDVI >0.2 to <0.5, it indicates a landscape mixed of both bare soil and vegetation pixels. The land surface emissivity between NDVI >0.2 to <0.5 is computed by applying Equations (3) and (4). From Equations (3) and (4), consequently, the land surface emissivity was computed using the following formula as;

$$\varepsilon = 0.004 * P_v + 0.986 \qquad (6.6)$$

An emissivity value of 0.986 corresponds to a correction value of the equation, which is designated for pixels with a NDVI of ≥0.5. The land surface emissivity corrected LST values were computed as follows;

$$\mathrm{LST} = \left[\frac{T_B}{1+(\lambda\sigma T_B/(hc))\ln\varepsilon}\right] - 273.15 \qquad (6.7)$$

where LST = land surface temperature, T_B = at-satellite brightness temperature, λ = wavelength of emitted radiance (λ = 11.5 µm for Landsat TIRS Band (10), σ is Boltzmann constant (1.38×10^{-23}J/K), h=Planck's constant (6.626×10^{-34}Js), c=velocity of light (2.998×10^{-8}m/s), ε is the land surface emissivity. The retrieved LST values were later converted from Kelvin temperature to degrees Celsius (°C) by subtracting 273.15 from the computed pixel values.

6.2.4. Land cover classification

Satellite images used in this study were classified into five land cover categories (i.e. vegetation, grassland, built-up, water and bareland) based on the supervised image classification approach using Support vector machine algorithm in the ENVI 5.3 image processing software. To derive the discrete information of vegetation patches, the classified land cover map was later reclassified into a binary vegetation and non-vegetation maps for the subsequent analysis.

6.2.5. The landscape connectivity pattern of vegetation

The structural connectivity, which considers the physical arrangement of the landscape elements can be used to describe spatial configuration in a landscape. It determines the fact that two adjacent habitat patches of the same type are spatially joined and connected, but independent of any attributes of the organism (Collinge and Forman 1998). It can also be used to quantify other properties such as the structural connectivity of vegetation at the landscape scale (Tzoulas et al.2007). In this study, the Patch Cohesion Index (%) (Schumaker l996) was used to measure the vegetation connectivity (i.e. connectivity to other urban green spaces) based on the vegetation and non-vegetation map as input data. While structural or landscape connectivity can be evaluated using a wide variety of landscape pattern indices and distance-based connectivity indices like Mean Euclidean Nearest Neighbour Distance and Proximity Index, we selected Patch Cohesion Index because it is a relatively simple to compute and interpret.

Patch Cohesion Index can be used to determine how physically connected one patch is to corresponding patch types or focal class (McGarigal et al. 2002). Patch cohesion index increases as the patch type or focal class becomes more clumped or aggregated, hence, more physically connected (McGarigal et al. 2002). Therefore, a higher value of Patch Cohesion Index indicates a more physically connected pattern of patches in a landscape and vice versa (McGarigal et al. 2002). The Patch Cohesion Index was computed using Fragstats 4.2 software (McGarigal et al. 2002). It is quantified as a range from 0 to 100 (McGarigal et al. 2002). Patch Cohesion Index is expressed as

$$\text{Patch Cohesion Index} = \left(1 - \frac{\sum p}{\sum(p\sqrt{a})}\right)\left(1 - \frac{1}{\sqrt{N}}\right)^{-1} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6.8)$$

6.2.6 Spatial configuration (dispersed and clustered) patterns of vegetation

The local Moran's I was used to compute the spatial configuration patterns of vegetation using NDVI as input data. The local Moran's I has been previously found to be effective in characterising the spatial configuration pattern (clustered to disperse) of land cover features (Fan and Myint 2014). Local Moran's I can identify the extent to which homogenous and heterogeneous observed values of spatial objects cluster around geographical locations. When local Moran's I values are significantly higher than the mean, the spatial objects in a geographical location are assumed to be clustered or homogenous. On the other hand, significantly low values of local Moran's I indicates that the spatial objects in a geographical location are dispersed (Fan and Myint 2014). Local Moran's I is computed based on the following formula;

$$1_i(d) = \frac{x_i - \bar{x}}{\sum_i (x_i - \bar{x})^2} \sum_{\mathrm{j}} w_{ij}\ (d)\left(x_j - \bar{x}\right) \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (6.9)$$

where x_i and x_j denotes the attribute values at locations *i* and *j*. $\bar{x}$ denotes the average attribute values of all the pixels in the geographical area. Furthermore, $\{w_{ij}(d)\}$ is a spatial weight matrix where the diagonal elements are all zero, and the off-diagonal elements are either one or zero, depending on whether the corresponding pixels are neighbour. The neighbourhood is defined by the distance *d*. Therefore, pixels values that are found within a distance of *d* are presumed to be adjacent. The local Moran's *I* values were standardized and normalized to the range of −1 to 1. In this regard, the positive values of the Local Moran's I represents clustered spatial configuration patterns, while the negative values of the local Moran's I indicates dispersed spatial configuration patterns and a value of zero represents random configurations.

6.2.7. The computation of the urban thermal field variance index (UTFVI)

The urban thermal field variance index (UTFVI) was used to evaluate the ecological effects of UHI for the city in all seasons. The UTFVI (dimensionless) was computed based on the following formula (Liu and Zhang 2011, Zhang 2006).

$$\mathrm{UTFVI} = \frac{T_s - T_{mean}}{T_{mean}} \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots \text{(6.10)}$$

where UTFVI= Urban Thermal Field Variance Index, Ts= LST , represents the land surface temperature of a certain area, and Tmean= Mean LST of the study area. The UTFVI was further divided into six different ecological evaluation thresholds levels of the UHI effect (Liu and Zhang 2011, Zhang 2006). The widely used thresholds levels of UTFVI are shown in Table 6.2 (Zhang 2006).

Table 6.2. The threshold of ecological evaluation index using urban thermal field variance index (UTFVI) (Zhang 2006).

Urban thermal field variance index	Urban heat island Phenomenon	Ecological evaluation Index
Less than 0	None	Excellent
From 0.000 to 0.005	Weak	Good
From 0.005 to 0.01	Moderate	Normal
From 0.01 to 0.015	Strong	Bad
From 0.015 to 0.02	Stronger	Worse
More than 0.02	Strongest	Worst

6.2.8. Computing urban and vegetation indices

Heterogeneous land cover surfaces are responsible for producing different amount of sensible and latent heat resulting in diverse heat exchanges and thermal processes affecting surface temperature at varying seasons (Berger et al.2017, Chen et al. 2017). Hence diverse land cover categories in the study in different seasons were assumed would have an influence on land surface temperature. In this study, spectral indices derived from Landsat image data were used to extract information of bareland, impervious surface and vegetation cover (Table 6.3).

Table 6.3: Computation of urban and vegetation indices derived from Landsat 8 data

Index	Computation	Reference
Normalized Difference Bareness Index (NDBaI)	$NDBaI = \frac{SWIR1-TIRS1}{SWIR1+TIRS1}$	(Zhao and Chen 2005)
Bare Soil Index (BI)	$BI = \frac{(SWIR1-RED)-(NIR-BLUE)}{(SWIR1+RED)+(NIR+BLUE)}$	(Chen et al. 2004)
Urban Index (UI)	$UI = \frac{SWIR2-NIR}{SWIR2+NIR}$	(Kawamura et al. 1996)
Normalized Difference Built-up Index (NDBI)	$NDBI = \frac{SWIR1-NIR}{SWIR1+NIR}$	(Zha et al.2003)
Normalized Difference Vegetation Index (NDVI)	$NDVI= \frac{NIR-RED}{NIR+RED}$	(Tucker 1979)
Soil-Adjusted Vegetation Index (SAVI)	$SAVI= \frac{(NIR-RED)}{(NIR+RED+L)} *1+0.5)$	(Huete 1988)
Enhanced Vegetation Index (EVI)	$EVI= \frac{(NIR-RED)}{(NIR+C_1*RED- C_2*BLUE+L)}$	(Liu and Huete 1995)

The spectral indices included the Urban Index (UI) and Normalized Difference Built-up Index (NDBI) for quantifying the distribution of built-up, developed area and impervious surface. The Bare Soil Index (BI) and Normalized Difference Bareness Index (NDBaI) were used to extract bareland or bare soil. The Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI) and Normalized Difference Vegetation Index (NDVI) were used to extract vegetation cover (Table 6.3). High values of vegetation indices indicate areas covered by substantial proportions of healthy and dense vegetation. The spectral indices of water bodies were not included, since water bodies cover an insignificant part of the study area. The computation of the spectral indices is shown in Table 6.3.

6.2.9. Correlation analysis

The normal distribution of each dataset (LST,Patch Cohesion Index, local Moran's I, urban and vegetation indices) was tested using the Kolmogorov–Smirnov test. The Kolmogorov–Smirnov test (K–S test/ KS test) confirmed that all significant indicators were normally distributed, meeting the basic requirements of Pearson's correlation analysis. Thus, the Pearson's product-moment correlation coefficient was used to quantify the correlation between seasonal LST and urban and vegetation indices and the Patch Cohesion Index (%) and local Moran's I of urban vegetation. The Pearson correlation coefficient is often used to show the relationships between variables and ranges from −1 to 1. A higher absolute value of Pearson correlation coefficient indicates a stronger correlation and vice versa. Figure 6.2 illustrate the research methodology and the processing steps presented in this study.

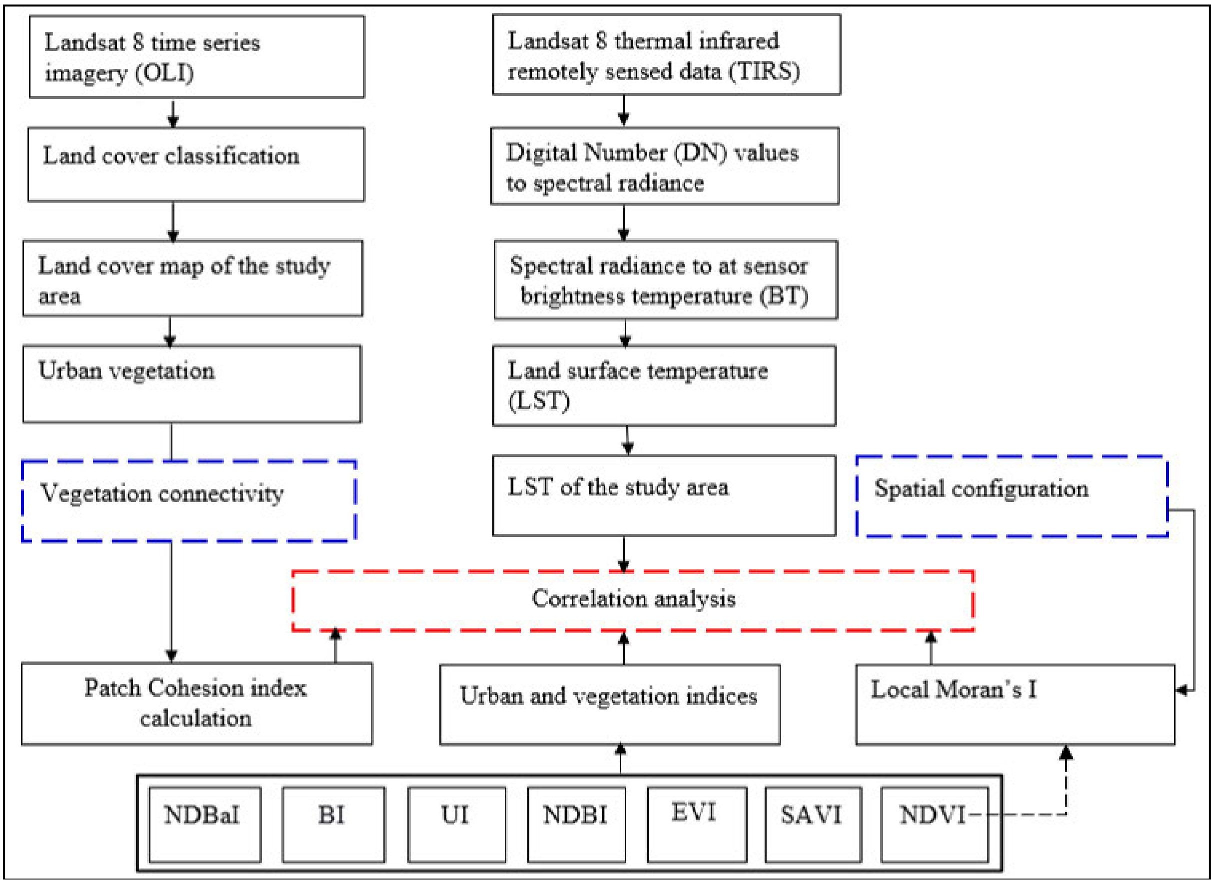


Figure 6.2. Flowchart of the methodology and the processing steps presented in this study

6.3. Results

6.3.1 Seasonal LST variations

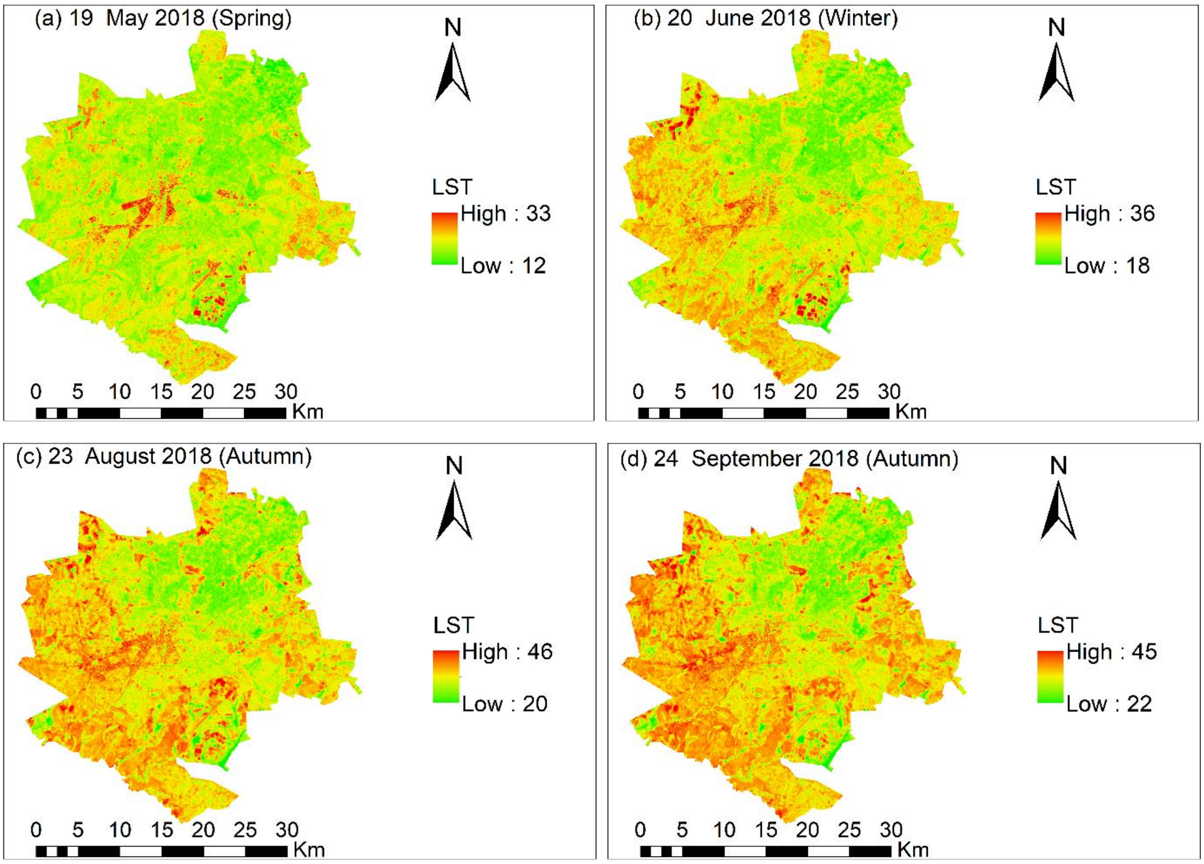
Table 6.4 shows the descriptive statistics of derived LST from May-November 2018 for Harare metropolitan city. The spring season (May) had the lowest LST values for all the descriptive statistics. During the spring season, LSTranged from 10.79°C to 33.61°C (Table 6.4). The maximum land surface temperature values of 54°C and 56°C were observed in summer season (26 October 2018 and 11 November 2018). This indicates that seasonally, UHI intensities are higher during the warmer and hot summer months (26 October 2018 and 11 November 2018). The LST in autumn (August and September) was lower than in hot and summer seasons (October and November). Generally, LST increased in intensity and spatial extent with change of season from spring, winter, autumn to summer (Table 6.4 and Figure 6.3).

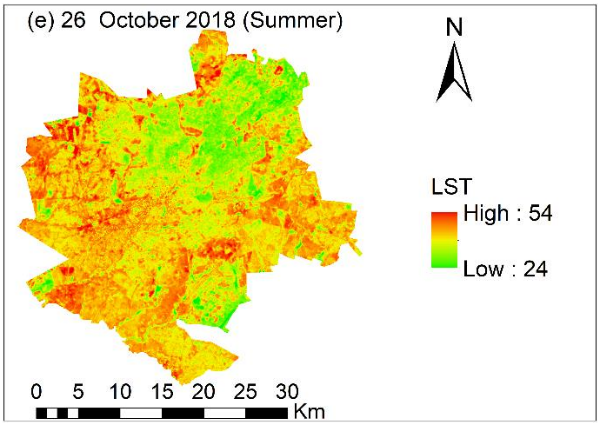
Table 6.4. Descriptive statistics of LST from 19 May 2018 to 11 November 2018

Acquisition date	Season	Minimum	Maximum	Range	Mean	*Std Dev
19 May 2018	Spring	10.79	33.61	22.82	22.04	1.75
20 June 2018	Winter	17.38	35.68	18.3	24.73	2.22
23 August 2018	Autumn	20.18	45.60	25.42	31.10	2.65
24 September 2018	Autumn	22.16	46.13	23.97	34.63	2.99
26 October 2018	Summer	23.32	54.21	30.89	41.22	4.08
11 November 2018	Summer	25.00	56.86	31.86	43.03	4.42

*Standard deviation

The largest range of land surface temperature was found in the summer (26 October 2018 and 11 November 2018)(Table 6.4). It was 30.89°C on 26 October 2018 and 31.86 °C on 11 November 2018. The lowest range of LST was found in the winter. It was 18.3°C on 20 June 2018.The spring season (May) and winter month (June) were characterized by the lowest spatial variability of LST as shown by low standard deviation (Table 6.4). On the other hand, the hot (October) and summer months (November) were characterized by high standard deviations (Table 6.4). In all seasons, the highest LST values were mainly found in the highly urbanized western, eastern and southern side of Harare that has significant presence of high-density residential areas. The highly vegetated northern part of the Harare had relatively low land surface temperature (Figure 6.3).





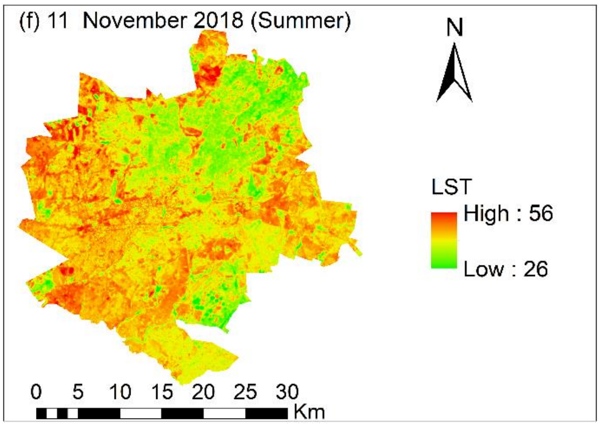


Figure 6.3. The seasonal patterns of land surface temperature LST in Harare metropolitan city between 19 May 2018 to 11 November 2018. The highly vegetated northern part of the city has relatively low land surface temperature than the highly built-up areas in the western, southern and eastern parts of the city.

6.3.2. Ecological assessment of the city based on UTFVI

An ecological assessment of Harare metropolitan city based on urban thermal field variance index (UTFVI) from 19 May 2018 to 11 November 2018 is shown in Figure 6.4 and Table 6.5. In all seasons, the city had a proportion of two extreme groups of ecological conditions. These were the excellent category (UTFVI < 0) and the worst category (UTFVI > 0.020). The largest portion (52.8%) of Harare metropolitan city experienced optimal and excellent thermal conditions for living (i.e. UTFVI <0) in the spring season (19 May 2018) (Table 6.5). In general, the northern part of Harare metropolitan city experiences favourable thermal conditions (i.e. UTFVI < 0) due to the abundance of dense vegetation. Excellent thermal conditions represent either no or weak urban heat island.

Table 6.5. The threshold of ecological evaluation index

		Percentage of area (%)					
Acquisition date	Season	Excellent	Good	Normal	Bad	Worse	Worst
19 May 2018	Spring	52.80	2.60	2.52	2.45	2.40	37.24
20 June 2018	Winter	47.06	1.91	1.93	2.00	2.04	45.05
23 August 2018	Autumn	45.83	2.23	2.30	2.33	2.39	44.92
24 September 2018	Autumn	43.68	2.23	2.33	2.40	2.46	46.90
26 October 2018	Summer	43.61	2.15	2.24	2.32	2.36	47.32
11 November 2018	Summer	45.46	2.04	2.07	2.11	2.17	46.15

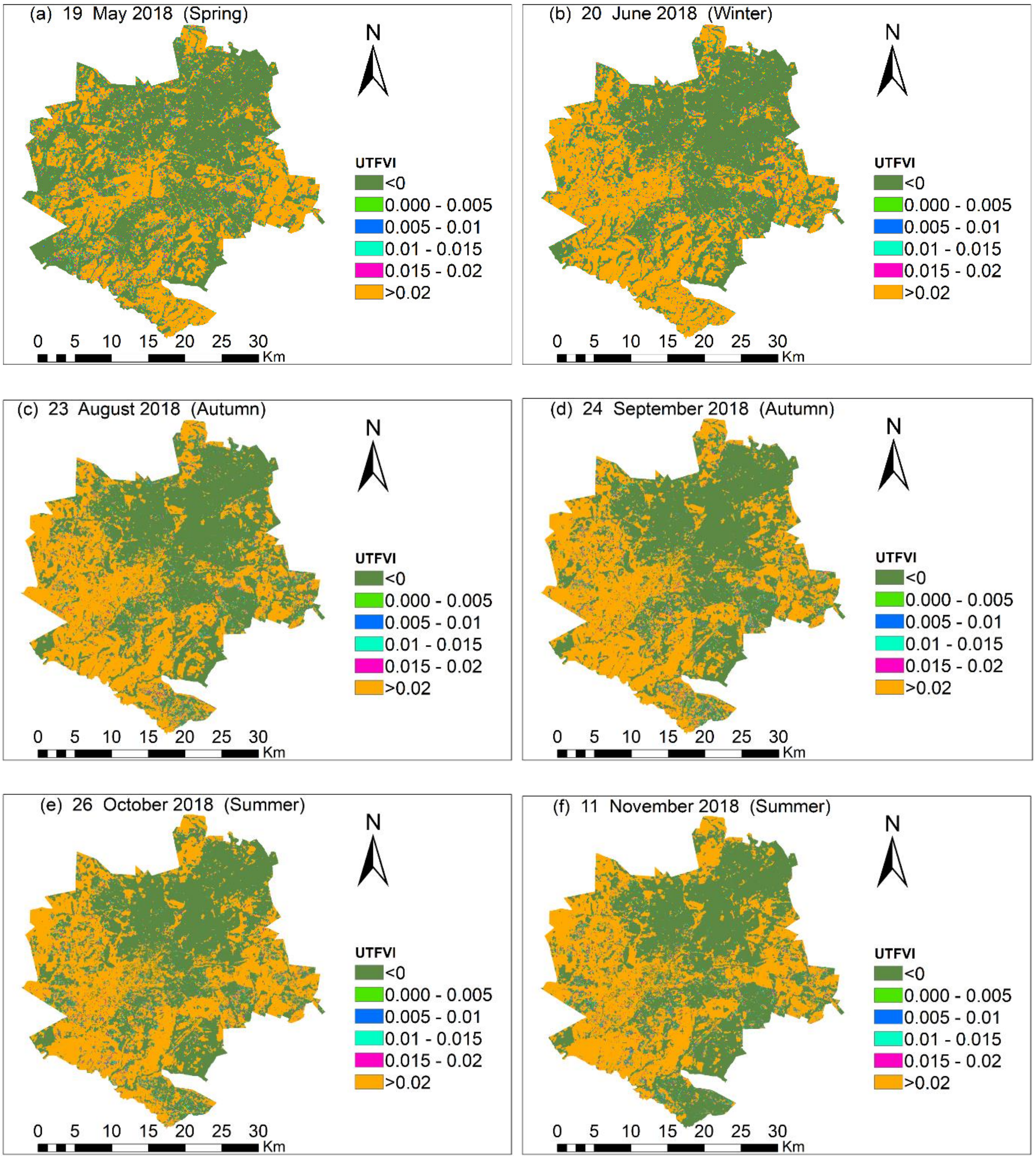


Figure 6.4.Seasonal ecological evaluation index of Harare metropolitan city based on the Urban Thermal Field Variance Index (UTFVI). The northern part of Harare metropolitan city experiences favourable thermal conditions (i.e. UTFVI < 0) representing either weak or no urban heat island. The western, southern and eastern parts of the city experience the worst category (UTFVI > 0.020) representing extremely strong heat islands.

However, the worst category (i.e. UTFVI > 0.020), which represent the extremely strong heat islands exists in a moderate to a significant portion (37%-47%) of the city for all the seasons (Figure 6.4 and Table 6.5). This portion extends from the western, eastern and southern side of Harare. In areas with the worst category, most of the land is highly urbanized, with a huge concentration of built-up areas intermixed with either bare or vacant land. On the other hand, areas that are characterised by worse category (i.e.UTFVI > 0.01), which indicates very strong UHI effects are also located around built-up areas albeit in relatively small proportion (2.0%-2.5%) being lower in winter (June) and higher in autumn (September). Areas that experienced bad thermal comfort accounts also ranged between 2.0% -2.5% of the study area in all seasons. The good and the normal thermal conditions (i.e. 0 < UTFVI < 0.010), which represent weak to middle (moderate) urban heat islands category are located in small portions surrounding the geographical locations under excellent conditions.

6.3.3. Correlation between LST and urban and vegetation indices

The correlation analysis between the urban and vegetation indices and LST were significant at the 0.05 level in all seasons (Table 6.6). There was a positive relationship between land surface temperature and UI, BI, NDBaI and NDBI spectral indices in all four seasons, suggesting that increasing land cover types of bareland and impervious surfaces could raise LST . However, the magnitudes of correlation coefficients between LSTand UI were slightly higher compared with BI, NDBaI and NDBI (Table 6.6).

Table 6.6. Pearson correlation coefficients between LST and urban and vegetation indices

Acquisition date	Season	UI	BI	NDBaI	NDBI	EVI	SAVI	NDVI
19 May 2018	Spring	0.36	0.32	0.29	0.31	-0.31	-0.31	-0.78
20 June 2018	Winter	0.43	0.40	0.28	0.38	-0.40	-0.40	-0.80
23 August 2018	Autumn	0.42	0.36	0.19	0.34	-0.40	-0.41	-0.76
24 September 2018	Autumn	0.46	0.40	0.20	0.41	-0.46	-0.47	-0.78
26 October 2018	Summer	0.46	0.39	0.23	0.42	-0.44	-0.45	-0.74
11 November 2018	Summer	0.46	0.36	0.19	0.41	-0.45	-0.45	-0.74

Urban Index (UI)**,** Bare soil (BI), Normalized Difference Bareness Index (NDBaI), Normalized Difference Built-up Index (NDBI), Enhanced Vegetation Index (EVI), Soil-Adjusted Vegetation Index (SAVI), Normalized Difference Vegetation Index (NDVI). Correlation was significant at the 0.01 level (two-tailed).

There was an inverse relationship between LST and NDVI, EVI and SAVI values in all four seasons, suggesting that increases in vegetated cover decreases LST. However, NDVI had a much stronger negative correlation with LST (°C) than EVI and SAVI ranging from (R=-0.74) in summer (11 November 2018) to (R=-0.81) in winter (20 June 2018) (Table 6.6).

6.3.4. The effect of spatial configuration on LST based on local Moran's I

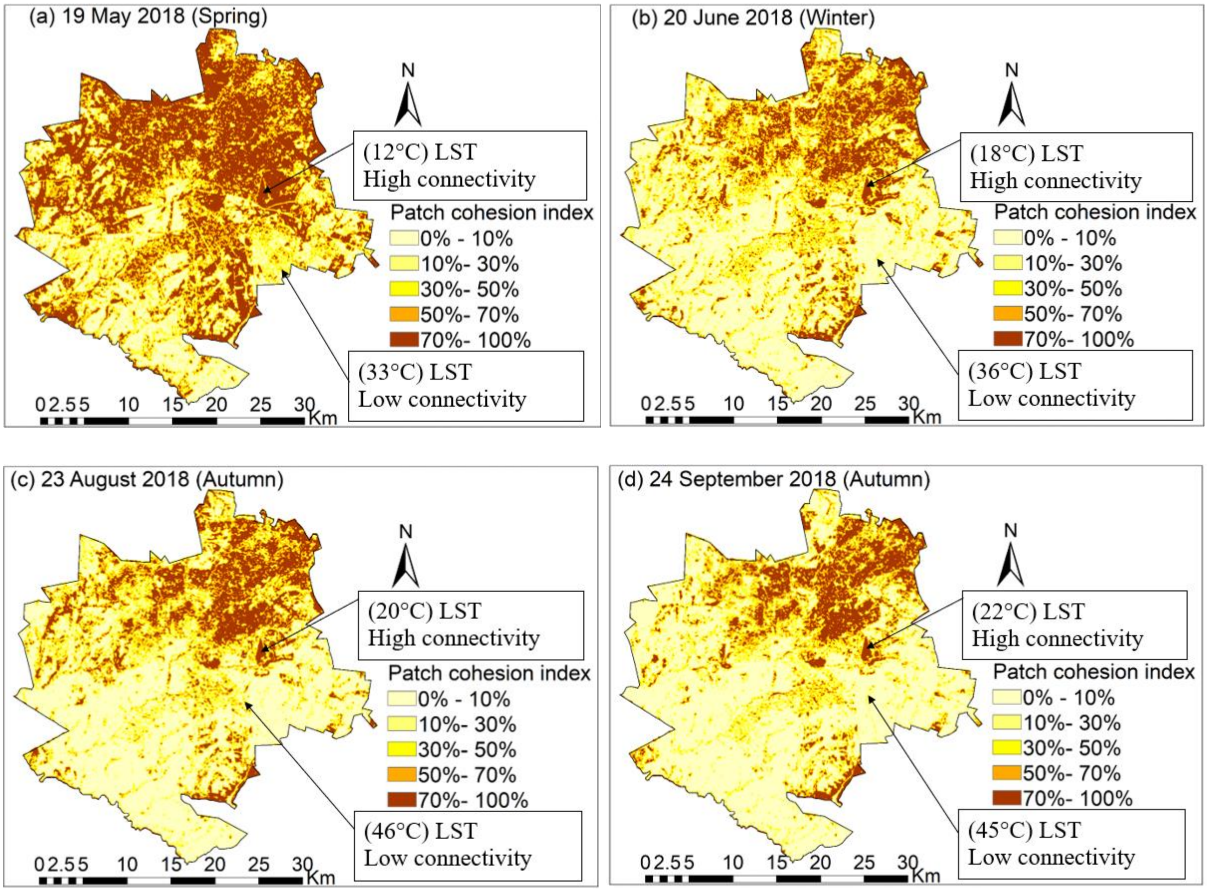
The Pearson correlation coefficients indicated a relatively moderate to strong negative correlation between LST and local Moran's I (Table 6.7). The correlation coefficients ranged between R=− 0.69, p <0.05 in spring (19 May 2018) to R=− 0.74, p <0.05 in hot, dry and summer (26 October 2018, 11 November 2018). The results suggest that as local Moran's I of vegetation become more clustered, land surface temperature decreases, resulting in cooler surface temperatures. The low LST values were heavily concentrated in the highly vegetated northern part of the city. Land surface temperature was high in geographical locations with dispersed vegetation patches in the western, southern, and eastern side of Harare.

Table 6.7. Pearson's correlation between LST and local Moran's I and Patch Cohesion index (COHESION)

Acquisition date	Season	local Moran's I	Patch Cohesion index (COHESION)
19 May 2018	Spring	-0.69	-0.54
20 June 2018	Winter	-0.74	-0.54
23 August 2018	Autumn	-0.74	-0.47
24 September 2018	Autumn	-0.74	-0.57
26 October 2018	Summer	-0.71	-0.59
11 November 2018	Summer	-0.70	-0.58

6.3.5 The relationship between vegetation connectivity and seasonal LST

Table 6.7 indicates a moderate negative correlation between LST and Patch Cohesion index (%) in all four seasons. The Pearson product-moment correlation coefficient (*R*) ranged between (*R*= -0.47, p<0.05) in autumn (23 August 2018) to (*R*=-0.54, p<0.05) in hot, dry summer (26 October 2018). This indicates that highly and well-connected vegetation patterns have a better cooling effect, hence more beneficial in decreasing high LST



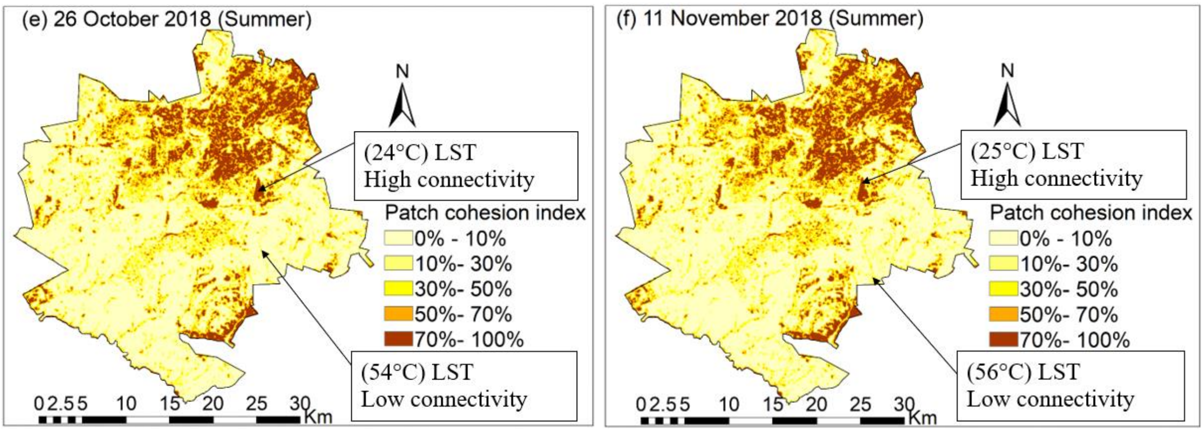


Figure 6.5. Patch cohesion index from May 2018 to November 2018 in Harare metropolitan city.

Higher vegetation connectivity (i.e. less isolation of vegetation patches) are associated with greater proportion of high, contiguous vegetation patterns reflecting shorter distances between the vegetation patches and may contribute to low LST values as indicated in Figure 6.5. In all seasons, the low LSTvalues were dominant in the northern part of Harare, corresponding to the high vegetation connectivity range (<50%-70%). On the other hand, lower vegetation connectivity (higher degree of isolation of vegetation patches) contributes to high LST values (Figure 6.5). Areas with less connected vegetation are found in the western, southern and eastern part of the Harare. These are illustrated with lower vegetation connectivity ranges (<0%-30%). Less connected vegetation (<0%-30%) represent the highly fragmented nature of vegetation patches that are smaller, isolated and scattered across the landscape.

6.4. Discussion

6.4.1. Spatial variability and seasonal urban heat island (UHI) patterns

This study examined how the spatial configurations and connectivity of urban vegetation affect variations of LST across different seasons in Harare metropolitan city in Zimbabwe using Landsat 8 data acquired from 18 May 2018 to 11 November 2018. The research findings of the study showed that LST intensities in Harare tended to be lower during the cool spring season. On the other hand, the LST intensities tended to be higher during the warm, hot summer months, which is consistent with most studies (Arnfield 2003) and findings of Mushore et al.(2018). Higher LST values have also been recorded in warm and summer seasons than in other seasons in Beijing (Wang et al. 2007, Yang et al. 2010) and in the United States of America (Ackerman 1985).

The southern, eastern and western parts of Harare metropolitan city experience high LST , hence stronger urban heat island (UHI) effects, confirming previous findings by Mushore et al.(2017). This is because the southern, eastern and western parts of Harare are more densely urbanized than the northern part. The research findings of this study also indicated a positive relationship between land surface temperature and UI, BI, NDBaI and NDBI spectral indices in all seasons, suggesting that the presence and amount of land cover types of bareland and impervious surfaces increases LST in the study area. A significant positive correlation between the LST and an index-based built-up index (IBI) was observed in Xu (2008). Another study by Odindi et al.(2015) in the eThekwini Municipal Area, South Africa noted that built-up areas were heat sources and while urban green spaces were heat sinks indicating that areas with a higher proportion of impervious and bare land generate more heat than urban green spaces. Highly urbanized and built-up areas commonly have higher solar energy absorption (lower albedo) resulting in higher surface heat storage during the day (Peng et al. 2011) especially in hotter and summer months (Memon et al.2009, Sun et al.2013, Zhou et al. 2014).

Our results indicated a moderate to strong negative relationship between LST and NDVI, EVI and SAVI indices. Similar results showed that the significant negative relationship between NDVI and LST in Indianapolis in the United States of America (Wilson et al. 2003), Hong Kong in China (Liu and Zhang 2011) and Nanjing (China) (Lu et al.2009). This underlines the significant role of vegetation in reducing LST. Vegetation through the evapotranspiration process absorb heat energy and releases water vapour, delivering cooling effects to the surrounding air. Furthermore, vegetation cover through shading can prevent direct solar radiation from heating the surface, thereby helping reduce high surface temperature resulting in better thermal comfort and mitigating the UHI effects.

6.4.2 Ecological conditions of the city

The ecological evaluation for Harare metropolitan city indicated that the northern part of Harare was generally cooler than the heat-stressed western, eastern and southern parts of the city. The northern part of the city has higher vegetation density than the heavily built-up western, eastern and southern side of Harare. Guha et al. (2018) found almost equal proportion of excellent and worst ecological conditions in two cities, Florence and Naples in Italy. The UHI zones (urban areas) were under severe heat stress compared to non-UHI areas (vegetation coverage and water bodies) that had excellent thermal conditions. In another study by dos Santos et al.(2017), for an ecological evaluation of municipality of Vila Velha, in Brazil during

2008–2011, the urbanized areas of the city for all the dates examined were categorized as having worst ecological conditions.

Furthermore, the spatial patterns of the eco-environmental conditions of two Asian cities, Beijing of China and Islamabad of Pakistan were compared (Naeem et al.2018). Comparatively, the worst eco-environmental conditions were found in urban zones of both cities where the proportion of vegetation was very low (Naeem et al. 2018). However, the eco-environmental conditions were more severe in Beijing, as more than 90% of its total population was living under the worst eco-environment conditions, while only 7% of the population was enjoying comfortable conditions. In contrast, close to 61% of the total population of Islamabad lived under the worst eco-environmental conditions, and close to 24% was living under good conditions (Naeem et al.2018). Overall, all these studies show that in densely built-up areas with less vegetation, the eco-environmental conditions are worse because of stronger urban heat island effects (dos Santos et al.2017, Guha et al.2018, Liu and Zhang 2011, Naeem et al.2018).

6.4.3 The relationship between spatial configuration and seasonal LST (ºC)

The research findings of this study indicate a moderate negative correlation between local Moran's I and LST in all seasons, However, a study by Fan et al.(2015) found out that the influence of local Moran’s I of green vegetation on LST was higher during summer daytime whilst it was weakly correlated to the local Moran’s I during winter nighttime LST in the central part of Phoenix, Arizona in the United States of America. However, our results corroborates previous research findings that indicate that dense and clustered urban vegetation are more effective in reducing surface temperature than dispersed urban vegetation patterns (Li et al. 2012, Peng et al. 2016, Zhang et al. 2009). The impact of clustered vegetation in providing cooling effects was found to be significant for both daytime and nighttime surface temperature in geographical areas with dry and warm summer climate such as Phoenix and Portland in the United States of America (Wang et al.2019).

It can be expected that large and contiguous vegetation patches have higher cooling effects through evapotranspiration and shading and thereby lowering the sensible heat released from the ground and efficiently mitigating the UHI effect (Imhoff et al. 2010, Myint et al. 2013, Peng et al. 2011, Zhou et al. 2014). In our study, low surface temperatures were found in the highly vegetated northern part of Harare. Such cooler conditions may be of particular importance to the well-being of urban dwellers as they can enjoy greater thermal comfort conditions provided by higher cooling effects of urban vegetation. Small, isolated vegetation patches commonly have a high thermal load and do not deliver significant cooling effects (Bao et al. 2016). Furthermore, such areas maintain lower rates of evapotranspiration, hence weaker mitigating effect on the UHI effect. Generally, the more densely urbanized western, southern and eastern of the Harare metropolitan city has many isolated and sparse vegetation and is more densely urbanized than the vegetated northern part of the city.

6.4.4 The relationship between vegetation connectivity and seasonal LST

Our results showed a moderate negative relationship between Patch Cohesion index and LST in all seasons, implying that well-connected urban vegetation patches are effective in reducing land surface temperature in all seasons. Similar to our findings, Kim et al.(2016) showed that Patch Cohesion index (COHESION) of neighbourhood trees and forests had a negative relationship with LST on residential areas in Austin, Texas. The positive effects of higher connectivity of vegetation on LST are demonstrated in other studies of Asgarian et al.(2015) and Zhibin et al.(2015). Well and higher-connected vegetation patches lower surface temperatures and act as heat sinks (Chen et al. 2016, Li et.al. 2017). However, in urban areas, vegetation is heterogonous, usually fragmented by human infrastructure, such as settlements, transport networks and commercial buildings, leading to low vegetation connectivity and high vegetation fragmentation. Lower vegetation connectivity act as heat sources, promoting warmer and higher surface temperatures.

However, some contradictory results exist as other studies including Chen et al. 2014a; Li et al. 2012; 2013a and Zhou et al. 2011 found that the landscape connectivity of urban green spaces elevate LST. Zhou et al.(2011) reported that a clustered pattern of woody vegetation quantified using the mean nearest neighbour distance tends to increase land surface temperature. The contradictory results can be explained by several factors among them is the significant influence of spatial composition (percentage and abundance) on the relationships between the spatial patterns of vegetation and land surface temperature. Due to the high correlation between mean nearest neighbour distance and the proportion of vegetation (Zhou et al. 2011), other connectivity metrics and robust spatial regression models are noteworthy exploring to control the confounding effects of spatial composition of vegetation on LST.

6.4.5 Implications for urban planning and management

Urban green spaces and vegetation such as woodland, grass and street trees play a key role in reducing urban surface temperatures. Increasing vegetation cover in response to observed climate change and global warming by planting more trees could provide shading and evapotranspiration; two ecosystem services that can reduce heat loads and lower LST . Optimizing the spatial configuration of urban vegetation to seasonal LST is important for urban design and landscape planning. Due to the continuing fragmentation of green spaces in urban areas, conservation and restoration efforts should target green vegetation that is fragmented and scattered. Our results show that less dispersed or spatially clustered vegetation is effective in alleviating urban surface temperatures in all seasons.

Increasing landscape connectivity of urban vegetation to minimize the adverse impacts of habitat loss and fragmentation induced by rapid urban expansion is significant in achieving sustainability of the city. The negative relationship between land surface temperature and vegetation connectivity in all seasons has implications on how to spatially arrange and organize urban vegetation patches to reduce the UHI effects in urban areas. Vegetation fragmentation can be reduced by creating well-connected urban green spaces networks and corridors instead of small, isolated vegetation patches that increase the thermal heat and energy exchange between non-vegetated area areas and green areas. Landscape connectivity between urban green patches maximizes and increases the cooling effects of the surrounding areas (Doick et al. 2014) which are important for the human health and physical well-being of urban dwellers.

6.4.6. Limitations

Although the findings of this research are conclusive within the scope of the study, some limitations deserve further research and extensive analysis. The role of spatial configuration and connectivity patterns of urban vegetation on LST should be further examined to better guide urban design and to maximize higher cooling effects in urban areas. Our research findings indicate that the spatial configuration (clustered and dispersed) and landscape connectivity of vegetation has moderate to a strong negative relationship with LST , regardless of the season. We did not find significantly different negative relationships between the local Moran's I and LST in different seasons as reported by Fan et al. (2015). Fan et al.(2015) found out that local Moran's I of urban vegetation was highly and negatively correlated with land surface temperature during summer daytime whilst local Moran's I had a weak correlation with the winter nighttime surface temperature. The divergent results mentioned above have several possible reasons: (1) different methodological approaches that were used such as the choice of landscape metrics employed. However not all landscape metrics can produce and convey material heat exchange fluxes and thermal processes in a city (2) a small number of studies that mainly reported on single cities. Cities are different in their urban forms (monocentric or dispersed), socioeconomic, geographical settings and regional climatic conditions (3) the characteristics of urban vegetation are not equally distributed across cities regarding their size, shape and particular land cover category.

6.5. Conclusion

The objective of this study was to examine the impact of the spatial configuration (clustered or dispersed) and connectivity of vegetation patterns on seasonal LST in Harare metropolitan city, Zimbabwe. To achieve this objective, the local Moran's I and the Patch Cohesion Index methods derived from Landsat 8 optical data were combined with Landsat 8 thermal data of 2018. The research findings showed that the spatial configuration (clustered or dispersed) and connectivity of vegetation patches can significantly lower surface temperatures in all four seasons of spring, winter, autumn and summer. The research findings demonstrated the significant role of landscape connectivity, clumping and aggregation of urban vegetation in reducing urban surface temperature. Based on these research findings, we suggest that landscape ecologists should optimize the spatial arrangement by clustering, clumping and connecting vegetation patches (woodland and grassland) rather than dispersing, which is essential for urban landscape design, urban planning and sustainable development.

CHAPTER 7. SUMMARY AND SYNTHESIS OF THE THESIS

7.1. Introduction

An effective and accurate representation of the landscape structure of urban vegetation and vegetation fragmentation is an important goal towards addressing the linkages of the fundamental ecological processes and patterns at multiple scales (McGarigal and Marks 1995, Turner 1990, Turner et al.2003, Uuemaa et al. 2009, Wang et al.2014, Wu 2008, Wu and Hobbs 2002). Landscape metrics derived from categorical maps and land cover classifications of remote sensing data are the traditional methods and an existing paradigm within which landscape structure of urban vegetation and vegetation fragmentation can be quantified (Qian et al. 2015, Wang et al. 2014). However, the challenges of discrete landscape pattern analysis or patch mosaic model of indiscriminately categorizing maps into homogenous units are well established, making it difficult for landscape ecologists to accurately and effectively quantify important spatial heterogeneity patterns (Fan and Myint 2014, McGarigal and Cushman 2005).

Many landscape pattern metrics are highly correlated with each other, capturing similar qualities of landscape or spatial patterns, making their use as a measure of habitat fragmentation (grassland, forest etc.) challenging (Wang et al. 2014). Due to the challenges of discrete landscape pattern analysis, a growing amount of work has been dedicated to evaluating the potential of continuous models or gradient models in mapping landscape patterns (Fan and Myint 2014,Levin 2009, McGarigal and Cushman 2005, Pearson 2002, Roberts et al. 2000, Southworth et al. 2004,). The continuous methods appear to be one way of effectively representing fine scale heterogeneity of vegetation fragmentation in urban areas. To undertake this task, the following objectives of the research were considered:

(i) To examine the spatial patterns of vegetation fragmentation using spatially explicit approaches of the forest fragmentation model and local spatial autocorrelation indices.
(ii) To quantify the long-term changes in vegetation fragmentation using forest fragmentation model, landscape metrics, local spatial association indices (LISA) and Tasselled Cap Transformation indices.
(iii) To develop spatial analytical tools to quantify the impacts of the spatial configuration of vegetation patches on urban warming and cooling using the landscape metrics and LISA indices.
(iv) To compare and assess the applicability of Spatial Lag Regression and Ordinary Least Regression models in examining the impact of spatial configurations of urban vegetation on urban warming and cooling.
(v) To examine spatial resolution sensitivity of different satellite data on the quantitative relationship between surface temperatures and spatial configurations of urban vegetation.

(vi) To examine the seasonal impacts of the ecological, spatial configuration and connectivity of urban vegetation on urban thermal environment using the landscape metrics and LISA indices.

7.2. Exploring the spatial patterns of vegetation fragmentation

The literature review in Chapter 2 showed that most of the previous studies conducted over the last decades that quantified changes in the spatial patterns of vegetation fragmentation across worldwide cities have commonly used Landsat data. The increasing low cost and freely availability of Sentinel 2 offering 10m–60m spatial resolution have the capability of providing detailed information on patterns of vegetation fragmentation in many cities and may be needed for local scale and land management decisions. Chapter 3 examined the vegetation fragmentation patterns in Harare metropolitan city by combining the moving window forest fragmentation model and local spatial statistics of Getis-Ord G* and Local Moran's I derived from Sentinel 2 data of 2016 and 2018.

As demonstrated in Chapter 3, the forest fragmentation model can identify and spatially show the level or degree to which vegetation is fragmented (core or interior, perforated, edge, transitional, patch). Based on the forest fragmentation model, the results showed that in both 2016 and 2018, patch category of vegetation pattern, which represents the severe level of vegetation fragmentation, was the dominant spatial pattern across the city. This therefore, implied that more conservation attention and priorities should be given to patch category of vegetation pattern, as they usually consist of many smaller and isolated vegetation patches. Most of the patch vegetation patterns were concentrated in heavily built areas of the southern, eastern and western side of the city. On the other hand, the core category of vegetation pattern which represents undisturbed, lowly fragmented, covered a small portion of the study area as they were dominant in the northern part of the Harare.

Another potentially useful feature of the forest fragmentation model is that it works well for any discrete and continuous land cover and vegetation data at any scale. Multiple-scale approaches are needed because no single scale can apply to all of the landscape that is affected by vegetation fragmentation. Unlike other distance and connectivity based methods, for instance the proximity index and the Euclidean nearest neighbour distance (ENN), the forest fragmentation model has an added advantage that it does not require arbitrary edge and Euclidean distance specification to define a core, interior, perforated, transitional and edge area within a contiguous vegetation pixel. It explicitly accounts for the amount or proportion of a landscape occupied by vegetation patches and thereby helps to evaluate their significance to conservation efforts. The forest fragmentation model could in future become an important spatial analytical tool in landscape and urban planning for the conservation of urban green spaces. For instance, one strategy to target large vegetated areas for restoration efforts might be based on the existence of core or interior vegetation conditions. The forest fragmentation model could also be used to assess restoration potential. A restoration strategy to expand the area of core or interior vegetation conditions might be to fill in the perforated urban vegetated areas.

Chapter 3 went on to further highlight the spatial explicit value of LISA indices of Getis-Ord Gi* and Local Moran's I in revealing where the more homogeneous (clustered) and heterogeneous (fragmented) areas of vegetation exist spatially within the city. The small, isolated and scattered vegetation patches were associated with low positive and negative spatial autocorrelation of LISA indices. The highly fragmented and heterogeneous patterns of small, isolated and scattered vegetation patches detected as cold spots in LISA indices were mainly concentrated in the highly and densely built-up western, eastern and southern part of the Harare. On the other hand, the more homogeneous (clustered) vegetation showed high positive spatial autocorrelation of Getis-Ord Gi* and Local Moran's I statistics. The significant spatial clusters of vegetation (hot spots) representing the highest proportion of undisturbed and core vegetation, were located in state protected and large parks in the northern side of Harare.

The implication of these results is that local spatial statistics and indices like Getis-Ord G*and Anselin Local Moran's I can be used as spatial explicit tools to statistically characterize the local spatial variability patterns indicating whether vegetation is clustered or dispersed and also distinctively revealing the extent of vegetation fragmentation across the landscape. The approach used in Chapter 3 enabled the continuous (i.e. LISA indices) as well as discrete (forest fragmentation model) representations of spatial heterogeneity and vegetation fragmentation in an urban landscape.

7.3. Long-term changes in vegetation fragmentation using discrete metrics and continuous models

Based on the spatially explicit methodology of LISA indices and the forest fragmentation model, the results in Chapter 3 identified the key geographical locations where conservation efforts can be directly targeted on highly fragmented and isolated vegetation patches. Chapter

4 sought to develop a generic approach for conceptualizing the landscape structure of vegetation patches and capturing long-term changes that may not be abrupt and discrete or observable in a landscape. To do this, Chapter 4 uniquely combines discrete (landscape metrics, forest fragmentation model) and continuous methods (LISA, Tasselled Cap Transformation) in examining their ability to understand spatial clustering, connectivity and vegetation fragmentation patterns between 1994–2017 in Harare metropolitan city in Zimbabwe using multi-temporal Landsat data.

Despite the sensor's relatively coarse resolution, Chapter 4 indicated that time series Landsat imagery data is valuable for assessing the pattern, change and extent of vegetation fragmentation over time in an urban landscape highlighting whether vegetation fragmentation was increasing or decreasing. The combination of LISA indices (local Moran's I and Getis Ord Gi*), Tasselled Cap Transformation indices, the forest fragmentation model and landscape metrics established that vegetation patterns in the study area after 1994 were becoming increasingly fragmented and less connected than being clustered (homogeneous). The 2017 image had fewer numbers of contiguous, highly connected and large vegetation patches than all the previous satellite images. Landscape metrics showed that vegetation fragmentation in the study area experienced an increase in the number of vegetation patches, a decrease in mean patch size, an increase in shape complexity and edge density and increasing isolation between habitat vegetation patches.

Unlike landscape metrics, the usefulness of continuous LISA indices corroborated same results found in Chapter 3 in providing more information on where the more dispersed (fragmented) and clustered vegetated patterns occurred spatially in the study area. The decrease of large, connected and contiguous vegetation to a more scattered and fragmented vegetated patches were common across the city but were more dominant in the western, eastern and the southern side of Harare indicating the adverse impact of urban development. Furthermore, the Landsat derived indices of Tasselled Cap Transformation (TCT) indices enabled additional interpretation of change that might have been confounded with LISA indices techniques. Tasselled Cap Transformation (TCT) indices are uncorrelated and contain enhanced biophysical information into known characteristics (vegetation wetness, soil brightness and vegetation greenness). The Tasseled Cap Angle (TCA) derived from Tasselled Cap Transformation indicated that vegetation cover in the landscape between (1994–2017) was constantly changing, significantly not maintaining a higher amount of vegetation to non-vegetation coverage. Overall, the combination of spectral indices of Tasseled Cap Angle, Tasseled Cap Wetness, Tasseled Cap Greenness, Tasseled Cap Brightness, NDVI and local Moran's I that were derived from Landsat data when analysed against vegetation connectivity, revealed that the landscape pattern of vegetation became more spatially disperse and widespread after 1994.

Overall, the spatially explicit approach employed in this research work can be utilised for future studies in identifying areas of exceptionally high or low vegetation cover for conservation and restoration purposes. The extent of vegetation connectivity and fragmentation are important indicators of ecosystem function and landscape integrity. A highly connected and less fragmented pattern of vegetation has a higher probability of maintaining their ecological functions and balance than small habitat (forest, grassland, woodland) patches. In urbanized areas, the green spaces may be smaller than the actual area of habitat due to the great human disturbance. Large and contiguous vegetated areas are suitable habitats that can support a large population and are more likely to maintain the species persistence (Arifin and Nakagoshi 2011).

7.4. The impact of spatial configuration of urban vegetation on urban warming and cooling

One of the objectives of this study was to use spatial explicit analytical methods to enable accurate estimates of spatial configuration (size, density, shape complexity, connectivity, clustering and fragmentation) of urban vegetation patterns and evaluate its influence on urban warming and cooling. A better understanding of the role of the spatial configuration and landscape patterns of urban vegetation is important in mitigating urban warming effects so that cities can have liveable, healthier and comfortable conditions. Using the continuous local spatial autocorrelation index of Getis Ord Gi* proposed in Chapter 3 and 4, Chapter 5 sets out by examining the influence of spatial configuration of urban vegetation on LST in Harare. ASTER (September 2010), Sentinel 2 (October 2017) and two Landsat-8 OLI/TIRS (October 2013 and 2017) were used.

The correlation analysis between LST and Getis Ord Gi* of vegetation patterns indicated that Getis Ord Gi* had a moderate negative correlation with daytime LST in the dry and summer season. This implied that spatially clumped vegetation patterns could decrease surface temperatures more significantly than fragmented patterns of vegetation in dry summer season. The five landscape metrics used in this study that included AWMPFDI, AWMSI, Edge Density, Mean Patch size and Patch Cohesion index of vegetation also showed a negative relationship with LST at three different spatial resolutions (10m, 15m and 30m). The results illustrated that vegetation patterns with larger mean patch sizes, edge density, irregular in shape and highly connected all contribute to better cooling effects.

It is sometimes impractical to increase patch size, enhance connectivity of green space and to install cool roofs across an entire city due to the limited vacant and open spaces, existing land use constraints and high pressure of urban developments. Therefore, optimizing spatial configuration for mitigating UHI effects is particularly desirable in effectively mitigating urban warming in tropical cities during the summer when excessive heat increases thermal discomfort and puts a huge demand on water and energy consumption.

7.5. Sensitivity of spatial resolution of satellite data on the quantitative relationships between LST and spatial configurations of urban vegetation

The landscape metrics have been shown to be susceptible to changing grain size and spatial scales (Wu et al.2000). A multiscale analysis was carried out in Chapter 5 to reveal the extent to which the impacts of landscape patterns of vegetation on urban warming and cooling vary across different spatial resolutions of remote sensing data. Results showed that the landscape metrics of urban vegetation patterns based on the mean patch size, density, shape complexity and connectivity had consistently weak to moderate negative relationships with LST. However, the magnitude of the relationship varied with spatial resolution at 10m (Sentinel 2), 15m (ASTER) and 30m (Landsat 8).

Except Patch Cohesion index, the results indicated that the negative correlations between land surface temperature and landscape metrics indices of AWMPFDI, AWMSI, Edge Density and Mean Patch size of vegetation patterns were significant at finer spatial resolution of 10m (Sentinel 2) and 15m (ASTER) spatial resolution than at 30m of Landsat 8 imagery. This provided important indications of the spatial resolutions at which maximum warming and the cooling effect is achieved. This implied that finer spatial resolution is more sensitive to the response of changing spatial configurations of vegetation patches on LST as they contained more detailed land cover features (e.g., trees, grass) than coarse resolutions.

On other hand, the effect of Patch Cohesion index of vegetation on LST increased with the subsequent decrease of spatial resolution becoming stronger at 30m of Landsat 8 imagery than at 15m (ASTER) and 10m (Sentinel 2). Since this study only used moderate spatial resolutions (Sentinel 2, Aster and Landsat) due to data costs challenges, other satellite data with better and finer spatial resolution such as QuickBird, GeoEye and WorldView are recommended. They should be employed to gain concise conclusions of their individual effects upon LST (°C). The higher spatial resolution permits identification of more detailed land cover classes such as trees, grass, buildings, and paved surfaces.

7.6. Comparison of spatial regression models and ordinary regression models in examining the impact of spatial configurations of urban vegetation on urban warming and cooling

Owing to the spatial autocorrelation of LST because of land surface heat fluxes, the underlying assumption that the observations of dependent variables are all independent cannot be true as it is influenced by its values at nearby locations. Therefore, using traditional and global regression methods like the Ordinary least squares regression model (OLS) without considering spatial autocorrelation or spatial dependency of the dependent variable like LST, can lead to misleading parameter estimates and unreliable significance tests. Chapter 5 demonstrated that better modelling performances can be achieved when spatial non-stationarity (spatial heterogeneity) is highlighted and spatial autocorrelation of land surface temperature effects are controlled to promote the practicality of city resilience to adapt to urban warming and heat island effects at a detailed local scale. It was important to model geographical phenomena of LST at small, meaningful spatial scale, where reliable quantitative regression models can provide effective supporting tools for specific locational decisions.

As demonstrated in chapter 5, results showed that Spatial Lag Model (SLM) was more powerful than the OLS regression model in improving the estimation and accuracy of the relationships between mean LST and spatial configurations of vegetation. In both OLS and SLM models, R^2 significantly increased with subsequent decrease in spatial resolution. The OLS model explained about 11% (R^2 = 0.1158) for Sentinel 2 (10m), 13% (R^2 = 0. 1304) for Aster data (15m) and 53% (R^2 = 0.5285) for Landsat 8 data (30m) of the predicted estimate of the relationship between mean LST and landscape metrics of vegetation. On the other hand, SLM model explained 51% (R^2 = 0.5076) for Sentinel 2 (10m), 52% (R^2 = 0.5153) for Aster data (15m) and 64% (R^2 = 0.6353) for Landsat 8 data (30m) of the predicted estimate of the relationship between mean LST and spatial configuration of vegetation. This indicated that the SLM model could explain more than 50% of the variance between mean LST and selected landscape metrics of vegetation at different spatial resolutions. This also demonstrated that the influence of spatial configuration of urban vegetation patterns in reducing UHI effects were underestimated in the OLS model. This research complements previous studies that emphasise the importance of using robust spatial regression methods in examining the spatial configurations of vegetation in mitigation the UHI effects. The SLM analysis of spatial configuration of urban vegetation patterns can provide detailed, reliable information for specific locations for UHI mitigation in urban areas.

7.7 The spatial configurations and connectivity of urban vegetation patterns and their impact on seasonal urban surface temperature

The spatial configuration and connectivity of urban vegetation is an essential factor that affects the heat fluxes and exchanges between patches of vegetation and the LST in an urban area. The necessity for maintaining and promoting landscape connectivity of vegetation is gaining increased acceptance in urban and landscape planning as a key management objective in mitigating urban heat islands. Previous research work on the influence of spatial configurations of urban vegetation patterns on LST was solely focused on explaining the spatial patterns of UHI at a specific time, generally in dry and summer season as highlighted in Chapter 5.

However, the spatial configurations (clustered and dispersed) and connectivity of urban vegetation patterns may affect surface temperatures in urban thermal environments across the year or across different seasons (spring, winter, autumn and summer) in different ways and at different levels. Therefore, a comprehensive and cost-effective strategy for improving the outdoor urban thermal environment should encompass all seasons (summer, winter, autumn and spring). The purpose of Chapter 6 was to build this framework of understanding how the spatial configuration (clustered and dispersed) and connectivity of urban green vegetation affect the urban thermal environments across different seasons (spring, winter, autumn and summer) in Harare metropolitan city using Landsat OLI data measured over the period from May 2018 to November 2018.

The spatial configuration of urban vegetation was quantified using local spatial statistic of local Moran's I, while vegetation connectivity was calculated using Patch Cohesion Index (%). Correlation analysis based on a Pearson correlation coefficient (r) was applied on both Patch

Cohesion Index and local Moran's I against LST, which was a dependent variable. The local spatial statistic method of local Moran's I is very efficient and useful in providing the continuous and true depiction of the spatial arrangement and distribution (random, dispersed or clustered) of the landscape that cannot be easily detected by the discrete and widely used landscape metrics (Fan et al. 2015). Results in Chapter 6, indicated that landscape configuration and connectivity of urban vegetation estimated from both Local Moran's I and Patch Cohesion Index (%) had a moderate to strong negative correlation with LST in all seasons (spring, winter, autumn and summer).

Overall, the research findings of the relationship both local Moran's I and Patch Cohesion Index against LST implied that less fragmented but highly clustered and connected vegetation are more effective in reducing urban warming and providing cooling effects than dispersed patterns in all seasons. The overall information provides important insights to policy makers, urban planners and designers in considering optimizing different spatial configuration patterns of vegetation so that cities can have comfortable living environments in all seasons. In particular, urban and landscape planners should provide highly connected and less fragmented urban vegetation patches, optimizing clustering rather than dispersing vegetation focusing on specific time and season to derive maximum and higher cooling effects for mitigating increasing surface temperatures in cities. In response to observed urbanization and global warming and continuing vegetation fragmentation in urban areas, reduced surface temperatures in all seasons are important in achieving sustainability objectives.

7.8. Limitations

In this study, the following limitations were identified;

1. This research did not consider the influence of urban expansion and other land cover and land uses on vegetation fragmentation across space and time. Worldwide, the urban expansion and other land cover and land uses (roads and transportation) are a threat to vegetation fragmentation.

2. The continuous spatial LISA approach used in this research have shown much promise in effectively characterizing the spatial patterns of vegetation from a continuous and gradient perspective. However, in this study, we did not examine other continuous methods for landscape pattern analysis of vegetation fragmentation and urban warming and cooling.

3. In examining vegetation fragmentation and urban thermal environment across the study area, we did not dealt with the impact of varying spatial resolution on the relationship between the local spatial statistics (local Moran's I and Getis Ord GI* statistic) and

landscape metrics of vegetation at higher spatial resolutions from satellite images like QuickBird, IKONOS and SPOT.

4. The forest fragmentation model used in this research work has been efficient in examining and analysing the pattern and degree of vegetation fragmentation. The analysis of vegetation fragmentation derived using forest fragmentation model is however much affected by the choice of spatial scale (window size). Generally, a large spatial window size in the forest fragmentation model may overestimate and underestimate the amount of patch and core categories of vegetation areas, respectively.

5. Although we chose and used the most relevant and appropriate landscape pattern indices to capture important aspects of spatial configurations of vegetation, the contributions of other landscape indices, land cover and land use classes are important to consider when studying vegetation fragmentation and urban thermal assessments. Generally, not all landscape metrics are responsible for the heat exchanges, energy flows and thermal processes in a city.

6. This study employed coarse resolution satellite data that included the ASTER, The Sentinel-2 and Landsat data which showed promising results in examining vegetation fragmentation and urban thermal environment. However, in heterogeneous urban landscapes, remote sensing images with medium resolution may fail to depict the highly dynamic and changes of vegetation fragmentation and urban thermal environment.

7. In this research work, we only used land surface temperature to characterize the urban warming and cooling of the city. When employing the land surface temperature data instead of in situ air temperature data to explain landscape patterns of urban vegetation on the urban warming and cooling, the correlation between land surface temperature and air temperature in a city might be dramatically different in the daytime and nighttime.

8. This research indicated that spatial regression methods are reliable, robust and effective tools for characterizing landscape patterns and spatial configuration of urban vegetation on LST (°C) for UHI mitigation to address location specific and spatial autocorrelation issues when compared to global regression models like Ordinary Least Squares (OLS). However, our results may generalize the role of spatial regression models since this study only tested one spatial regression model, the Spatial Lag Model (SLM).

7.9 Recommendations for future studies

Although the findings of this research work are conclusive within the scope of the study, they lay a foundation for further research in this area. Therefore, the following future research directions are recommended based on this study.

1. In future, the impact of urban expansion and other land cover and land uses (roads and transportation) on vegetation fragmentation across space and time should be examined. Furthermore, future studies could also examine how alternative urban form patterns (i.e. clustered or monocentric verses dispersed or polycentric) significantly influence the spatial patterns of vegetation fragmentation and urban heat island formation. There are indications that different urban form patterns in a landscape in a city may have important influences on landscape patterns of vegetation patches (Huang et al.2018) and urban heat island (Yin et al.2018).

2. While the local spatial autocorrelation indices themselves are illuminating, in future, other continuous spatial indices like fractal measures, image texture methods, Fourier decomposition, wavelet transforms should be employed for evaluating vegetation fragmentation and urban heat island.

3. In evaluating vegetation fragmentation and urban heat island across the study area, further research is required to analyse the impact of varying grain size and spatial resolution on the relationship between the local spatial statistics (local Moran's I and Getis Ord GI* statistic) and landscape metrics obtained from high resolution remote sensing data.

4. In quantifying and analysing the dynamics of landscape connectivity of green vegetation and its influence on surface temperature regulation, further studies should explore and compare methods used in this study like the forest fragmentation model with other connectivity tools like Morphological Spatial Pattern Analysis and landscape pattern indices and fragmentation methods like Effective mesh size (Jaeger 2000, Moser et al.2007).

5. Future studies, should explore the influence of spatial configuration and composition of other land use and land cover classes (e.g. impervious surfaces and water) on LST and biophysical factors (rainfall, slope, elevation) and socioeconomic factors (income, housing value and distance from urban core, population density, Gross Domestic Product, the urban form, vertical structures and building densities). Such an undertaking will aid the understanding of urban warming and cooling because of the diverse heat exchanges and thermal effects and processes posed by different land cover categories and drivers during different times and seasons.

6. The high resolution images such as such as WorldView 1/2/3, IKONOS, Quickbird, unmanned aerial vehicles (UAV) or drones, LIDAR, RADAR are much detailed. Such data permits computing and analysing vegetation fragmentation and the identification of more detailed examination of spatial configurations of diverse land use and land cover classes on LST (°C) at finer spatial scales and at an individual city level. Furthermore, airborne data like LIDAR are effective identifying and mapping vegetation in dry seasons, when optical data is inefficient for mapping senescent vegetation

7. In situ air temperature data across the study area should be collected to calibrate and validate the estimation and relationship between land surface temperature and spatial configurations of vegetation at different times in the daytime and nighttime. Future studies should also explore the seasonal impact of spatial configurations of vegetation on nighttime UHI which would complement the results reported here; making use of land surface temperatures derived from thermal imagery data.

8. Future research should explore other spatial regression models like the Spatial Error Model (SEM) and Geographically Weighted Regression (GWR) modelconcerning residual spatial autocorrelation and goodness-of-fit in exploring the landscape pattern of urban vegetation on LST (°C).

9.0 Conclusions

Spatially explicit methods derived from multispectral remote sensing data of Sentinel 2, Aster and Landsat sensors enabled the analysis of pattern, change and extent of vegetation fragmentation in an urban landscape and its impact on urban warming and cooling in the study area. The results of this research established that vegetation in the study area was increasingly becoming fragmented and less connected over time. The findings of this research established and concluded:

- Unlike discrete landscape metrics, the usefulness of continuous LISA indices provided more information on the specific geographical location of heterogeneous and clustered vegetated areas in the study area.
- The decrease of large, connected and contiguous vegetation to a more scattered and fragmented and small vegetated patches were more pronounced in the dense and heavily built-up areas in western, eastern and the southern side of the Harare indicating the impact of urban development on conversions of naturally vegetated areas.
- The northern part of Harare metropolitan city was comprised primarily of lowly fragmented and undisturbed core vegetation patterns.
- Highly clustered and connected vegetation patch performs better in urban cooling than smaller ones in the summer season.
- The relationship between spatial configuration (size, density, shape complexity and cohesion) of urban vegetation and LST was negative across different spatial resolution (Aster, Sentinel and Landsat) but conferred different levels of cooling.
- Except for Patch Cohesion Index, the responses of correlations between configuration metrics and LST to spatial resolution fell into two categories: (1) the significance of correlation decreased as the spatial resolution decreased (coarse) (Landsat 8) (2) the significance of correlation increased as the spatial resolution increased (fine)(Sentinel 2 and Aster).
- Due to spatial autocorrelation of data like land surface temperature, there is need of controlling the effects of the amount of vegetation cover (spatial composition) to avoid misleading parameter estimates and unreliable significance test results in regression models.
- SLM is more powerful than the OLS regression model in improving the prediction and estimation of the relationship between mean LST and spatial configurations of vegetation.

The present study is important in identifying general patterns, trends and extent of vegetation fragmentation. It also enhanced our understanding of the effects of spatial configuration of urban vegetation on urban heat island (UHI). The research provided a useful guide to urban planning and landscape design and suggested that optimizing of spatial configuration and landscape connectivity patterns of vegetation is an effective and practical measure to reduce urban warming effects and maximise cooling effects. At most, the availability of vacant land for increasing vegetation cover, the greening of roofs buildings is usually limited, expensive and impractical in mitigating the UHI effects. Landscape configurations (size, density, shape complexity and cohesion) of vegetation confer different levels of cooling. The urban design and landscape planning strategies can be enhanced by considering the different spatial configuration to obtain maximum and larger cooling effects provided by different landscape configurations of vegetation. Overall, the methodological framework outlined here can be extended to obtain spatially explicit information on urbanization, land cover changes, land degradation in addressing pattern-process interactions in the context of conservation.

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