EVALUATING THE SPATIOTEMPORAL CHANGES OF URBAN WETLANDS IN KLIP RIVER WETLAND, SOUTH AFRICA

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DECLARATION

My original study is presented in this research paper. Every attempt is taken to explicitly identify any contributions from others, cite relevant literature, and appreciate collaboration in research and conversations.

Ms. Nolwazi Nxumalo

Signature…… ...   Date:…11 September 2023..

DEDICATION

My parents taught me always to be patient and trust the process, and they also taught me that there will always be obstacles in life that stand in the way of reaching your goals, but never give up. This research is dedicated to them, and my grandfather Cleophus Nxumalo, my role model, also deserves my gratitude for being there for me.

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ABSTRACT

This study assesses the impacts of land use / land cover (LULC) change in an urban wetland over the past 30 years utilizing machine learning and satellite-based techniques. This study looked at LULC distributions in the Klip River wetland in Gauteng, South Africa. The aims and methods used in this study were: (1) to conduct a comprehensive analysis to map and evaluate the effects of LULC changes in the Klip River wetland spanning from 1990 to 2020, employing Landsat datasets at intervals of 10 years, and to quantify both spatial and temporal alterations in urban wetland area. (2) To predict the change in urban wetland area due to specific LULC changes for 2030 and 2040 using the MOLUSCE plugin in QGIS. This model is based on observed LULC including bare soil, built-up area, water, wetland, and other vegetation in the quaternary catchment C22A of the Klip River wetland, using multispectral satellite images obtained from Landsat 5 (1990), Landsat 7 (2000 and 2010) and Landsat 8 OLI (2020). (3) For the results of this study, thematic maps were classified using the Random Forest algorithm in Google Earth Engine. Change maps were produced using QGIS to determine the spatiotemporal changes within the study area. To simulate future LULC for 2030 and 2040, the MOLUSCE plugin in QGIS v2.8.18 was used. The overall accuracies achieved for the classified maps for 1990, 2000, 2010, and 2020 were 85.19%, 89.80%, 84.09%, and 88.12%, respectively. The results indicated a significant decrease in wetland area from 14.82% (6949.39 ha) in 1990 to 5.54% (2759.2 ha) in 2020. The major causes of these changes were the build-up area, which increased from 0.17% (80.36 ha) in 1990 to 45.96% (22 901 ha) in 2020—the projected years 2030 and 2040 achieved a kappa value of 0.71 and 0.61, respectively. The results indicate that built-up areas continue to increase annually, while wetlands will decrease. These LULC transformations posed a severe threat to the wetlands. Hence, proper management of wetland ecosystems is required, and if not implemented soon, the wetland ecosystem will be lost.

Keywords: Urban wetland, machine learning algorithm, Random Forest, remote sensing, MOLUSCE, land use/land cover change, Klip River wetland

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ANN	Artificial Neural Network
CA	Cellular Automata
CART	Class and Regression Tree
DEA	Department of Environmental Affairs
DEM	Digital Elevation Model
DFFE	Department of Forestry, Fisheries and the Environment
DN	Digital Number
EIA	Environmental Impact Assessment
GEE	Google Earth Engine
GIS	Geographic Information System
ha	hectares
LULC	Land Use Land Cover
LULCCs	Land Use Land Cover Changes
MOLUSCE	Modules for Land-Use Change Simulation
QGIS	Quantum Geographic Information System
RF	Random Forest
RS	Remote Sensing
SAR	Synthetic Aperture Radar
SVM	Support Vector Machine
USGS	United States Geological Survey
WMAs	Water Management Areas
WWTP	Wastewater Treatment Plan

CHAPTER 1: INTRODUCTION

1 Introduction

Wetlands are sensitive, complex ecosystems with a wide variety of life that are vulnerable to climate change, human activity, and changes in land cover (Schlaffer et al., 2016; Olefeldt et al., 2017; Thamaga et al., 2021). Wetlands are located where the land surface has been saturated or flooded by water. The biological processes within wetlands are significantly influenced by the hydrological processes of dissolved material and sediment inputs and outputs. Surface water and groundwater recharge dynamics, alongside sediment inputs and outputs, also play a substantial role in shaping these biological processes (Hu et al., 2017). The most productive ecosystems are wetlands, but they are also the most ignored or underappreciated in Africa. Although constituting a minor fraction of the landscape, their prevalence extends across the entirety of sub-Saharan Africa, bestowing various socioeconomic and ecohydrological advantages to local communities (Tiner et al., 2015; Gxokwe et al., 2020).

In hydrological and biological systems, wetlands are crucial. They control floods, regulate the water cycle, and serve as a sponge by soaking up water during floods and gradually releasing it during dry or drought seasons (Penatti et al., 2015). Water quality is maintained and enhanced by wetlands. Wetlands are excellent habitats for a variety of rare plant and animal species because they supply food, clean water, store carbon, and filter pollution (Mahdianpari et al., 2018). However, over the course of the previous century, a multitude of African wetlands have succumbed to disappearance, a consequence of escalated human activities. The surviving wetland areas' natural habitats have drastically decreased (Hong et al., 2010; Dzurume et al., 2021). Due to increasing industrialisation of the urban footprint into urban wetlands, concerns such as land reclamation, water pollution, and excessive deforestation have recently increased (Hu et al., 2017). To help the conservation of wetlands, urban wetland monitoring and change detection throughout time are essential. According to Thamaga et al. (2021), the unprotected Maungani wetland in South Africa's Limpopo Province lost 47% of its spatial extent between 1982 and 2019. Similar findings were made by Marambanyika et al. (2016) in the South African eThekwini Local Municipality, demonstrating how population growth and industrial development reduces urban wetlands. To ensure wetland management, protection, and sustainable use, urban wetlands must be monitored, and their changes must be detected during specific periods.

Wetland systems require careful planning, monitoring, and protection. Extraction of wetland water must also be done accurately. Due to difficulties capturing regional variability and sample errors, conventional methods for monitoring marsh ecohydrological dynamics (topographic, sediment, and vegetation heterogeneity) have been ineffective. Moreover, these methods are costly, labour-intensive and have limited spatial coverage (Kecha et al., 2010; McCarthy et al., 2018; Thamaga & Dube, 2019). The most important source of spatial data on the condition, distribution, and spatial patterns of wetland ecosystems at a local to global scale is the availability of automated, reliable, and near-real-time remotely sensed data (Mahdianpari et al., 2018). According to Thamaga & Dube (2019), the spatial distribution of wetlands can be examined at different times using multi-spectral and hyperspectral remote sensing satellite systems such as Landsat, MODIS, SPOT, and RapidEye. Superior spectral and spatial properties in some of these platforms allow for more precise monitoring and mapping of wetland ecosystems (Kecha et al., 2010; Penatti et al., 2015; Mahdianpari et al., 2018).

The exploration of transformations in land use / land cover (LULC), which pose threats to the functionality and services of wetland ecosystems, holds significant prospects due to recent strides in remote sensing technology (Pettorelli et al., 2017). Additionally, advancements in sensor capabilities have facilitated the acquisition of publicly available satellite imagery, such as the Sentinel dataset. For instance, Sentinel-2 boasts enhanced attributes, including a more precise geographical coverage (285 km^2), finer spatial resolution (10 m), and improved spectral resolution (13 spectral bands, encompassing critical red-edge bands), all of which contribute to the accurate assessment of wetland dynamics (Truus, 2011; Orimoloye et al., 2018).

The regular acquisition of images from the same geographical area via remote sensing permits the identification of temporal trends and shifts within wetland ecosystems. Notably, Sentinel-2 ensures the provision of remotely sensed data with a consistent revisit frequency ranging from 5 to 19 days. Scholars in sub-Saharan Africa have used both passive and active sensors to map and define the spatial distribution of wetlands. This strategic employment of remotely sensed data aims to enhance comprehension of wetland conditions in light of evolving environmental and anthropogenic pressures (Farda, 2017; Phethi & Gumbo, 2019; Gemechu et al., 2021). By delving into the historical context, current dispersion, and inherent characteristics of wetlands, researchers can garner a more comprehensive understanding of wetland evolution and patterns, as well as the manifold ecosystem services and commodities they contribute.

Making informed choices regarding the most effective wetland protection and restoration approaches also requires knowledge of the degree of degradation, vegetation cover, biodiversity, water level, erosion, and sedimentation rates (Gxokwe et al., 2020). There are attempts to incorporate geospatial data products into various land surface models (Näschen et al., 2019) to enhance wetland ecosystem monitoring and evaluation. Google Earth Engine (GEE), a cloud computing platform that can handle and process such time series data, will be used in this investigation. With GEE, users may evaluate petabytes of data quickly without dealing with the challenges of cloud-based parallelisation. The conventional mapping methods Classification and Regression Trees (CART), Random Forest (RF), Support Vector Machine (SVM), and others that are freely implementable (Gemechu et al., 2021). Research methods for LULC change analysis have evolved in terms of geographical modelling, and altering transition potentials. It is possible to research the variables affecting past, present, and future projections and their significance in various scenarios using effective and reliable simulation models using GEE. For the analysis and projection of LULC, researchers have created a number of models, including CA-ANN, artificial neural network-Markov chain, Markov-FLUS, CLUE-S, artificial neural network-Markov chain, Dinamica, and SLEUTH cellular automata (Muhammad et al., 2022). Each model uses a different strategy to deal with the complex problems of LULC. Neural network models are a typical method for LULC modelling because they accurately reflect nonlinear spatially probabilistic land-use transitions. Compared to artificial neural networks, CA is more adept at comprehending land-use patterns and the dynamics that underlie them. It is helpful in land transformation and development simulation studies since it uses CA-foundation ANNs in "what-if" scenarios. Using traditional techniques, beginning with transitions and change-detecting devices, the spatial scope of LULC change can be assessed.

1.1 Problem Statement

Wetlands constitute vital ecosystems that provide a multitude of practical and ecological benefits. These unique environments, characterized by the presence of water, play a crucial role in maintaining the overall health of the planet. From a practical standpoint, wetlands serve as natural infrastructure that helps regulate water flow and mitigate floods by absorbing excess water during heavy rainfall, subsequently reducing the risk of damage to surrounding areas. Moreover, wetlands offer significant ecological advantages. They provide essential habitats for a diverse range of plant and animal species, many of which are specially adapted to thrive in these water-rich conditions (Nemutamvuni et al., 2020; Gemechu et al., 2021). These areas often act as breeding grounds for various wildlife and contribute to overall biodiversity.

Wetlands also contribute to water purification by filtering pollutants and nutrients from water sources, improving water quality downstream. They are also instrumental in carbon sequestration, aiding in the reduction of greenhouse gases and playing a role in climate change mitigation. In addition to their environmental significance, wetlands have practical benefits for human communities (Bellard et al., 2012). They offer recreational opportunities, such as birdwatching, fishing, and nature appreciation. Wetlands can also play a role in supporting local economies through activities like eco-tourism and sustainable resource harvesting.

Recognizing the multifaceted advantages of wetlands is crucial for their conservation and sustainable management. Efforts to protect and restore wetland ecosystems contribute not only to the preservation of unique and fragile environments but also to the well-being of both natural systems and human societies (Munizaga et al., 2022). Nonetheless, studies show that wetlands have substantially decreased because of urbanization and human activity in many parts of the world (Adeeyo et al., 2022). The need for land for diverse activities, including residential areas, industry, and the agricultural sector, has increased during the previous few decades (Nemutamvuni et al., 2020). Wetlands in South Africa are challenged by deterioration because of rising land demand. Because of this, there are fewer wetlands, which eventually means fewer ecosystems and waters of high quality and safety. In order to prevent the extinction of the present, finite wetland resources, the best monitoring and management measures are required. Wetlands are frequently found in isolated locations, where hydrology, vegetation cover, and topography make ground surveys difficult and expensive (Dahl, 2006; Stacy, 2014; Young & Dahl, 2015).

Using satellite images and machine learning techniques, remote sensing has effectively been able to monitor wetlands (Mahdianpari et al., 2018; Adeeyo et al., 2022). These new technologies have demonstrated numerous shortcomings of conventional techniques for monitoring wetlands, including accessibility and repeatability (Gemechu et al., 2021). High spatial resolution and temporal resolution imagery are crucial for many applications, at global and regional levels, such as change detection and LULC mapping (Zhao et al., 2018). According to Sieben (2011), wetland vegetation is an important indicator of the ecosystem's habitat units' character and integrity. Consequently, environmental managers and ecologists can plan and choose wetland land management strategies by mapping LULC aspects that endanger the wetland ecology using remote sensing and GEE.

African urban wetlands are in danger due to urbanisation and landscape changes (Landmann et al., 2010; Mutanga et al., 2012; Boon et al., 2016). Due to increased pressure from anthropogenic land use change brought on by urbanisation and rapid population growth, these systems deteriorate, and their spatial scope may be reduced. Moreover, evolving climatic factors, including increasing temperatures, altered rainfall patterns, and evaporation, impact wetland processes. The absence of conservation expertise and understanding among local wetland users and managers further accelerates the rate of wetland deterioration. As outlined by Gardner et al. (2018), the pollution resulting from socioeconomic development and population growth plays a substantial role in the degradation and potential extinction of wetland systems. This impacts on how well the wetland functions, resulting in species habitat loss, degrades wetland vegetation and alters wetland hydrology, all of which lead to the extinction of the urban wetland ecosystem. Thamaga et al. (2021) revealed that in Limpopo, South Africa, about 57% of the wetland area is lost to residential establishment, agricultural operations and dumping site in the urban region. Thus, anthropogenic activities, especially developing informal settlements, continue to be difficult on wetlands. This study uses remote sensing imagery to map wetlands in the South Africa Klip River wetland and estimate area change over the last 30 years.

1.2 Aim and objectives

1.2.1 Study Aim

The primary aim of this study is to assess the impacts of LULC change in the urban wetland of the past 30 years utilising machine learning and satellite-based techniques.

1.2.2 Specific objectives

The objectives are to:

- Conduct a comprehensive analysis to map and evaluate the effects of land use/land cover changes in the Klip River wetland spanning from 1990 to 2020, employing Landsat datasets at intervals of 10 years. Simultaneously, quantify both the spatial and temporal alterations in urban wetland areas over the same period, from 1990 to 2020.

- Predict the change of the urban wetland area due to LULC change for 2030 and 2040 using the MOLUSCE plugin in QGIS.

1.3 Overview of the report

Chapter 1 provides the general introduction, which includes background about the wetland's status, remote sensing technics and classification methods. Chapter 2 elaborates on the global and local overview of wetland mapping, factors contributing to wetland disappearance, and methods of monitoring LULC changes. The material used and methods applied are discussed in Chapter 3 after a brief description of the environmental and climate condition of the study site. Chapter 4 provides the findings of the study. Chapter 5 discusses the results and compares them with other studies. Chapter 6 summarises and outlines the major findings of the study.

CHAPTER 2: LITERATURE REVIEW

2 Literature review

2.1 Introduction

Urban wetlands are an important part of global ecosystems and are affected by many human activities, especially urban land development. One of the most significant anthropogenic impacts on the world's ecosystems is LULC change, which has various impacts on landscapes (Pettorelli et al., 2017; Chiloane et al., 2020; Festus et al., 2020). These changes also influence the composition and profile of the surrounding landscape in local habitat and ecosystem quality (Olefeldt et al., 2017). Therefore, the resulting landscape patterns significantly regulate the form, function and resource quality of many urban ecosystems, including most urban wetlands (Assefa et al., 2021).

Quantifying these land cover changes requires mapping and monitoring the landscape dynamics of urban wetlands within terrestrial habitats. Wetlands are essential because they benefit the natural environment and human livelihoods in various ways. According to Wdowinsk et al. (2007), wetlands play two key roles in climate change being to sink carbon and adaptive impacts due to the capacity to store and manage water. They are also habitats for organisms such as fish, birds, and invertebrates (McCarthy et al., 2018).

2.2 Key factors influencing changes in an urban wetland

Previous wetland research (Melly, 2016; Mahdianpari et al., 2018) has hypothesized that hydrology is a key element in determining the development of wetland ecosystems. Moisture in wetland soils can affect the distribution of wetland plants and larger ecosystems. Wetland hydrology is influenced by human factors such as drainage and infrastructure development (Bansal et al., 2007). The soil moisture content of wetlands is affected by changes in the physical landscape and regional or local hydrology; for example, the development of residential or industrial areas in wetlands alters the natural landscape and degrades hydrological features (Hu et al., 2015). The physical environment of urban wetlands can affect changes in local habitats, affecting ecosystems. Wetlands have undergone significant alteration, destruction and degradation over time.

It is estimated that almost half of the world's wetlands were degraded during the 20^{th} century (Luo et al., 2018). Despite strict regulations for their protection and maintenance or restoration, the remaining wetlands are threatened by human activities and the effects of climate change (Athukorala et al., 2021). The resilience of wetland ecosystems is influenced by multiple factors (Brinkmann et al., 2020). Agriculture, recycling, water use, infrastructure development, pollution, and unsustainable exploitation of wetland resources are human factors (Brinkmann et al., 2020). According to Gardner et al. (2018), one of the main causes of the degradation and loss of urban wetlands is pollution caused by socioeconomic development and population growth. The desire for flat, fertile land with access to water for agriculture is the primary motivator behind wetland destruction (Rebelo et al., 2010). Slagter et al. (2020) noted that the loss of wetlands in South Africa is impacted by urbanization, development, pollution, agricultural output, dam construction, erosion, overgrazing, and poor land resource management.

Climate change seriously threatens wetlands, especially changes in rainfall patterns (Boon et al., 2016). These changes vary greatly in time and space, from local to global scales, leading to major reconfigurations of wetland biodiversity and biochemical processes (Dawson et al., 2011; Bellard et al., 2012). According to Titus et al. (2009) climatic change and intentional human activity, particularly in urban wetlands, have the potential to cause changes in species composition, habitat degradation, and habitat loss in already existing wetlands. The vulnerability of these fragile systems has been exacerbated by severe pollution and siltation.

2.3 Satellite-based remote sensing for urban wetland mapping and monitoring

The most effective method of gathering data on wetland features, wetland ecosystems' response to climate change, species richness and productivity, and wetland hydrological processes since the 1960s have been earth observation systems (Luo et al., 2018; Basu et al., 2021; Thamaga et al., 2021). Remote sensing datasets and replicable methodologies offer the means to address various aspects such as wetland delineations, classification, hydrological and vegetative attributes, productivity, identification, aquatic vegetation or biomass, hydromorphic soils, and density (Athukorala et al., 2021). Over the years, remote sensing applications have advanced considerably. In sub-Saharan Africa, wetland ecosystems (i.e., swamps or wooded wetlands) may now be efficiently mapped and quantified because of earth observation technological advancements (Basu et al. 2021). Most of these studies have focused on Ramsar-designated wetland habitats, which have overlooked small or unprotected wetlands that support surrounding communities.

Wetland remote sensing is more commonly used in Ramsar wetlands than non-Ramsar wetlands (Landmann et al., 2010). These results suggest that remote sensing of small wetland ecosystems offers a lifeline to underutilised urban communities, especially in sub-Saharan Africa (Thamaga & Dube, 2021). With the advancement of multispectral scanners and aerial photography in remote sensing, researchers can now map and monitor wetland ecosystems using publicly available satellite imagery from Landsat and Sentinel, utilizing the improved spatial, temporal, and spectral capabilities of contemporary technology. Most African surveys have used multispectral remote sensing datasets. According to Thamaga & Dube (2019), the above-mentioned techniques mainly replace aerial imagery, impractical for collecting data over large areas. Thus, most studies on wetlands in Africa are conducted using aerial imagery such as Landsat, Sentinel and MODIS datasets (Adam et al., 2012; Mutanga et al., 2012; Han et al., 2015). Remote sensing research on wetland vegetation, soil and hydrology needs further improvement (Horadik & Alber, 2012; Tiner et al., 2015; Athukorala et al., 2021).

2.4 Methods used to monitor wetlands

The study of gathering data on the Earth's surface without being in physically in contact with it is known as remote sensing. This is accomplished by detecting and registering reflected or radiated energy, then processing, analysing, and using this data (Oberholster & Ashton, 2008). Remote sensing techniques have generated LULC change information (Dahl, 2006). The ability to monitor wetlands via remote sensing has the advantages of being economical and covering a substantial portion of the area (Young & Dahl, 2015). A Geographic Information System (GIS) is computer software that captures, stores, and analyses geographically referenced data. ArcGIS/Arc Info and Quantum GIS are commonly used GIS software. ArcGIS is commonly offered in universities and is licence based while QGIS is an open source.

Remote sensing is a valuable approach employed in the cartographic depiction of LULC alterations, as well as the ongoing surveillance of wetland ecosystems (Dahl, 2006). Landsat TM, MSS, and SPOT are the most commonly used satellite images/images to study wetlands (Ozesmi & Bauer, 2002). However, in the study conducted by Ogawa et al. (2014), used Landsat 8 OLI, to map the LULC change, and found that its spectral and radiometric properties were superior to other platforms, such as Landsat 7 ETM+ and MODIS (Ogawa et al., 2014).

On April 3, 2014, Sentinel-1A (S1), a synthetic aperture radar (SAR) satellite, was launched. The satellite uses four imaging channels from two polar orbiters to acquire data via radar imagery in the C-band at 5.405 GHz.

Current methods for classifying remote sensing images range from pixel to object orientation, Supervised and unsupervised classifiers (Farda, 2017). To effectively capture the multi-temporal transformations of land cover within urban wetlands, the implementation of supervised classification stands as a crucial undertaking. This approach emerges as a pivotal solution to address the abundance of satellite imagery data and the diverse range of technological tools available for analysis. Supervised machine learning algorithms assist in investigating image data, uncovering occult connections between various potential input variables (parameters) and potential target variables (classification outcomes), and investigating potential entry points for numerous variables (Davranche et al., 2009). The classification method commonly used to map wetlands is unsupervised (Ozesmi & Bauer, 2002), where large-scale land use/cover are monitored.

Nonetheless, among the array of supervised classification methods, Maximum Likelihood Classification (MLC) emerges as the predominant choice, as underscored by its extensive utilization (Gemechu et al., 2022). Classifying wetlands presents a formidable challenge due to spectral similarities that exist between wetland areas and other categories of land use and land cover, as well as the diverse array of wetland types (Davranche et al., 2009). The classification of wetlands is frequently improved by multitemporal data and additional data, such as soil, elevation, or topographic data (Chen et al., 2008). Remote sensing, GIS, machine learning and Google Earth Engine have been used by researchers and institutions such as the US FAWS (Farda, 2017; Gemechu et al., 2022).

Butt et al. (2015) mapped and analysed land use changes in 1992 and 2012 using Landsat 5 and SPOT 5 in the Umzintlava watershed (T32E) characterised by five main LULC categories: agriculture, bare soil/rock, settlement, vegetation, and water. Their findings demonstrated a major transition from agricultural cover, bare land, and settlements to vegetation and water cover, with reductions of 38.2% and 74.3%, respectively. Butt et al. (2010) suggested there was a need for proper watershed management otherwise watershed resources were going to be degraded. Butt et al. (2015) focused on large wetlands; small-scale wetland ecosystems should be included. There is a need for more studies to focuses on small-scale wetland ecosystems.

LULC classes are assigned to pixels during the process of image classification. There are three types of image classification techniques, namely supervised, unsupervised image classification, and object-based image analysis (Ballant et al., 2017). The commonly used classifications from the three are unsupervised and supervised. However, object-based classification is more useful for classifying high-resolution data; therefore, it has recently gained popularity (Ogawa et al., 2014). With RS and GIS software, analysts build land cover maps using image clustering methods like K-means and ISODATA. The supervised classification users can collect samples of the observed LULC classes. The trained samples are representatives of ArcGIS or other software that apply the samples to the entire image (Dronova et al., 2015).

Satellite images map land use land cover by utilising several classification algorithms. The supervised classification uses algorithms such as MLC, Random Forest and Support Vector Machine (SVM) on the other hand, the unsupervised classification uses K-mean and Isodata (Chen et al., 2008; Villa et al., 2016; Mahdianpari et al., 2018). However, maximum likelihood classification and random forest are often used to map changes in LULC. These classifiers are frequently employed in mapping LULC changes, primarily due to their capability to provide precise land cover classifications. Notably, these classifiers have demonstrated a remarkable overall accuracy rate of 92% and a Kappa index of 0.92 (Muhammad et al., 2022). Synthetic Aperture Radar (SAR) imagery inventories demonstrate LULC classification, particularly when it comes to wetland mapping and monitoring, by addressing the limitations of optical imagery. SAR sensors can detect through clouds, the ground, and plants and are immune to sunlight (Liu & Abd-Elrahman, 2018).

To improve land cover mapping, high spatial resolution imagery integration with cutting-edge image analysis methods such as object-based image analysis (OBIA) could be considered. Advantages of remote sensing in wetland monitoring are that it covers a considerable landscape area and is relatively inexpensive (Young & Dahl, 2015). Understanding the dynamics of the landscape can be aided by digital change detection algorithms using multitemporal satellite imagery (Rawat & Kumar, 2015). Using multitemporal remote sensing data to assess the historical impact of events and identify changes linked to land cover/use characteristics in multitemporal datasets is known as "change detection" (Shuqing et al., 2007).

2.5 Spatial and temporal change in urban wetlands

In the context of geo-registered multi-temporal remote sensing data, the process of detection plays a pivotal role in discerning alterations associated with land cover and land use characteristics (Oberholster & Ashton, 2008). Change detection algorithms enable detecting a change between two or more temporal datasets lacking conventional variation characteristics (Cobelas et al., 2005). Wetlands have been successfully identified and tracked using remote sensing methods in the USA and Canada (Fajar et al., 2018) as well as in southern Africa. Thamaga & Dube (2019) mapped small scale wetlands and LULC changes in the Limpopo Province of South Africa. Studies on change detection have used archival data and repeat coverage provided by satellite remote sensing (Ozesmi & Bauer, 2002, Sibanda et al., 2022). By examining the time series of change and comprehending the system of processes, change detection can be applied to utilise short- and long-term time sequence images (Ballanti et al., 2017). Studies have successfully detected short-term changes in vegetation colonisation using remote sensing techniques to restore tidal wetlands (Ahmad & Erum, 2012; Ballanti et al., 2017). The novel remote sensing methods on historical aerial photos also enable studying the relationships between environmental and anthropogenic factors and quantifying ecological changes in wetlands (Nhamo et al., 2017; Muhammad et al., 2022).

CHAPTER 3: METHODOLOGY

3 Materials and Procedures

3.1 Area of study

According to the country's water boards, South Africa is organised into nine Water Management Areas (WMAs) (Revised National Water Resource Strategy, 2012). Each WMA comprises quaternary catchments connected to South Africa's drainage zones, which are listed from A to X (excluding O). Based on the size, these drainage areas are grouped into four groups. The primary drainage catchment is denoted by the letter A; the letter A2 denotes the secondary drainage catchment; the letter A21 denotes the tertiary drainage catchment. The quaternary drainage catchment, which is the lowest subdivision, is denoted by the letter A21D in the Water Resources of South Africa (2012) manual. There are hydrological parameters that are specific to each of the quaternary catchments (DWS, 2016).

According to the National Water Act (Act No. 36 of 1998) as amended, this inquiry is focused on the quaternary catchment C22A within the Vaal Water Management Area. The major river systems within this area include the Klip River. The study area covers four local municipalities, the major local municipality being the City of Johannesburg, followed by small portions of Midvaal, Westonaria and Mogal City. The research area experiences a subtropical environment with year-round average temperatures of 10-28^{o}C (Ndlala & Dube, 2021). The region experiences 700 mm annual average rainfall, most of which falls between October and March during the summer months (Thamaga & Dube, 2019). The Klip River wetland is at the centre of the urban environment south of Johannesburg (Figure 1).

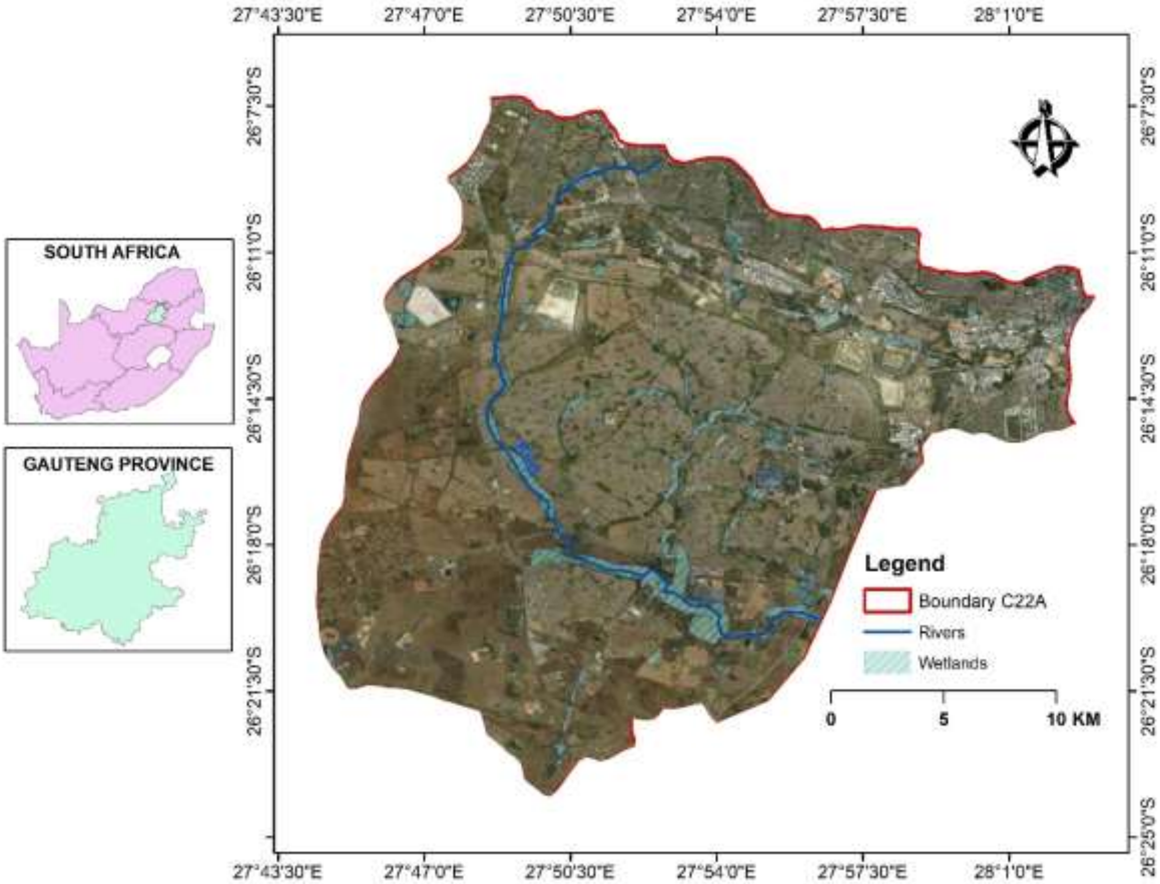


Figure 1: Klip River (quaternary catchment C22A) locality map in Gauteng Province.

The southern Witswatersrand region is drained by the Klip River which is located in South Africa's Gauteng Province. The river continues south to Vereeniging, where it merges with the Vaal River. As it continues to flow west, the Vaal-Orange River system eventually reaches the Atlantic Ocean. One of the most developed urban regions in Africa, Johannesburg's southern half is included in the Klip River catchment. This river is considered one of South Africa's most extensively damaged river systems, as it is susceptible to nearly every form of pollution (Phethi & Gumbo, 2019). The Klipspruit and Rietspruit, are two of the major tributaries to the Klip River, which are also considered highly polluted rivers. The Klip River originates in the Witswatersrand range of hills and flows east to west through the Witswatersrand urban complex (Krugersdrop to Springs). The drainage border between the bigger Vaal River watershed (to the south) and the Crocodile River catchment is also formed by this mountain (to the north). This area is rich in flood plain wetlands; however, the wetlands are polluted and there are informal settlements that are established around the area (Bhaga et al., 2020).

3.2 Reference data

The collection of field verification data for this study was conducted October 11, 2020. The chosen date of data acquisition aligns with the methodology's inherent capability for discerning and delineating wetland areas from alternative land cover classifications, thereby establishing a promising avenue for precise wetland mapping and ongoing monitoring endeavours. This approach is further informed by the LULC characteristics within the Klip River wetland region.

To accurately pinpoint the coordinates of distinct LULC classes within the Klip River wetland, a Trimble hand-held Global Positioning System (GPS) was employed. Prior to conducting on-site evaluations, a preliminary desk-based assessment was carried out. This preliminary evaluation involved a comprehensive analysis utilizing Google Earth Pro to identify predominant LULC categories. The identified categories encompassed bare soil, built-up areas, vegetation, water bodies, and the wetland area of interest.

The demarcation of sample sites was achieved through the utilization of GIS v10.4 in conjunction with Hwath's analytical approach. The coordinates of these samples were subsequently input into a GPS device, facilitating accurate navigation to the designated sampling locations. A total of 250 sampling points were randomly gathered and documented, with each LULC type being represented by a sample subset of n=50 points. The amassed data also played a pivotal role in the assessment of image accuracy and served as a foundation for the LULC classification process.

In summary, the approach taken in gathering field verification data on 11 October 2020, aligns with the methodology's aptitude for discriminating wetland areas from alternative land cover types. The integration of GPS technology, desktop assessments, GIS tools, and meticulous site selection contributed to the comprehensive and methodologically robust data collection process, thereby underpinning the accuracy of subsequent analyses and classification effort. Each LULC type employed in this study is described in Table 1. Table 2 demonstrate reference data, for 1990, 2000 and 2010 reference data were sampled from google earth Pro.

Table 1: Land uses land cover changes identified to assess wetland area.

Classes	Description of the classes
Bare soil	Area that has no vegetation cover.
Build up	Built-up includes all the developed areas, such as residential areas and commercial and built infrastructure.
Water	Rivers, streams and waterbodies
Wetland	Water and wetland vegetation.
Other vegetation	Vegetation, vegetation on traditional lands, and mixed grassland. Only managed land areas that fit the classes mentioned above are included in this class.

Table 2: The study's reference data identification numbers. Training data (Tr), test data (Te) and total

Classes	1990			2000			2010			2020		
	Tr (70%)	Te (30%)	To	Tr (70%)	Te (30%)	To	Tr (70%)	Te (30%)	To	Tr (70%)	Te (30%)	To
Bare soil	79,8	34,2	114	66,5	28,5	95	70	30	100	77	33	110
Build up	70,7	30,3	101	70	30	100	94,5	40,5	135	75,6	32,4	108
Other vegetation	71,4	30,6	102	70	30	100	70	30	100	74,2	31,8	106
Water	59,5	25,5	85	63	27	90	72,1	30,9	103	73,5	31,5	105
Wetland	72,1	30,9	103	70	30	100	84	36	120	72,1	30,9	103

3.3 Satellite image acquisition and pre-processing

To detect trends in LULC change, time-series remote sensing data that is multitemporal and multisource is necessary (Brinkmann et al., 2021). In conducting these analyses, open-access satellite data with comparable spatial resolution were employed. The data from Landsat are comparable to those from earlier missions and are openly accessible. This makes it possible to evaluate long-term regional and global changes in land cover. To evaluate 1990, 2000, 2010 and 2020, Landsat 5, Landsat 7, Landsat 8 OLI, and Sentinels 1 and 2 were retrieved and used in GEE (https://earthengine.google.com/). The images were collected for the summer season because it is early the identify wetlands during rainy season which in South Africa it is during summer. The images were acquired in October for 1990, 2000, 2010 and 2020.

In order to replicate 2030 and 2040 in QGIS, Sentinel 1 and 2 data that we fused to train and classify LULC for 2020 were used as reference data. Combining the strengths of SAR and optical data enables accurate change detection and land cover classification. The fusion helps differentiate between changes caused by factors like land use changes, natural disasters, and human activities. The benefits of fusing Sentinel-1 SAR and Sentinel-2 optical data captures both structural and spectral information. This results in a more comprehensive feature representation of the landscape, including surface characteristics, vegetation patterns, and human-made structures. Using this fused image as a base can provide a richer set of input features for prediction model. Landsat data, like Sentinel-2 optical data, can also be hindered by cloud cover. A classification model trained on Landsat data might encounter challenges in regions with persistent cloud cover. Using the fused image as a base reduces this limitation and ensures consistent input data. Using a fused Sentinel-1 and Sentinel-2 classification image as a base for predicting land use in a model using Landsat classification images leverages the complementary strengths of different sensor types. This approach enhances feature representation, accuracy, and the model's ability to capture temporal and structural changes in the landscape.

The study area was classified using Java scripting. The pre-processing steps in Google Earth Engine included the following tasks: GEE provides access to a wide range of satellite and remote sensing datasets, such as Landsat, Sentinel, MODIS, and more. Pre-processing included collecting data from the source being Landsat and Sentinel using Java scripting. Pre-processing in Google Earth Engine involves a series of data transformations and enhancements to make the data suitable for analysis, visualization, or other tasks. These steps ensure that the data is accurate, consistent, and aligned with the objectives of your geospatial analysis. GEE's processing capabilities make it convenient to perform these tasks in a scalable and efficient manner.

Using the Digital Elevation Model (DEM), Digital Surface Model that was acquired from the United States Geological Survey (USGS) website at https://earthexplorer.usgs.gov/, the slope was determined in ArcGIS using the DEM by using the “Slope” tool, which calculates the change in elevation between neighbouring cells in the DEM. The projection and coordinate system were used to WGS 1984 to ensure the accuracy of the calculations. The GIS layer of Roads was downloaded from International Steering Committee for Global Mapping portal. The spatial analyst tool in ArcGIS and the road data were used to compute the distance between the critical roads using the Euclidean Distance function. The data sources are listed in Table 3.

Table 3: Data sets and their descriptions to be employed in the study.

Datasets	**Description Acquisition Date**	**Derived Variables**	**Sources**
Landsat satellite images	Landsat 5 for 1990, Landsat 7 for 2000 and 2010, Landsat 8 OLI for 2020	NDWI, NDVI, NDBI, Bare Soil BSI	USGS https://landsat.usgs.gov/ Access ed 24 July 2022 in GEE
Ground truth data	Coordinates were recorded using GPS. (Oct 2020)	5 types (Built-up, bare soil, vegetation and water, wetland) of LULC classes were observed	Field observation
Google Earth	Images	Land use land cover	Google Earth Pro.
VARIABLES USED TO TRAIN MOLUSCE PLUGIN ON QGIS			
Datasets	**Source**		
Slope	Calculated from DEM in ArcGIS		
Digital Elevation Model (DEM)	Downloaded from USGS https://earthexplorer.usgs.gov/ on 16 December 2022		
Roads	Downloaded from https://maps.princeton.edu/catalog/stanford-fz199pb2459 on 16 December 2022		
Distance from major roads	Calculated from the road network		

3.4 Image classification: Random Forest machine learning classifier

For 1990, 2000, 2010 and 2020, the Klip River wetland's impact on LULC changes was evaluated using the RF classifier. RF is a classifier for supervised machine learning. Each tree in the RF classifier depends on the values of a random vector sampled independently from the rest of the forest's trees and with a uniform distribution (Breiman, 2001). Combining numerous weak classifiers into a single robust classifier is the basic principle behind RF, which uses classification trees (Xi, 2022). The hyperparameters that were considered in this study was the Number of Trees, this hyperparameter defines the number of decision trees in the forest. It can be chosen using techniques like cross-validation or grid search. A reasonable range of values could be tested, and the value that yields the best cross-validation performance is selected. The influential spectral variable considers domain knowledge to interpret the importance of influential variables. Certain spectral bands might correspond to specific land cover characteristics. Visualize the feature importance scores using bar plots or other graphical representations. Rank the spectral variables based on their importance scores.

The input data is divided into many subsets, with the root node as the training set and each leaf node as a labelled training or test set. Every internal node acts as a weak classifier, dividing the data into various groups. The most advantageous answer determined by voting on all classification trees is the ultimate decision result of RF (Ndlala & Dube, 2021). RF is one of the most frequently utilised machine learning techniques for classification issues (Chabalala et al., 2022). The RF classifier was used on GEE to assess the regional and temporal evolution of LULC on the Klip River wetland from 1990-2020.

3.5 Classification Accuracy Assessment

The LULC change maps' accuracy for 1990, 2000, 2010 and 2020 were evaluated. Training samples comprised 70% of the field data samples, while testing samples comprised 30%. Here, 70% of the field data samples were used for training (175 points), whereas 30% were used for testing (75 points) (Table 2). An error matrix was used to assess the classification process' accuracy relative to the reference data on a global, user, and producer level. The Error matrix is used to compute all the classification accuracy assessment instruments between the classification results and training data, as well as evidence of how the classification mistakes were produced, according to Pontius & Millones (2011).

3.6 Spatial and temporal change detection

The amount of the several LULC types currently located in the Klip River wetland for the duration of the study was calculated. The change detection technique employed was post-classification comparison, wherein this approach involves the assessment and analysis of satellite images that have been categorized independently across various historical timeframes. The benefit of this approach is that it provides data on the size and direction of change. Although if the time gap between the two temporal images is small in multi-temporal data, spectral variances are anticipated to occur in the same LULC classes due to atmospheric circumstances and sun angle changes (Munyati, 2000). To calibrate these circumstances Dark

Object Subtraction (DOS) atmospheric correction was used to remove atmospheric effects from the satellite imagery. This helps to standardize the reflectance values. Also, cross-validation was conducted to validate the accuracy of the calibrated data. Overlapping LULC maps from various dates created by the classification technique are used to identify the change pixel-by-pixel based on the post-classification comparison technique. After the procedure, it is possible to determine which areas were transformed and which class has changed. To demonstrate the LULC conversion, an overall change detection map was created from 1990 to 2000, 2000 to 2010, 2010 to 2020, and 1990 to 2020. With the help of this kind of study, it was possible to spot changes in the LULC classes, such as an increase in built-up areas and a reduction in the size of the wetland.

3.7 Prediction of LULC change: CA-ANN analysis on QGIS

Multi-temporal remotely sensed data from 1990 to 2020 at intervals of ten years were used to simulate the spatiotemporal change transition potential and future LULC simulation. Future LULC change was predicted using integrated CA-ANN approach within the MOLUSCE plugin of QGIS and independent variables including distance from roadways, DEM, and slope. This study modelled the spatiotemporal transitional prospects and future possibilities of LULC using the Modules for Land-Use Change Simulation (MOLUSCE) plugin in QGIS v2.18.28. Asia Air Survey created the open-source MOLUSCE plugin for QGIS v2.18.28 and higher to assess, model, and simulate changes in LULC (Muhammad et al., 2022). A variety of methods for simulating land use change are provided by the MOLUSCE plugin, including ANN, LR, WoE, and MCE. Kappa statistics are also applied. For verification, kappa statistics are also employed (Yulianto et al., 2018).

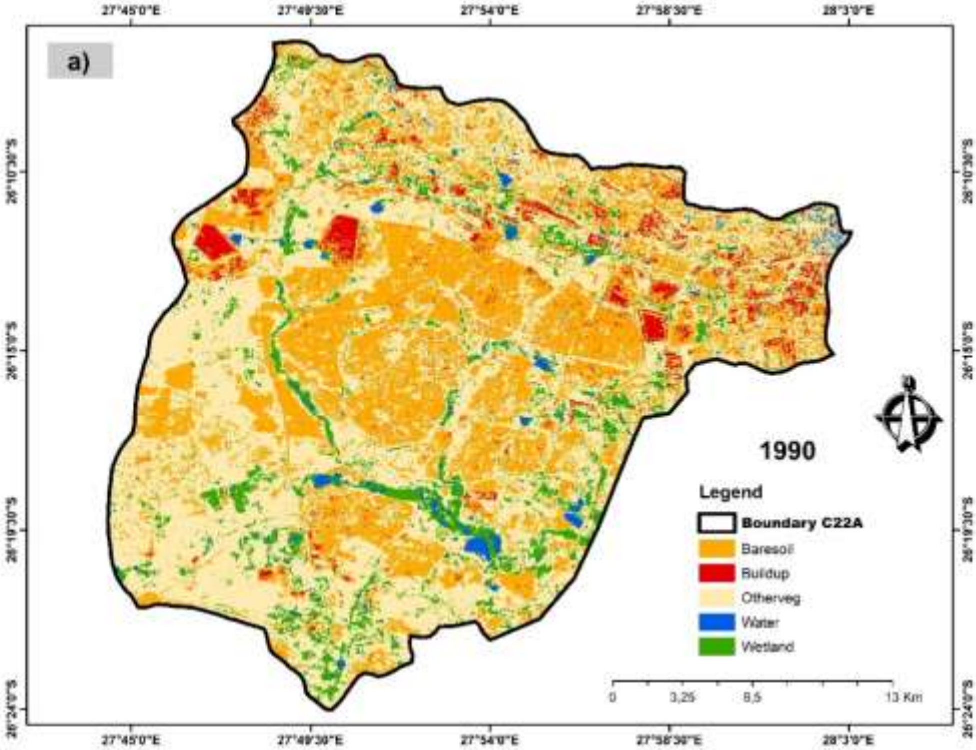
Using simulated models, the dynamics of composite urban buildings are made less complex and easier to understand. The transition potential was modelled using the ANN multilayer perceptron method. DEM, slope, and the separation from highways were used as the explanatory variables (Table 2). Because they offer reproducible information on the effects of both natural and anthropogenic factors on land use land use dynamics, these variables are commonly utilized in land use land cover change analyses (Yulianto et al., 2018; Muhammad et al., 2022). The MOLUSCE plugin efficiently calculates assessments of land use change, aids in analysing spatiotemporal changes in wetlands, forests, and land use, forecasts transition probabilities, and models probable futures. Explanatory variables, transition matrices, and LULC data for 2000 and 2010 were used to simulate the 2020 LULC. In order to evaluate the model and prediction accuracy, the MOLUSCE plugin offers a kappa validation technique that examines actual and projected LULC images. The LULC for 2020 was projected using an ANN learning process, and the classified image of 2020, which used the fused Sentinel-1 and Sentinel-2, was used as reference data. This was done because the fused image had high accuracy (92.52%) compared to the Landsat data. The LULC for 2030 was predicted using data from 2010 and 2020, while the LULC for 2040 was predicted using data from 2020 and 2030. The level of correctness was above 50%.

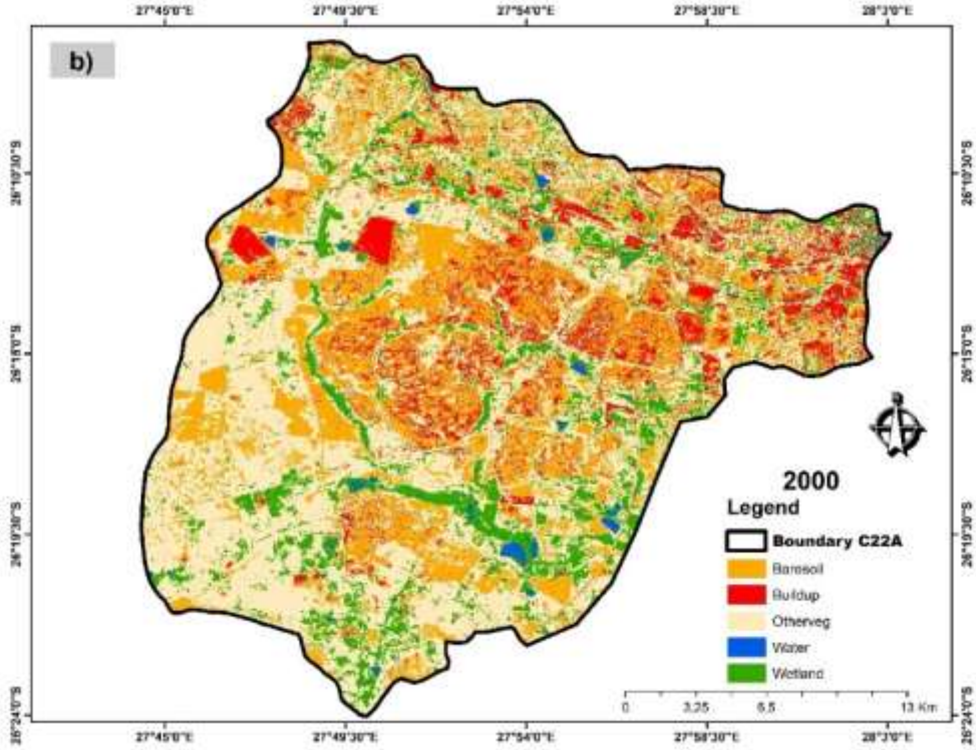
CHAPTER 4: RESEARCH FINDINGS

4 Results

4.1 Land use land cover maps

Individually categorized LULC maps were produced for 1990 (Landsat 5), 2000 and 2010 (Landsat 7), and 2020 (Landsat 8 OLI). Figure 2 indicates the result of the classified LULC maps, which demonstrate spatial changes over the past 30 years. The map from the year 1990 (a) indicates that there was approximately 0.17% of the build-up area. Bare soil was the dominant land cover in 1990, followed by other vegetation. The wetland covered a fair percentage of the area and water, on significant parts of the wetland area. The map from the year 2000 (b) shows an increase in build-up area by 22.44% (12 321.04 ha) compared to 1990, replacing primarily bare soil. In contrast, the wetland area remains the same as in 1990 (a). A significant change was observed in the year 2010 (c), where the build-up area increased by 8.38% (4596.6 ha) from 12 401.4 ha in 2000 to 16 998 ha in 2010, replacing most parts of vegetation (from 20 338,9 ha in 2000 to 18 676,8 ha in 2010) and bare soil (from 10 947,3 ha in 2000 to 9289.1 ha in 2010). The build-up area is observed to be closer to the Klip River wetland and wetlands associated with the tributaries of the river. The map from the year 2020 (d), shows that the build-up area was at full scale covering approximately 45.96% (22 901 ha) and starting to replace wetland areas by approximately 95.69 ha in the south of the study area. Build-up areas at a large scale replaced vegetation and bare soil compared to other LULC observed in the study. The overall accuracies for 1990, 2000, 2010 and 2020 were 85.19%, 89.80%, 84.09% and 88.12%, presented in Table 3 to Table 6, respectively, for the classification of 1990, 2000, 2010 and 2020.


a)
27°45'0"E
27°49'30"E
27°54'0"E
27°58'30"E
28°3'0"E
1990
Legend
Boundary C22A
Baresoil
Buildup
Otherveg
Water
Wetland
0
3,25
6,5
13 Km


b)
27°45'0"E
27°49'30"E
27°54'0"E
27°58'30"E
28°3'0"E
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Boundary C22A
Baresoil
Buildup
Otherveg
Water
Wetland
0
3,25
6,5
13 Km

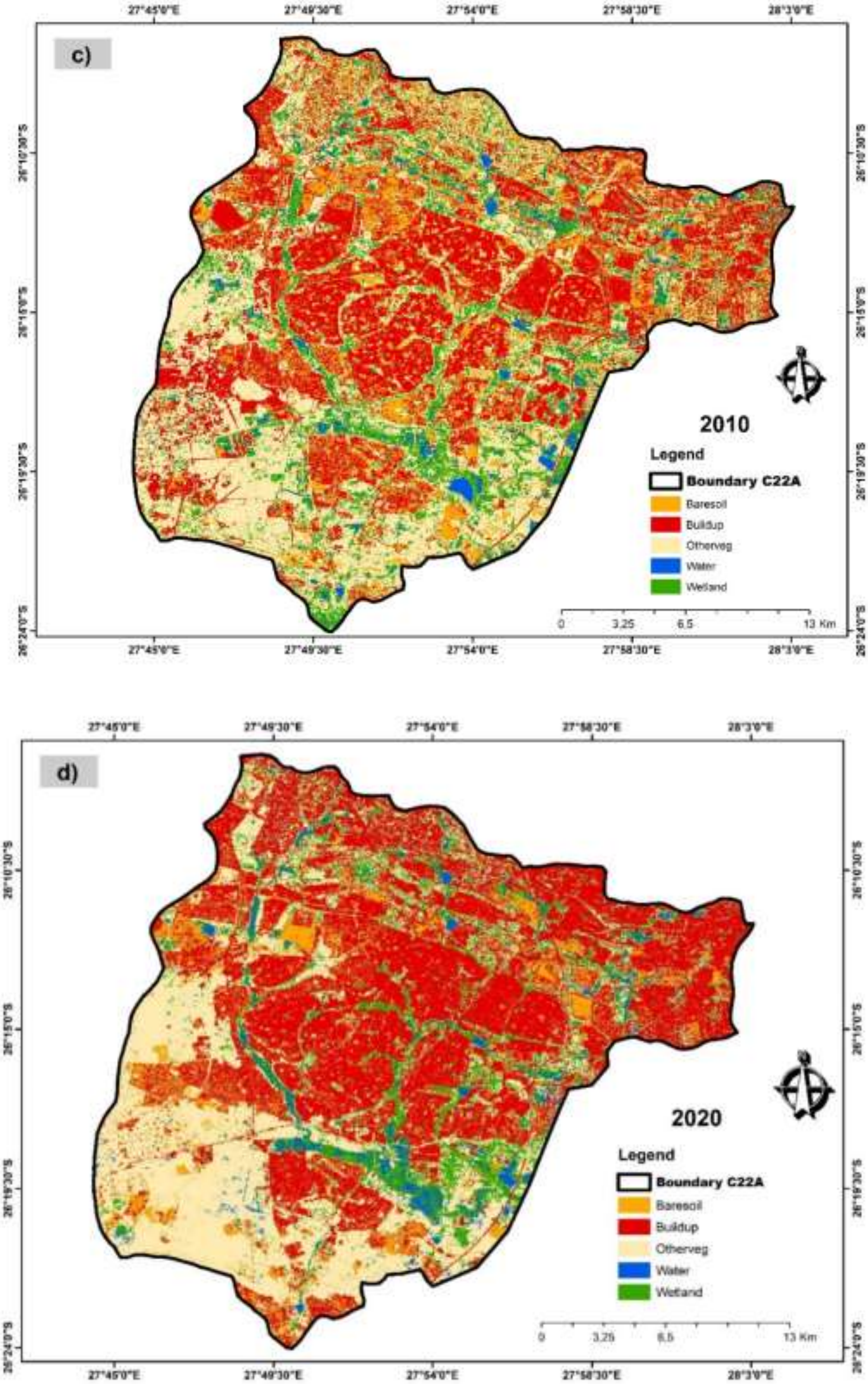


Figure 2: Wetland maps classified using Landsat data and Random Forest in Klip River: (a) 1990, (b) 2000, (c) 2010 and (d) 2020

4.2 Wetland area spatiotemporal change analysis over time (1990, 2000, 2010 and 2020)

The Klip River wetland region has undergone substantial alteration over the past 30 years, according to the area coverage data for the observed LULC. Table 4 shows how much of the study area is covered and how the built-up area grows while the wetland area shrinks. For example, in 1990, the wetland covered approximately 14.82% (6949.9 ha) of the total area. However, the wetland area coverage fell to 5.54% in 2020 (2759.2 ha). The built-up area, however, kept on growing year after year. In 1990, the built-up area covered 0.17% (80.36 ha), increasing to 54.96% (22 901 ha) in 2020. One of the many factors that contributed to the growth of a built-up region is population growth.

Table 4: An overview of the land usage and land cover area coverage from 1990 to 2020 (area in ha)

LULC type	Spatial coverage							
	1990		2000		2010		2020	
	Area	%	Area	%	Area	%	Area	%
Bare soil	20870,9	44,51	10947,3	19,69	9289,1	16,93	5566,4	11,17
Build up	80,36	0,17	12401,4	22,61	16998	30,99	22901	45,96
Other Vegetation	15549,5	33,17	20338,9	37,09	18676,8	34,06	15840,8	31,79
Water	3433,9	7,33	1044,6	1,9	1537,4	2,8	2759,2	5,54
Wetland	6949,9	14,82	10108,1	18,43	8335,8	15,2	2759,2	5,54

4.3 Accuracy assessment report

Table 5 demonstrates the accuracy assessment report of Landsat 5 image of 1990. The image managed to map the urban wetland with an overall classification accuracy of 85.19%. The producer and user accuracy range from 59.5% to 84.62%, where wetland area produced user accuracy of 84.62% and 84.62% compared to other LULC classes, and bare soil produced higher user and producer accuracy.

Table 5: Error matrix obtained by Landsat 5 image of 1990.

1990	Bare soil	Build up	Other vegetation	Water	Wetland	Total	Producer Accuracy (%)
Bare soil	29	1	0	0	0	30	**85.71**
Build up	2	25	1	0	0	28	**83.33**
Other vegetation	1	0	15	0	0	16	**59.5**
Water	0	0	0	20	3	23	**76.92**
Wetland	0	0	0	3	25	28	**84.62**
Total	32	26	16	23	28	250	**OA**
User Accuracy (%)	**75**	**90**	**59.5**	**76.92**	**84.62**		**85.19**

The accuracy assessment report for the year 2000 Landsat 5 image is demonstrated in Table 6, indicating that the image managed to map wetlands and acquired an overall accuracy of 89.80%. The producer accuracy ranges from 10% to 92.86%, where wetland acquired user accuracy of 77.78% at this point, bare soil and built-up produced 92.85% and 81.82% user accuracy compared to other LULC classes.

Table 6: Error matrix obtained by Landsat 7 image of 2000.

2010	Bare soil	Build up	Other vegetation	Water	Wetland	Total	Producer Accuracy (%)
Bare soil	22	1	1	0	0	24	62.5
Build up	2	25	0	0	0	27	71.43
Other vegetation	0	0	27	0	2	29	83.33
Water	0	0	0	23	1	24	88.89
Wetland	0	0	0	0	21	21	90.61
Total	24	26	28	23	24	250	**OA**
User Accuracy (%)	62.5	71.43	71.43	88.89	92.3		84.09

Table 7 demonstrates the accuracy assessment report of Landsat 7 of 2010; it is indicated that the image produced an overall accuracy of 84.09%. The wetland has a user accuracy of 92.3% and the producer accuracy of 90.61%; nevertheless, user accuracy ranges from 62.5% to 92.3% and produce accuracy ranges from 62.5% to 90.61%.

Table 7: Error matrix obtained by Landsat 7 image of 2010.

2010	Bare soil	Build up	Other vegetation	Water	Wetland	Total	Producer Accuracy (%)
Bare soil	22	1	1	0	0	24	62.5
Build up	2	25	0	0	0	27	71.43
Other vegetation	0	0	27	0	2	29	83.33
Water	0	0	0	23	1	24	88.89
Wetland	0	0	0	0	21	21	90.61
Total	24	26	28	23	24	250	**OA**
User Accuracy (%)	62.5	71.43	71.43	88.89	92.3		84.09

Landsat 8 OLI 2020 image, the accuracy assessment report demonstrated in Table 8, indicates that the image managed to map wetlands and acquired an overall accuracy of 88.12%. The producer accuracy ranges from 10.65% to 92.30%, where wetland acquired user accuracy of 88.89%; at this point, water produced 91.67% user accuracy compared to other land cover classes.

Table 8: Error matrix obtained by Landsat 8 OLI image of 2020.

2020	Bare soil	Build up	Other vegetation	Water	Wetland	Total	Producer Accuracy (%)
Bare soil	20	1	1	0	0	22	**10.65**
Build up	2	19	6	0	1	28	**80**
Other vegetation	0	2	23	1	2	28	**92.30**
Water	0	0	0	20	1	21	**91.67**
Wetland	0	0	1	0	25	26	**72.72**
Total	22	22	31	21	29	250	**OA**
User Accuracy (%)	81.81	10.65	85.71	91.67	88.89		**88.12**

4.4 Gains and loss of land use land cover

The spatiotemporal change data for the current study under the observed years is presented in Table 9, and it demonstrates both increases and losses in LULC inside the Klip River wetland. Figure 4 displays the overall gains or losses for each LULC between 1990-2000, 2000-2010, 2010-2020, and 1990-2020. Between 1990 to 2000, it was observed that the wetland gained approximately 3158 ha in the only year that the wetland gained. In contrast, the built-up area gained about (12 321.04 ha). From 2000 to 2010, the wetland lost (1772.3 ha) and vegetation lost (1662.1 ha) compared to the previous years, while the built-up area gained (4596.6 ha). It was observed that between 2010 to 2020, the wetland had already lost (5576.6 ha), while the build-up area gained (5903 ha), and the other LULC slowly decreased. The result indicates that the wetland area declined between 2000 and 2010 as the build-up area rapidly increased. Vegetation and bare soil also indicate a significant loss over the past 30 years.

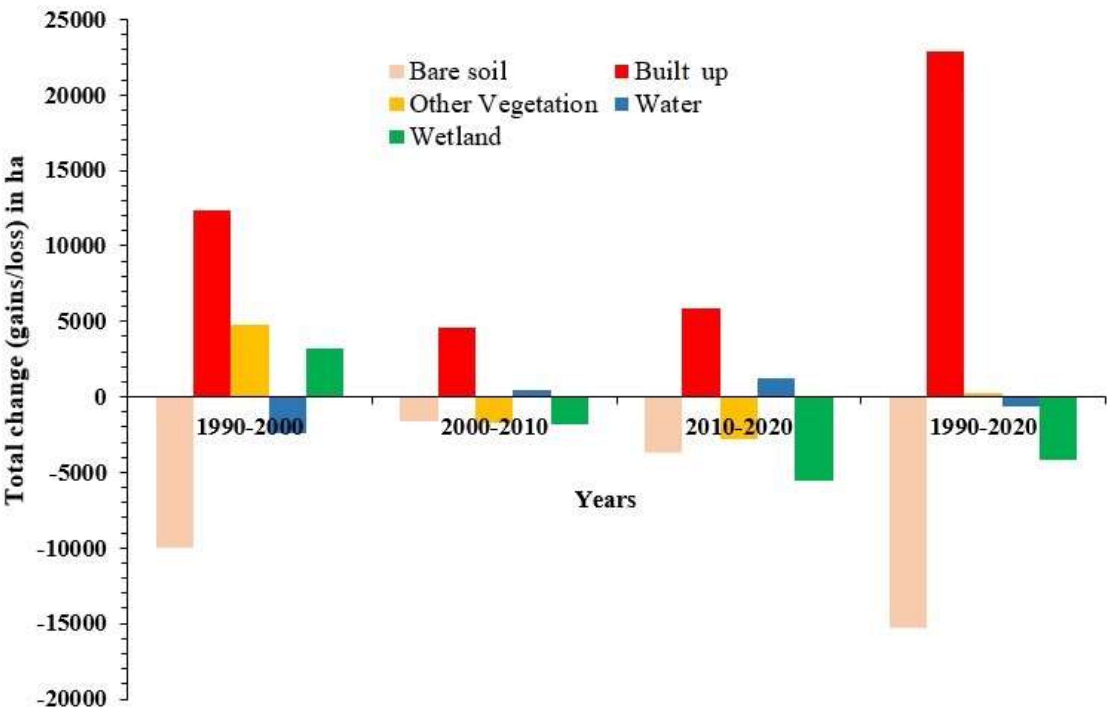


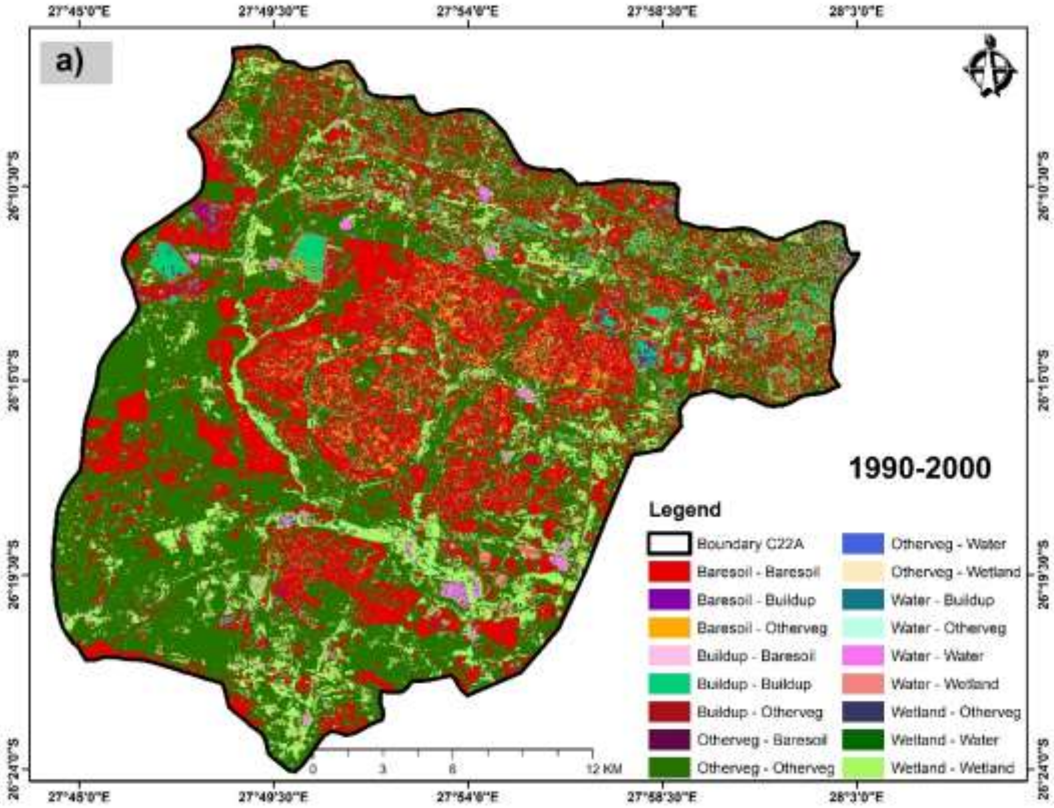
Figure 3: Between 1990 and 2020, the total area and the volume of land use and land cover changes (net change: gains/losses) in wetland area.

Table 9: Area change occurred over 30 years period (area in ha).

	Area coverage per year				Change occurred between years			Change over time
	1990	2000	2010	2020	1990-2000	2000-2010	2010-2020	1990-2020
Bare soil	20870,9	10947,3	9289,1	5566,4	-9923,6	-1658,2	-3722,7	-15304,5
Built up	80,36	12401,4	16998	22901	12321,04	4596,6	5903	22820,64
Other Vegetation	15549,5	20338,9	18676,8	15840,8	4789,4	-1662,1	-2836	291,3
Water	3433,9	1044,6	1537,4	2759,2	-2389,3	492,8	1221,8	-674,7
Wetland	6949,9	10108,1	8335,8	2759,2	3158,2	-1772,3	-5576,6	-4190,7

4.5 LULC changes observed in the 30 year period 1990 to 2020

The spatial extent of urban wetlands associated with the Klip River has significantly decreased over the past 30 years. Figure 4 demonstrates LULC changes observed between 1990 to 2000, 2000 to 2010, 2010 to 2020 and 1990 to 2020. The change between 1990 and 2000 showed they are still dominated by bare soil, vegetation and wetland area. However, between 2000 and 2010 built-up area started to increase, which was further noticed between 2010 and 2020. The increase in the build-up area encroached into the wetland, vegetation and bare soil. This resulted in the loss of wetlands because wetlands are the most sensitive ecosystems. Table 10 demonstrates the transitional changes, indicating that between 1990 and 2020, bare soil transmitted from built-up (819.54 ha) to other vegetation (372.74 ha). However, bare soil to water or wetland remained the same between 1990 and 2000. Table 10 shows that there was a significant change in the wetland between 2000 and 2010; it shows that built-up areas primarily replaced the wetland (175.42 ha), bare soil (1445.76), and other vegetation (367.66 ha). Between 2010 and 2020, it was observed that wetlands were transformed by 268.34 ha into the built-up area, bare soil (3851.86), water (34.48 ha) and other vegetation (3034.69 ha). It was demonstrated that significant occurred between 2010 and 2020 within the observed years. The LULC changes observed indicated a significant wetland change from bare soil (1724.01 ha) to built-up (95.96 ha) and other vegetation (7591.05 ha) in the years 1990 and 2020.


a)
1990-2000
Legend
Boundary C22A
Baresoil - Baresoil
Baresoil - Buildup
Baresoil - Otherveg
Buildup - Baresoil
Buildup - Buildup
Buildup - Otherveg
Otherveg - Baresoil
Otherveg - Otherveg
Otherveg - Water
Otherveg - Wetland
Water - Buildup
Water - Otherveg
Water - Water
Water - Wetland
Wetland - Otherveg
Wetland - Water
Wetland - Wetland
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12 KM
27°45'0"E
27°49'30"E
27°54'0"E
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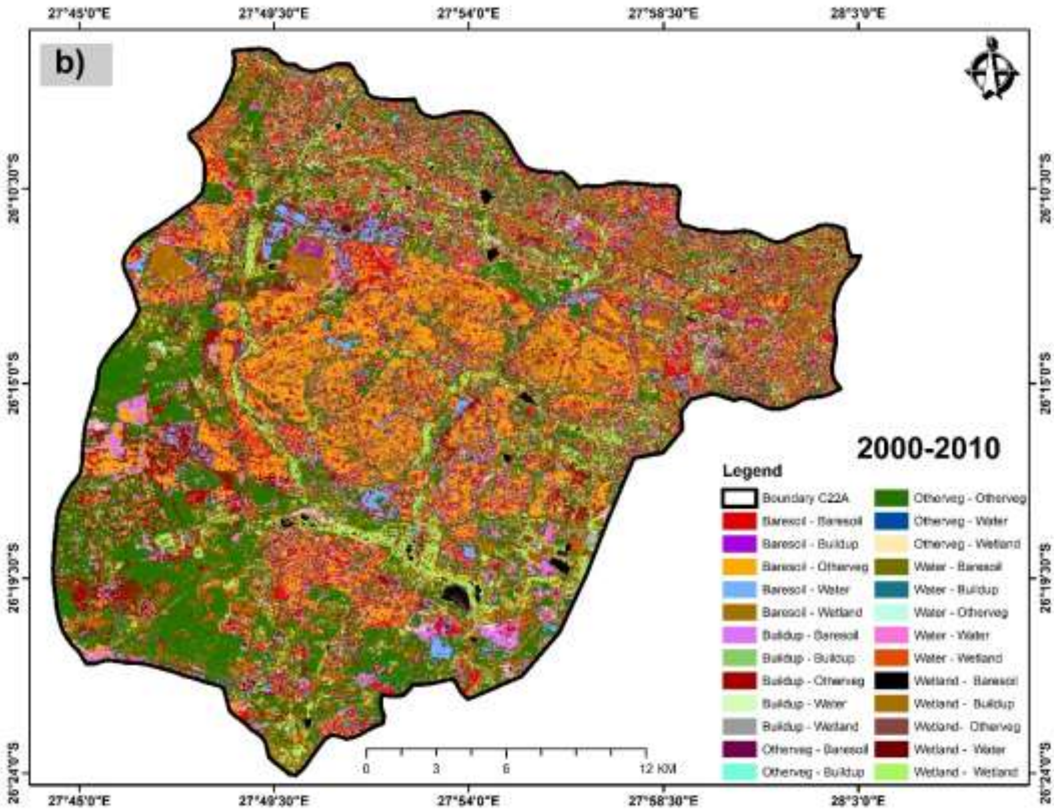
28°3'0"E
26°10'30"S
26°15'0"S
26°19'30"S
26°24'0"S


b)
2000-2010
Legend
Boundary C22A
Baresoil - Baresoil
Baresoil - Buildup
Baresoil - Otherveg
Baresoil - Water
Baresoil - Wetland
Buildup - Baresoil
Buildup - Buildup
Buildup - Otherveg
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Otherveg - Wetland
Water - Baresoil
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Wetland - Buildup
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Wetland - Water
Wetland - Wetland
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12 KM
27°45'0"E
27°49'30"E
27°54'0"E
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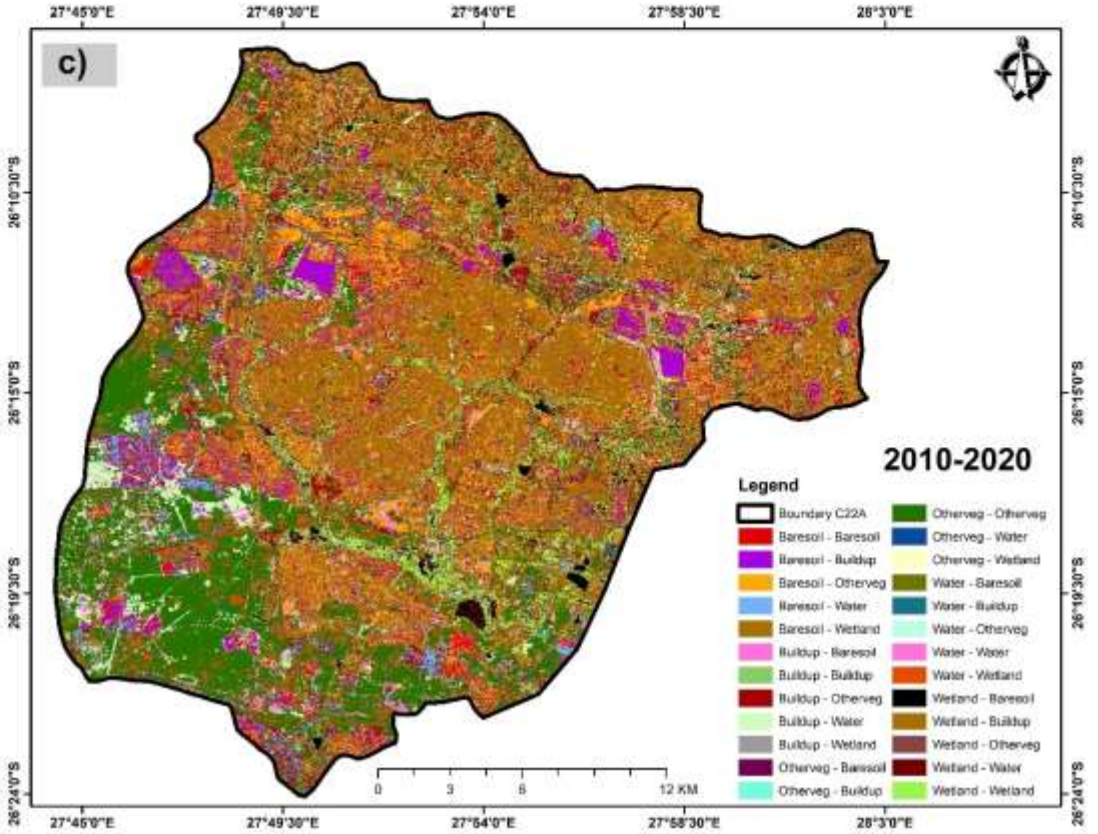
28°3'0"E
26°10'30"S
26°15'0"S
26°19'30"S
26°24'0"S



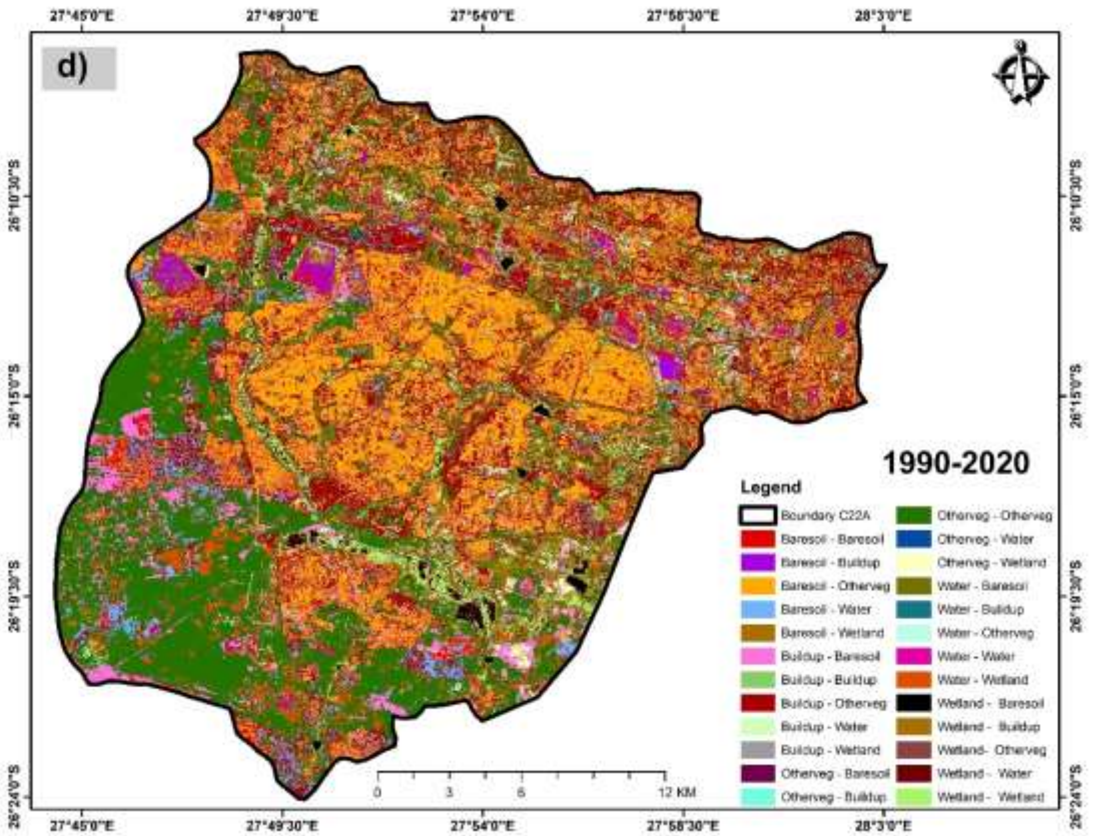


Figure 4: Change detected (1990-2000); (2000-2010); (2010-2020) and (1990-2020).

Table 10: Transitional change between (a) 1990-2000, (b) 2000-2010, (c) 2010-2020, (d) 1990-2020 (area in ha) shading means no change.

1990/2000 (a)	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	22970,18	819,45	372,74	0	**0**
Build up	3867,59	2230,40	1181,14	0	**0**
Other Vegetation	846,11	0	45294,20	1,31	**162,45**
Water	0	4,65	13,53	572,91	**10,62**
Wetland	**0**	**6993,43**	**840,72**	**0**	**11549,79**

2000/ 2010 (b)	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	8273,89	1445,76	5503,39	13,71	**875,12**
Build up	9862,32	5279,58	6756,44	33,02	**814,86**
Other Vegetation	4755,39	367,66	24674,20	51,17	**7204,03**
Water	57,95	10,72	681,17	400,15	**2203,98**
Wetland	**1212,82**	**175,42**	**8688,88**	**103,65**	**8285,93**

2010/2020 (c)	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	4179,11	3851,86	2035,81	53,37	**569,43**
Build up	8536,98	15556,86	6370,10	152,73	**2423,11**
Other Vegetation	2583,22	3034,69	22064,70	895,33	**8053,91**
Water	40,80	34,48	734,05	1278,86	**1947,75**
Wetland	**771,76**	**268,34**	**5847,79**	**973,70**	**5472,50**

1990/2020 (d)	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	5664.53	974.44	3653.93	43.29	**353.39**
Build up	15335.53	1840.33	14699.84	205.97	**958.07**
Other Vegetation	4862.63	135.33	26648.68	297.25	**4687.96**
Water	97.19	8.69	1261.53	532.71	**2135.81**
Wetland	**1724.01**	**95.69**	**7591.05**	**335.70**	**3587.64**

4.6 Detected changes for wetland cover for the period 1990-2000, 2000-2010, 2010-2020 and 1990-2020

The change detected between 1990-2000, 2000-2010, 2010-2020 and 1990-2020 was primarily focused on the wetland changes. Table 11 demonstrates a transition from the observed LULC classes to wetlands between 1990-2000; it indicates no change from wetlands to bare soil and water. However, the wetland transitioned to the built-up area (6993.43 ha), followed by vegetation (840.72 ha). When observing the change between 1990-2020, the change from wetland to bare soil and vegetation was significant compared to the other LULC types. This could result from the change in landscape dynamics due to the development of infrastructure, increase built up area, where wetlands have not received enough water to sustain the ecosystem and dry up. Wetland changed vegetation (7591.05 ha), followed by bare soil (1724.01 ha). Built-up changed to wetland (95.69 ha) and water (335.70 ha).

Table 11: Transition occurred from the observed LULC classes to wetland between 1990-2020.

	1990-2000	2000-2010	2010-2020	1990-2020
Change (from-to)	**Area**	**Area**	**Area**	**Area**
Wetland to Bare soil	0	1212.82	771.76	1724.01
Wetland to Build up	6993.43	175.42	268.34	95.69
Wetland to Other Vegetation	840.72	8688.88	5847.79	7591.05
Wetland to Water	0	103.65	973.70	335.70
Wetland to Wetland	1149.79	8285.93	5472.50	3587.64

4.7 Spatial variables selected to train MOLUSCE.

Due to rising land demand and population expansion, the built-up area experienced tremendous growth, as seen by the transition matrix analysis. These transformations were all based on underlying physical and socioeconomic forces. These spatial variables are mostly used by researchers to examine LULC dynamics (Yulianto et al., 2018). Figure 5 demonstrates the variables used to train the MOLUSCE model to predict the LULC for 2030 and 2040. These variables were factored in because changes in LULC impact the slope and the DEM of the area; thus, predicting future LULC depends on the landscape of the area. the incorporation of slope and DEM data into algorithms is a crucial step in understanding and mitigating the effects of urbanization on wetland ecosystems. These data points allow for a comprehensive assessment of how changes in elevation and built-up areas impact the flow of water, ultimately aiding in the conservation and sustainable management of wetland environments. By considering these factors, decision-makers can make informed choices to preserve these critical and sensitive ecosystems. The use of distance from major roads was due to consideration of the current distribution of road network and to guide the model in terms of the current LULC.

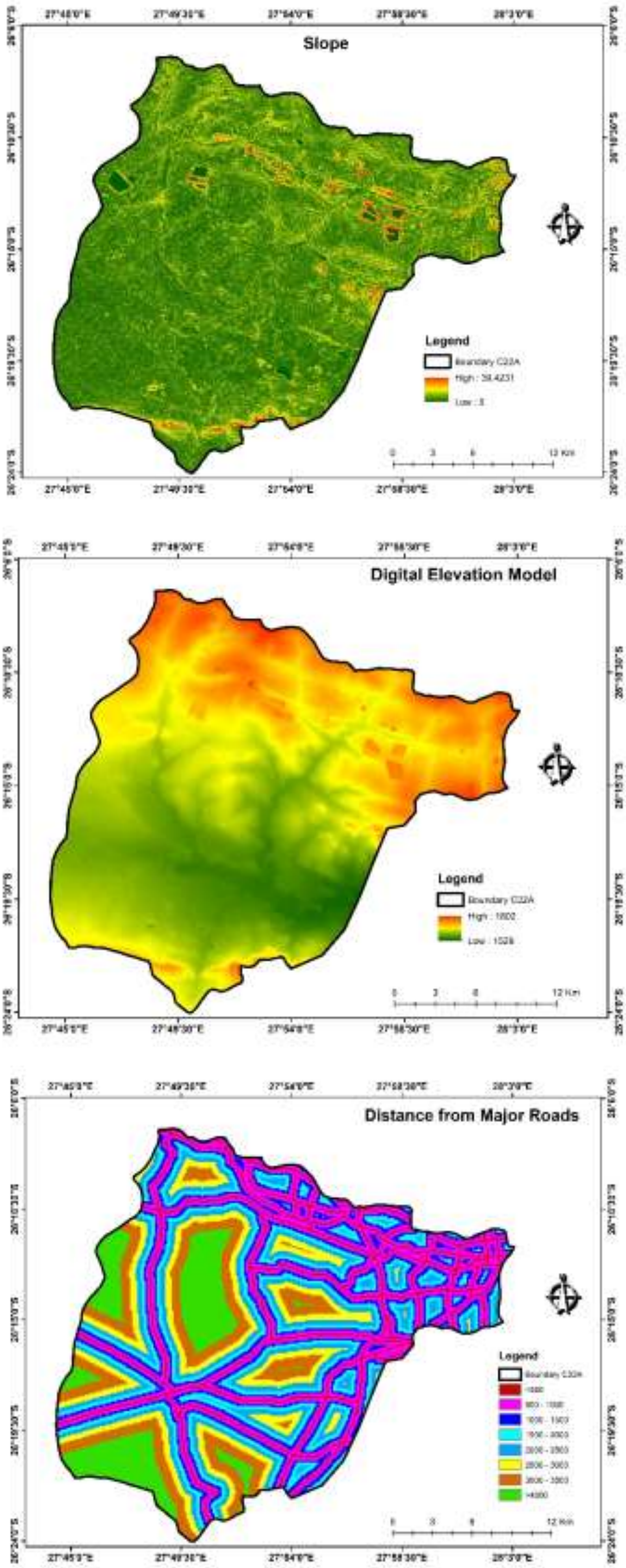


Figure 5: Used spatial factors in the research (Slope, DEM and Distance from major roads)

4.8 Transition Potential Modelling and Model Validation

The projected LULC for 2020 were predicted from LULC data from 2000 to 2010 and spatial factors, and the outcome kappa validation value of 0.71. Figure 6 demonstrates the actual LULC observed in 2020; the projected 2020 is the estimated LULC from 2020. The simulated LULC obtained an overall accuracy of 62.45%, an ANN of 0.71 and a kappa validation of 0.28 (Table 12). It was observed that the kappa validation was low indicating that the was a disagreement between the classified images. It is visible in the results that water class was not accounted for in the simulation image. It was observed that the projected LULC has a difference ranging from 3.01% to 2.27. For example, the actual LULC for 2020 shows that the built-up area covered 45.96% of the total area; however, the projected 2020 indicates that the built-up area covered 48.23%. On the other hand, the wetland was also projected to cover 7.66%; however, the actual LULC shows that the wetland covered 5.54% of the study area.

Table 12: Actual and projected LULC area coverage for 2020

	Actual		Projected		Accuracy	Kappa Value	
LULC TYPES	**ha**	**%**	**ha**	**%**		**ANN**	**Validation**
Bare soil	5566,4	11,17	6958	14,18			
Build up	22901	45,96	23658	48,23			
Other Vegetation	15840,8	31,79	14598	29,76	62,45	0,71	0,28
Water	2759,2	5,54	80	0,163			
Wetland	2759,2	5,54	3758	7,66			

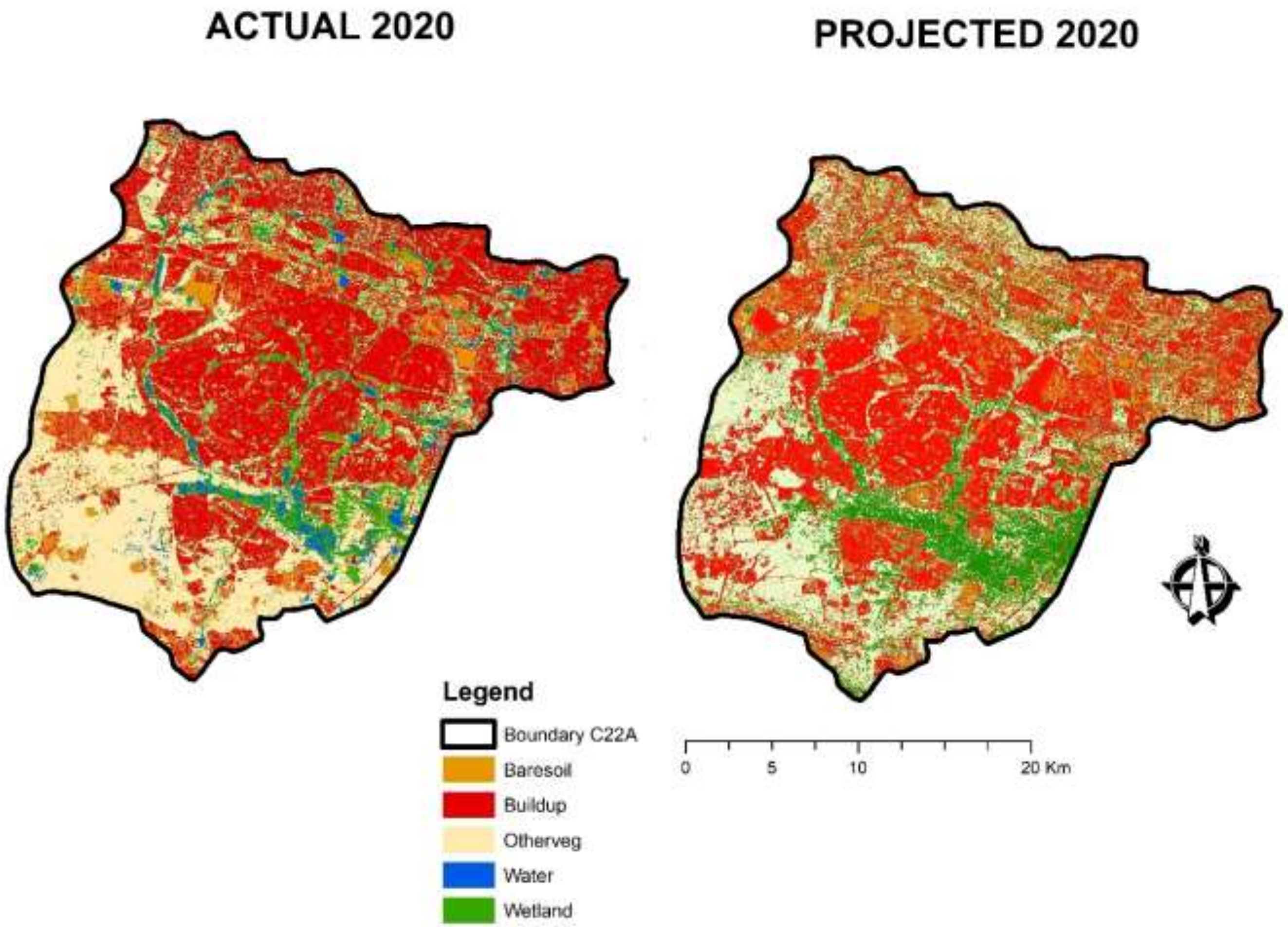


Figure 6: Actual and projected LULC maps for 2020

4.9 Prediction of LULC

Predicted the LULC for 2030 and 2040 after receiving encouraging model validation results. LULC for 2030 was estimated using spatial variables and temporal LULC data from 2010 and 2020, and a kappa value of 0.61 was obtained (Table 13). Also, we predicted 2040 using the LULC of 2020 and 2030 together with the explanatory variables, and a kappa value of 0.51 was achieved. Figure 8 indicates the simulated LULC for 2030 and 2040. The results show that the build-up area will continue to increase. The built-up area is projected to cover 66.67% (36 572 ha) in 2030, while the wetland area will continue to be 3.93%. The wetland further decreases to 2.91% (21 985 ha) in 2040.

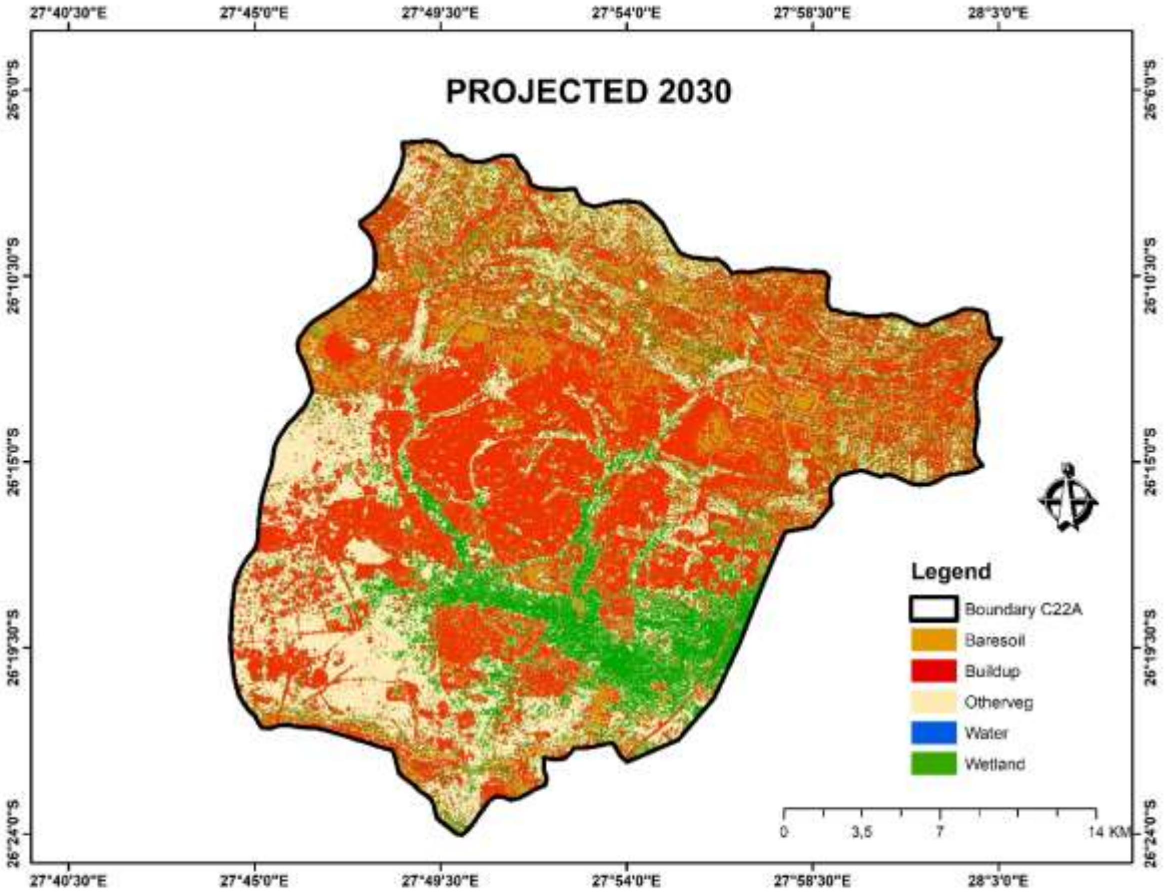


Figure 7: Projected LULC for 2030

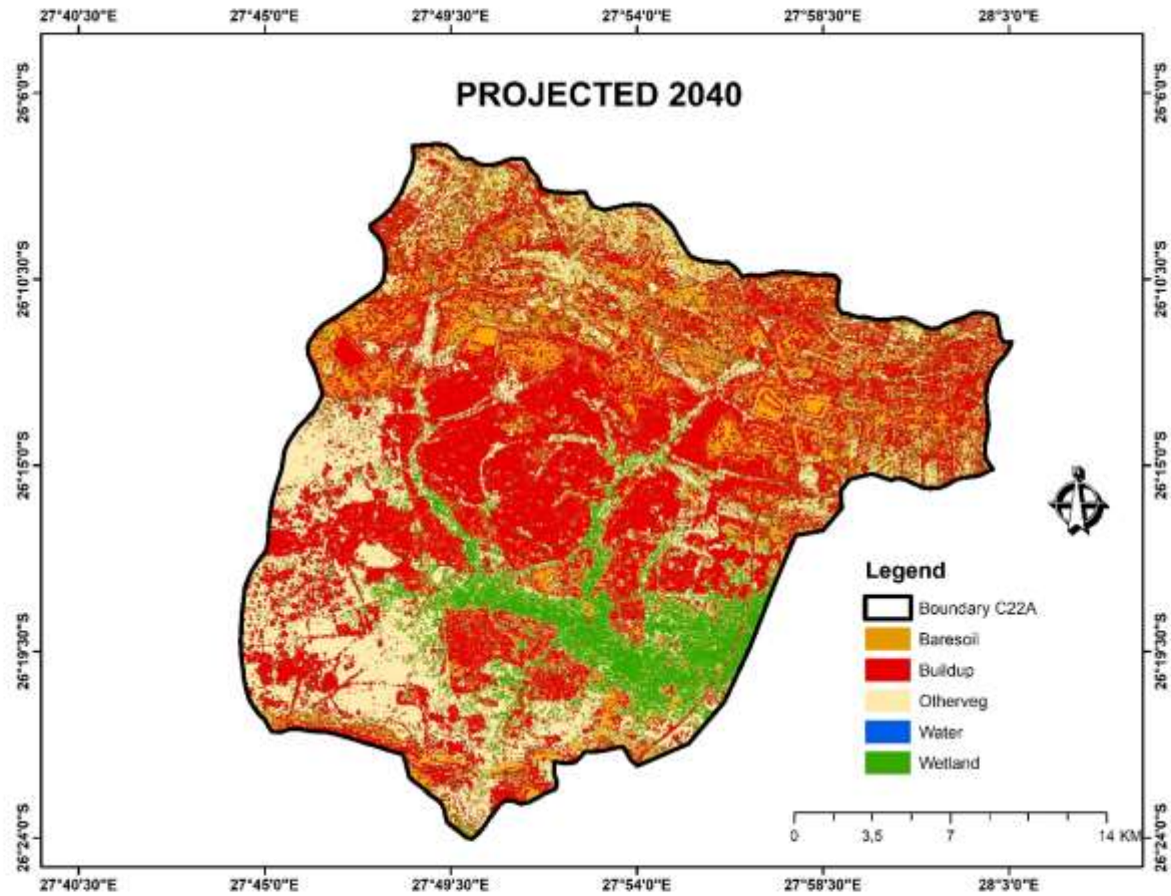


Figure 8: Projected LULC for 2040

Table 13: Predicted area statistics for 2030 and 2040.

LULC TYPES	2030		Kappa	2040		Kappa
	ha	%		ha	%	
Bare soil	4495	8,19		3568	5,24	
Build up	36572	66,67		43751	64,22	
Other Vegetation	10568	19,27	51	9865	14,48	51
Water	1065	1,94		8958	13,15	
Wetland	2154	3,93		1985	2,91	

4.10 Prediction of Change

The LULC change analysis looks into how the LULC pattern has changed spatially and dynamically over the course of the study. The predicted LULC between 2020 and 2030 indicates an increase in the build-up area, while the other observed LULC classes are decreasing. Figure 9 shows that the build-up area replaces bare soil, vegetation and wetland. Between 2030 and 2040, the built-up area replaced bare soil by 4134.95 ha, followed by the wetland area at 1543.69 ha. The change observed throughout the years indicates that the build-up area is significantly increased, replacing other observed LULC.

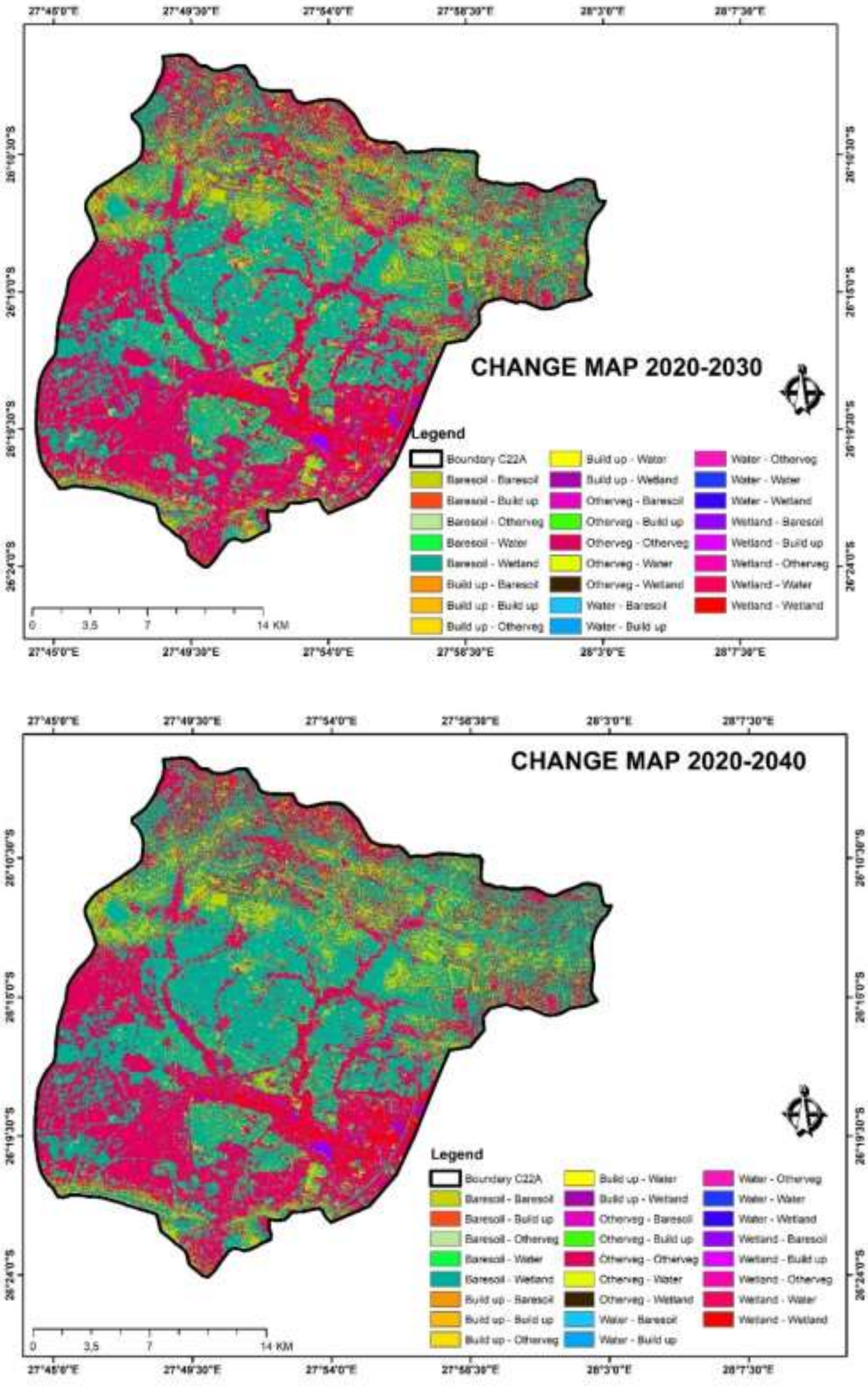


Figure 9: Change detection for (2020-2030) and (2030-2040)

Table 14 demonstrates the change between 2020 and 2030, and 2030 and 2040. It was observed that between 2020 and 2030 build-up area increase to cover 21 195.34 ha of the study area which is approximately 38.67% of the total area. Built-up replaced vegetation by 1966.80 ha followed by the wetland area at 284.39 ha. It was observed that between 2030 and 2040 the build-up area replaced the vegetation by 9792.65 ha and wetland by 1543.69 ha, at this point the build-up area is covering 23705.66 ha which is approximately 43.25% of the study area.

Table 14: Predicted transitional change between 2020-2030, and 2030-2040

2020/2030	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	6196,29	521,52	638,66	88,04	**721,70**
Build up	776,99	20641,46	1966,80	36,02	**284,39**
Other Vegetation	450,61	29,35	13769,18	71,93	**790,79**
Water	12,42	0,35	10,75	672,23	**105,11**
Wetland	**487,34**	**2,66**	**966,31**	**45,35**	**5519,12**

2030/2040	**Bare soil**	**Build up**	**Other Vegetation**	**Water**	**Wetland**
Bare soil	66837,00	2957,84	6552,68	455,65	**6055,15**
Build up	4134,95	233703,44	9792,65	209,37	**1543,69**
Other Vegetation	515,17	274,67	126477,22	477,66	**6886,97**
Water	112,14	12,78	118,17	6469,64	**655,45**
Wetland	**5426,32**	**107,88**	**8177,99**	**396,39**	**55066,66**

CHAPTER 5: DISCUSSION

5 Spatial distribution of land use/ land cover classes

The Klip River wetland is situated in quaternary catchment C22A in the Vaal Water Management Region. This study examined the effects of LULC change dynamics on this wetland. Using GEE to acquire Landsat data, Sentinel data, and Random Forest enables the study of urban wetland and LULC changes between 1990 to 2020 (30 years). The classified maps of the study area demonstrate that LULC change significantly impacts the urban wetland system. The wetland area covered approximately 14% (6949.9 ha) of the study area in 1990, in 2000 an increase was observed (10 108.1 ha) to 18.45%, and in 2010 the wetland area decreased to 15.2% (8335.8 ha). The wetland increased significantly between 1990 and 2000. This may be due to the introduction of the Bushkoopies Wastewater Treatment Plant which may have impacted on the effluent that is released into the wetland. In 2020 the wetland covered 5.54% (2759.2 ha).

The findings show that over the previous 30 years, the wetland area has decreased. The wetland region has seen a major shift, in terms of the observed LULC. Researchers have identified one common factor that influences LULC changes which is population growth. Due to increasing population growth, the demand for land use has increased (Kecha et al., 2010; McCarthy et al., 2018). Population growth increased as indicated by the increase in the built-up area. According to Statistics South Africa (StatsSA), South Africa's population grew from under 5 million at the beginning of the 1900s, to 45 million by 2000. In 2020, South Africa's population is now approximately 59.62 million, with Gauteng being the largest share of the country's population, with approximately 26% (15.5 million). For example, people were informed that they could build a house where there was space. This information led to people building houses in wetlands and flood line areas. This study observed that the built-up area in 1990 covered 0.17% (80.36 ha), and in 2020 it covered 45.96% (22 901 ha), currently being the most dominant LULC in the study area. Kashaigili and Majaliwa (2010) indicated that increased anthropogenic activities decrease the wetland coverage while establishing both the regulated and unregulated residential development has increased.

Built-up areas replace urban wetlands, resulting from the high land demand in the urban areas relatively caused by urbanization (Zhoe, 2017). According to this study, the landscape of the study area was altered by the construction of residential areas and industrial development, which led to a decline in the wetland area. The build-up area went from covering 0.71% in 1990 to being the dominant LULC type in 2020, covering 45.96%. The built-up area between 1990 and 2000 replaced the wetland area by 6993.43 ha between 2000 and 2010 (175.42 ha), 2010 and 2020, it replaced the wetland by 268.34 ha. Phethi and Gumbo (2019), in Limpopo indicated that wetland areas are replaced by residential and croplands due to the high demand of land and population growth. The current study also observed that within 30 years, the build-up area has increased, replacing wetlands, bare soil and other vegetation. Between 2010 and 2020 build-up replaced wetlands by 268.34 ha, bare soil by bare soil by 3851.56 ha and other vegetation by 3034.69 ha. The findings of this study are supported by Phethi and Gumbo's (2019) findings that as the population increases, the demand for land also increases to establish residential, agricultural, and industrial areas. In urban areas, the land is mainly needed for residential and industrial use.

Climate change plays a pivotal role in wetland reduction in this study, and it was observed that bare soils also replace wetland areas. Bare soils in a wetland area result from drought, dry season and removal of wetland vegetation while further enhancing soil moisture loss. The temporal and seasonal zones of the wetland area are the most affected due to anthropogenic activities such as the development of informal or illegal land occupation. In this study, the temporal and seasonal zone of the wetland was occupied by informal residential development of temporal and permanent structures. It was observed that rainwater was captured in between the informal settlement on site (Figure 10).

A wetland delineation was undertaken to demonstrate the finding that the delineated area for part of the wetland, however, was used for residential purposes. An auger was used to collect the soil sample demonstrated in Figure 11. To show that the area where the informal settlement is a season/ temporal zone of the wetland, mottles were observed in the soil sample collected in the area (Gemechu et al., 2021). Mottling within the wetland soil is associated with periodic to permanent waterlogging in the soil (Slagter et al., 2020). These informal settlements are one of the significant impacts on the wetland system within urban areas. Therefore, city planning, and wetland managers need to monitor by mapping consistently and predicting the LULC changes to develop strategies for rehabilitation and preserving the wetland systems. Studies focusing on mapping spatial changes in an urban area will help develop preservation strategies to save wetlands.

Figure 10: Temporal and seasonal zone occupied by informal settlements.

Figure 11: Mottling within wetland soil (photo taken by Nolwazi Nxumalo)

The study used the MOLUSCE plugin to simulate the spatiotemporal change transition potential and future LULC for 2030 and 2040. The results from 2020 were simulated to validate the model. The finding from the simulated LULC indicates that the built-up area will continue to grow and dominate the study area while the wetland and other LULC will decrease. The study by Muhammad et al. (2022) using the MOLUSCE simulating 2030-2050 indicated that built-up and agricultural production continues to replace the wetlands and vegetation. The simulation model was designed to predict the future LULC to assist in properly planning the cities to minimise the risk of losing essential landscape features and provide mitigation measures to deal with the foreseeable landscape changes. With the possibility of predicting the LULC, wetland managers and city planners can protect the wetland areas. In a study conducted by Yulianto et al. (2019) based on the information generated using optimistic scenarios, the built-up area continues to increase. The projected LULC for 2030 and 2040 indicates that there will be little to no water in the wetland areas. The absence of water could mean that because of the changes in the area's landscape, little to no water can be stored in the wetlands.

5.1 Long-term urban wetland monitoring using Landsat dataset

Consistent mapping of the spatial patterns of wetland regions through time is necessary in order to comprehend the effects of the LULC changes on the integrity and ecological functioning of urban wetland areas. Researchers and wetland managers can map the spatial patterns and track LULC changes throughout wetlands using cost- and time-effectively by using remotely sensed data. The technique improves the utilization of multi-temporal mapping of wetland regions by wetland characterisation systems to comprehend the pattern of LULC changes damaging wetland ecosystems (Thamaga et al., 2022). Phathi & Gumbo (2019) indicated that significant land use activities around the wetland regions include cultivated land, construction of roads, and agricultural production. The current study identified that the dominant land use activities around the urban wetland include road infrastructure, informal settlements, Formal settlements, illegal dump sites and Wastewater Treatment Plants (WWTP). These activities stress the wetland ecosystem and deteriorate wetland vegetation and the wetland's hydrology leading to flooding. Thus, resulting in the loss of wetlands. These findings indicate that wetlands need to be protected no matter their size. Small wetlands are neglected, which aggravates their loss. In South Africa, 23 wetlands are designated Ramsar sites, and this does not represent the population of wetlands in South Africa and also exclude the small wetlands. Therefore, mapping LULC spatiotemporal changes contributes to monitoring small wetlands.

The study offers an overview of unprotected urban wetlands, but comprehension of these ecosystems might be improved by combining information from a variety of sources, such as indigenous populations' perspectives and seasonal dynamics. Additionally, because wetland LULC characterization used broadband and high-resolution satellite data, certain inherent alterations might have gone unreported. Landsat's poor discrimination is hampered by its 30 m spatial resolution and spectral mixing. Examining spatially explicit approaches that analyze changes in soil moisture, various forms of vegetation or indices, as well as high-resolution data, is important in this context. It is necessary to include meteorological and soil data in order to establish whether these changes are solely due to human activity. The study also found that the wetland saw increased vegetation (bush encroachment), which may have been caused by climate variability and climate change. Water resources have been adversely affected by climate change and frequent droughts in the majority of regions, especially in the arid and semi-arid ones.

5.2 Implications for LULC management and wetland conservation

The LULC alterations have an impact on the richness, water flow, spatial distribution, and eventual spread of alien plant species in wetlands. An understanding of the LULC transition is needed for wetland ecohydrological processes. The findings of this study demonstrate that the wetland ecosystem area has been rapidly shrinking since 1990; from 1990 to 2020, it shrank by about 9.28%. It is projected that in 2030 and 2040 the wetland will lose up to 11.91% of its area. This information gives environmental and wetland managers the necessary baseline data to develop long-term intervention strategies and steps to prevent further degradation of the wetland systems due to potential hazards arising from anthropogenic and natural causes. They call for responsive management measures, especially for unprotected wetlands that have been disregarded in policy creation, to slow or stop the rate of wetland deterioration or disappearance. Inadequate integrated data collection, trustworthy information, and evaluations do not support increased management techniques focusing on wetland rehabilitation and restoration. Critical questions about the biological significance of wetlands and LULC change are raised by the uncertainty surrounding earlier policy outcomes for these two areas and recent efforts to increase their preservation. To slow down the rate of wetland decline, ecosystem managers must restrict the expansion of urban landscape patterns, and they also need to tighten their implementation strategies.

CHAPTER 6: CONCLUSIONS AND RECOMMENDATIONS

6 Conclusion

The objectives of this study were to (1) conduct a comprehensive analysis to map and evaluate the effects of land use/land cover changes in the Klip River wetland spanning from 1990 to 2020, employing Landsat datasets at intervals of 10 years. Simultaneously, quantify both the spatial and temporal alterations in urban wetland areas over the same period, from 1990 to 2020; 2) predict the change of the urban wetland area due to Land Use/Land Cover Change for 2030 and 2040 using the MOLUSCE plugin in QGIS. The study's goal was effectively accomplished when LULC was mapped on Google Earth Engine utilizing Javascript and the Landsat dataset and Random Forest classifier. To analyze the shifts in the LULC classes over time, change detection was used. The findings showed that the expansion of the built-up area had a major impact on the wetland area. The built-up area increased from 0.17% (80.36 ha) in 1990 to 45.96% (22 901 ha) in 2020, while the wetland decreased from 14.82% (6946.9 ha) in 1990 to 5.54% (2759.2 ha) in 2020. When the LULC for 2030 was simulated using the MOLUSCE plugin for QGIS, for the year 2030 a kappa value of 0.61 and 0.51 was achieved. The models showed that while the wetland area continues to shrink, the built-up area continues to grow annually. Built-up area will be 66.67% of the total area (36 572 ha) in 2030, and wetland will be at 3.93% (2154 ha). The findings demonstrate that wetlands are servery threatened by anthropogenic activities. As the population increases, the demand for land also increases, resulting in wetlands being replaced by built-up areas. Also, this analysis demonstrates that over the past 30 years, the Klip River wetland has steadily deteriorated. In order to address the issues brought on by LULC change and preserve the sustainability of the catchment regions, this article proposes a thorough framework approach to managing wetland resources. Future LULC assessments, monitoring, and planning can use this detailed data as a model.

6.1 Recommendations

Environmental awareness is a way to educate communities about the environment and its impacts on their surroundings. People need to be made aware of the benefits of wetlands. For example, wetlands store water during floods and slowly release it during drought. Therefore, dumping waste and the establishment of informal settlements in the wetland deteriorate the present ecological status of the wetland and result in a dysfunctional system that cannot perform its ecological function. Ultimately the communities will be prone to flooding. Establishing the residential area can only be done by city planning to reduce the risk of flooding even that claims the lives of people in South Africa. People must be allowed to occupy vacant land after undergoing the legal procedure. DFFE encourage people to obtain an Environmental Authorisation prior to any development triggering listed activities within the NEMA (Act No. 107 of 1998) under the EIA Regulations. This process is conducted to monitor development and prevent them from occurring in regions posing a threat to the environment and people's safety. The NWA (Act No. 36 of 1998) stipules that any development occurring within a 500-metre radius of a watercourse requires a WUL. The application is made through DWS as there are the custodians of water. Therefore, it is crucial to create environmental programs to educate people from primary schools so that they grow up knowing the importance of wetlands in the environment. Environmental consultants conduct wetland assessments using the guidelines provided by DWS and the WET-EcoServices, a tool provided by Water Research Commission should include remote sensing to monitor the development's influence of change in wetland area.

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