Mapping the changes in vegetation spatial extent within the Khayelitsha wetlands, Western Cape Province, utilizing remotely sensed data

A thesis submitted in the fulfilment of the requirements for a Master's degree in Geography and Environmental Studies in the Department of Geography, Environmental Studies and Tourism, Faculty of Arts and Humanities, University of the Western Cape.

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Abstract

Urban wetlands play an important role in providing ecosystem services and supporting biodiversity as a habitat. These ecosystem services include reducing severe impacts of floods by helping slow the overland flow amongst other services. However, despite the importance of wetland ecosystems and their services, their value and role across the board, is under threat from anthropogenic, and climate change-related events. Rapid urbanization and human encroachment are the major drivers of wetland vegetation fragmentation which leads to their degradation in urban areas. To prevent further destruction of urban wetland areas, it is essential to develop robust methods for inventorying their spatial distribution, and Land Use Land Cover (LULC) types. This information is important for inform decision- making and formulation of long-term strategies for wetland conservation. In this regard, this study sought to estimate changes in the spatial extent of the Khayelitsha wetland between the years 2000 - 2023 using freely available remotely sensed data obtained from Landsat 7 Enhanced Thematic Mappper Plus (ETM+) and Landsat 8 Operational Land Imager (OLI). By using satellite imagery and wetland fragmentation analysis techniques, this study sought to understand the patterns of wetland vegetation fragmentation during the years 2000, 2010, and 2023 as a proxy for assessing wetland degradation. To address the main objective this study (1) conducted a systematic review of the literature on the progress, gaps, and opportunities in the application of earth observation data in assessing and mapping changes in the spatial extent and productivity of wetland species, 2) assessed the performance of Support Vector Machines (SVM), Naïve bayes (NB) and Random Forest (RF) machine learning algorithms mapping wetland land use land cover types during the years 2000, 2010, and 2023, and 3) compared the performance of various vegetation Indices in classifying urban wetlands during the years 2000, 2010, and 2023 and assess the LULC fragmentation, thereof. Results from the systematic review showed that Landsat and aerial photographs were the most used sensors in remote sensing of wetlands along with RF as the most used machine learning algorithm. There were no significant performance differences between SVM and RF even though RF outperformed SVM and NB on average. The RF attained mean accuracy of 95% and a mean kappa value of 93%, while SVM had a mean overall accuracy of 93% and a mean kappa value of 88%. The NB attained the lowest mean overall accuracy and kappa of 29.6% and 12% respectively. The assessment of various vegetation indices revealed that the method that combined spectral bands, machine learning algorithms, and vegetation indices outperformed the methods that used the spectral indices in solitude by an average overall accuracy of 98% and an average kappa of 97.3%. Results from the fragmentation analysis showed a common trend of decline in vegetated areas and bare land, while water bodies and built-up areas increased in spatial coverage during the 2000,

2010 and 2023 period. The findings of this study underscore the prospects of remotely sensed data in mapping and monitoring urban wetlands and vegetation reserves in them.

Keywords: Urban Wetlands, Land Use Land Cover (LULC) changes, Random Forest (RF) classifier, Support Vector Machine (SVM), Google Earth Engine (GEE), Landsat 8 OLI, Landsat 7

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Abbreviations

AGB	Aboveground Biomass
AVIRIS	Airborne Visible/Infrared Imaging Spectrometer
CART	Classification and Regression Tree
CNN	Convolutional Neural Network
DEFF	Department of Forestry, Fisheries, and the Environment
ED	Edge Density
EL	Edge Length
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
GEE	Google Earth Engine
GF	Gaofen
GIS	Geographic Information System
GLCM	Grey Level Co-Occurrence Matrix
GNDVI	Green Normalized Difference Vegetation Index
GPS	Global Positioning System
LAI	Leaf Area Index
LULC	Land Use Land Cover
MLC	Maximum Likelihood Classifier
MNDWI	Modified Normalized Difference Water Index
MODIS	Moderate Resolution Imaging Spectroradiometer
MPA	Mean Patch Area
MSAVI	Modified Soil Adjusted Vegetation Index
MSI	Multispectral Instrument
MSS	Multispectral Scanner
NB	Naïve Bayes
NDBI	Normalized Difference Build-up Index
NDPI	Normalized Difference Pond Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Vegetation Index
NIR	Near Infrared
NP	Number of Patches
OA	Overall Accuracy

OLI	Operational Land Imager
PA	Producer's Accuracy
PD	Patch Density
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analysis
QGIS	Quantum Geographic Information System
RF	Random Forest
RMSE	Root Mean Square Error
RS	Remote Sensing
SANBI	South African National Biodiversity Institute
SAR	Synthetic Arpeture Radar
SAVI	Soil Adjusted Vegetation Index
SPOT,	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
SWIR	Shortwave Infrared
TM	Thematic Mapper
TSAVI	Transformed Soil Adjusted Vegetation Index
UA	User's Accuracy
UAV	Unmanned Aerial Vehicles
VI	Vegetation Index
WOS	Web of Science

1. Introduction, Aims and Objectives

1.1. Introduction

Wetland ecosystems are one of the most important yet complex environmental systems. They play an invaluable role in protecting biodiversity within ecosystems, maintain the global hydrological cycle and protect human welfare (Henderson and Lewis 2008). In their healthy state, wetlands provide environmental and socio-economic benefits to communities. Such benefits include reducing severe impacts of floods by helping slow the overland flow amongst other services (de Groot, Veeneklaas et al. 2011). However, despite the importance of wetland ecosystems and their services, their value and role across the board, is under threat from anthropogenic, and climate change-related events. At a global scale, above 85% of wetlands are estimated to have been transformed resulting in the loss of wetland essential ecosystem services. Therefore, monitoring such ecosystems is of paramount for environmental managers across the globe to ensure sustainable management (Oteman, Scrieciu et al. 2021). In South Africa, the extent of wetland transformation is unknown, even though sub-national studies in the 1990s showed that 58% of wetlands in the Umfolozi catchment in KwaZulu-Natal had already experienced irreversible transformation (Gangat, Van Deventer et al. 2020).

It is in this regard, estimating the biophysical characteristics of wetlands has become an important an urgently required step in wetland management to assist in reducing their rate of deterioration. Properties of wetland vegetation are not easily detectable making it challenging to physical distinguish between different wetland vegetation communities through time and space. This necessitates the use of techniques that can effectively distinguish spatial variations and characteristics of wetland vegetation communities given that these can vary due to wetland conditions such as soil moisture and hydrological properties (Tshabalala 2020). Remote Sensing and GIS technologies have been demonstrated to be the most effective techniques for mapping and monitoring wetland ecosystems(Yuan, Sawaya et al. 2005). Remote sensing presents the opportunity to monitor large areas of land at the same time using improved spatial and temporal resolutions (Ablat, Liu et al. 2019, Ahmed, Akter et al. 2021, Gxokwe, Dube et al. 2023). Optical remote sensing techniques provide information at canopy level by responding to wetland vegetation characteristics such as leaf area index, and chlorophyll content.

Literature shows that Landsat has been the most widely used sensor to source information on spatial extent changes and Leaf Area Index (LAI) since it boasts of being the longest serving sensors which has significantly improved from the Landsat 1's characteristics. In this regard, it has data archives that could be used to characterize the spatial extent of wetlands over a long period of time. Other than the robust spectral and spatial characteristics of Landsat in mapping wetland vegetation attributes, literature shows that most studies that accurately mapped wetland vegetation attributes employed vegetation indices and robust machine leaning algorithms. For instance, Fu, Xie et al. (2021) utilized random forest and obtained an overall accuracy (OA) of 91% in mapping wetland vegetation species. Meanwhile Han, Chen et al. (2015) evaluated the utility of Support vector machines and attained accuracies of 91%. Overall, the findings of these studies suggest that there is no algorithm that could be used specifically for wetland vegetation attributes mapping. Therefore, there is need to assess different machine learning algorithms in mapping the spatio-temporal dynamics of wetland vegetation.

In this regard, this study aimed to map the spatial distribution and extent of wetland vegetation as a proxy or assessing the health of selected wetland ecosystems in a peri urban area. To address this over aching aim, the study assessed the utility of remotely sensed data covering the period between 2000 and 2023, in conjunction with different machine learning algorithms, to map the spatial distribution and extent of wetland vegetation. The study also assessed the rate of change as well as the magnitude of wetland vegetation's fragmentation, based on fragmentation metrics which included patch density, edge density, and mean patch size.

1.2. Aims and objectives.

The overall aim of this study was to map the changes in the spatial extent of wetland vegetation in the Khayelitsha between the years 2000, 2010 and 2023 using the freely available Landsat remotely sensed data.

1.2.1. Specific objectives

This over aching aim was addressed through the through the following specific **objectives**:

1. To conduct a systematic review of the literature on the progress, gaps, and opportunities in the application of earth observation data in assessing and mapping changes in the spatial extent and productivity of wetland species.
2. Assess the performance of Support Vector Machines, Naïve bayes and Random Forest machine learning algorithms mapping wetland land use land cover types during the years 2000, 2010, and 2023.
3. To compare the performance of various vegetation Indices in classifying urban wetlands during the years 2000, 2010, and 2023 and assess the LULC fragmentation, thereof.

1.3. Thesis outline

The main objective of this study was addressed through five chapters in a paper format. The first and last chapters serve as an introduction and synthesis, respectively, while the second, third, and fourth chapters are standalone papers. Consequently, there are irreconcilable overlaps between these chapters. Specifically,

Chapter 1: Gives a brief background and introduction to the study. Also highlights the overall aims and objectives of the paper.

Chapter 2: is a systematic literature review which was conducted to assess the progress, challenges and opportunities of utilizing remotely sensed data in mapping and monitoring wetland communities.

Chapter 3: is the first classification paper which utilized spectral band and a machine learning algorithm (Random Forest) to classify different wetland classes in the Khayelitsha wetland.

Chapter 4: is the second classification paper which utilized spectral bands, machine learning algorithms (Random Forest and Support Vector Machine) in conjunction with vegetation indices to classify wetland classes. This section also calculated fragmentation metrics to assess the extent of change in wetland vegetation between 2000, 2010 2023.

Chapter 5: is a synthesis chapter which highlights the objectives, implications, limitations, opportunities, and conclusions of the research paper.

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2. Assessing the Spatial Extent and Vegetation Productivity of Wetlands Using Remote Sensing: A Systematic Review of Progress, Challenges, and Prospects in Developing Regions

Abstract: Wetlands are crucial ecosystems that provide a variety of important services, such as water purification, carbon sequestration, and habitat for a range of plant and animal species. However, these ecosystems are under threat from human activities, including land-use change, pollution, and climate change. Remote sensing technologies offer an effective means of monitoring these ecosystems across different scales, providing insights into wetland extent, health, and changes over time. In recent years, there has been an increasing focus on the accuracies and uncertainties of these products as a key area of attention. It is in this regard that this paper conducted a systematic literature review on the progress, gaps and opportunities in the application of remotely sensed data in assessing changes in the spatial extent of wetland vegetation following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The databases considered for literature search in this study included Scopus, Web of Science, Science Direct, and Google Scholar for backward searching. A total of 104 studies were considered and reviewed. Results showed that the extensively used sensors were the Landsat series followed by aerial photographs. Remote sensing was employed in retrieved literature to track vegetation and water quality and to identify shifts in wetland size and health over time. However, the utilization of remotely sensed data to map wetland attributes, as depicted in literature, comes with a range of challenges and opportunities. These encompass the need for refined data processing and analysis techniques, the integration of diverse data sources, and the establishment of standardized methodologies to enhance the effectiveness of wetland mapping and monitoring. Overall, this literature review offers a comprehensive overview of the use of remotely sensed data for wetland monitoring and underscores the potential of these technologies for improving the management and conservation of these important ecosystems in developing countries.

Keywords: wetland vegetation, plants species, remotely sensed data, and classification

2.1. Introduction

Though there has been a worldwide uproar on the appropriate description of wetlands, we acknowledge these features in our landscapes for their ecological importance and the services they provide to human society (Bird 2012). According to the Ramsar convention, wetlands are "areas of marsh, fen, peatland or water, whether natural or artificial, permanent or temporary, with water that is static or flowing, fresh, brackish, or salt, including areas of marine water, the depth of which at low tide does not exceed six meters" (Irvine, Dickens et al. 2022). Reddy and DeLaune (2008) state that wetlands cover up to 6% of the Earth's land surface, therefore, play an important role in housing and conserving biodiversity by providing habitat to range of flora and fauna species such as birds, amphibians and terrestrial & aquatic plants. Wetlands play a huge role in maintaining the hydrological cycle, and protecting human welfare through services such as water purification and flood impact alleviation (Xu, Weng et al. 2019). The wetland classification system employed in this paper is now known as the Classification System for Wetland and other Aquatic Systems in South Africa. Previously, it was referred to as the 'National Wetland Classification System'. The terminology had to be altered to prevent ambiguity arising from the term 'wetland,' which holds distinct definitions within various regulation bodies such as the Ramsar Convention and the South African National Water Act (Act No. 36 of 1998) (Ollis, Ewart-Smith et al. 2015)

Based on this brief description, wetlands would appear to be ecosystems worth protecting. However, according to Bird (2012), wetlands have not always received significant attention and effort. Bird (2012) argues that until recently (the late 1960s), wetlands were subject to non-legal activities such as draining, infilling, and other forms of wetland destruction, leading to the deterioration of these precious systems. Wetlands were viewed as productive land for crop farming and there were limited statutory instruments that sought to protect them (Swanepoel and Barnard 2007). In the recent past, wetlands have been undergoing dramatic changes due to intensive climate change, invasive species, and human activities which compromise wetland ecosystem productivity (Finlayson, Cruz et al. 2005, Zedler and Kercher 2005, Son, Chen et al. 2014). For instance, it is reported that South Africa has lost about 50% of its original wetlands due to invasive plant species, erosion, and anthropogenic factors. Sub-national studies in the 1990s showed that 58% of wetlands in the Umfolozi catchment in KwaZulu-Natal had already experienced irreversible transformation (Gangat, Van Deventer et al. 2020). Traditionally, on-site visits and manual field surveys were the most commonly utilized methods of monitoring and mapping the wetland extent. Remote sensing data and GIS applications were not commonly used for this purpose. However, with the advancements in technology, the use of these tools has become more widespread, allowing for time efficient and accurate monitoring and management of wetlands.

Remote sensing has emerged as a viable option for mapping and monitoring wetlands due to its ability to cover large areas efficiently while providing accurate information on their extent, vegetation cover, and LULC changes over time. Remote sensing provides a cost-effective and time-saving alternative for wetland management and conservation compared to traditional methods. Multispectral remotely sensed data is increasingly being used in conducting Land Use Land Cover changes owing to sensors' ability to acquire LULC information across extensive geographical areas at minimal expense. However, despite these technological advances, accurate LULC mapping remains challenging because urban wetlands are inherently complex, with variations in their species composition resulting in high intra-class spectral heterogeneity.

Wetland vegetation has been reported as a crucial component of wetland ecosystems and plays an important role in various ecological processes and services. Instead of focusing on wetlands as ecosystems, the primary objective of this paper was to narrow down the scope of the investigation to the specific challenges and opportunities associated with monitoring and remote sensing of wetland vegetation and its changes in spatial extent over time. Spatial extent of wetland vegetation refers to the geographic distribution and coverage of wetland vegetation. Within the remote sensing context, there has been a growing number of studies that assessed the utility of remote sensing technologies in wetland studies. Subsequently, there is still a need to extend these efforts by systematically assessing the literature on the utilization of remotely sensed data in mapping the wetland extent, vegetation species composition and their productivity attributes such as leaf area index. It is in this regard that this study conducted a systematic review of the literature on the progress, gaps, and opportunities in the application of earth observation data in assessing and mapping changes in the spatial extent and productivity of wetlands. While there is a specific section on South Africa due to its relevance to our study, the overall goal is to capture a global perspective on the use of remote sensing technologies in monitoring terrestrial vegetation within wetlands.

2.1.1. Wetland classification system in South Africa

The wetland classification system referred to in this paper (Figure 2.1) is founded on the Classification System for Wetland and Other Aquatic Systems in South Africa, developed by the South African National Biodiversity Institute (SANBI) (Ollis, Ewart-Smith et al. 2015). It classifies wetlands based on their biophysical properties such as plant species, soils, hydrology, animal types, function, and value (Ollis, Ewart-Smith et al. 2015) as illustrated in Figure 2.1. To provide a more precise characterization of these wetlands, we further classified wetlands as marine (Whitfield 1992), estuarine (Whitfield 1992), and inland systems based on their connectivity to the ocean (Figure 2.2). These are all founded on the South African Classification System for Wetland and Other Aquatic Systems.

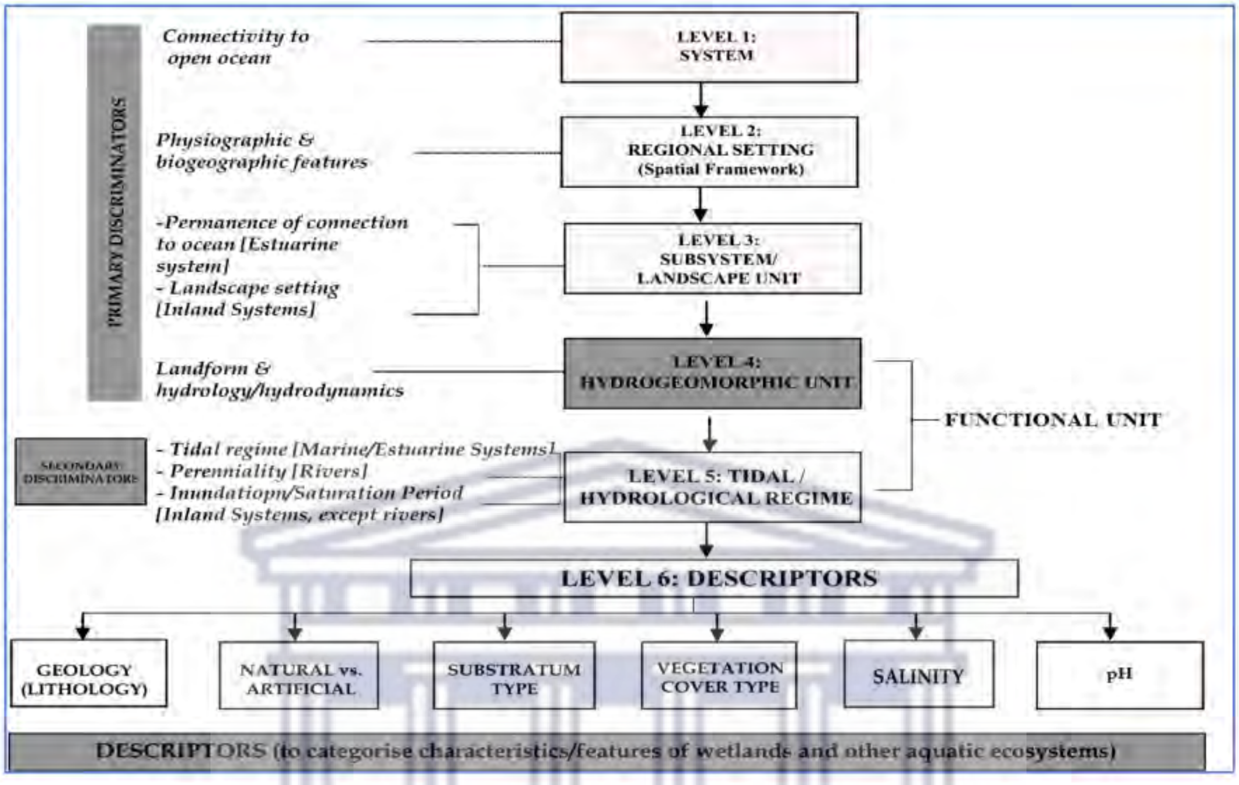

Figure 2-1: Overview of the classification system for wetlands and other aquatic ecosystems (Ollis, Ewart-Smith et al. 2015).

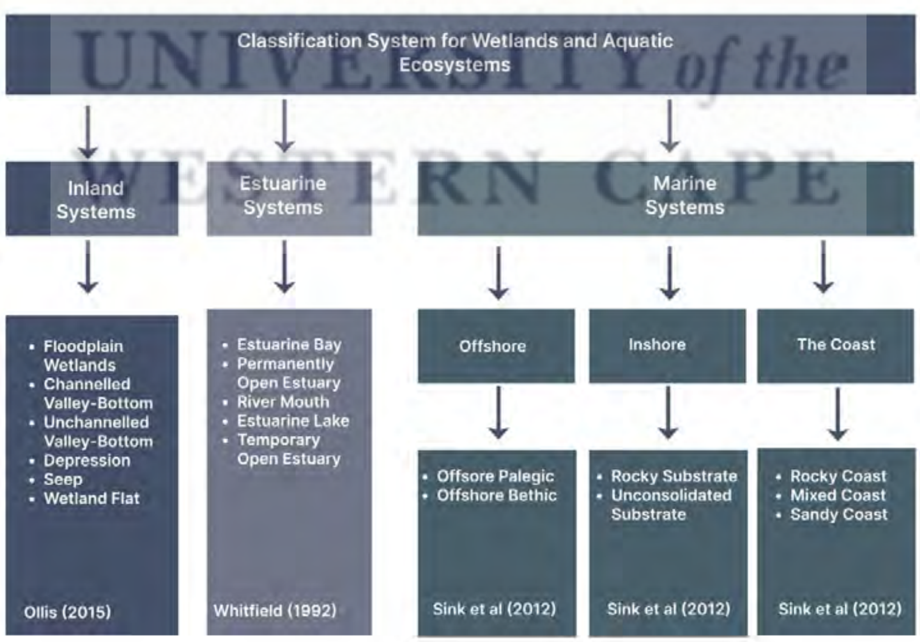

Figure 2-2: Components of the classification system for wetlands and other aquatic ecosystems.

2.2. Methods and Materials

The Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) procedure was followed in conducting this systematic literature review. The first section of the method covered the search for literature, inclusion, and exclusion strategy. The second section then covered data extraction, while the third section covered the methods employed to analyze the data. The studies included in this review were gathered by searching for peer-reviewed articles published in journals catalogued in Scopus, Web of Science (WOS), and Science Direct databases without imposing any specific temporal time frame. Google Scholar was used to search for publications obtained through backward search.

2.2.1. Literature Search, inclusion, and exclusion strategy

The literature search started with a 'scoping search' which helped to determine if there were enough articles to conduct a systematic review. This process involves identifying key concepts, keywords and specific criteria that will help guide the exploration of existing literature within remote the application of remote sensing technologies in wetland vegetation monitoring. Considering that key search terms are not effective on their own, multiple methods of literature search, such as controlled vocabulary, use of parentheses, phrase-searching, and subject heading, were incorporated during the main literature search. The following key-word combinations were established and used in searching for peer-reviewed literature in all the aforementioned databases: ((("Wetland vegetation" OR "wetland plants" OR "wetland species") AND ("remote sensing")) AND ("classification" OR "chlorophyll" OR "biomass")) (Table 1). The selection of these keywords was informed by the acknowledgement of terrestrial wetland vegetation as a key indicator of overall health and wetland dynamics. The search results from the databases were refined by assessing the title and abstract, document type, and language (English) from accredited journals before being exported to Endnote. In a South African context, 'accredited journals' are journals recognized and reputable within the academic community based on the Department of Higher Education and Training's criteria for inclusion. The literature search was limited to one language, English, as a result of limitations in resources (translation services) and time. A total of 252 articles were selected from Web of Science, 159 from Scopus and 941 from Science Direct. The exclusion and inclusion criteria in this literature review were guided by the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) checklist and procedure (Figure 2.3). Each article had to match the following criteria to be considered in the meta-analysis stage;

i. The study focuses on wetland vegetation and no other ecosystem type.
ii. The studies focused on wetland vegetation productivity concepts (i.e., Leaf Area Index).
iii. The study utilized GIS and remote sensing techniques in wetland vegetation productivity mapping and monitoring.

iv. The study needed to present the outcomes of prediction and classification accuracies associated with wetland attributes and extent using remotely sensed data.

v. The article had to be published in an accredited journal.

vi. The article should have been written in English.

vii. The article had to be available in full length either as PDF or Word document.

After completing the literature search process and assessing the literature using the titles, the relevant articles (n = 1209) with their bibliographic information were exported to the Endnote v20 software and subjected to a screening process. The first phase of the screening process involved screening references to remove any duplicates. A total of 140 duplicate references were found and removed from the references. From the remaining articles (n = 1069), essential bibliographic information (abstract and titles) was examined to check whether the studies applied GIS or remote sensing in mapping changes in the spatial extent of wetlands or in estimating wetland vegetation parameters such as chlorophyll and vegetation biomass. A total of 63 studies in the resulting literature were conducted in the year 2023 and therefore were excluded from the reviewed literature. The reason behind this is the publication lag- some studies might be conducted in 2023 but are not available in databases by the time literature search was conducted. So, to avoid any biases, studies published in 2023 were excluded. After a review of the bibliographic information, a further 739 studies were excluded from the articles as they fell outside the search scope. This means that some of these studies were not wetland-related studies, and for those that were wetland studies, their key research focus was outside wetland vegetation and the application of remote sensing. Of the remaining 267 articles, a further 23 studies were excluded as they were not accessible in full length due to subscription access. Through backward search from Google Scholar and reference lists, 46 articles were added, resulting in a total of 290 articles considered for the final assessment in this study. Table 2.1 and Figure 2.3 represent the methodology applied in the literature search phase.

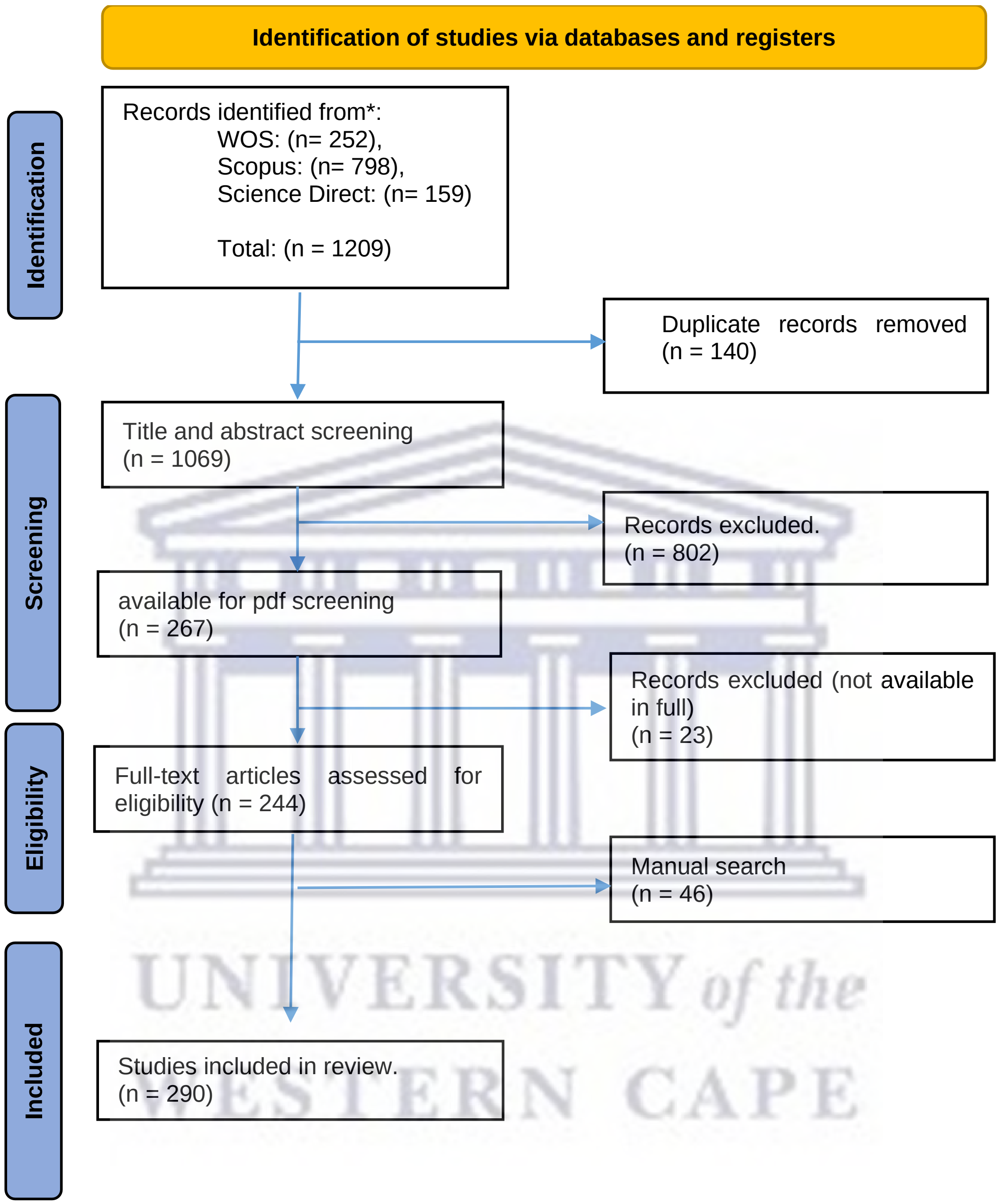

Figure 2-3: PRISMA flow diagram for selection of studies in the review.

Table 2.1: Search scope for the databases used in this review.

Search scope	Database	Total number of articles	No. of articles retained
(((“Wetland vegetation” OR “wetland plants” OR “wetland species”) AND (“remote sensing”))) AND (“classification” OR “leaf area index” OR “LAI” OR “chlorophyll” OR “biomass”)	Scopus	159	159
	Web of Science	252	252
	Science Direct	798	798
Articles considered for screening after removing duplicates.			1069
Articles available after excluding 2023 studies			1006
Articles available after bibliographic screening			267
Articles available after excluding articles not available in full text			244
Backward reference search in google scholar			46
Articles available for final review			290

2.2.2. Data extraction

The bibliographic data was exported from the Endnote database as an Excel spreadsheet with bibliometric information on the publications, such as author name, article title, abstract, year of publication, name of the journal and keywords, and the digital object identifier. The articles were used to identify and outline elements of progress, challenges, gaps, and a way forward regarding the utility of earth observation data in mapping and monitoring the attributes of wetland vegetation. Information on the area of study, vegetation productivity, earth observation sensors, remote sensing algorithms, and accuracies were extracted from the selected articles. For classification studies, accuracy assessment measures such as the Overall classification accuracy and Kappa coefficient values were recorded.

2.2.3. Data analysis

At this stage, retrieved data were subjected to qualitative and quantitative analysis. A bibliometric analysis was conducted first to visualize trends from the co-occurrence of key terms in the titles and abstracts of selected literature that mapped changes in the spatial extent of wetland vegetation using remotely sensed data. This was performed using VOS viewer software. This bibliometric analysis method is a widely used quantitative method for identifying and enumerating occurrences and co-occurrences in key terms related to a specific field of study (Han, Kang et al. 2020). Specifically, the titles and abstracts from the reviewed articles were used in VOS viewer to map the occurrence and co-occurrence of key terms. The co-occurrence of terms provided insights into the trends and progress in the utilization of remote sensing technologies in mapping changes in spatial extent and productivity of wetland vegetation species.

To address research objectives, the review was divided into two sections: the first section aimed at exploring progress in remote sensing technologies applied in wetland studies – specifically to map changes in the spatial extent and vegetation productivity elements. More specifically, this section showcased the use of earth observation sensors in assessing and monitoring wetland vegetation properties over a period. The second section discussed the challenges, gaps and opportunities for future studies in mapping changes in the spatial extent of wetland vegetation species using remotely sensed data.

2.3. Results

2.3.1. Bibliometric analytical outputs

Figure 2.4 further shows four topical clusters, green, blue, red, and yellow derived from co-occurrence analysis of key terms in articles' titles. The largest of these three clusters was the red cluster with key terms "classification", "spatial distribution", "vegetation communities", "wetland area", "phragmites", and "China", which relates to the classification of vegetation communities in estimating the spatial extent of wetland with most of the studies conducted in China (Figure 2.4). The second largest cluster is green with keywords "reflectance", "LAI", "LAI estimation", "RMSE", "MODIS", "Lidar", and "vegetation height". This cluster could be related to the importance of optical sensors (reflectance) (MODIS) and Lidar in accurately estimating the Leaf Area Index of wetland vegetation as a vegetation measurement. The third cluster is yellow with key terms "Worldview", "RapidEye", "spectral band", and "red-edge band". This reflects on the influence of broadband multispectral sensors with red edge bands such as "Worldview", and "RapidEye" in remote sensing wetland attributes. The last cluster is blue and had key terms "Sensor", "High resolution", "High accuracy" and "Above Ground Biomass". This articulates the high accuracies associated with high spatial resolution sensors in estimating wetland plants' ground biomass.

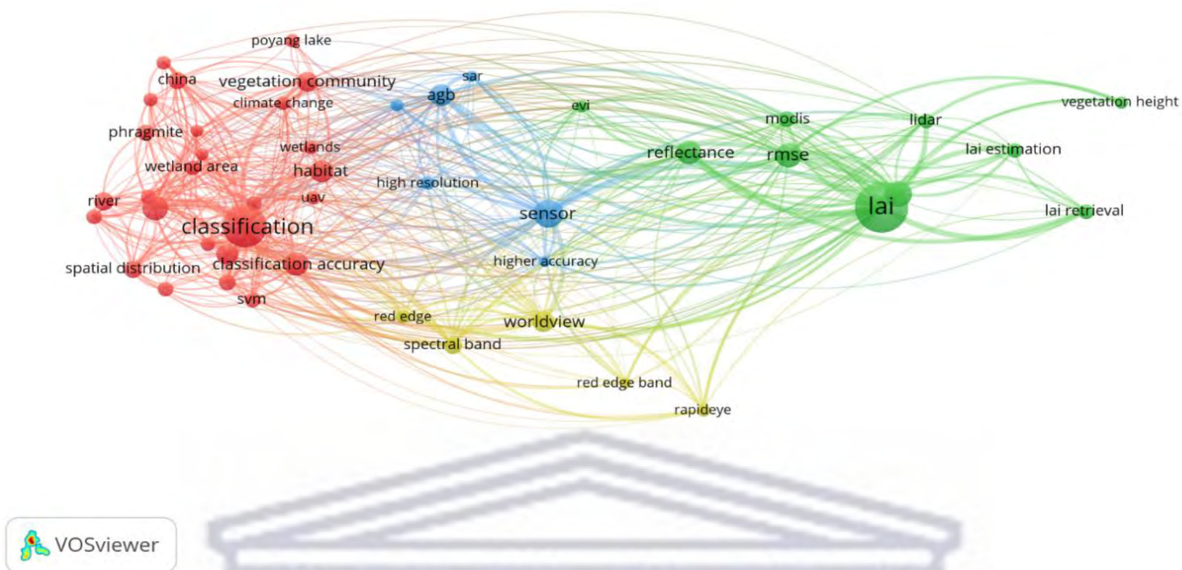

Figure 2-4:Topical concepts derived from titles only.

Figure 2.5 shows a network map derived using both abstracts and titles of retrieved literature. The map is categorized into five clusters. The largest cluster was the green cluster with key terms “Wetland”, “Spatial extent”, “high resolution”, “spectral band”, “conservation”, “sensor”, and “Worldview”. This reflects the popularity of high-spatial-resolution sensors such as Worldview with optimal spectral bands suitable for mapping the spatial extent of wetlands and identifying different wetland landuse/landcover types. The second largest cluster was the red cluster with keywords “NDVI”, “China”, “landuse/landcover”, “climate change”, and “Phragmites”. These keywords could be attributed to how the analysis of NDVI trends in China using remote sensing techniques has been utilized to reveal changes in landuse/landcover patterns, including the spread of species like Phragmites, which could be linked to climate change. The third cluster was purple with keywords “LAI”, “reflectance”, “LAI estimation”, “pixel”, “forest”, and “MODIS”. This highlights how spectral reflectance data can be used to estimate LAI at the pixel level in forested wetland areas using sensors such as MODIS. The second last cluster was the yellow cluster with keywords “biomass”, “RMSE”, “wetland vegetation”, “LiDAR”, and “vegetation height”. This highlights the strength of LiDAR-based estimates of vegetation height in wetland vegetation productivity (Gilmore, Wilson et al. 2008, Luo, Wang et al. 2015). The last cluster was blue with the keywords “classifier”, “overall accuracy”, “random forest”, and “google earth engine”. This speaks to how using the random forest classifier in platforms such as Google Earth Engine could improve overall accuracy values in wetland classification.

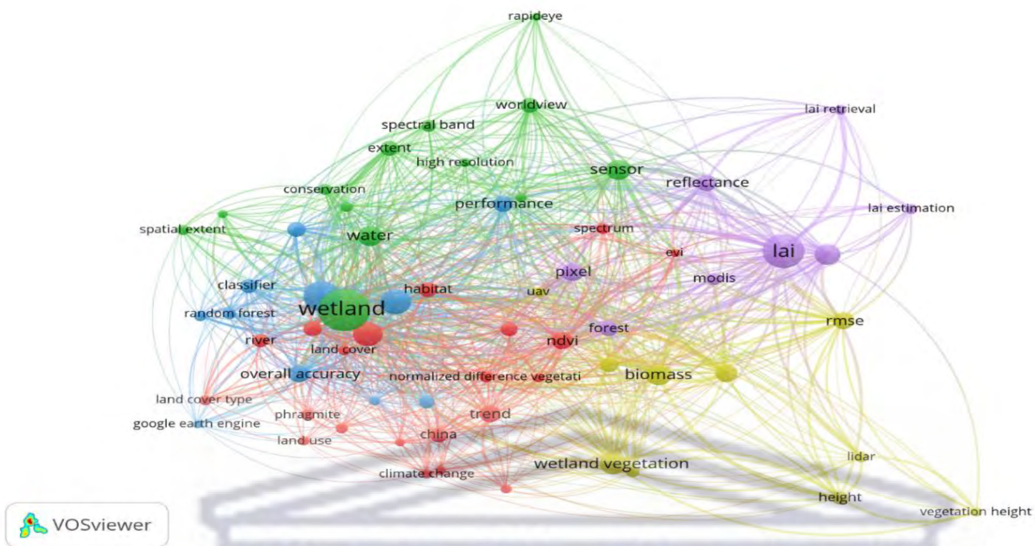

Figure 2-5: Topical concepts in mapping the change in the spatial extent of wetlands using remotely sensed data derived using data from abstracts and titles.

2.3.2. Progress in remote sensing wetland vegetation productivity and spatial extent changes

The results of this study illustrate that there has been a general increase in literature on remote sensing wetland vegetation and spatial extent changes (Figure 2.6). Figure 2.6 shows that the past two decades (2000 – 2020) have seen a gradual increase in the frequency of studies that applied remote sensing technologies in mapping changes in wetland spatial extent and vegetation ecosystem elements. The earliest article from the reviewed literature was published in 1995 and it used aerial photographs as a form of Earth Observation for mapping attributes of a wetland ecosystem. Guo, Li et al. (2017) reveal that aerial photographs were the earliest form of remotely sensed data used in wetland studies. From the year 2008 onwards, there was a constant number of articles being published, while a considerable increase was observed then after (Figure 2.6). The number of articles that utilized remotely sensed data in wetland studies increased steadily, reaching a total of 49 articles in 2022.

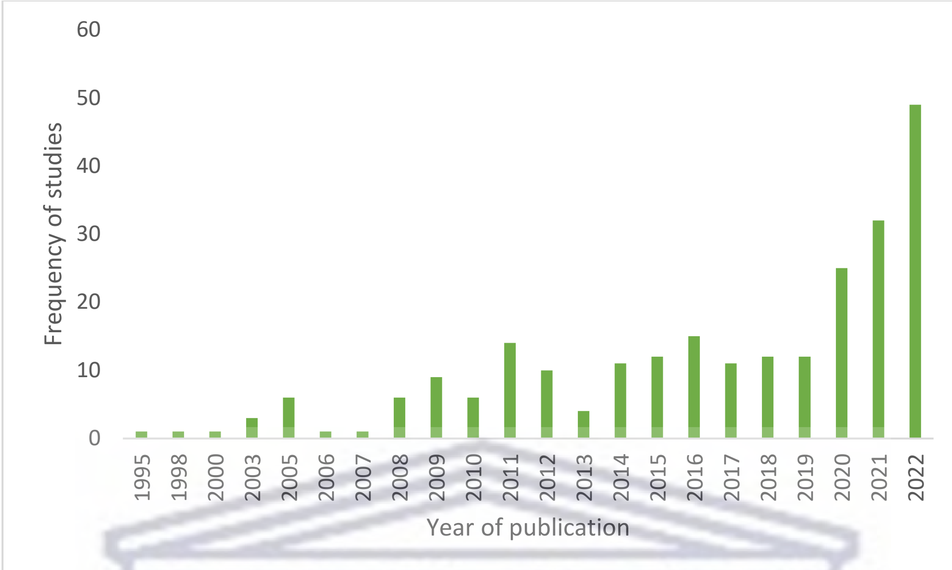

Figure 2-6:Frequency of studies that applied remote sensing technologies (sensors) in wetland studies per year.

Figure 2.7 illustrates 15 types of wetlands that were considered in the reviewed literature. For quite some time, wetlands did not receive as much research attention specifically in relation to the application of remote sensing technologies in studying these complex systems. From the retrieved literature, a total of 95 studies focused on both salty and freshwater marshes, making them the highest-studied wetland in the reviewed literature. The Karst and Depression wetlands were the least studied wetlands in the reviewed literature. Most of the wetlands in this study were situated in wet terrains (riverbanks, deltas, floodplains). Results revealed that most of these wetlands were not located in urban areas but were in the outskirts. Some of the studies in the reviewed literature did not specify their study area's wetland type and were omitted from the results shown in Figure 2.7.

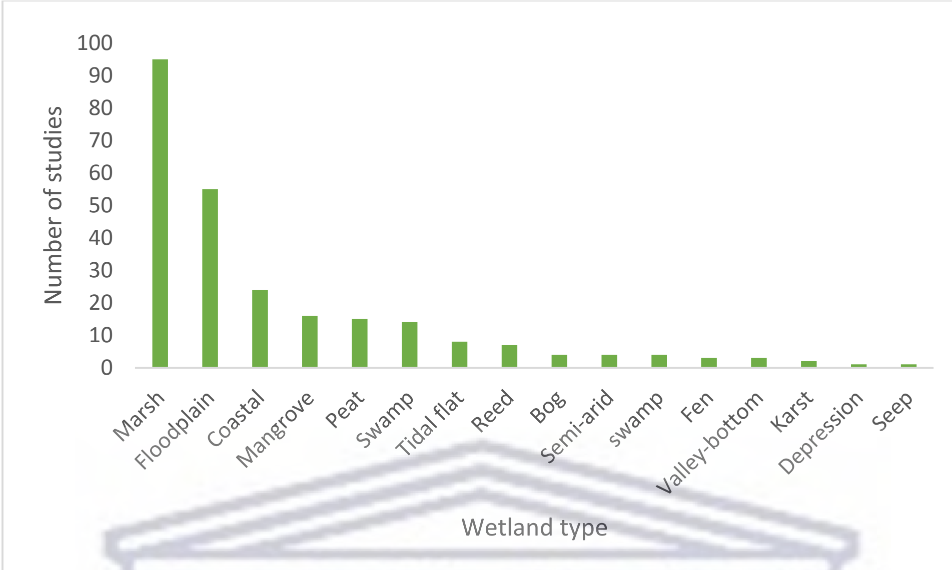

Figure 2-7: Different types of wetlands involved in the reviewed literature

The selected and retrieved studies included in this review were conducted in 48 different countries across different continents (Figure 2.8). It was noted that the studies were spread across all regions, except for the polar regions (Arctic and Antarctica). The top three countries with the most number of studies on wetland vegetation remote sensing were China (108), USA (42), followed by Australia (13) respectively (Figure 2.8). Asia had the highest number of studies, 51%, compared to all other continents. About 10.04% of studies were conducted in Africa, mostly in the Southern African region, particularly in South Africa. Then 10% were conducted in Europe, 5.22 % in Australia, and 2.4 % in South America.

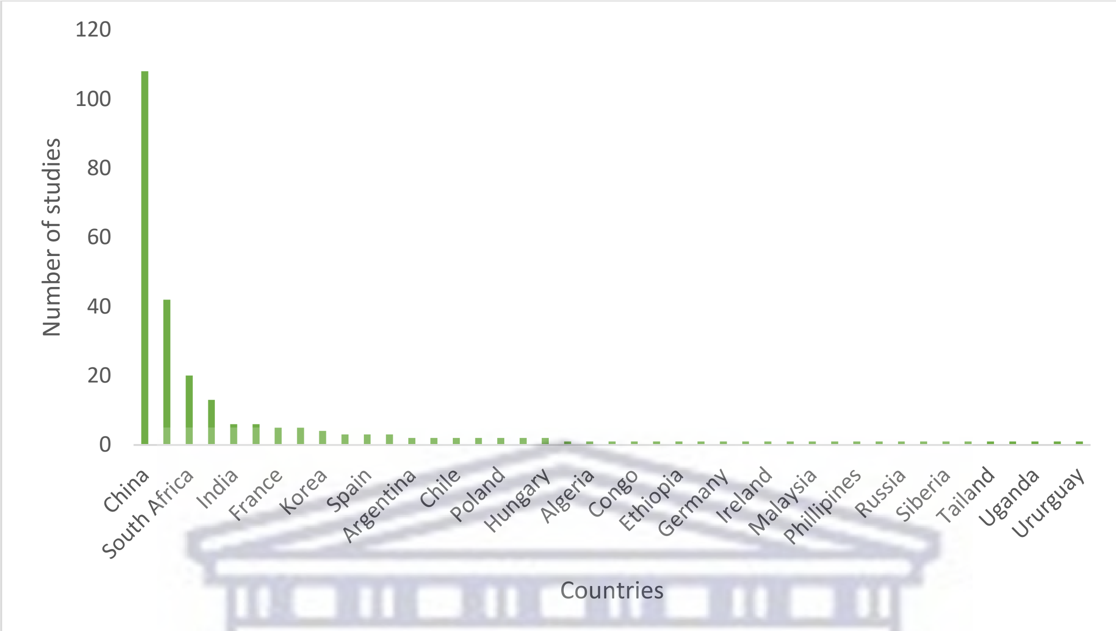

Figure 2-8: Frequency of wetland studies that utilized geospatial data per region.

2.3.3. Remote sensing technologies, Spectral settings and derived vegetation indices

Research conducted on wetland environments has seen an increase in the application of remote sensing technologies from poor-resolution satellites to more advanced and freely available satellites such as Sentinel 2 multispectral imager (MSI). The past two decades have seen considerable advancements in remote sensing sensors in terms of their accessibility to the public, and increased spatial, radiometric, spectral, and temporal resolutions. From the reviewed literature, about thirty-two sensors were utilized to characterize wetland attributes (Figure 2.9). The extensively employed satellite sensors were Landsat OLI-1, Aerial photographs, Landsat TM, LiDAR, and Landsat ETM+, in order of frequency in the literature.

The top three most used sensors in the reviewed literature were all sensors from the Landsat mission (Landsat TM, Landsat ETM+, and Landsat OLI). Sentinel-2 multispectral instrument (MSI), which is one of the new generation earth observation satellites, was the 5th most utilized sensor in the literature with 31 studies. High spatial resolution satellites such as Quick Bird and Worldview-3 were utilized in 10 and 16 studies, respectively. Moderate Resolution Imaging Spectroradiometer (MODIS), SAR, SPOT , and IKONOS, were also among other earth observation satellites that were used in 34, 27, 12, and 6 studies, respectively (Arzandeh and Wang 2003, Proisy, Couteron et al. 2007, Lee and Yeh 2009, Chen, Jin et al. 2014, Mohammadimanesh, Salehi et al. 2018, Battaglia, Banks et al. 2021). Unmanned Arial Vehicle (UAV-borne sensors) were also utilized in the mapping and classification of wetlands in 20 studies (Figure 2.9).

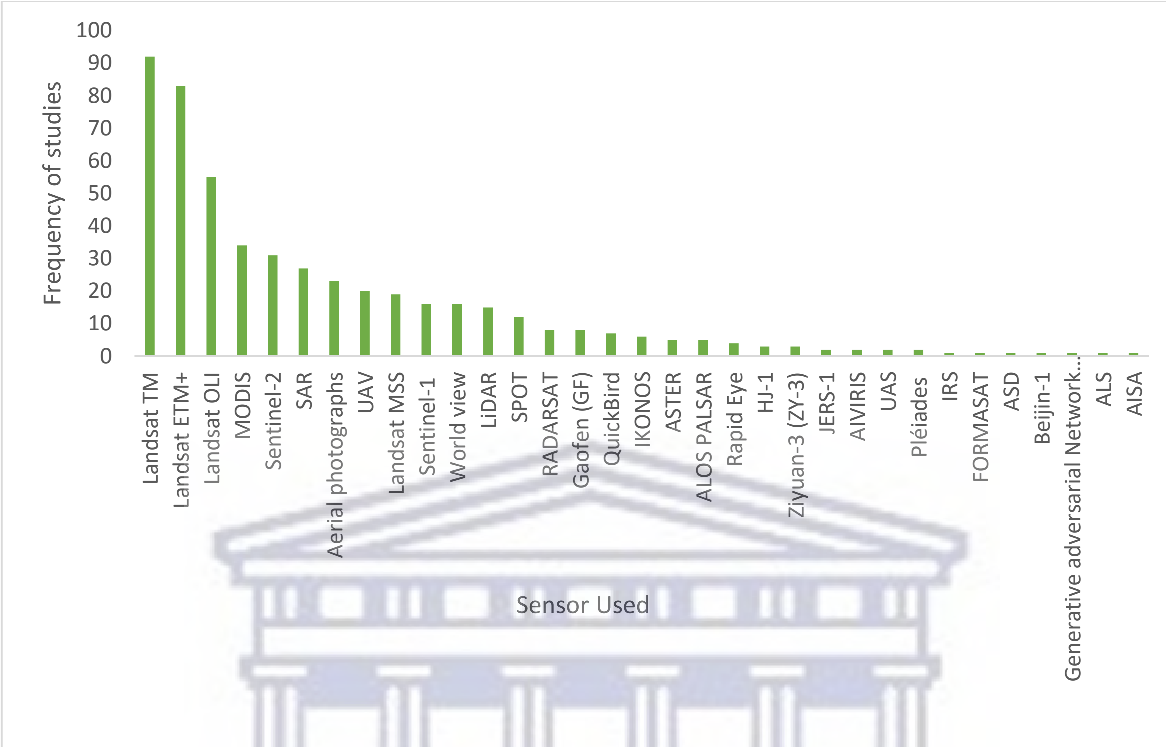

Figure 2-9: Frequency of studies that used a specific sensor within the reviewed studies.

Even though there has been an increase in the number of earth observation sensors, an assessment of the reviewed literature shows that about 66% of the studies utilized remotely sensed data with data from field surveys. This highlights the importance of training data in remote sensing. From the retrieved literature, Aerial photographs started trending within the context of wetland mapping in 1997 (Williams and Lyon 1997) (Figure 2.10). The late 1900s saw the introduction of sensors such as the Landsat multispectral scanners (MSS), thematic mapper (TM), SPOT, and SAR. It was not until the late 2000s that a range of other medium-high resolution and laser technology earth observation sensors such as Quick Bird, LiDAR, IKONOS, and Landsat operational land imager (OLI) were launched. From Figure 2.9, it can be observed that the Landsat's satellites were the most utilized sensors in the reviewed literature. Figure 2.10 further illustrates the progression in the utilization of each sensor with time. It can be observed that Landsat 7 started trending around 2003 and has been consistently utilized since then. Additionally, Landsat 8 OLI started trending in 2015 and has also been widely utilized up until the time of writing this paper. Meanwhile, Sentinel 2 MSI was launched in 2015 and started trending in 2017 in the reviewed literature.

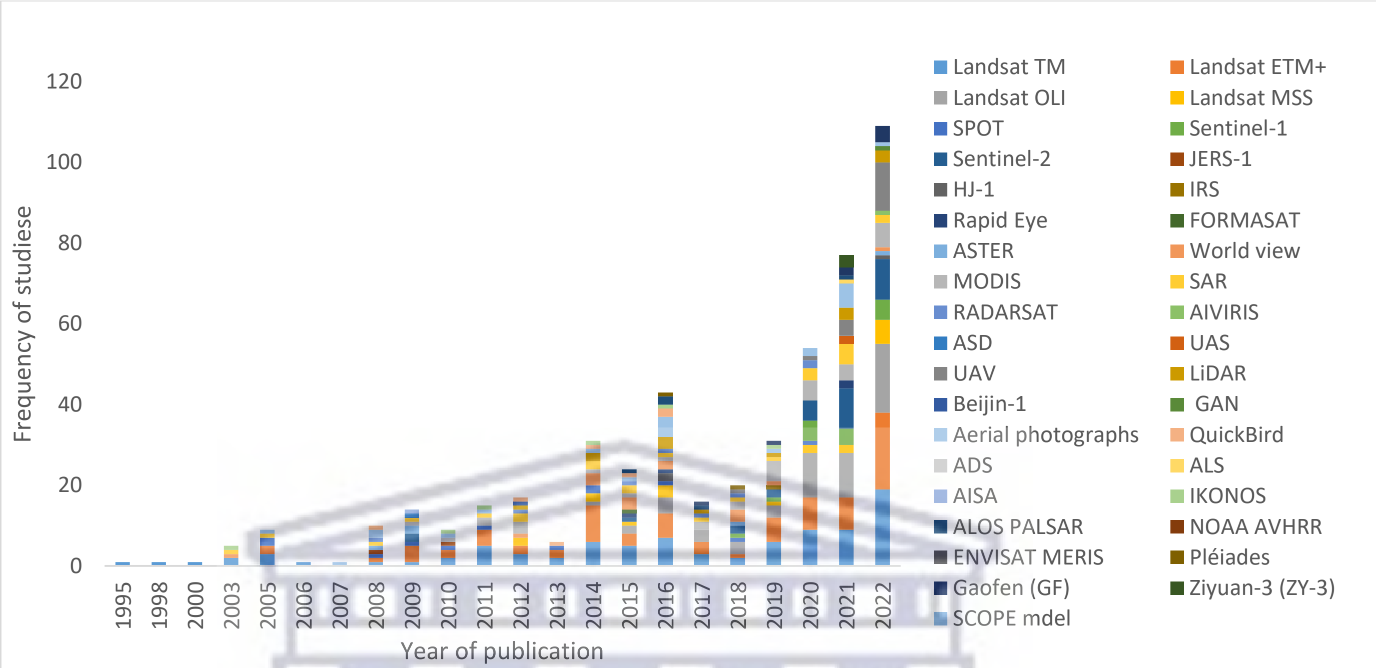

Figure 2-10: Progression of sensors used within the reviewed literature between 1995 and 2022.

Generally, all sensors exhibited very high overall classification accuracies in discriminating wetland vegetation either at the species level or at the community level as well as discriminating different land use land cover types within the wetland area (Liang, Abidi et al. 2020) . The overall classification accuracies ranged between 63% and 95%. These accuracies were not only obtained using remotely sensed data but also in conjunction with several robust machine learning algorithms (Figure 2.11). Various algorithms were employed for classification, including Random Forest (RF), Maximum Likelihood Classification (MLC), Support Vector Machine (SVM), C5.0 Decision tree (C5.0 DT), Classification and Regression Trees (CART), Fuzzy, ShuffleGAN, Convolutional Neural Network (CNN), and Adaptive stacking as illustrated in Figure 2.11. Across all algorithms, random forest (RF), and support vector machine (SVM) were the most widely used classification techniques followed by the Maximum-likelihood classifier, Decision tree, Classification and Regression Trees for Machine (CART), in order of frequency.

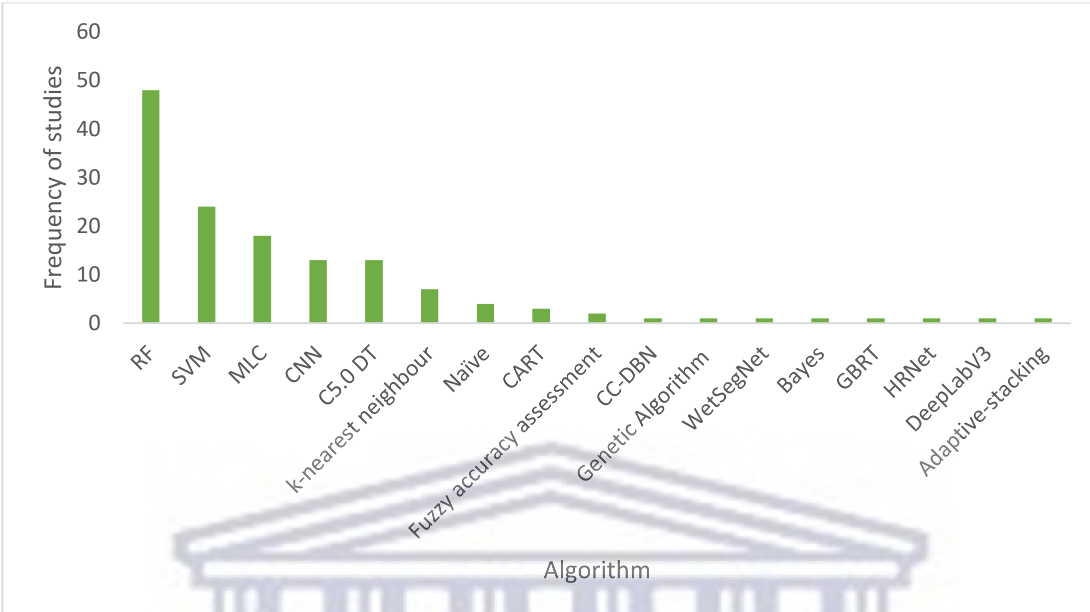

Figure 2-11**:** Machine learning algorithms used to classify and map wetland vegetation. RF is Random Forest, SVM is Support Vector Machine, MLC is Maximum Likelihood Classifier, CNN is Convolutional Neural Network, CART is Classification and Regression Tree, and GRBT is Gradient Boosted Regression Tree

Several earth observation sensors have been used to derive a couple of vegetation indices and texture metrics for mapping and monitoring wetland ecosystem elements (Figure 2.12). Specifically, 172 articles utilized vegetation indices while only 11 articles utilized texture metrics to characterize wetland attributes. In the reviewed literature, the widely used vegetation indices included the Normalized Difference Vegetation Index (NDVI) (Mutanga, Adam et al. 2012, Dabrowska-Zielinska, Budzynska et al. 2014, Thito, Wolski et al. 2015), Enhanced Vegetation Index (EVI), Normalized Difference Water Index (NDWI), Soil Adjusted Vegetation Index (SAVI), and Green Normalized Difference Vegetation Index (GNDVI). As expected, NDVI was utilized in nearly every study in the gathered literature as shown in Figure 2.12.

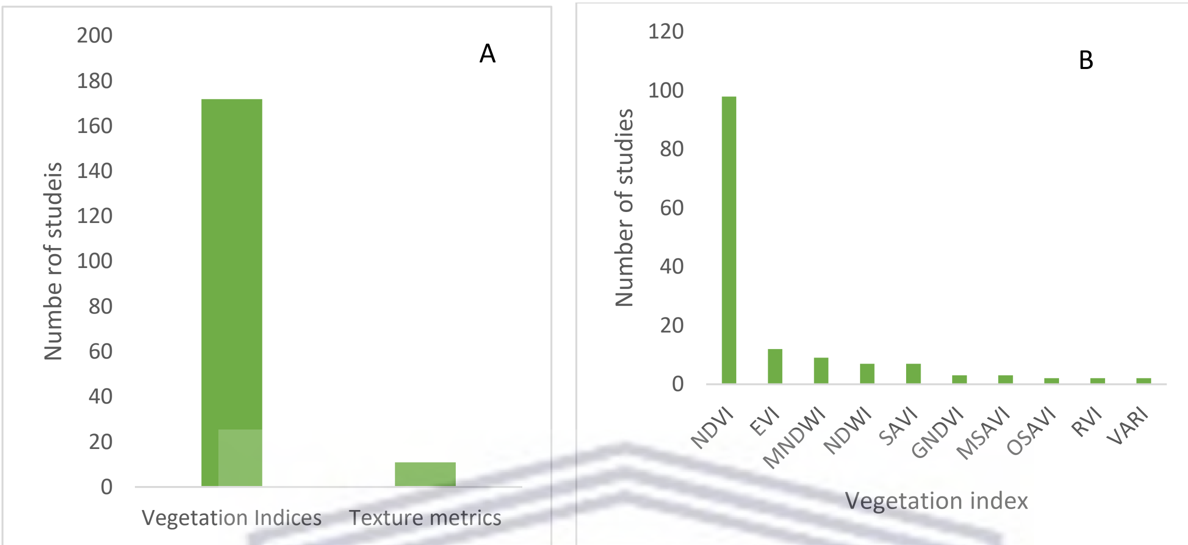

Figure 2-12**:** Frequency of different vegetation indices and Texture Metrics, and various vegetation Indices used in the reviewed literature.

Results show that more than 71% of the studies used the Gray-Level Co-Occurrence Matrices (GLCM). The GLCM image transformations were followed by Gabor Filter (GF), Segmentation-based-fractal analysis (STFA), and Wavelet Texture Analysis (WTA) as shown in Figure 13(a). The GLCMs are image transformation techniques that can be utilized to measure how often certain combinations of pixel values (grayscale values, or colors) appear in an image and how they are arranged spatially (at a given offset) (Aggarwal 2022). Generally, texture features from images can be useful in various applications such as image classification, segmentation, and object recognition (Anand, Shanthi et al. 2022). The GLCMs can be categorized into two types, the first-order and second-order texture features. Second-order GLCM features were the most widely utilized in the reviewed literature. Figure 2.13(b) shows the most influential and optimal GLCM texture features in the context of wetlands. The Mean, a first-order GLCM, was the most widely utilized followed by second-order GLCMs. Homogeneity, Entropy, Dissimilarity and Standard Deviation (Figure 2.14(b)). There is an overlap in the frequency of studies that used GLCM in Figure 2.13(a) and the total frequency of GLCM texture features in Figure 2.13(b) because some of the studies that used the GLCM texture matrices applied more than one texture feature.

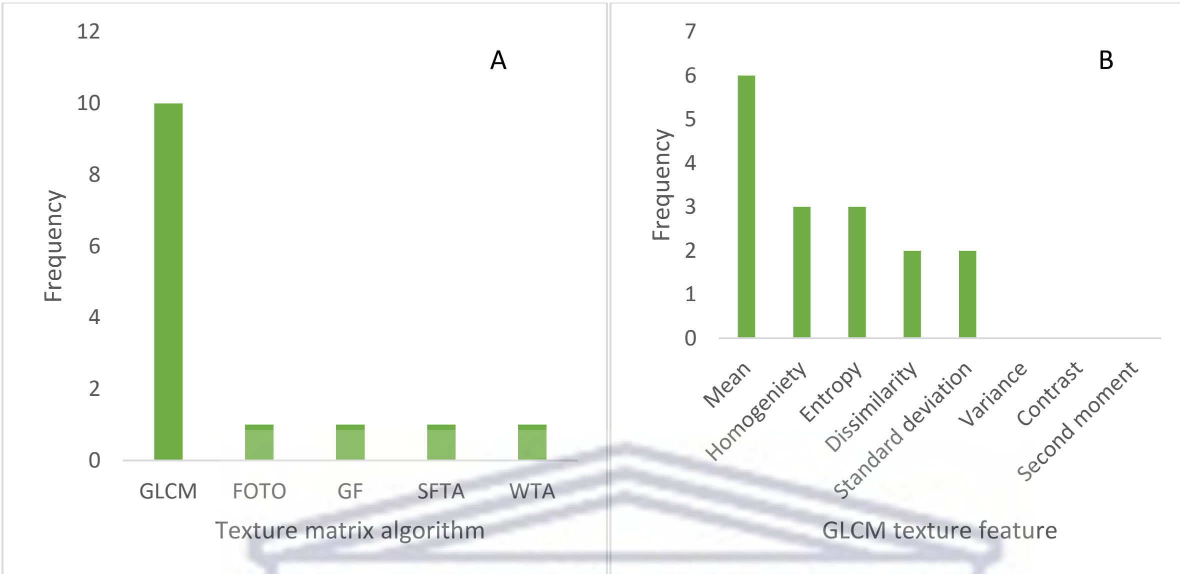

Figure 2-13: (a) Frequency of different Texture types and (b) Gray-Level Co-Occurrence Matrix (GLCM) texture metrics utilized in the literature. GF is Gabor filter, SFTA is Segmentation-based-fractal analysis, and WTA is wavelet texture analysis.

After assessing the different sensors, image transformation techniques and algorithms utilized in the retrieved literature, the paper assessed the context of South Africa as a case study. South Africa was chosen because it is a typical third-world country with diverse wetlands.

2.1 Wetlands in South Africa

In assessing the South African wetlands, a total of 20 studies were retrieved and analyzed separately. The retrieved literature, particularly from South Africa, identified four distinct types of wetlands, as illustrated in Figure 2.15. These were Depression, Floodplain, Seep, and Valley-bottom wetlands. The SANBIs classification system for wetlands and aquatic systems was used to help identify the wetland types. Coordinates of the wetland areas from the South African studies were overlaid on SANBIs 2018 National Wetland Map. The map shows a distribution of the inland ecosystem types in South Africa. Floodplain wetlands are those wetlands that are found in floodplains of rivers, while coastal wetlands are associated with coastal areas (Perillo, Wolanski et al. 2018). Valley-bottom wetlands, both channeled and unchanneled, had the greatest number of studies as depicted in Figure 2.14. In terms of the spatial distribution of these studies, wetland studies were conducted in the KwaZulu-Natal, Limpopo, Mpumalanga, Eastern and Western Cape provinces. These findings underscore the significance of utilizing remotely sensed data in mapping and monitoring wetlands in South Africa. It's worth noting that all wetlands characterized using remotely sensed data in this study were of the inland type, in accordance with the Classification System for Wetland and Other Aquatic Systems. Hence, there is an urgent requirement to extend these efforts into additional wetland domains, including estuarine and marine wetlands.

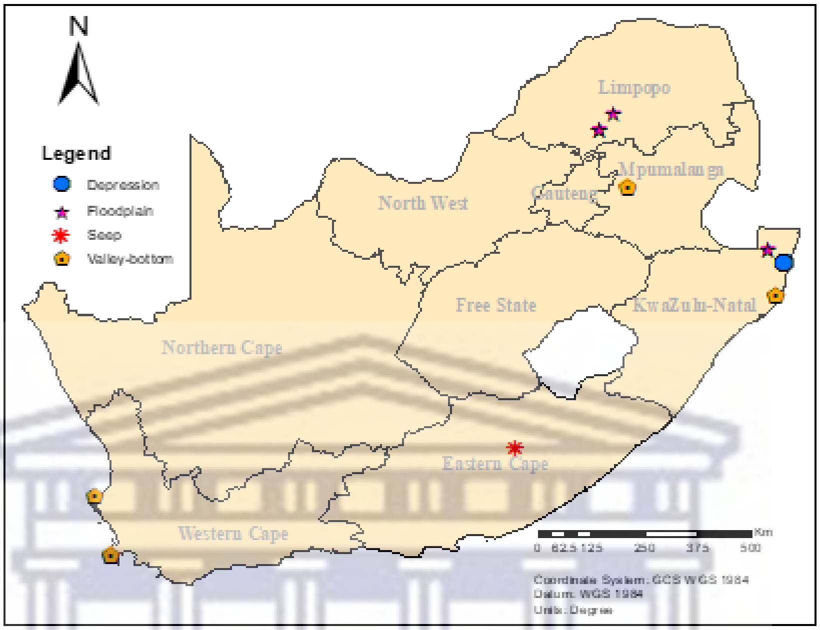

Figure 2-14**:** Spatial distribution of wetland studies, with their associated wetland types, in South Africa.

In terms of earth observation sensors that were used in these wetlands, Landsat was the most extensively used throughout the years. As anticipated, Sentinel-2 MSI was the second most utilized sensor followed by Worldview, MODIS, Aerial photos and Aster (Figure 2.15(a)). To process and analyze these images, machine learning algorithms seem to be the most widely utilized technique. Random Forest classification was the most extensively utilized algorithm for mapping wetlands in South Africa Figure 2.15(b), in the gathered literature.

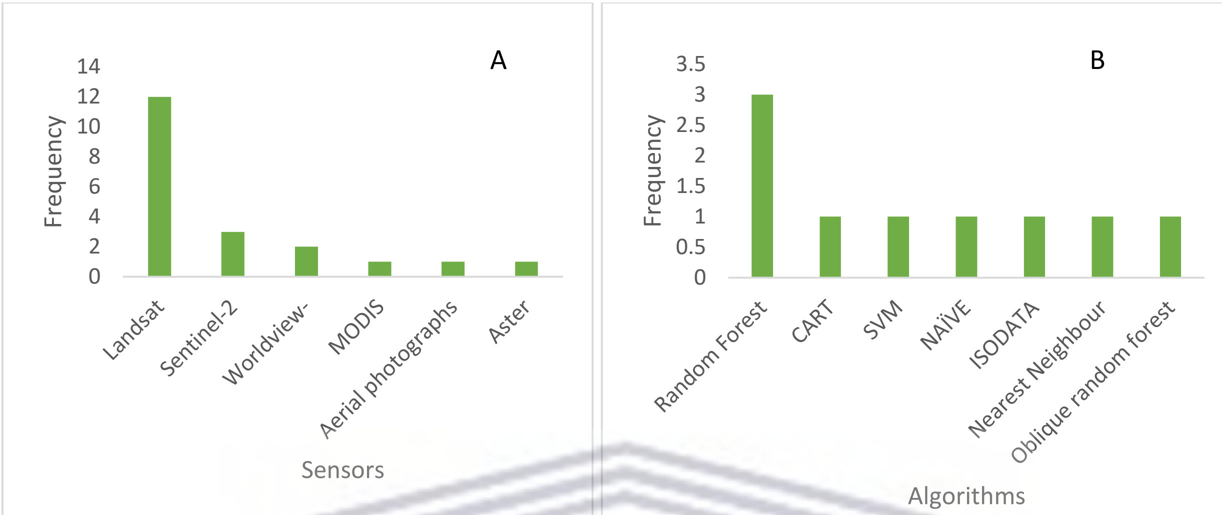

Figure 2-15**: (a)** Different sensors, and **(b)** classification algorithms used in mapping spatial extent and productivity of wetland vegetation in South Africa.

Throughout the years, South Africa has seen a growth in the number of publications that employed remote sensing technologies in wetland research. Figure 2.16 shows that there have been improvements in the variety of sensors employed in wetland remote sensing studies. However, Landsat remains the preferred sensor for characterizing the changes in the spatial extent of wetlands in South Africa. This indicates a highly promising future for the application of remote sensing technology, not only in South Africa but throughout the entire Southern African region in mapping and monitoring of wetlands.

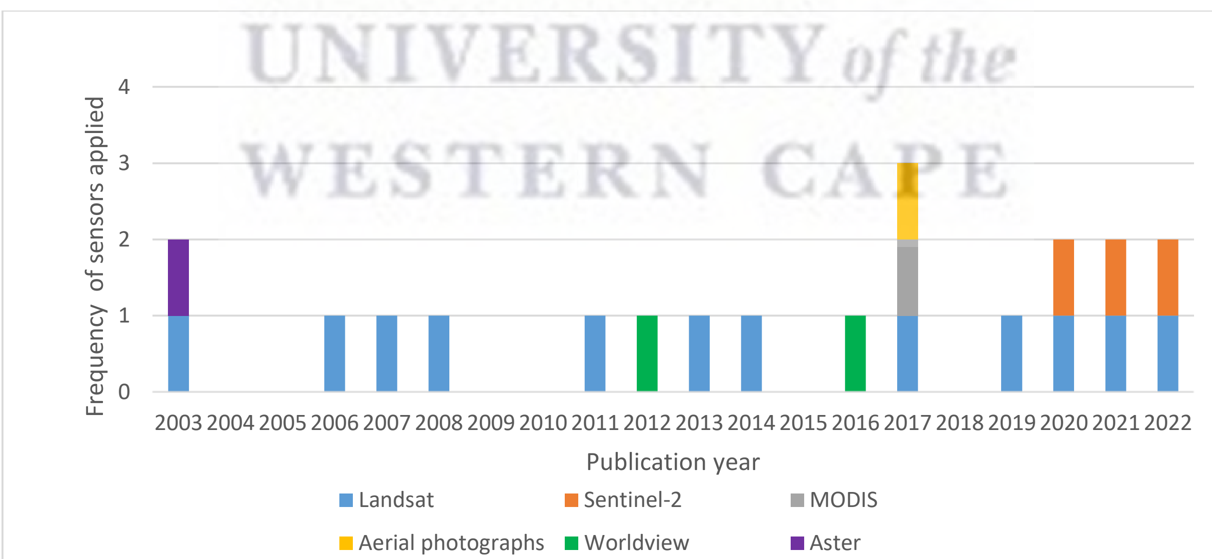

Figure 2-16**:** Application of remote sensing satellites through the years

2.4. Discussion

2.4.1. Progress in remote sensing of wetland vegetation

The application of remotely sensed technologies in monitoring and managing wetlands has gained quite some attention from the wetland research community because of its potential for an efficient and accurate approach to monitoring wetland ecosystems. The objective of this systematic review was to assess the use of remotely sensed data in mapping the extent of wetland vegetation.

2.4.1.1. Publication trends and spatial distribution of studies

Literature shows that there has been an evolution in wetland remote sensing trends over the years. The results of this review showed that during the early years (between 1997 and 2003), there were only a few publications in this field, but with the advancement of technology and increased interest in wetland conservation, the number of publications has grown significantly. This increase in publications could be attributed to the increase in the number of earth observation sensors along with the advancement of their spatial, spectral, and radiometric resolutions (Ustin and Middleton 2021). For instance, a study by Tatem, Goetz et al. (2008) argues that there have been advancements from low resolution satellites available to a few, to satellites capable of daily acquisitions at over 10 terabits of information available to all. Furthermore, the impact of human activities in wetlands was not yet widely understood to attract research efforts in the context of geospatial data application (Hettiarachchi, Morrison et al. 2015). Presently, a multitude of statutory instruments have been put into effect, complemented by various research funding initiatives that play a crucial role in raising awareness among the global population about the significance of wetlands. These efforts not only foster a culture of conservation but also ignite a quest for comprehensive understanding and insights into the functions of these ecosystems (Ramsar 2008, Gardner and Davidson 2011).

In terms of the geographic distribution of the studies, it was observed that studies that used remote sensing technologies in wetland monitoring were spread across the globe, with a bulk of them originating from China, USA, and South Africa. A contributing factor to this might be that these regions have got funding opportunities available for research and development as well as stronger research institutions that can support the development and implementation of remote sensing techniques for wetlands. On the other hand, these regions are geographically diverse countries and boast in a wide range of wetland ecosystems which have attracted a lot of attention (Ollis, Jennifer et al. 2016, Baloloy, Blanco et al. 2020, Adeeyo, Ndlovu et al. 2022, Qiu, Mao et al. 2022, Zheng, Hao et al. 2022). This may result in a wider pool for potential study sites and more impactful and interesting. The high frequency of studies in these regions might also be attributed to their strong international collaborations facilitating knowledge while increasing the visibility of their research efforts. Finally, it must be understood that these countries have well-established environmental policies and regulations that prioritize the generation and gathering of information on wetlands for generating effective conservation approaches(Ollis, Jennifer et al. 2016, Zheng, Dong et al. 2022). Although not much, Africa has seen a steady increase in the number of publications since the early 2000s to date. This trend could be attributed to the increase in the number of sensor missions that offer remotely sensed data at very nominal costs. For instance, in 1999 Landsat 7 thematic map was launched followed by Landsat 8 OLI in 2013, Sentinel 2 MSI in 2015, and Landsat 9 OLI in 2021. Subsequently, there are numerous sensors freely offering earth observation data suitable for mapping and monitoring various wetland attributes.

2.4.1.2. Types of wetlands vegetation attributes mapped using remotely sensed data.

From the results of the gathered and reviewed literature, it was noticed that the most studied wetland types were marshes, followed by floodplain wetlands, and coastal wetlands. Marshes are found globally under a variety of climatic conditions. They cover an estimated global area of 2.2 – 40 million hectares (Alam and Hossain 2021). In addition to other ecosystem services, marshes also offer livelihood opportunities through aspects such as food supply, flood control, and carbon and sediment storage (Carle, Wang et al. 2014, Sun, Liu et al. 2016, Lou, Fu et al. 2020). Marshes are discriminable from other wetlands because, in them, water covers the ground for long periods. In this regard, they are associated with a plethora of diverse vegetation, avian and mammalian species. Despite their ecosystem services and the high biological diversity associated with them, literature shows that most marshes have deteriorated significantly due to climate change and anthropogenic activities (Sun, Fagherazzi et al. 2018, Alam and Hossain 2021). As a result, marsh communities have received comparatively more attention from remote sensing and ecological research community (Carle, Wang et al. 2014, Sun, Liu et al. 2016, Lou, Fu et al. 2020).

From the viewed literature it can be noted that remote sensing technologies have been applied in wetland studies to characterize different aspects of wetland vegetation such as aboveground biomass (ABG) and leaf area index (LAI). It was observed that biomass is the most studied wetland vegetation productivity element because studies have proven that AGB is one important wetland biophysical parameter that can be used to assess the health and functioning of wetland ecosystems (Aslan et al., 2016; Doughty et al., 2021; Jensen et al., 2021; Jensen et al., 2019; Mutanga et al., 2012a; Proisy et al., 2007; Wan et al., 2019). A study by Mutanga et al. (2012a) utilized WorldView-2 derived NDVI to assess the aboveground biomass of a densely vegetated wetland areas in Isimangaliso wetlands, South Africa. On the other hand, Doughty et al. (2021) conducted an assessment to compare the performance of UAV-borne sensors and Landsat data in estimating the aboveground biomass of wetland vegtation and characterizing its spatial extent. Results from that study revealed that the data acquired from UAV-borne sensors outperformed Landsat imagery in estimating aboveground biomass due to its spatial resolution.

The systematic review also revealed that of the retrieved articles, only a very few (2 articles) (Chaurasia, Bhattacharya et al. 2006, Luo, Wang et al. 2015) applied remotely sensed data in estimating the leaf area index of wetland vegetation. Buthelezi, Mutanga et al. (2023) refers to LAI as an important as an important biophycical parameter that quantifies the amount of foliage present in a canopy. It plays a vital role in characterizing processes such as carbon uptake, photosynthesis, and transpiration (2023). However, both LAI and biomass are subject to spatial saturation which impacts medium resolution sensors such as Landsat (Mutanga, Masenyama et al. 2023). As a result, there are limited studies which focus on estimating LAI of densely vegetated wetland areas using advanced remotely sensed data and machine learning techniques.

*2.4.1.3. **Performance of Earth Observation sensors in mapping wetland attributes***

The reviewed literature has brought forth the evolution of remote sensing applications in wetland areas, starting with aerial photographs in the 1900s (Reimold and Linthurst 1975, Scarpace, Quirk et al. 1981, Dale, Hulsman et al. 1986). The approach then shifted to coarse-resolution data (Wang, He et al. 2009, Petus, Lewis et al. 2013, Son, Chen et al. 2014) and then transitioned to medium-resolution data (Johnston and Barson 1993, Florenzano 1998, Kovacs, Wang et al. 2001, Son, Chen et al. 2014) and finally to high hyperspectral, radar, LiDAR and unmanned aerial vehicles acquired data. The findings of this study specifically indicated that Landsat, Sentinel-2, Aerial photographs, QuickBird and Worldview-2 received significant attention from the wetland remote sensing community (Laba, Downs et al. 2008, Lane, Liu et al. 2014). These sensors cover the visible (including the red edge), near, and thermal infrared sections of the electromagnetic spectrum and have an optimal spatial and spectral resolution suitable for monitoring wetland vegetation, water quality, and land use changes which made them preferred by the research community (Kaplan and Avdan 2018, Krina, Xystrakis et al. 2020).

Aerial photographs are reported to be the earliest method of remotely sensed data applied in wetland studies. Some of its applications were to analyze the general spatial variations phenomena in wetlands (Guo, Li et al. 2017). For example, in a study by Johannessen (1964), aerial photographs were applied to generate and compare marsh boundary variations and the results revealed that the marsh area had expanded significantly between 1939 and 1974 because of a combination of vegetation changes and sedimentation. In recent years, aerial photographs have been used as high spatial resolution imagery in classifying wetland species, testing the accuracy of other classifications, and identifying other wetland species (Guo, Li et al. 2017). However, aerial photographs were often associated with challenges when it came to data acquisition over large areas by flight. Another hindrance is the fact that aerial photos have limited spectral and temporal resolutions which makes it difficult to differentiate between spectrally similar wetland classes. Meanwhile, aerial data such as Airborne Visible/ Infrared Imaging Spectrometer (AVIRIS) could offer rich spectral and temporal resolutions but tend to be very costly to acquire. Also, these tend to be significantly limited to small wetland areas (Guo, Li et al. 2017)

Most studies in the retrieved literature were conducted using Landsat imagery and Aerial photographs. The high frequency of Landsat could be explained by the fact that it boasts of being the longest-operating earth observation mission with extensive archival data suitable for assessing land cover changes in wetland areas. Landsat has been observing the earth's surface from 1972 until the present day at a 30-meter spatial resolution suitable for capturing the landscape dynamics in wetlands (Hemati, Hasanlou et al. 2021). Literature underscores the fact that when monitoring wetland change over longer periods, the Landsat archive is the most optimal and considerable freely available sensor. Hemati, Hasanlou et al. (2021) argue that Landsat, specifically Landsat 4's thematic mapper sensor, was a turning point in the monitoring of land cover change over longer periods. This was followed by Landsat 5, launched in 1982. The retrieved and reviewed literature shows that one of the most recent Landsat sensors, Landsat 8 OLI was amongst the most utilized sensors in wetland monitoring. Landsat 1 had a low radiometric resolution of 6 bits and currently Landsat 9 has 12 bits. Landsat 9 also features a 16-day revisit frequency, which is optimal for mapping wetlands and other rapidly changing land cover types. When Landsat 8 and 9 are combined, the sensors will cover the entire planet in 8 days (Hemati, Hasanlou et al. 2021). Furthermore, its open-source nature facilitates consistent access to data in regions with limited spatial data such as third-world countries. Landsat has global coverage and constantly provides scientists with new remotely sensed imagery for earth observation. Overall, the improvements made to the Landsat mission have greatly enhanced our ability to monitor and understand the Earth's surface including the spatiotemporal variations extent and productivity of wetland vegetation.

The switch in remote sensing techniques from ground observations and aerial photographs to airborne satellites had a huge impact on the wetland remote sensing community. Particularly, the launch of satellites such as the JERS-1, MODIS, LiDAR, SAR, and QuickBird in the late 1990s and early 2000s had an impact on the wetland remote sensing research community and explains the frequency of publications from around 2003 till the time of writing of this review. The increase in the frequency of these sensors is accompanied by increased publications along with model accuracies in mapping and monitoring wetland vegetation.

Since the Landsat sensors are optimal for assessing the spatial variations in the extent of wetlands, the Sentinel 2 multispectral imager is optimal for characterizing the vegetation's attributes of wetlands. Sentinel-2 MSI is a pair of satellites, Sentinel 2A and Sentinel 2B, that captures moderate to high spatial resolution imagery covering 13 spectral bands at an optimal radiometric resolution of 12 bits and revisit frequency of five days (Phiri, Simwanda et al. 2020). The sections of the electromagnetic spectrum covered by the 13 bands include the visible, red edge, near and thermal infrared spectrum. Like Landsat, the Sentinel-2 MSI's remotely sensed data is freely accessible on the Copernicus Open Access Hub (https://scihub.copernicus.eu/). Subsequently, Sentinel 2 MSI coverage of the red edge section of the electromagnetic spectrum has significantly improved the mapping of vegetation elements, especially in third-world countries with limited access to quality spatial data.

Research has shown that data obtained from Sentinel-2 MSI can be used for the accurate estimation of wetland vegetation parameters including biomass, which is associated with spectral saturation (Kaplan and Avdan 2018). Studies by Mutanga, Masenyama et al. (2023) and Mutanga, Adam et al. (2012) have successfully proven that the application of red edge section of the electromagnetic spectrum in estimating vegetation biomass is very instrumental. Moreover, Sentinel-2 MSI data has been widely applied in various other studies as well such as classifying wetland vegetation communities, surface water dynamics, and wetland delineation (Castillo-Riffart, Galleguillos et al. 2017, Slagter, Tsendbazar et al. 2020). However, even with sentinel-2 pool of possibilities in wetland ecosystems, the reviewed literature revealed that there were quite a few studies that leveraged Sentimel-2s technologies in estimating wetland leaf area index. Studies by Castillo-Riffart, Galleguillos et al. (2017), Slagter, Tsendbazar et al. (2020) bring to light the importance and use of Sentinel-2 MSI in classifying wetland communities at different levels of classification which include surface water dynamics, and wetland delineation in third world countries. The results from those studies demonstrate the Sentinel-2 MSI performed better in wetland delineation, and this highlights the need for freely accessible remote sensing data in developing countries.
In addition to Sentinel-2 MSI, PlanetScope is a high-resolution satellite which provides free remote sensing data at 3-meter spatial resolutions. This sensor can be very useful in supporting researcher in third-world countries on mapping and monitoring wetland vegetation. For instance, Miller, Morris et al. (2019) proved that this sensor can be optimally used in wetland remote sensing. However, there are a very few studies that have tested the use of PlanetScope and presented high accuracies therefore making it difficult to reach conclusions on the sensor's overall performance.

Some of the least used satellite from the reviewed literature were JERS-1, IKONOS, Ziyuan-3, and IRS. This could be attributed to the fact that these are commercial sensors only accessible to a select few and are often associated with exorbitant charges. Upon assessing the geographic location of the studies that utilized these sensors, it was noted all of these sensors were used for studies in economic powerhouse countries such as China and USA which can afford data acquisition costs. Despite the potential impact and contribution these sensors on mapping wetland ecosystems, they are often not used for wetland mapping due to high data acquisition costs. Proisy, Couteron et al. (2007) mentions that most African countries and countries in South America still find it challenging to access high spatial resolution data which has detailed information on wetland traits, substrate composition, and water depth.

2.4.2. **Image transformation techniques**

The most widely used vegetation transformation technique in wetland remote sensing the use of vegetation indices (Thito, Wolski et al. 2015, Kaplan and Avdan 2018). Bannari, Morin et al. (1995) describes vegetation indices as spectral variables that are mathematically computed from multispectral optical bands based on the spectral reflectance of vegetation. Vegetation Indices are associated with a myriad of applications within the wetlands ecology field, such as their improved sensitivity to vegetation attributes which makes them ideal for detecting changes in vegetation cover as they are designed to enhance the signal of vegetation (Thenkabail, Smith et al. 2002). Their ability to combine the strength of multiple bands makes them more robust when compared to spectral bands. This gives them the ability to find a way around the effects of soil background, vegetation density, atmospheric influences, and sun angle (Jiang et al., 2008). As a result, they are more capable of detecting slight changes in the traits of wetland vegetation. One of the most common challenge in the remote sensing of wetland is the presence of standing water and the effects soil moisture, however, vegetation indices such as EVI re more robust against such effects (Wan, Wang et al. 2019).

The reviewed literature highlighted that the Normalized Difference Vegetation Index (NDVI) was the most used VI. The NDVI was developed to quantify vegetation by measuring the difference between the infrared and red light and can be very useful in measuring vegetation health (Xue and Su (2017). However, Mutanga, Masenyama et al. (2023) writes that the shortfall of NDVI is that it is impacted by spectral saturation when vegetation is sparse and when the leaf area index increases to 2.5 and 3. In this regard, other indices including EVI and SAVI were developed to address these shortcomings (Xue & Su, 2017). Furthermore, some studies advanced toward utilizing texture indices such as the GLCM instead of VI. Texture metrics are influential spectral variables that also surpass the influence of atmospheric interferences, soil background sun angle, zenith angle of the sensor, vegetation density and spectral saturation. For instance, a study Arzandeh and Wang (2003) demonstrated that texture metrics from SPOT images could optimally map invasive alien species in marsh wetlands. Their results showed that incorporating the texture features into the model improved the classification accuracy of these species significantly.

2.4.3. Performance of various algorithms in remote sensing wetlands

The reviewed literature showed that other than advancements in remote sensing technologies, statistical classification algorithms have also facilitated an improvement in the classification and prediction model accuracies of wetlands over the years. Results from machine learning classification algorithms exhibited overall classification accuracies ranging from 63% to about 95% for some studies. Machine learning algorithms have hyperparameters that can be tuned in relation to the dataset type. This makes them to be able to detect subtle differences in wetland features using remotely sensed data. Results of this study indicated that the Adaptive-stacking algorithm had the highest mean overall classification accuracy (94.95%) but was only utilized in a single study in the reviewed literature. Long, Li et al. (2021) applied a Google Earth Engine derive algorithms, adaptive stacking, on Sentinel-1/2 imagery in order to map vegetation distribution in Dongting Lake, China. Results from the study showed that some of the most popular machine learning algorithms in wetland mapping, random forest (RF) and support vector machine (SVM), were outperformed by the adaptive-stacking algorithm. However, there were limited number of studies that utilized the adaptive-stacking algorithm, and this calls for more studies to extend these research efforts.

The top three most used algorithms in the reviewed literature were Random Forest (RF), Support Vector Machine (SVM), and Classification and Regression Tree (CART). All these algorithms are computed and trained to yield different classification accuracies, some higher than others A number of factors such as setting the training parameters, feature selection, and the selection of sampling points play huge role on an algorithm's classification accuracies. The popularity of RF in the retrieved literature could be attributed to its robustness and effectiveness in both classification and prediction. The works of (Mahdianpari, Salehi et al. 2017, Yang, D'Alpaos et al. 2020) argue that random forest has the capabilities of handling high-dimensional datasets and can model linear relationships between input variables and the classification outcome. One capability that enhances random forest's performance is its ability to select optimal classification/prediction features. It is also capable of handling data with missing values, which is very common in the application of remotely sensed data (Du, Mao et al. 2021, Wu, Shi et al. 2021). A combination of all these spectacular capabilities makes random forest an ideal and reliable machine learning algorithm that can be effectively used to characterize wetland extent and its vegetation attributes.

Qian, Zhou et al. (2014) define SVM as a nonparametric algorithm that defines a hyperplane between training samples of two classes and then classifies other pixels/objects based on this hyperplane. The SVM is also less sensitive to the amount of sample entered and can result in higher classification accuracies given a relatively small number of samples compared to other classifiers. However, SVM needs a kernel function, and defining one can be very subjective and time-consuming (Qian, Zhou et al. 2014). is among the most used classification algorithms in this review. Its advantages include the fact the MLC adopts a clear statistical approach to classification and many studies have used it for wetland classification (Lane, Liu et al. 2014, Rapinel, Clément et al. 2014)

In summary, results from the reviewed literature show that there is a range of classification algorithms and there is no specific optimal classification algorithm that is suitable for all applications. This means that the selection of the desired algorithm should be based on the requirements of the study (Adam, Mutanga et al. 2010).

2.4.4. Challenges in remote sensing wetlands

Due to the unique and complex characteristics of different wetland communities, the remote sensing of these ecosystems is not without challenges. Below are some the most common challenges noted from the reviewed literature:

1. Spectral complexity: Due to the presence of water, soil, and vegetation, wetland communities present different spectral characteristics and this makes it difficult to distinguish wetland features from other types of landcovers.
2. Wetland variability: Characteristics of wetlands vary because of their vegetation and soil type, water depth, and size. This makes it challenging to fully capture their dynamics especially when broadband, moderate spatial resolution multispectral data are utilized at both local to regional scales.
3. Sensor limitations: Different sensors have different spectral and spatial resolutions, which can impact their ability to accurately capture wetland features. Additionally, sensors with high spatial resolutions can be expensive and may not be accessible to all researchers. Meanwhile, those that are available have moderate spatial resolution which often masks out the critical optical attributes of wetlands.

Overall, remote sensing of wetlands requires careful consideration of these challenges to develop effective and accurate wetland mapping and monitoring programs.

2.5. Conclusion

The main aim of this section was to conduct a systematic literature review while identifying gaps and opportunities in wetland remote sensing. Data on the applied sensor, wetland type, machine learning algorithms and geographic location of publications was extracted from the studies reviewed in this study to get a broader sense on trends in publications. About 15 wetland types and 32 different sensors were noted in this systematic literature review. The large number of different wetland types and sensors reported from the review reveal that there has been an increasing pattern in the number of publications on wetland remote sensing over the past decades. Leaf Area Index estimation is of vital importance when it comes to monitoring and managing wetland communities. However, there is still a gap in research considering this aspect of wetland management. This gives room for future research efforts in understanding the effective contribution of remote sensing-derived LAI in wetland management.

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3. Remote sensing spatial dynamics of a typical urban wetland using Landsat data, Google Earth Engine, and machine learning.

Abstract: Urban wetlands play a vital role in providing ecosystem services and supporting biodiversity as a habitat. However, rapid urbanization and human encroachment pose significant threats to these fragile ecosystems, leading to their fragmentation and degradation. Advancements in earth observation technologies and data accessibility such the introduction of Google Earth Engine (GEE) offers a computationally efficient platform for utilizing large-scale satellite imagery in mapping spatial dynamics of wetland vegetation. This study therefore aimed to assess the utility of Google Earth Engine cloud-computing platform in detecting and mapping the spatial changes of wetland vegetation using Landsat remotely sensed data in conjunction with machine learning algorithms. Specifically, a comparative analysis of the performance of Random Forest (RF), Support Vector Machine (SVM) and Naïve Bayes (NB) in GEE was conducted to map changes in landuse and land cover types (LULC) in the Khayelitsha wetland, Cape Town South Africa, during the years 2000, 2010, and 2023, based on Landsat remotely sensed data. The LULC classes that were considered in this study were wetland vegetation, water bodies, bare land and built-up areas. The results from the classification yielded average overall accuracies of 96% for Random Forest, 93% for Support Vector Machine, and 30% for Naive Bayes. Overall, RF outperformed the other two algorithms. The results highlight the robustness of Random Forest and the usefulness of the Google Earth Engine platform in classifying urban wetlands. This has practical implications for decision-makers on the efficient management of wetland ecosystems.

Keywords: Urban wetlands, Land Use Land Cover (LULC) changes, Random Forest (RF) classifier, Support Vector Machine (SVM), Landsat 8 OLI, Landsat 7

3.1. Introduction

Wetlands are defined as areas of transition from an aquatic to terrestrial environments. They are areas of soil covered in water or have a water table close to the surface throughout the year. Wetlands are critical ecosystems that provide a multitude of vital ecosystem services and play a crucial role in supporting biodiversity as important habitats for various flora and fauna. They provide a multitude of ecological services including water purification, habitat provision, and flood control. Literature on ecosystem services assessment continues to site wetlands as the most valuable parts of our landscapes (Costanza, d'Arge et al. 1997, De Groot, Brander et al. 2012, Costanza, De Groot et al. 2014). They are one of the most complex landscapes because of their unique hydrological, and geological characteristics. The dynamic nature of these landscapes is shaped by various factors, including human activities, which have significantly impacted the alteration of landscapes over time. Human migration to cities has caused rapid alterations in ecosystems, biodiversity and the environment (Verburg, Van De Steeg et al. 2009). Despite their ecological significance, wetlands have long been subjected to anthropogenic alterations, resulting in their loss and degradation worldwide. Land use land cover change, particularly over the last decade, has emerged as a prominent anthropogenic factor that influences wetland ecosystems. On a recent study, Fluet-Chouinard, Stocker et al. (2023), argues that about 21% of global wetlands have been lost. United States, Europe, Central Asia, India, China, Japan and Southeast Asia were labeled as ‘regional hotspots of loss’ where 50% of the wetlands were lost between 1700 and 2020 (Fluet-Chouinard, Stocker et al. 2023). This has significant impacts to biodiversity, water quality, and climate resilience, and livelihoods, especially in semi-arid regions where wetlands are important role players in the economy.

Considering that South Africa is characterized as a water-scarce country due to its low rainfall, wetlands contribute greatly to the country’s water resources (Ollis, Jennifer et al. 2016). Recent studies showed that wetlands cover approximately 2.4%, 30 000 km^2 of the total land area in South Africa, but 48% of wetland ecosystem types are critically endangered (Ollis, Jennifer et al. 2016). However, despite the limited coverage of wetlands in South Africa, they still face degradation. It was reported that South Africa has lost approximately 50% of its original wetland areas due to factors including erosion, invasive alien plants, developments within and around wetlands and draining of wetlands (DEFF, 2021). Only 11% of South Africa’s wetland ecosystems are well protected, and about 70% have no protection. This continued degradation of wetland ecosystems in South Africa is contributing to the reduction in the amount of quality and safe water for use.

In the past decades, the introduction of Earth Observation technologies, such as remote sensing and Geographic Information Systems (GIS), has revolutionized wetland monitoring and conservation efforts

(Rebelo, McCartney et al. 2011). Remote sensing presents the opportunity to collect data from vast areas in a non-intrusive manner, providing critical insights into wetland dynamics and changes over time. Satellite imagery allows for the detection of changes in wetland extent, vegetation health, and water levels, facilitating the identification of vulnerable areas in near-real-time (Lück-Vogel, Mbolambi et al. 2016, Orimoloye, Kalumba et al. 2020, Gxokwe, Dube et al. 2022). Remote sensing technology has been applied to monitor important wetland aspects such as aboveground biomass and leaf area index (Mutanga, Adam et al. 2012, Doughty, Ambrose et al. 2021). Multispectral sensors, coupled with classification algorithms, have also been used in studies on land use land cover changes. These studies sought to understand shifts in land cover classes over extended periods and broad geographical coverage. Quite a large number of wetland remote sensing studies used Landsat data and this is due to the fact that Landsat boasts for being the longest running earth observation mission with plenty of freely available archival data (Alam and Hossain 2020, Hemati, Hasanlou et al. 2021, Hu, Myers Toman et al. 2021). Landsat data, specifically Landsat 7 Enhanced Thematic Mapper (ETM), and Landsat 8 Operational Land Imager (OLI) provide good quality imagery with a 30-meter spatial resolution at a 16-day interval, making them ideal for historical mapping and monitoring of wetland dynamics at optimal accuracies (Hemati, Hasanlou et al. 2021).

In recent years, the integration of machine learning algorithms, such as Random Forest (RF) and Support Vector Machine (SVM), with remotely sensed data has resulted in remarkable advancements in accuracy and efficiency across various mapping and monitoring applications (Qian, Zhou et al. 2014, Du, Mao et al. 2021). Random Forest leverages multiple decision trees to improve classification and regression tasks (Tian, Zhang et al. 2016). When combined with remotely sensed data, RF can effectively handle complex and high dimensional datasets, identifying subtle patterns and relationships among spectral and spatial information, thus achieving higher accuracies in land classification and change detection studies (Paul, Mukherjee et al. 2018). Similarly, SVM is a powerful supervised machine learning algorithm which excels in binary classification and has proven particularly effective in mapping landcover boundaries when fed with feature-rich remotely sensed datasets (Qian, Zhou et al. 2014). The synergy between these machine learning algorithms and remote sensing data has brought about a paradigm shift in environmental monitoring, and resource management, fostering a new era of data-driven decision-making with unprecedented accuracy and efficiency.

In this regard, the objective of this study was to integrate Landsat-7 ETM and Landsat-8 OLI data in characterizing changes in wetland LULC classes using RF algorithm embedded in GEE in a typical Southern African urban area. To address this objective, this study conducted a comparative analysis of the performance of Random Forest, Support Vector Machine, and Naïve Bayes in mapping the LULC changes in Khayelitsha wetland, Cape Town South Africa during the years 2000, 2010, and 2023.

3.2. Methods

3.2.1. Study Area

The Khayelitsha wetland area is situated in Khayelitsha township, in Cape Town South Africa. This wetland is located east of Spine Road and is bordered by the Silvertown and Makhaza settlement and the 9th South African Infantry to the south, east and north, respectively (Figure 3.1). Khayelitsha is situated in the Cape Flats lowlands which lies on Malmesbury bedrock with Sandveld Group sediments (Mathenjwa 2017). The topography of the area consists of sand dunes which were deposited because of sea-level rise movement and deposition of sand along the coast. This resulted in a retarding river flow which then led to the formation of the Cape Flats wetlands, including Khayelitsha wetlands (Wall 2010). Since the region is situated in a Mediterranean-type climate zone, it experiences dry warm summers and cold wet winters. The Khayelitsha wetlands park forms a part of the greater Khayelitsha Wetlands, which fall under the Kuils River Catchment. It is part of the Cape Floristic kingdom characterized by the Fynbos-type vegetation which is endemic to this region. However, the Khayelitsha wetlands have become invaded by alien invasive species such as wattles. This wetland ecosystem is a habitat for a variety of birds, which include herons and various other migrant birds.

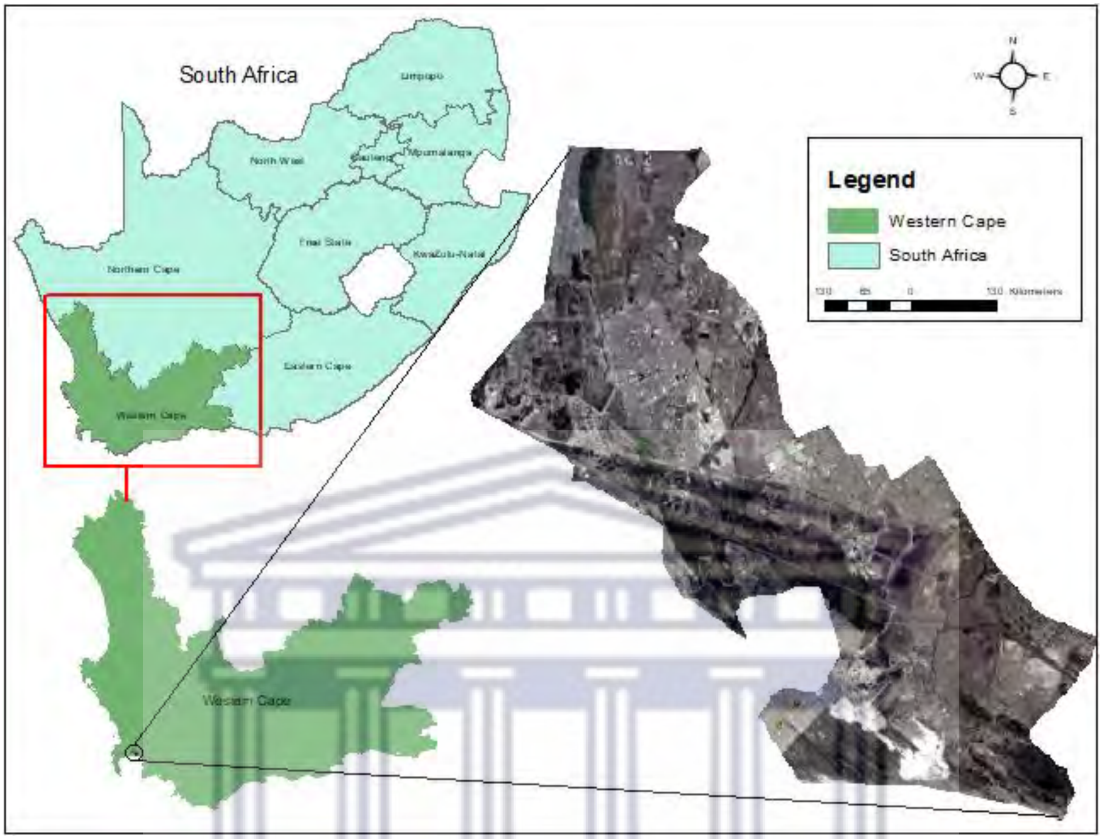

Figure 3-1:: Location of the studied wetland area.

3.2.2. Ground control points for classification

For the years 2000 and 2010, the sampling points were generated by digitizing Google Earth Pro images, leveraging its fine spatial resolution images. These points were then used as training and testing datasets in Google Earth Engine for the random forest classifier. The dataset comprised of 130 – 150 points for each land cover class, which were then divided to training and testing sets. In 2023, land cover data were collected during the dry summer period (December - April), which coincided with the image acquisition date. A handheld Geographical Positioning System was used to collect the locations of more than 400 ground truth points. A stratified random sampling method was employed while collecting the points. Ding, Haieh et al. (1996) described stratified random sampling as an approach that involves dividing the data into smaller subgroups based on attributes, then random sampling is applied on those subgroups. This method was chosen on the premise that each class is equally likely to occur. For the sampling, the study area was subdivided to 30m x 30m quadrants based on Landsat 8 OLI pixel sizes. After that, ground truth data were collected in each quadrant depending on the dominating land cover classes. These ground truth points were then used for image classification, further enhancing the accuracy of the proposed classification methods.

3.2.3. Classified Remotely sensed data.

For wetland classification, the study utilized multispectral remotely sensed data acquired from Landsat 7 +ETM and Landsat 8 OLI sensors as shown in Table 3.1. Considering that wet cloudy winters in the study area, this study utilized images that were acquired during the summer months (December – April). To further reduce the impact of clouds in this study, images that had < 20% cloud cover were selected. Top of Atmosphere (TOA) images were retrieved from Google Earth Engine's Landsat library. Google Earth Engine (GEE) images do not require atmospheric correction because they are often preprocessed and corrected for atmospheric effects (Long, Li et al. 2021). Spectral bands 1-5 namely Blue, Green, Red, Near Infrared and Shortwave infrared respectively, were used in generating LULC spectral curves using Landsat 7 ETM images for exploring the separability of classes in this study. For Landsat 8 OLI images, Bands 1-7 namely Blue, Green, Red, Near Infrared, Shortwave Infrared 1, and Shortwave Infrared 2, respectively, were used to generate the LULC spectral curve. For this study, Landsat was deemed as the optimal sensor because of its moderate spatial resolution and multi-spectral capabilities which allows Landsat to capture detailed information across a range of spectral bands.

Table 3.1: Landsat 7 ETM+ and Landsat 8 OLI used for classification.

Satellite	Sensor Id	Layers	Grid cell size (m)
Landsat 7 ETM+	LANDSAT/LE07/C02/T1_TOA	7	30
Landsat 8 OLI	LANDSAT/LC08/C02/T1_TOA	11	30

3.2.4. Machine Learning Algorithms used for classification.

Machine learning algorithms, specifically Random Forest (RF), was used for classification of different land cover classes in the study area. The images were classified into four land cover classes namely bare land, water bodies, built up areas, and vegetated areas. Random Forest (RF) is a non-parametric ensemble, composed of multiple tree classifiers and is well-suited for handling high-dimensional data (Belgiu and Drăguţ 2016). The RF classification process involves assigning labels to pixels by considering the majority vote of these "*trees*." Each tree is grown by randomly selecting a subset of input variables at each node, which helps prevent overfitting and leads to a more reliable classification compared to other classifiers (Breiman 2001). To generate the forest trees in the RF algorithm, two parameters specify, the number of decision trees to be created (*Ntree*) and the number of variables to be randomly selected and tested for the optimal split during tree growth (*Mtry*) (Breiman 2001). The key hyperparameters, ntrees was set to 10. Other hyperparameter values were left as default, leverage GEE default behavior capabilities.

3.2.5. Accuracy assessment

Prior to classification, the sampling points obtained from Google Earth Pro and field sampling were prepared for classification by creating a training dataset from different LULC classes. The '*randomColumn*' function from Google Earth Engine was then used to randomly split the dataset into 80% for training, and 20% for the testing set to be used by the proposed classification methods. To evaluate the classification accuracies of the Random Forest, Support Vector Machine, and Naïve Bayes algorithms in classifying different wetland classes, the overall accuracy (OA), User Accuracy (UA), Producer Accuracy (PA), and Kappa statistics were generated from confusion matrices, and their values recorded. The overall accuracy of the classified image assesses the correspondence between the assigned classification of each pixel versus the land cover conditions derived from ground truth data. The producer's accuracy was measured to see how accurate the classification is in capturing the presence of these land cover types in the actual environment. The User's accuracy was calculated to measure the probability of the classified pixel on an LULC map accurately represents that category on the ground (Gxokwe, Dube et al. 2022). Furthermore, the variable importance and spectral reflectance values were assessed to get an understanding of the most influential spectral discrimination features that yielded the highest OA and Kappa. The identification of variable importance is regarded as an important phase in LULC classification as it helps identify which variables are optimal for the desired outcome. According to Sage, Genschel et al. (2020), the classifier used in a classification study influences the variable importance depending on the algorithm's architecture. In some instances, some features are given more weight in relation to others. In this study, Google Earth Engine was utilized to help identify the optimal Landsat bands and wavelengths that can be employed to properly identify different LULC classes. This was done to assess the key drivers that influenced the classification outcomes especially in areas such as wetlands where the landscape is influenced by a myriad of environmental factors. Figure 3.2 illustrates the methodological approach followed in acquiring and processing remotely sensed data in this study.

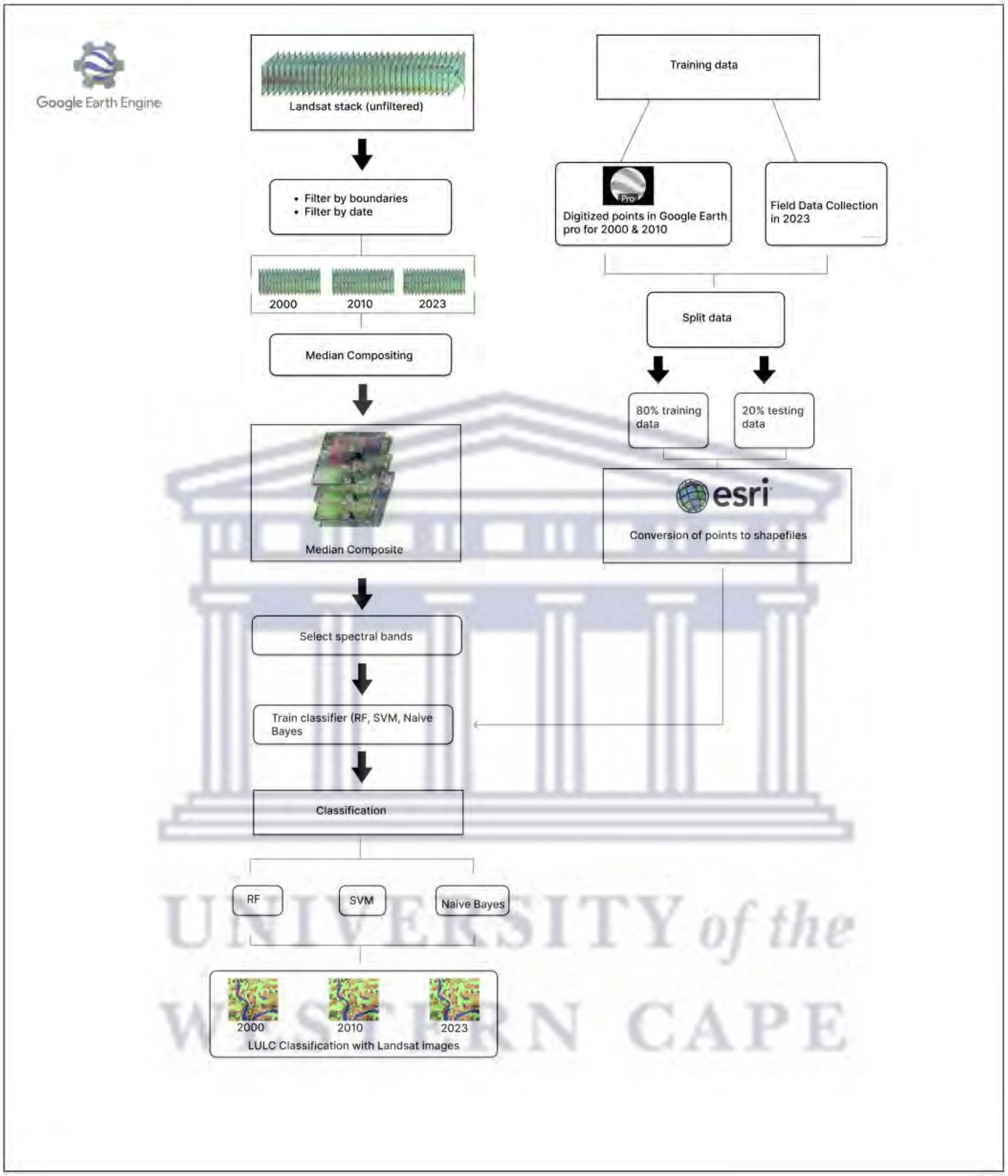

Figure 3-2**:** Steps taken to characterize the wetland area.

3.3. Results

3.3.1. Spectral Reflectance Curves

Figure 3.3 shows that various LULC classes exhibit distinct spectral reflectance curves (SRCs). These curves vary in terms of their reflectance values across different bands. Figure 3.3 a, and b display spectral reflectance curves for 2000 and 2010 respectively which were obtained from Landsat 7 imagery. Figure

3.3c displays spectral reflectance values obtained from Landsat 8 OLI imagery for the year 2023. It can be observed in Figure 3.3 that the wetland classes are not clearly distinguishable using Bands 1-3 but are more distinguishable by the NIR bands and higher. Bare land, built-up areas, vegetated areas, and water bodies are more distinguishable in bands 3 -7 and this is represented by sparsity of their reflectance values. As expected, the water class's reflectance values drop as the graphs move away from the blue band. It can also be observed that water shares similar spectral reflectance values with built up areas (Figure 3.3b) and vegetated areas (Figure 3.3b) for bands 1-3.

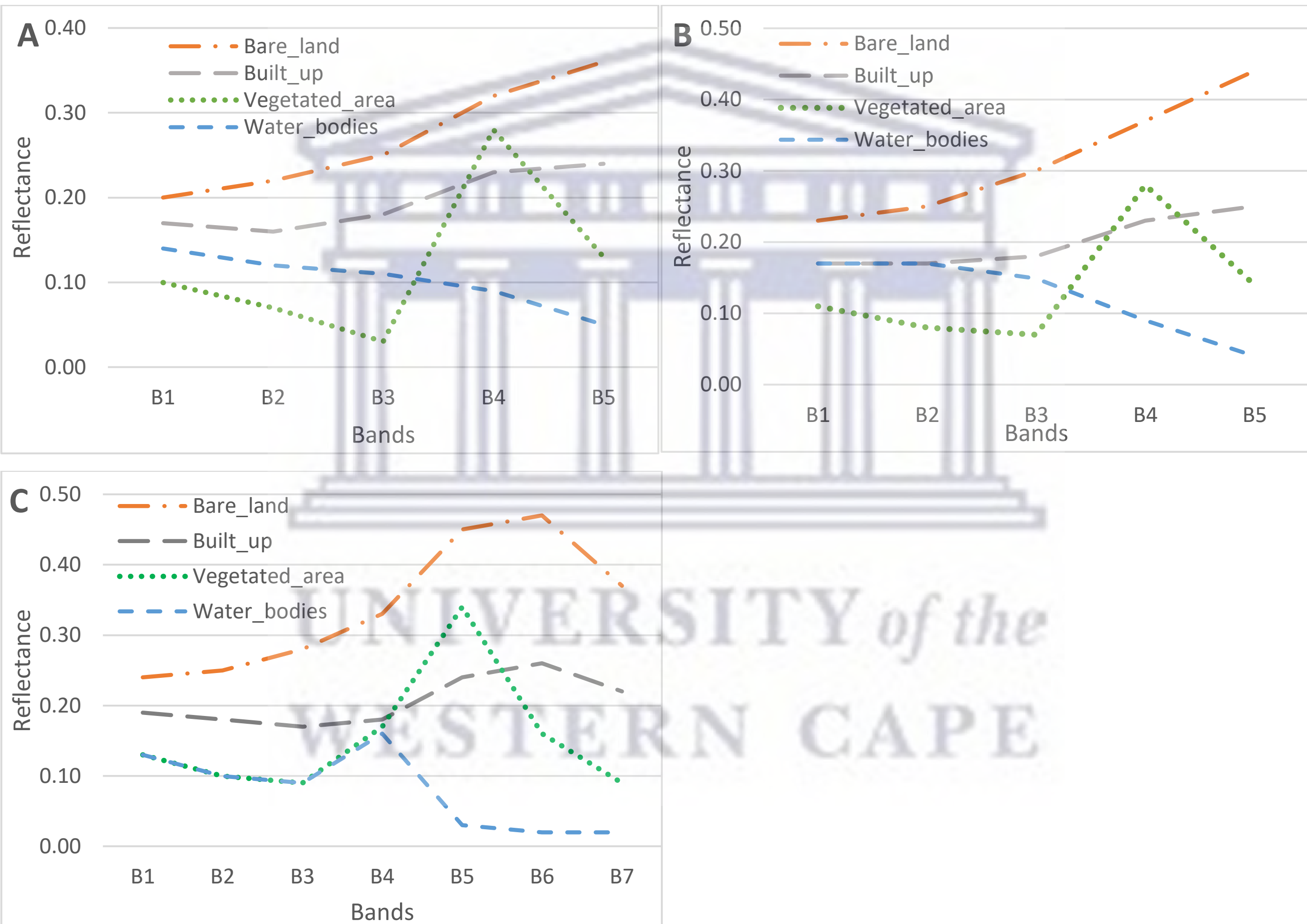

Figure 3-3: Spectral reflectance curves of bare land, vegetated areas, water bodies, and built-up areas for the years 2000 (a), 2010 (b), and 2023 (c)

3.3.2. Comparison of Machine learning algorithms in Mapping wetland LULCs

Results showed that Random Forest outperformed the other two classifiers in terms of the overall performance of the algorithm in classifying different wetland LULC classes. The overall accuracies for the RF algorithm were 97% in 2000, 96% in 2010, and 94% in 2023. The SMV had reasonable OA values of

100% in 2000, 94% in 2010, and 85% in 2023. From the three algorithms employed, Naïve Bayes obtained the lowest recoded overall accuracy values of 27%, 40%, and 22% in 2000, 2010, and 2023 respectively. Figure 3.4 (a) shows the overall performance of RF, SVM and NB in mapping LULC classes within the Khayelitsha wetland. It was observed that on average, RF performed better than the other two algorithms. RF obtained a high average OA of 95%. Falling second to RF, SVM had a reasonable average OA value of 93%. NB was the least accurate algorithm with an average OA value of 29.6%. Results from figure 3.4 (c & d) show the kappa statistic and mean kappa statistic for the algorithms through the years. The kappa values from figure 3.4 (a) show that RF and SVM performed optimally well with kappa values ranging between 85 – 100%, while NB had the lowest kappa accuracy values ranging from 0 -12%. Results from the kappa stats show that RF had a mean kappa value of 93%, SVM, 88%, and NB had a mean kappa value of 12%.

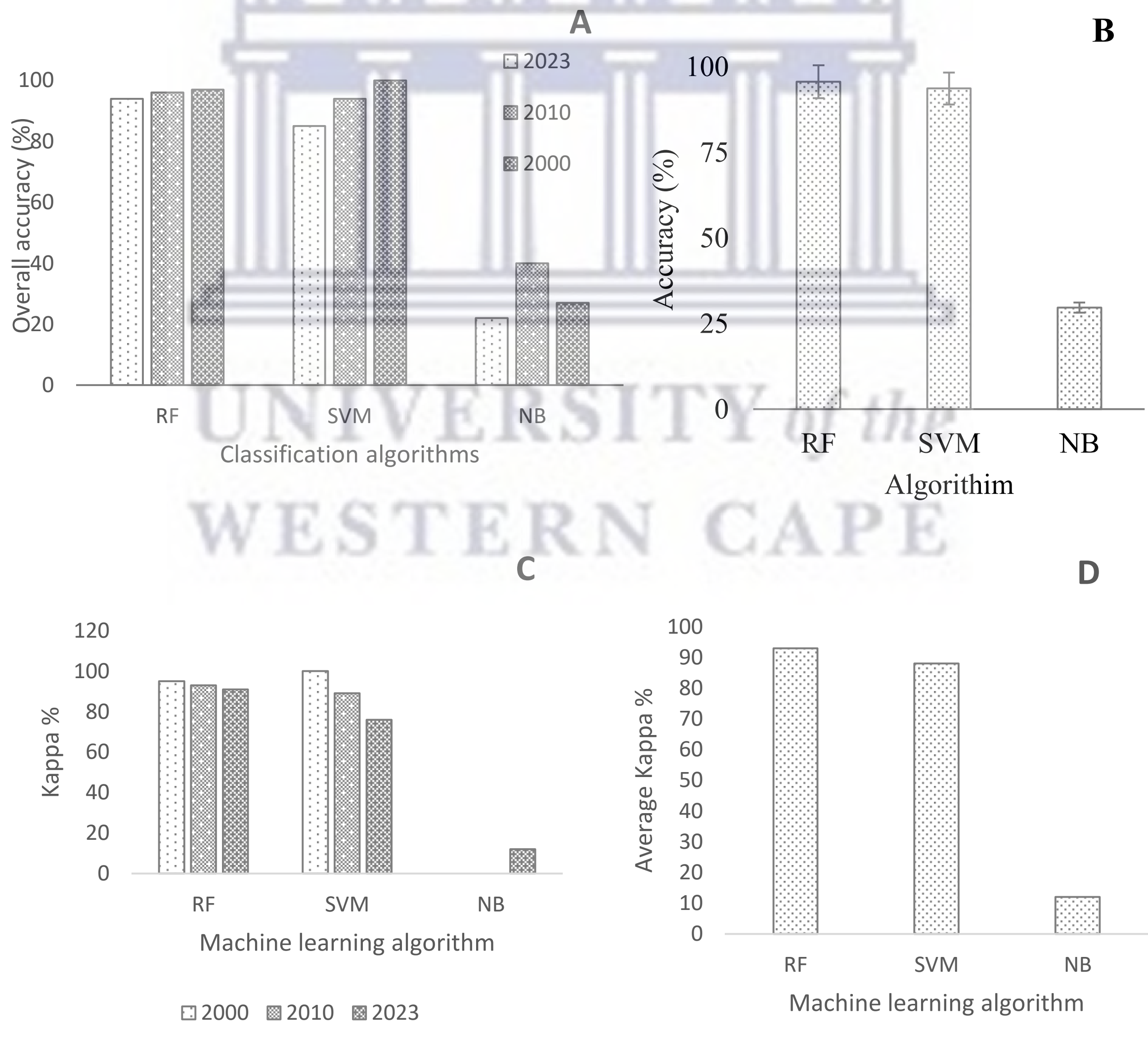

Figure 3-4**:** Classification A overall classification accuracies for the years 2000, 2010 and 2023, (b) a comparison of mean overall accuracies exhibited by RF, SVM and NB in mapping wetland LULC classes (c) Kappa statistic, and (d) mean Kappa statistic.

3.3.3. Performance of Random Forest in mapping wetland LULC classes

For the year 2000, the most influential spectral features which exhibited an OA of 94% were Bands 4 (NIR) and band 7 (SWIR 2) (Figure 3-5). For the year 2010 the most influential spectral feature which yield an OA of 96% were bands 5(SWIR 1) and 7(SWIR 2) (Figure 3-5). Finally, the optimal spectral feature for the year 2023 which exhibited a highest RF's OA of 97% were Band 5 (NIR) and band 6 (SWIR) (Figure 3-5). It can be observed from Figure 3.5 that the NIR and SWIR bands were consistently the most important bands in wetlands classification through the years 2000, 2010, and 2023 on both Landsat 7 ETM+ and Landsat 8 OLI images (7). The shortwave infrared bands are sensitive to water absorption and soil content, which makes this section of the electromagnetic spectrum influential in discriminating wetland characteristics such as vegetation type and soil moisture levels (Goward 1985).

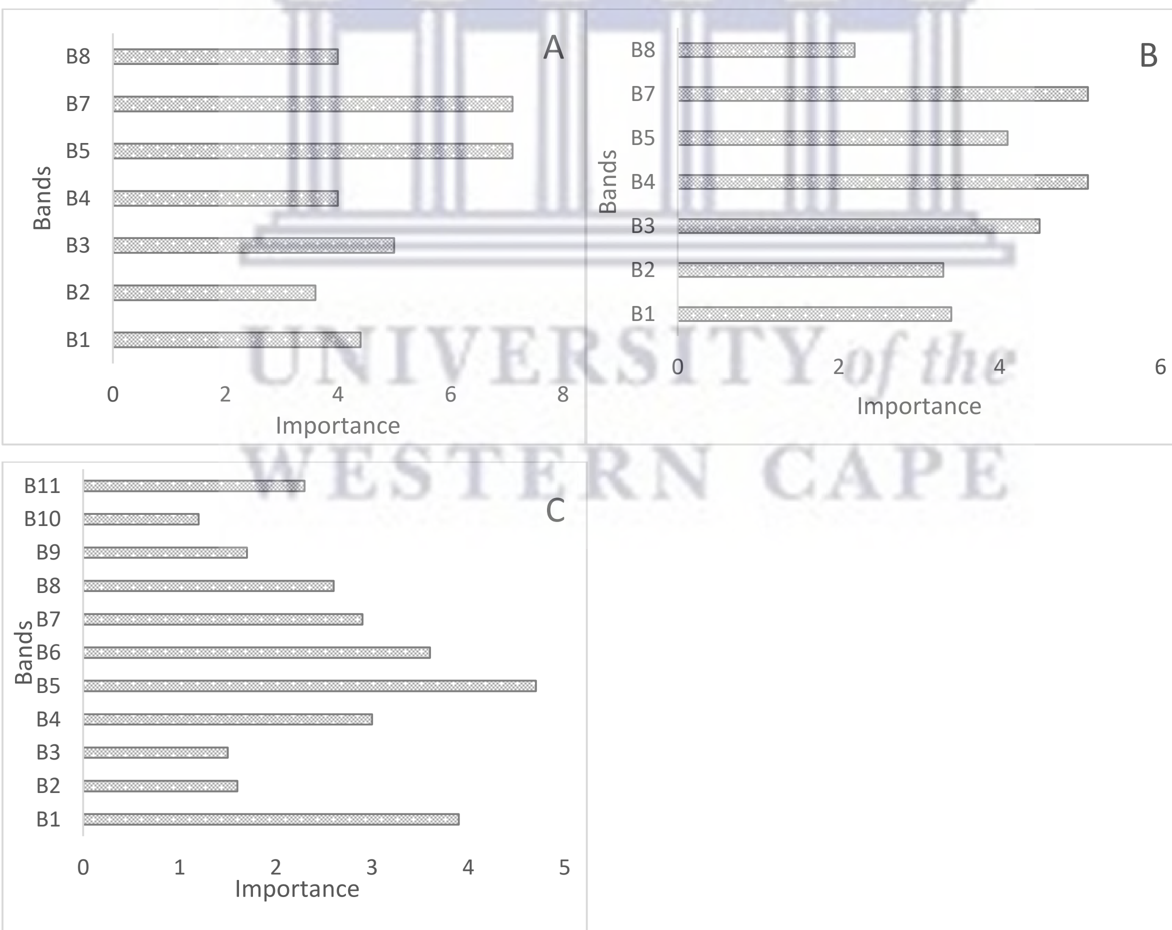

Figure 3-5: RF variable importance scores derived for the years 2000 (a), 2010 (b), and 2020 (c) respectively.

3.3.4. Spatial extent Dynamics of different LULC classes

Figure 3.6 depicts overall patterns in terms of different LULC classes during the year 2000,2020 and 2023. It can be observed that there has been a decline in the bare land and vegetated area classes through the years (Figure 3.7). The area covered by bare land dropped from 3718 ha in the year 2000 to 1007.97 ha in 2023. Results showed that the area covered by vegetated area showed an increase from 2000 (853.5 ha) to 2010 (3244 ha), then decreased again between 2010 and 2023 (2590 ha). The one class that showed an exponential increase between 2000 and 2023 was the built-up area. The results recorded that the area covered by built up land increased from 2062.81 ha in 2000 to 3071.27 ha in 2023. Some anomalies were noted in the classification as the results from 2010 did not show the water bodies class. This could be ascribed to the fact that the images were collected during the warm dry summer season which experiences high evaporation. Subsequently, this could have resulted in limited sampling points for the water bodies class.

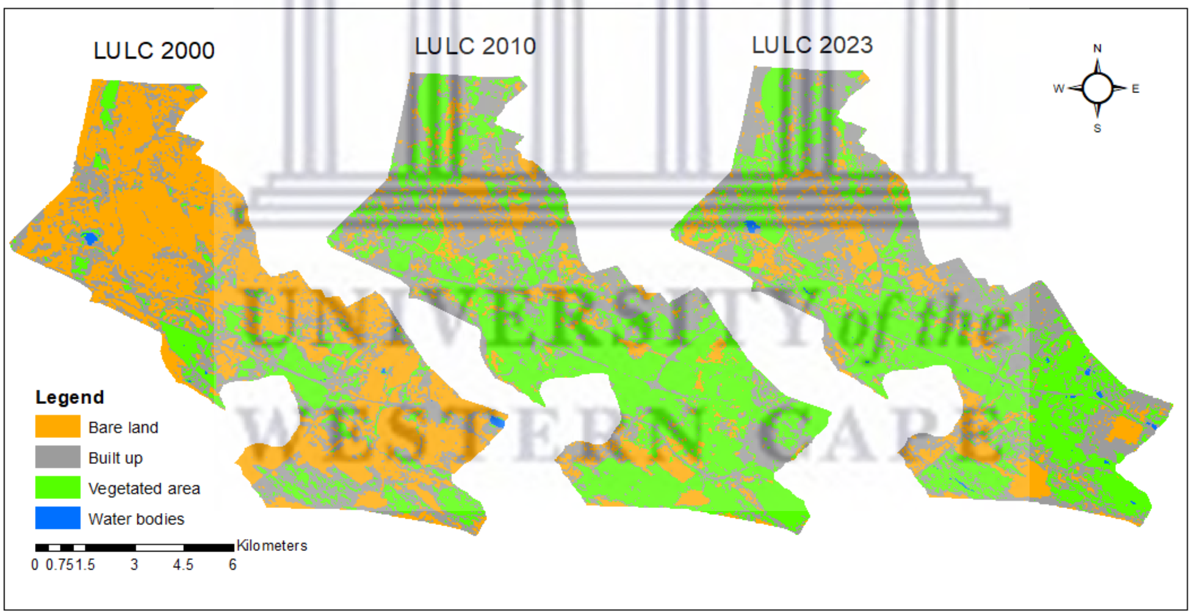

Figure 3-6: LULC classification using Random Forest

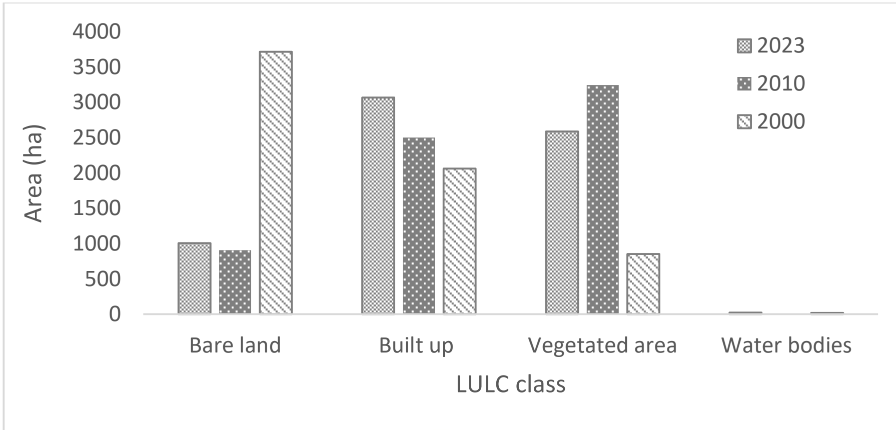

Figure 3-7: Area covered by different LULC types in the wetland in 2000,2010, and 2023.

3.4. Discussion

The objective of this study was to assess LULC changes in the Khayelitsha wetland during the 2000 to 2023 period using Landsat 7 ETM+ and Landsat 8 OLI. The study conducted a comparison between different machine learning algorithms in Google Earth Engine in mapping wetland LULC types.

3.4.1. Assessing the RF LULC classifications within the Khayelitsha wetland during the years 2000, 2010 and 2023.

Overall accuracies of 97%, 96% and 94% and Kappa statistics values of 95%, 93%, 91% were obtained based on NIR and SWIR sections of the electromagnetic spectrum. The optimal performance of the NIR could be attributed to the unique information it provides about the target object. The combination of the NIR bands and the visible spectra offers additional information about ground objects, especially vegetation and vegetation properties such as chlorophyll (Yuan et al., 2023). The NIR spectral band is important in remote sensing because of its sensitivity to plant attributes such as chlorophyll. Healthy vegetation reflect NIR radiation which provides insight to plants' photosynthetic activity and overall health (Petus, Lewis et al. 2013). Our findings are similar to those of Ali and Johnson (2022) who noted the optimal influence of the NIR in detection and mapping LULC types in wetland areas. The second most influential spectral feature was Landsat's SWIR section of the electromagnetic spectrum. This could be explained by the fact the SWIR is recognized for its sensitivity to moisture and this is correlated to principal metrics such as leaf water content (Stark, McGee et al. 2015). The spectral reflectance curves show that bare land and built-up areas exhibited similarities in terms of their reflectance. Band 5, the SWIR band in Landsat 7 ETM+, and band 6 in Landsat 8 OLI recorded the highest reflectance values for the built-up area and bare land classes. This band is of utmost importance when it comes to distinguishing between soil and cultivated plants, identifying crops, and delineating boundaries of water bodies in an image. Properties of the SWIR band have been in used in a study by Yue, Tian et al. (2019) to help inform the development of spectral indices sensitive to soil moisture.

3.4.2. Assessing the Spatial dynamics of Vegetation in relation to other classes within the Khayelitsha wetland across the years 2000, 2010 and 2023.

Bare land and built-up areas occupied most of the wetland in 2000 with areas of 3718.2 ha, and 2062.81 ha sequentially, while vegetated areas covered only about 853.42 ha. Results showed that the area covered by vegetated areas increased to 3244.714 ha during the 2000 – 2010. This increase in vegetated areas coincided with a drastic decrease of 75.6% in the area covered by bare land in 2010. This could be attributed to increased rainfall which resulted in vegetation expanding to areas that were previously bare land. One of the relationships worth taking note of is the relationship between vegetated areas and built-up areas. These two classes shared an inversely proportional relationship. As vegetated areas decreased to 2590.2 ha between 2010 and 2023, built-up land increased from 2501 ha to 3071.3 ha. This suggests that during the second lag of the study period, vegetation was fragmented by built-up areas. This mirrors the level of anthropogenic activities, such as the wetland encroachment by informal settlements and the construction of roads and other formal structures, which led to the reduction of vegetated areas in the wetland. Similarly, results from a study by Jamal and Ahmad (2020) revealed that the area covered by built-up areas showed tremendous growth through the course of the study owing to an increase in housing and infrastructure demand due to increased urbanization. This reflects negatively from a conservation and wetland management point of view because this loss leads to a loss of important wetland species and ecosystem services in the region. This behavior can be associated with lack of implementation of policies to protect wetlands against anthropogenic impacts. A study by Hu, Liu et al. (2018) reported that the area covered by wetland declined drastically before the declaration of the wetland as a National Wetland Park by the local government to protect the wetland. One class that showed least changes is the water. It increased in area from 20.09 ha in 2000 to 25.4 ha in 2023. In the 2010 images, water was not detected by all algorithms. Overall, the observed decline in these bare land and vegetated areas is a sign of the way the wetland landscape is being shaped by a variety of natural and human influences. Anthropogenic impacts like urbanization and changes in land use may have an impact on the amount of loss, while environmental variables like climate fluctuations and hydrological changes may contribute to changes in water bodies.

3.4.3. Comparing the performance of Classification Machine Leaning Algorithms

Generally, the classification results demonstrate the capabilities of GEE while highlighting the performance of different machine learning algorithms. The RF and SVM proved to be superior to the NB algorithm which had very low classification accuracies throughout the study period. Random Forest obtained higher UA accuracy values ranging from 90 - 100% and PA values ranging between 83% - 100%. It proved to be a more robust and was the favorable algorithm. Its optimal performance could be explained by the fact that it has the capability to handle large datasets well, can provide variable importance values in a classification, and unlike other models, it does not overfit (Shaik and Srinivasan 2019). Support Vector Machine produced acceptable accuracies, falling slightly behind RF. The similarities in the performance of RF and SV could be attributed to the algorithms' ability to capture complex relationships in data. In addition, NB also showed low user's and producer's accuracy values, ranging from 0 – 66%. This is attributed to some of the algorithm's limitations such as its inability to model dependencies amongst classes (Gxokwe, Dube et al. 2022).

3.4.4. Implications of the study's findings

The study employed machine learning algorithms, RF, SVM, and NB in classifying different wetland LULC classes and the results provide insights for future application and research. The study only focused on the use of spectral bands to identify the optimally performing algorithm in classifying changes in wetland LULC. Future studies need to include multi-source datasets and various spectral derivatives such as vegetation indices and water indices to improve the classification of specific classes, especially water bodies within the context of urban wetlands. Limitations from this study highlight the need for more explorations of different analytical approaches, especially in cases where discrimination of distinct and dynamic classes such as water bodies pose a challenge for classification based on solely spectral bands. Addressing these limitations will lead to a more robust understanding of the different methodologies for LULC change classification.

3.5. Conclusion

This study sought to assess changes in spatial extent of LULC classes in the Khayelitsha wetland using Landsat 7 ETM+ and Landsat 8 OLI imagery during 2000 – 2023. Specific objectives of the study were to:

- Evaluate the effectiveness of Google Earth Engine as a cloud-based platform for monitoring and classifying changes in the spatial extent of the Khayelitsha wetland over time.
- Examine the reliability of Landsat imagery and the Random Forest algorithm in accurately classifying urban wetlands.

- Compare the robustness of machine learning algorithms (Random Forest, Support Vector Machine, and Naïve Bayes) in classifying different wetland land use land cover classes
- Investigate the spectral separability of various wetland classes using imagery from Landsat 7 ETM+ and Landsat 8 OLI.

The findings of this study highlight the critical role played by emerging remote sensing platforms such as Google Earth Engine in monitoring spatiotemporal changes in urban wetlands. Findings from this study revealed that Google Earth Engine demonstrates effectiveness as a cloud-based platform for monitoring and classifying LULC changes in urban wetland, facilitating efficient analysis of wetland temporal dynamics. A comparative analysis revealed that the Random Forest algorithm outperforms Support Vector Machine and Naïve Bayes in classifying different wetland land use land cover classes, indicating its suitability for complex classification tasks in diverse environmental contexts. The reliability of Landsat imagery combined with the Random Forest algorithm in accurately classifying urban wetlands was affirmed, highlighting its potential as a robust tool for land cover analysis in similar settings. Investigation into spectral separability using Landsat 7 ETM+ and Landsat 8 OLI imagery underscores the advantage of Landsat 8 due to its superior spatial resolution, providing enhanced discrimination capabilities for delineating various wetland classes. Overall, the findings of this study highlight the critical need for well-informed conservation and management measures to maintain the biological integrity of urban wetlands as urbanization continues to have an impact on these ecosystems.

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4. Assessing the performance of various Landsat derived spectral indices in wetland landuse and land cover change and fragmentation analysis during the years 2000, 2010, and 2023

Abstract: Urban wetlands play a vital role in providing ecosystem services and supporting biodiversity as a habitat. However, rapid urbanization and human encroachment pose significant threats to these fragile ecosystems, leading to their fragmentation and degradation. To address this challenge, this study compared the performance of various Landsat derived vegetation indices and random forest classifier in mapping landuse land cover changes within an urban wetland during the years 2000, 2010 and 2023. To address this objective, this study assessed the magnitude and pattern of vegetation fragmentation within the wetland area across the study period. Google Earth Engine cloud processing platform was employed detected and map the spatial distribution of wetland vegetation, water bodies, bare land and built-up areas in this study using the Landsat bands and their derived spectral indices (Vegetation and water indices). Specifically, patch density, edge density, and mean patch size was computed and used to understand the fragmentation extent of wetland vegetation. Overall classification accuracies ranging between 93% and 100% were attained in this study based on vegetation indices, water indices, built-up area indices, and a combination of all the indices as optimal discrimination spectral features. Results also showed the spatial extent of built-up areas (informal settlements) significantly increased replacing wetland vegetation. Results revealed that fragmentation metrics such as patch size and mean patch size of wetland vegetation significantly decreased from 2000 to 2023. The findings of this study underscore the prospects of remotely sensed data in mapping and monitoring urban wetlands and vegetation reserves in them. This paper's findings imply that there is dire need for improved wetland management, conservation and restoration measures to minimize the threat posed by anthropogenic disturbances in urban wetlands.

Keywords: Urban wetlands, Random Forest (RF) classifier, Support Vector Machine (SVM), Google Earth Engine, Naïve Bayes (NB), Vegetation Indices (VI), Water Indices, Landsat 8 OLI, Landsat 7

4.1. Introduction

Wetlands are unique ecosystems, rich in both aquatic, terrestrial fauna and flora species diversity. They are found in regions of transition between terrestrial and aquatic environments and are comprised of traits from both (Gxokwe, Dube et al. 2020). Wetlands situated in urban areas provide a range of ecosystems services which play a significant role in various aspects of livelihoods, including water purification, recreational activities, habitat provision for different species, and floods prevention (Alikhani, Nummi et al. 2021). Wetlands are considered as one of the most important green infrastructure because of the range of services they provide (Alikhani, Nummi et al. 2021). However, despite their value, wetlands are currently facing considerable stress due to drastic urbanization. As a result, urban wetlands have been overlooked by monitoring and management programs, precipitating the challenges they face. Wetlands face degradation from several anthropogenic activities such as water contamination, direct distraction because of illegal settlement, biodiversity loss, and the introduction of alien species.

Therefore, over the years, the monitoring and preservation of wetlands have emerged as significant concerns within the field of wetlands ecology (Garg 2015, Orimoloye, Kalumba et al. 2020, Gxokwe, Dube et al. 2022). Monitoring changes in urban wetland communities helps identify shifts in carbon storage, water rentention capacity, and biodiversity, enabling targeted conservation efforts that mitigate climate change impacts (Kayranli, Scholz et al. 2010, Salimi, Almuktar et al. 2021). Some of tools that have proven quite useful in detecting, mapping, and monitoring changes in wetland communities at large scales over long periods of time are GIS and Remote Sensing techniques. The most fundamental tool for wetland management and monitoring is the spatially explicit thematic mapping of wetlands. The classification information plays a critical role in identifying threats and pressures to wetlands and assists in evaluating the effectiveness of wetland conservation policies (LaRocque, Phiri et al. 2020). The production of high quality accurate maps depends on the cost-effectiveness and quality of both ground measured and remotely sensed data (LaRocque, Phiri et al. 2020). Literature reveals that the earliest applications of remote sensing within the GIS field employed aerial photographs to map out wetland areas (Scarpace, Quirk et al. 1981, Williams and Lyon 1997). The past two decades have witnessed a significant increase in the number of studies that utilized data from optical sensors (Zhang, Lu et al. 2011, Peng, Xia et al. 2022, Wen, Mason et al. 2023) and Synthetic Aperture Radar (SAR) (Dabrowska-Zielinska, Budzynska et al. 2014, Munishi and Jewitt 2019, Hu, Tian et al. 2021) technologies for wetland mapping and monitoring.

The Landsat mission boast of being the longest serving sensor mission in the world providing multispectral data. In this regard, Landsat offers temporal consistency for time series assessments at an optimal spatial resolution and global coverage. Landsat's consistent spatial resolution of 30 m is suitable for capturing a wide range of applications including the assessment of LULC change dynamics in wetlands areas. Its multispectral resolution covers the critical sections of the electromagnetic spectrum suitable for a wide range of applications. For instance, the red, near infrared and the shortwave infrared sections are very critical in detecting and mapping typical wetland land cover classes which include vegetation, water, buildings, and bare ground. Above all, these sections of the electromagnetic spectrum when combined through image processing techniques provide even more robust spectral signatures which are sensitive to changes in various LULC types. Specifically, vegetation indices which are spectral derivatives of most of the sections of the electromagnetic spectrum covered by Landsat have been demonstrated to be robust in facilitating accurate and spatially explicit changes in LULC types in various contexts. For Example, Kool, Lhermitte et al. (2022) and (Doughty, Ambrose et al. 2021) utilized vegetation indices to map the changes in a wetland. Vegetation indices have been widely demonstrated to be more robust than standard sensor bands in mapping various LULC types. For instance, Saini (2023) demonstrated that vegetation indices exhibited higher classification accuracies in mapping LULC changes in Dehradum, India. However, various VIs have been generated and tested in various aspects such as detecting and discriminating various wetland species and assessing their productivity. Most of these studies utilized hyperspectral data. Therefore there is a need to assess the relative contribution of various types of vegetation indices in mapping the LULC dynamics in urban wetlands.

The advancement of geospatial technologies, demonstrated by the advent utility of platforms such as GEE, has brought about a new era in wetland classifications and mapping. The Google Earth Engine, which is one of the world's most advanced cloud-based spatial analysis platforms, offers researchers unprecedented access to a vast collection of satellite imagery, and geospatial data sets. By using GEE's processing power and large data archives, researchers can easily analyze large-scale time and spatial variations in wetlands landscapes. This platform also offers robust machine learning algorithms including Naïve Bayes (NB), Random Forest (RF), and Support Vector Machine (SVM). These algorithms are used to accurately detect and map wetland LULC classes. For example, RF was used by Gxokwe, Dube et al. (2022) to map the spatial extent of semi-aridwetlands in the Limpopo transboundary, South Arica to an overall accuracy of 80.55%. Similarly, van Deventer, Linström et al. (2022) utilized RF to map changes in aerial extent of wetland vegetation in a grassland biome to an OA of 91% - 99% . These studies demonstrate that other than the access to the robust Landsat data machine learning algorithms such as RF play a critical role in detecting and mapping complex LULC types associated with wetlands. By leveraging the GEE suite, which integrates large-scale remotely-sensed data from long-standing sensors missions such as Landsat, researchers can explore the intricate dynamics of wetland ecosystems. This approach holds promise in developing a solid basis for evidence-based decision-making for conservation, city planning, or sustainable development.
In this regard, this study aimed to detect and map the changes in an urban wetland LULC types during 2000, 2010 and 2023 using machine learning. Specifically, the study sought to utilize the GEE based random forest classification ensemble in conjunction with Landsat remotely sensed data covering the years 2000, 2010 and 2023 to map the changes in LULC types within the Khayelitsha wetland, in Cape Town South Africa. To address this objective, a comparative assessment of the performance of traditional, enhanced, and water-based vegetation indices was conducted in this study. Finally, the study assessed the magnitude of wetland vegetation fragmentation as proxy for evaluating the magnitude of wetland degradation.

Specifically, this study aimed to compare the performance of various Landsat derived spectral indices based on the GEE-based random forest classifier in mapping landuse land cover changes within an urban wetland during the years 2000, 2010 and 2023. Through the integration of earth observation data, and its derivatives with advanced techniques focusing on wetland vegetation fragmentation analysis, this study is a step towards the development of robust frameworks for wetland monitoring. These frameworks are designed to support the sustainable utilization of wetlands and the conservation of the ecosystem services they provide.

4.2. Methods

4.2.1.Study Area

The wetland area, Figure 4.1, is situated in the Cape Flats lowlands which lies on Malmesbury bedrock with Sandveld Group sediments (Mathenjwa 2017). It is bordered by the Delft South to the west, Silvertown to the north east and Mfuleni settlement & the 9th South African Infantry to the south, east and north, respectively The area topography consists of sand dunes which were deposited as a result of sea-level rise and movement and depositing of sand along the coast which resulted in a retarding river flow. Consequently, this resulted in the formation of the Cape Flats wetlands, including the Khayelitsha wetland (Wall 2010). The climate in this region of the world is influenced by the mass of the Table Mountain and the cold Benguela current of the South Atlantic Oecan. This means that the area experiences warm, dry summers and cold, wet winters. The vegetation found in this region is a combination of Cape Flats Sand Fynbos, and Cape Flats Dune Strandveld.

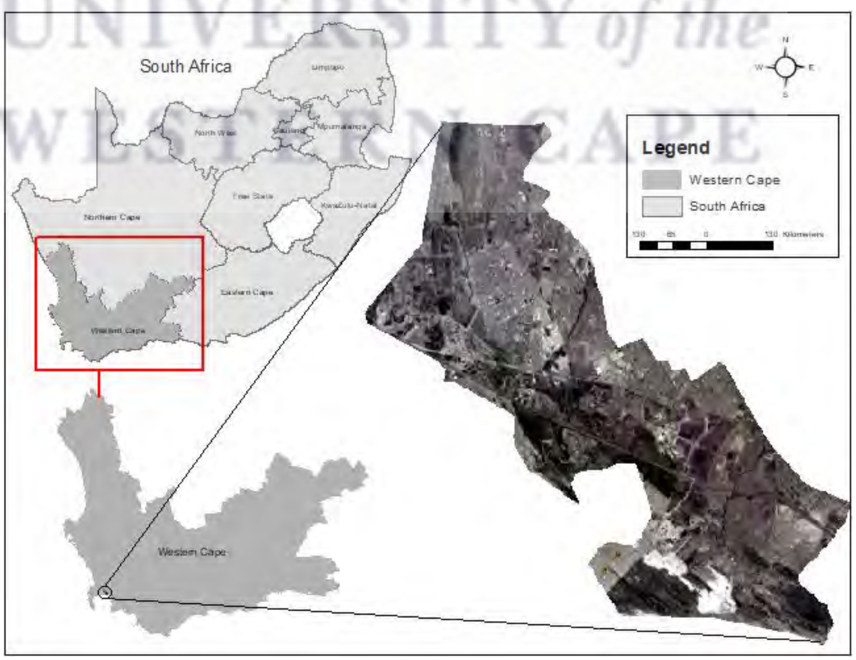


Figure 4.1:Location of the studied wetland area.

4.2.2. Landuse and Land cover data

In this study ground truth data for the LULC classification was obtained through a combination of methods depending on the time period. For the 2000 and 2010 images, Google Earth pro was used as the main tool for digitizing ground truth points. The points were selected carefully to represent the different LULC classes and were utilized as the foundation for training and testing datasets. The ground truth data was then exported from Google Earth Pro to Google Earth Engine and incorporated into the script, allowing for the data to be used when preparing the random forest classifier. For the 2023 image, field sampling was conducted during the summer period (December – April). A handheld Geographical Positioning System (eTrex GPS), which has an accuracy of approximately +-3m, was used to collect the precise location of sampling points. The points were transferred to point maps then incorporated into the GEE script and were used as a basis for the training and testing datasets for the RF classifier. A minimum of 120 points were collected for each LULC class. In GEE, the sum of points in each class were then divided into 80% for training and 20% for the testing dataset for classification.

4.2.3. Remotely sensed data and processing

Remotely sensed data for the years 2000, 2010 and 2023 was extracted from the earth observation sensors highlighted in the table below (Table 4.1). Landsat 7 ETM+ and Landsat 8 OLI Top of Atmosphere (TOA) images were acquired from the Google Earth Engine (GEE) database and were used in this study. GEE offers the capability of processing a stack of images at once instead of relying on a single date image (Gxokwe, Dube et al. 2022). Images that were acquired between December and April, had a cloud cover less than 10% were selected and used in this study. Specifically, images that were acquired between December and April were selected and used in this study to minimize the influence of cloud cover associated with wet Mediterranean climate in Cape Town. To some extent, Google Earth Engine images are atmospherically corrected to remove the influence of the Earth's atmosphere from the satellite image to improve accuracy of reflectance values(Amani, Ghorbanian et al. 2020). The median of the filtered images was calculated to create a composite image for further analysis.

Spectral indices were computed and used in this study. Specifically, vegetation indices, water indices, and built-up area indices were computed and used to classify the images. The vegetation indices were further divided into two groups, Original and Enhanced vegetation indices. The Traditional VIs considered in this study included Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and Green Normalized Difference Vegetation Index (GNDVI), while the Enhanced VIs included Soil-Adjusted Vegetation Index (SAVI), Modified Soil-Adjusted Vegetation Index (MSAVI), Transformed Soil Adjusted Vegetation Index (TSAVI). The set of water related indices were Normalized Difference Water Index

(NDWI), Modified Normalized Difference Water Index (MNDWI), and Normalized Difference Pond Index (NDPI). Lastly, Normalized Difference Built-up Index (NDBI) was also utilized in this study to help with the identification of spatial changes in the built-up environment.

4.2.4. Classification of the spectral data

Land use land cover classification was carried out using the Random Forest (RF) classifier and the image cubes for the respective periods considered in this study. Spectral bands from the Landsat 7 ETM+ and Landsat 8 OLI images were selected as input features and used to train the random forest classifier in this study. For the year 2000 and 2010, Google Earth pro was used to digitize the ground points, leveraging its fine spatial resolution images. In 2023, field surveys were conducted during the summer period (November –April) using a handheld GPS to collect the precise location of the points against each LULC class. Training data was sampled from the region of interest, associating each point with its corresponding LULC class. A total of 550 ground truth data points were used in training the RF algorithm. Ground truth data then divided into parts, 80% training and 20% testing dataset then used to train the random forest classifier. The RF classifier was set with key hyperparameters, with *ntrees* (number of trees) se to 10. The premise for setting *ntrees* to 10 was to strike a balance between computational efficiency and model accuracy. Other key hyperparameters such as *number of features* were set to default values, leveraging the default settings of Google Earth Engine.

4.2.5. Accuracy Assessment

Specifically, the data was split into 80 and 20% training and testing datasets, respectively. The training data was used to classify the images while the testing datasets were utilized to assess the accuracy of the classified map. To assess the classification accuracies the overall accuracy, and producer and user accuracy and kapa statistic were calculated from the generated confusion matrix. Then the OA and the Kappa statistics derived using RF and different vegetation indices were compared.

Table 4-1: Details of Landsat 7 ETM+ and Landsat 8 OLI used for classification.

Year	Satellite	Sensor Id	Layers	Grid cell size (m)
2000	Landsat 7 ETM+	LANDSAT/LE07/C02/T1_TOA	7	30
2010	Landsat 7 ETM+	LANDSAT/LE07/C02/T1_TOA	7	30
2023	Landsat 8 OLI	LANDSAT/LC08/C02/T1_TOA	11	30

The classification procedure in this study was conducted in four stages illustrated in Table 4.2. In the first stage utilized the traditional vegetation indices together with Landsat spectral bands and RF. In the second stage enhanced vegetation indices in conjunction with Landsat 7 ETM+ spectral bands were utilised. Then in the third stage water indices, Landsat 7 ETM+ spectral bands were employed. Lastly, traditional VIs, enhanced VIs, water indices, and Landsat 7 ETM+ & Landsat 8 OLI spectral bands were all combined and used to map the LULC types in the wetland.

Table 4-2: Details on the combinations of spectral variables used in the classification procedures.

Analysis stage	**Variables**	**Spectral indices used**
1: Traditional VI	Traditional VI + Bands	NDVI, EVI, GNDVI
2: Enhanced VI	Enhanced VIs + Bands	SAVI, MSAVI, TSAVI
3: Water Indices	Water indices + Bands	NDWI, MNDWI, NDPI
4: Combined	Traditional VI +Enhanced VI+ Water indices + Bands	NDVI, EVI, GNDVI, SAVI, MSAVI, TSAVI, NDPI, NDBI

VI is Vegetation Indices, NDVI is Normalized Difference Vegetation Index, EVI is Enhanced Vegetation Index, GNDVI is Green Normalized Difference Vegegtation Index, SAVI is Soil Adjusted Vegetation Index, MSAVI is Modified Soil Adjusted Vegetation Index, TSAVI is Transformed Soil Adjusted Vegetation Index, NDWI is Normalized Difference Water Index, MNDWI is Modified Normalized Difference Water Index, NDPI is Normalized Difference Pond Index, NDBI is Normalized Built-Up Index

4.2.6.Landscape metrics

To enhance the understanding of wetland landscape fragmentation, results from the combined classification for the years 2000, 2010, and 2023 were utilized to compute fragmentation statistics. The classified images were then imported into QGIS Desktop 2.18.2 to calculate landscape metrics. Specifically, five class level landscape metrics including number of patches (NP) edge length (EL), mean patch area (MPA), edge density (ED) and Patch Density (PD) (Table 4.3). Test of significant differences were conducted to assess the magnitude of fragmentation change detected by each of the seven metrics across the three years.

Table 4-3:Abbreviations and short descriptions of landscape metrics used.

Landscape Metrics	Abbreviation	Description
Number of Patches	NP	Represents the number of patches identified in each class; (no.)
Patch Density	PD	Is calculated as the number of patches of the similar patch types divided by the total landscape area (no. /100 ha)
Mean Patch Area	MPA	Is a fragmentation index. A landscape with smaller MPA for a certain patch is considered
Edge Length	EL	The sum of all the edges of a specific class (m)
Edge Density	ED	Sum of all edges in each grid divided by the total landscape area (m/ha)

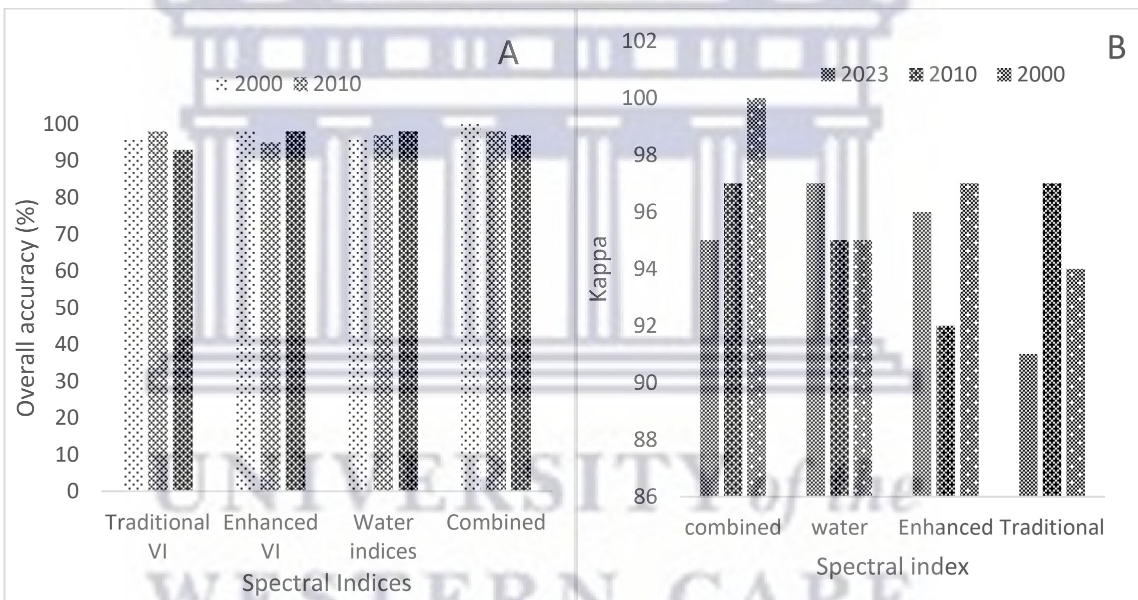
4.3. Results

4.3.1. Comparing the performance of Different types of spectra indices in mapping wetland LULC types during the year 2000,2010, and 2023.

Results showed that when traditional vegetation indices were used, overall accuracies of 96%, 98%, and 93% for the years 2000, 2010, and 2023, respectively. Then second method entailed conducting LULC classification using enhanced vegetation indices (SAVI, MSAVI, and TSAVI) exhibited overall accuracies of 98%, 95%, and 98% through the years 2000, 2010, and 2023, respectively. Even though the first two classification methods performed exceptionally well, the second method came out superior with a mean overall accuracy of 97%, while the first method obtained a mean overall accuracy of 95.3%. This means that enhanced vegetation indices yielded a slightly better suited to classify wetland LULC classes in urban wetlands. Although the first method performed better, both methods presented acceptable producer and user accuracy values ranging from 70% - 100% on all classes through the study period.

Water-based vegetation indices performed similarly to enhanced vegetation indices exhibiting overall accuracies of 96%, 97%, and 98% for the years 2000, 2010, and 2023, respectively. The application of these indices in the 3rd analysis stage improved the classification of water bodies throughout the years. This is reflected by user accuracy and producer accuracy values of 100%. When all the different spectral indices were combined with bands, overall accuracies of 100%, 98%, and 97% were attained for the years 2000, 2010, and 2023 respectively. Accuracy assessment results reveals constantly high UA and PA throughout the years, ranging from 91% to 100% for all the LULC classes. The mean kappa results in Figure 4.2 (d) showed that the combined method performed better than the others with an average kappa value of 97.3%. This suggested that the classification results from the 4th method are reliable in characterizing different wetland classes over time, therefore strengthening the credibility of the classification outcomes. Based on the optimal classification results of the 4th method, it was carried over to the next phase of the paper where it was used to compile highlighting changes in LULC of the different wetland classes

Overall, there was no significant difference ($p > 0.05$) in the performance of different types of vegetation indices in mapping the LULC types across the years 2000,2010, and 2023. However, combined data exhibited slightly higher OA and kappa statistic across all the years (Figure 4.2 (a & b). This suggests that all vegetation indices could accurately detect and map the changes of LULC types in the wetland although combining all the data exhibits better accuracies.



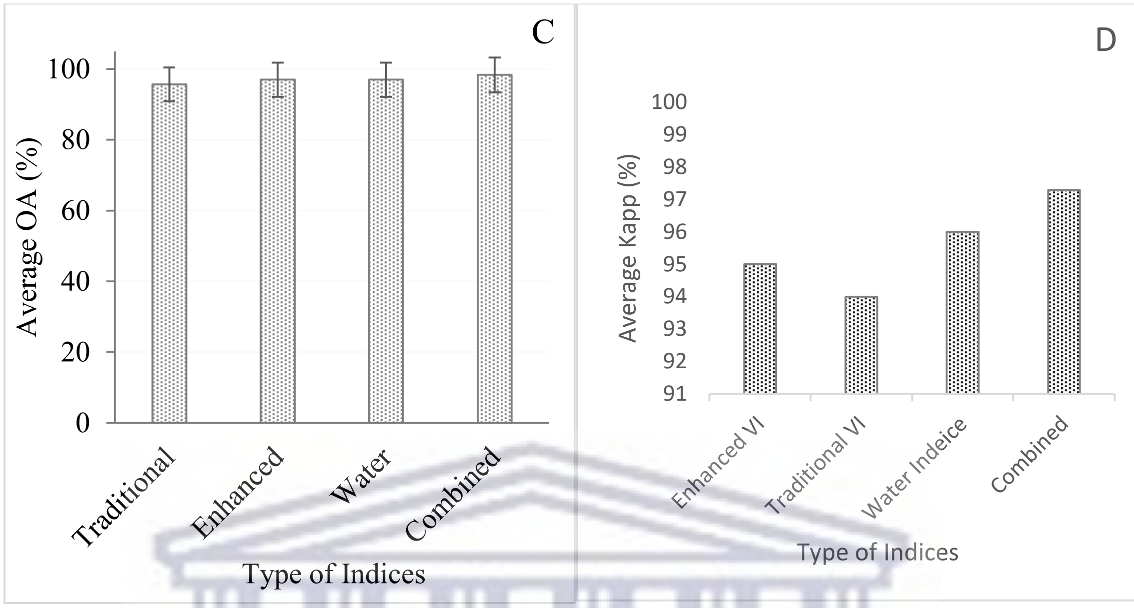


Figure 4.2: Classification (a) Overall accuracies (b) kappa statistics and comparison of classification methods(c) mean OA and (d) mean kappa statistics derived using different types of vegetation indices.

4.3.2. Comparing the wetland LULC types during the year 2000,2010, and 2023 using combined data.

Producer accuracy (PA) and User accuracy (UA) results from the combined data show that overall, the combined classification method achieved acceptable UA and PA values. The PA ranged between, 95% - 100% for vegetated areas and 90% - 100% for bare land, while the UA ranged between 95% - 100% for vegetated areas and 94% - 100% for bare land throughout the study period (Figure 4.3). Results reveal that the UA and PA values attained in this study did not show that much significant variation for the classes, except for the built-up areas. The producer's and user's accuracy for the built-up area's class ranged between 66% - 100% and 77% - 100% respectively. The user's and producer's accuracy for water bodies both ranged between 0% - 100%.

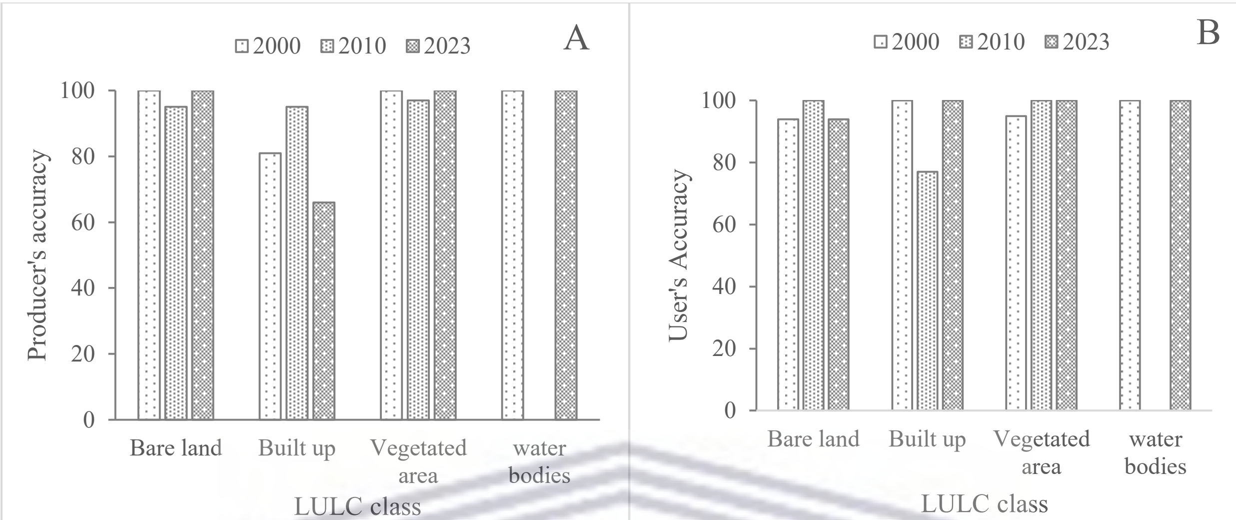


Figure 4.3: LULC user accuracy (UA) and producer accuracy (PA) derived using combined data.

Figure 4.4 illustrates the spatial distribution of LULC types in the wetland in 2000,2010, and 2023. The area covered by bare land dropped from 2668.4 ha in the year 2000 to 1298.02 ha in 2023. Results from the classification revealed that the area covered by vegetated area showed an increase from 2000 (464.6 ha) to 2010 (2316.6 ha), then decreased again between 2010 and 2023 (2032 ha) (Figure 3.4). The one class that showed an exponential increase between 2000 and 2023 was the built-up area. The RF classifier recorded that built up area increased from 2568.4 ha in 2000 to 3500 ha in 2023. The area covered by surface water bodies increased from the year 2000 (21.5 ha) to 2023 (96.7 ha).

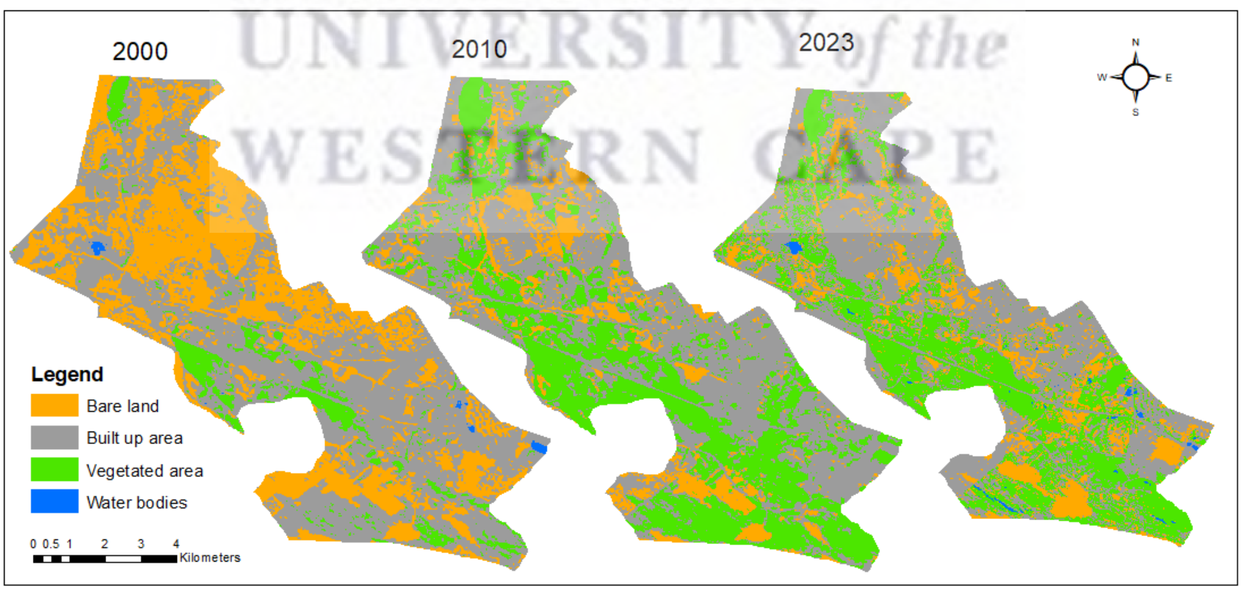


Figure 4.4: LULC classification using spectral bands, spectral indices and Random Forest classifier

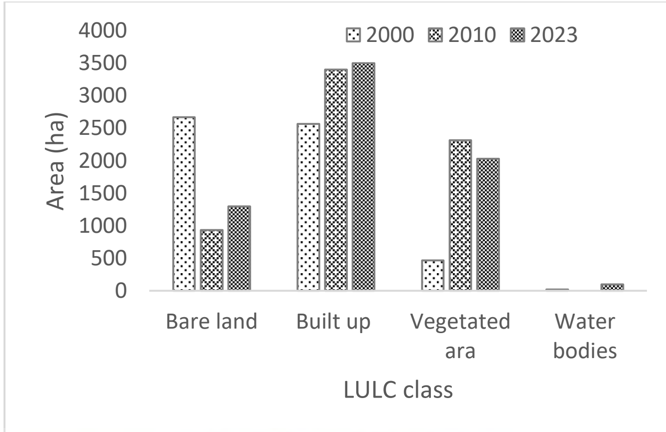


Figure 4.5: Area covered by different LULC types in the wetland in 2000,2010, and 2023.

4.3.3. Changes of fragmentation metrics in Khayelitsha Wetland

Table 4.4 shows the fragmentation statistics of wetland vegetation during the 2000, 2010, and 2023 periods. The number of patches generally increased through the years. The number of vegetation patches (NP) increased from 261 in 2000 to 381 patches in 2023, while those of built-up areas showed a decrease from 325 patches in 2000 to 257 patches in 2010, then increased again to 297 patches in 2023. The Mean Patch Area (MPA) for most classes declined through the years, except for bare land whose value remained constant. Specifically, the MPA for vegetation decreased from 42 in the year 2000 through 31.1 in 2010 and then 21.8 in 2023. Meanwhile, the MPA for built up areas significantly increased from 35.73 during the year 2000, to 51.71 in 2010 and finally increased to 44.35 in 2023. Both Edge Length and Edge Density values presented a pattern of decline during the first leg of the study period (2000 – 2010), then a slight increase during from 2010 – 2023.

Table 4-4: Landscape metrics computed for different classes during the 2000, 2010, and 2023 period.

Class	***EL***	***ED***	**PD**	***NP***	***MPA***
Bare_land (2000)	2300	0.03	6.18E-05	4	10508
Built_up (2000)	12838	0.19	0.005	325	35.73
Vegetated (2000)	9820	0.15	0.004	261	42
Water_bodies(2000)	338	0	0	31	4.93
Bare_land (2010)	2300	0.04	6.22E-05	4	10508
Built_up (2010)	12356	0.19	0.003	257	51.71
Vegetated (2010)	8210	0.13	0.004	289	31.11
Water_bodies(2010)	0	0	0	0	0
Bare_land (2023)	2300	0.04	6.28E-05	4	10508
Built_up (2023)	14028	0.22	0.004	297	44.35
Vegetated (2023)	10534	0.17	0.005	381	21.77
Water_bodies(2023)	358	0.005623537	0.000612	39	4.05

4.4. Discussion

Accurate detection and monitoring wetland land use land cover is an important aspect to wetland management and conservation. Advances in data analysis tools provide unique opportunities to improve the detection and monitoring of urban wetlands of various sizes not possible with traditional remote sensing techniques. In this regard, this study aimed to assess the performance of various Landsat derived spectral indices in detect and spatially quantifying the LULCs and their fragmentation dynamics in the Khayelitsha wetland during the years 2000,2010 and 2023 using rand forest in GEE.

4.4.1. Assessing the performance of different vegetation indices in classifying wetland LULC changes

The classification methods employed in this study utilized different combinations of vegetation indices, built-up area indices and water-based indices in conjunction with Landsat 7 ETM+ and Landsat 8 OLI spectral bands.

Results from the traditional and enhanced vegetation indices methods reveal that enhance VIs yielded a higher mean overall accuracy of 97% compared to the traditional classification method with a mean overall accuracy value of 95.6%. This could be attributed to the sensitivity of enhanced VIs in addressing certain limitations found in traditional VIs. Enhanced VIs were specifically designed to address issues such as soil background noise and atmospheric influences which directly affects the accuracy of traditional VIs (Taddeo, Dronova et al. 2019). This was reflected in the OA and Kappa stats attained for these methods. Consequently, the improved performance of enhanced VIs highlights their ability to produce more robust maps of vegetation parameters compared to traditional VIs. In a study by da Silva, Salami et al. (2020) enhanced vegetation indices, SAVI, were found to be the best indices to determine agricultural areas, planted forests, and waterbodies. Although all the methods performed optimally, the combined method performed superior to the other classification method overall. This could be attributed to the harmonious nature of the different indices employed. Bands on their own were designed to capture single entities of the environment such as chlorophyll, while vegetation indices capture more than one entity in the environment and combines more spectral features (da Silva, Salami et al. 2020). Each of the vegetation indices and water indices capture different aspects of the LULC classes which reflects different characteristics of the surrounding environment. By combining vegetation, water, and built-up area indices, this method offers a more comprehensive understanding of the environment. Furthermore, random forest used in conjunction with the combined method is well equipped to handle complex relationships within multi-dimensional data. The improved performance of the combined method underscores its ability to produce more accurate and robust classifications, making the method preferable over other methods.

4.4.2. Assessing RF LULC classification performance in the Khayelitsha wetland during 2000, 2010, 2023 period

Results from the classifications revealed that the most dominant LULC type in the year 2000 was bare land (3718 ha), then the area covered by bare land showed a sudden decrease to 906.8 ha in 2010, and 1007.9 in 2023. The sudden decrease in the bare land area can be attributed to an increase in rainfall which resulted in vegetation expanding to areas classified as bare areas in the year 2000. The built-up areas continued to increase in terms of spatial coverage with time. Specifically, built-up areas increased from 2062.81 ha in 2000 to 2501.82 and 3071.27 ha in 2010 and 2023, respectively. This could be attributed to anthropogenic activities such as the construction of houses, paving, roads, and informal settlements as wetland vegetated areas decreased. Built-up areas have been reported to be the LULC class that shows tremendous growth in a number of wetland monitoring studies, owing to the ever increasing urban population (Qin, Xiao et al. 2017, Thamaga, Dube et al. 2022). Specifically, vegetated areas increased from 853 in 2000 to 3244.7 in

2010. However, during the last lag, the vegetated area dropped by 20.16%. The images used were collected during the summer period (November – April) during which the study area experience less precipitation to avoid the influence of cloud cover. During the summer period, the area coverage of surface water is limited due to various factors such as evaporation and drainage. Some anomalies were noted with classification as the results did not pick up the area covered by water bodies in 2010. Subsequently, the area covered by water bodies increased in spatial extent from 20 ha to 25 ha in the years 2000 to 2023. This could be attributed to imbalance due to the variations in the number of training and testing datasets across the three years. A study by Amani, Brisco et al. (2020) highlight how unbalanced training data affects classification results, with underrepresented classes typically being associated with changes in the sensitivity of the algorithm in detecting and characterizing those classes. In the study area, the limited spatial coverage of water bodies resulted in a lower number of training and testing point samples for the water bodies class. As a result, there could have been bias introduced by this imbalance in the distribution of the data towards classes that had more training and validation points. This would have contributed to the areal extent covered by the water bodies class. Overall, the results from the classification show that there has been a decline in the wetland area during the period of this study. Thamaga, Dube et al. (2022) obtained similar results in a study to evaluate the impact of LULC changes in unprotected wetland ecosystems.

4.4.3. Landscape fragmentation analysis

Results showed that patch density (PD) statistics steady out during the last lag of the study period (2010 – 2023), which suggest that the level of fragmentation in the wetland was moderate during this period. This pattern was further explained by the values of edge density as they also exhibited a similar pattern of a decline from 2000 – 2010, then steady values from 2010 – 2023. The concurrent increase in edge density from 2010 – 2023 is consistent with the claim made by Tomaselli, Tenerelli et al. (2012) that higher edge density is a result of increasing fragmentation. The values obtained from PD, NP, and ED reveal that the wetland LULC types endured sever fragmentation during the study period. In this study, most Landscape Division (LD) values are high for all the classes, ranging from 0.9 -1, except for the water bodies class in the year 2010. This is reflective of a high degree of fragmentation for all the different LULC classes during the study period. Table 4.4 showed that overall, the mean patch area of all the classes decreases as the years progress, signifying that some degree of fragmentation occurred in the wetland through the study period. This is further supported by the values of NP continuously increased for all the classes from 2000 – 2023. However, the built-up area class showed a slight drop in NP in 2010, then increased again after.

4.5. Conclusion

This study aimed to assess the performance of various Landsat derived spectral indices in detect and spatially quantifying the LULCs and their fragmentation dynamics in the Khayelitsha wetland during the years 2000,2010 and 2023 using rand forest in GEE. Based on the findings of this study it can be concluded that

- Leveraging Google Earth Engine and random forest yielded optimal OA of 100%, 98%, and 97% for the years 2000, 2010, 2023 respectively and kappa stats of 1, 0.97, and 0.95 for the years 2000, 2010, and 2023 respectively using the combined classification method as the optimal spectral classification method.
- Combining bands and all vegetation indices slightly outperformed the traditional, enhance and water based spectral indices in mapping wetland LULC types during the years 2000, 2010, and 2023,
- The MPA, PD, ED showed that wetland vegetation was significantly getting reduced while built-up areas were increasing.

The study has determined that understanding the fragmentation model of urban wetland is important for analyzing the spatio-temporal dynamics of precious wetland ecosystems. These findings highlight the critical need for well-informed conservation and management measures to maintain the biological integrity of urban wetlands as urbanization continues to have an impact on these ecosystems.

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5. Synthesis

5.1. Introduction

Wetlands are regarded as the kidneys of the environment as they provide a myriad number of important ecosystem services. In urban areas, wetlands contribute to the living conditions by providing services such as carbon sequestration, water purification, and providing habitat for fauna and flora (Alikhani, Nummi et al. 2021). However, these precious ecosystems are still facing a lot of challenges that leads to their deterioration, especially within the urban context. There is alarming evidence shows that wetlands have undergone serious degradation over the past decades (Jin and Mountrakis 2022). In a recent study on wetland resources in South Africa, Adeeyo, Ndlovu et al. (2022) reported that about 48% of the wetlands had a low level of protection, thus making them susceptible to threats. Another study by Gangat, Van Deventer et al. (2020) showed that 58% of the wetlands found in the Umfolozi catchment, South Africa have undergone irreversible transformation. To prevent further destruction of wetland areas, it is essential to develop robust methods for inventorying their spatial distribution, and LULC types. This information is important for informed decision- making and formulation of long-term strategies for wetland conservation. However, because of their unique compositions and geographical locations, some wetlands are inaccessible, making it hard to conduct traditional field surveys. This has necessitated the adoption of innovative wetland monitoring techniques such as remote sensing and GIS. These technologies make it possible to observe large inaccessible areas without the need for physically presence. In this regard, this study sought to estimate changes in the spatial extent of the Khayelitsha wetland between the years 2000, 2010 and 2023 using freely available remotely sensed data. This main objective was addressed based on the following specific objectives;

1. To systematically review literature of the literature on the progress, gaps, and opportunities in the application of earth observation data in assessing and mapping changes in the spatial extent and productivity of wetland species.
2. Assess the performance of Support Vector Machines, Naïve Bayes and Random Forest machine learning algorithms mapping wetland land use land cover types during the years 2000, 2010, and 2023.
3. Compare the performance of various vegetation Indices in classifying urban wetlands during the years 2000, 2010, and 2023 and assess the LULC fragmentation, thereof.

5.2. Highlights of the findings

5.2.1. Conducting a systematic review of the literature on the progress, gaps, and opportunities in the application of earth observation data in assessing and mapping changes in the spatial extent and productivity of wetland species.

Systematically reviewing literature on the remote sensing of wetlands revealed that showed that the Landsat series of satellites, and aerial photographs were the most extensively used sensors in wetland remote sensing. The review highlighted that within wetlands ecology, remote sensing data was utilized to track vegetation and water quality and to identify shifts in wetland size and health over time. Moreover, the reviewed literature also showed that there are common challenges that arise with the utility of remotely sensed data in wetlands, and these include the need for refined data processing and analysis techniques, the integration of diverse data sources, and the establishment of standardized methodologies to enhance the effectiveness of wetland mapping and monitoring. Overall, this literature review offers a comprehensive overview of the use of remotely sensed data for wetland monitoring and underscores the potential of these technologies for improving the management and conservation of these important ecosystems in developing countries.

5.2.2. Assessing the performance of Support Vector Machines, Naïve bayes and Random Forest machine learning algorithms mapping wetland land use land cover types during the years 2000, 2010, and 2023.

The study assessed the utility of three machine learning algorithms namely, random forest, support vector machine, and naïve bayes. The overall accuracy and kappa stats for these algorithms showed that random forest outperformed the other algorithms. There were no significant performance differences between SVM and RF even though RF outperformed SVM and NB on average. Random forest attained mean accuracy of 95% and a mean kappa value of 93%, while SVM had a mean overall accuracy of 93% and a mean kappa value of 88%. The NB attained the lowest mean overall accuracy and kappa of 29.6% and 12% respectively Because RF's robustness, it was carried over to the next phase of classification which was aimed at assessing the performance of vegetation indices in accurately classifying wetland LULC classes. Results from the classification showed that the Near-infrared and Shortwave Infrared bands in Landsat 7 ETM+ and Landsat OLI were the most optimal band in characterizing different wetland land use land cover classes

5.2.3. Comparing the performance of various vegetation Indices in classifying urban wetlands during the years 2000, 2010, and 2023 and assess the LULC fragmentation, thereof

Results from the assessment of traditional vegetation indices (NDVI, EVI, GNDVI) against enhanced vegetation indices (SAVI, MSAVI, TSAVI) showed that overall enhanced vegetation indices performed slightly better that traditional vegetation indices even though there were not significant differences in the accuracies. Traditional vegetation indices attained an average overall accuracy and an average kappa of 96% and 94% respectively, while the enhanced vegetation indices obtained average overall accuracy and average kappa of 96% and 95% respectively. Water based vegetation indices presented results similar to those of the enhanced vegetation indices with an average overall accuracy and average kappa of 97% and 96%, respectively. However, the method that performed optimally better than all other methods was the combined method which leveraged the capabilities of different Landsat spectral bands in conjunction with vegetation and water indices and the random forest classifier. The combined method attained an average overall accuracy of 98% and an average kappa of 97.3%.

5.3. General Conclusion of the study

This study was aimed at conducting a comprehensive assessment of remote sensing technologies such as Google Earth Engine in characterizing different wetland land use land cover changes in urban wetland. In synthesizing the conclusions drawn from chapters 2, 3, & 4, it can be drawn than an understanding of the spatial changes in LULC classes with urban wetlands has been achieved. Chapter 2 served as a foundation by conducting a systematic literature review, pointing out trends, and highlighting the increased interest in wetland remote sensing over the past decades. Chapter 3 followed by utilizing some of the technologies identified as optimal for characterizing changes in wetland LULC classes in chapter 2 such as Landsat imagery and machine learning algorithms (random forest, support vector machine and naïve bayes). Results from chapter 3 proved the significance of Google Earth Engine in wetland LULC classification while highlighting the need for informed conservation measures. Chapter 4 followed suit by focusing in the utility of spectral indices and random forest in understanding wetland fragmentation dynamics. Overall, results from this study underscores the importance of a multidimensional approach which comprises of advanced remote sensing technologies and machine learning tools in comprehensively understanding change dynamics within urban wetlands in face of rapid urbanization. Insights from these chapters emphasize the need for well-informed conservation measures.

5.4. Implication of the study

The information from this study provided valuable information pertaining to the monitoring, mapping and fragmentation of wetland ecosystems within an urban context. The study highlighted that remote sensing data is a valuable tool that can be used to save wetland managers and policy makers some time and money when it comes to assessing changes in the spatial extent of wetlands. The findings of this study highlight the critical need for well-informed conservation and management measures to maintain the biological integrity of Khayelitsha wetlands as urbanization continues to have an impact on these ecosystems. Information provided in this study can be used to inform the South Africa National Wetlands Inventory which seeks to have an updated map of all wetlands throughout the country.

5.5. Challenges and limitations of the study

The study yielded very insightful results, but it also important to acknowledge some its shortcomings or limitations. Firstly, the low spatial coverage of the water bodies class meant that the class had fewer training data during the stratified random sampling stage. This might have introduced biases to the classification results, causing those classes with well-represented data to get higher classification accuracies. Furthermore, the study relied on satellite images obtained during the dry summer season and this made it a bit hard to detect wetland regions, especially small sporadically flooded systems. The application of landscape metrics measures on their own might have oversimplified the intricate ecological processes that influence the pattern, spatial distribution, and fragmentation of wetlands. The lack of ecological context of the measures restricts the ability to fully comprehend the causes of the trends noticed. In spite of these drawbacks, the research provides a foundation for further investigations into wetland landscape dynamics, prompting future research to integrate additional ecological variables and consider a broader spectrum of land cover classes when assessing wetland fragmentation.

5.6. Research gaps and future opportunities

Several gaps have been identified from the results of this study in the context of applications of remote sensing technologies in wetland studies:

- There is still a considerable gap in research focusing on the estimation of the LAI as a proxy for monitoring wetland vegetation productivity and health. The estimation of the LAI concerning wetland management has not received much attention from the research community, yet it is one of the most critical essential biodiversity variables (EBVs) for assessing changes in ecosystem function and structure.
- Few studies assessed the performance of the recently launched sensors such as Landsat 9 and Sentinel 2 MSI, PlanetScope, and UAV-borne sensors in mapping wetland attribute variations

through space and time. These sensors have robust spatial-spectral and radiometric features that could be suitable for wetland extent and vegetation mapping.

- While remote sensing has been widely used for wetland classification and mapping, there are still challenges in accurately identifying and mapping different types of wetlands, such as marshes, swamps, and bogs, due to their complex and dynamic nature. Developing improved algorithms and techniques for wetland classification and mapping, especially at fine spatial resolutions, is an ongoing research need.
- Remote sensing data, especially high-resolution data, can be expensive and may not always be readily accessible, particularly for researchers in developing countries or regions with limited data availability.
- To counteract the challenge of relying on satellite images obtained during the dry summer season, especially when detecting small sporadically flooded wetland systems, future studies can utilize mutli-temporal satellite imagery from different seasons and incorporate Synthetic Aperture Radar data which can penetrate through clouds to provide more information on surface moisture levels. Addressing these issues will help better inform wetland policy makers and managers on the current state of wetlands and a collaboration with researchers will result in advancements in wetland conservation.

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