Understanding land use and land cover dynamics and their effects on the surface water resources at Letaba catchment in Limpopo, South Africa

by

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Abstract

This work investigates the intricate dynamics of land use and land cover (LULC) due to pressures from population growth and environmental changes. The implications of these changes are particularly significant for water security, especially in semi-arid and water-scarce regions. Leveraging on the capabilities of Google Earth Engine (GEE), this comprehensive study seeks to unravel the spatial, seasonal, and long-term impacts of LULC changes on surface water bodies and water quality within these vulnerable regions. By exploring the interconnectedness of land dynamics and water resources, this research contributes valuable insights essential for sustainable water management in the face of evolving environmental conditions. This research encompasses a multi-faceted exploration of the Letaba catchment, offering a comprehensive understanding of its evolving LULC dynamics over a 31-year period (1990, 2000, 2010, 2021). LULC changes were classified using the random forest (RF) computed in GEE. The method of using remote sensing, especially GEE effectively mapped LULC dynamics with satisfactory accuracies ranging from 93 to 99% within four timeframes. The analysis unveils a noteworthy decline in natural forests (-3%), grasslands (-3%), bare surfaces (-2%), and water bodies (-4%), when compared with increases in shrublands (24%), plantations (41%), and built-up (47%) areas. This transformation underscores the imperative for adaptive strategies, with a particular focus on the pivotal role of climate-smart agriculture in harmonizing ecosystem services and human well-being. Further, the research assesses the effectiveness of Sentinel-2-derived spectral indices, such as Normalized difference water index (NDWI), Modified normalized difference water index (MNDWI), and Sentinel 2 water index (SWI), in conjunction with landscape metrics, to delineate the spatial and seasonal variations of surface water between 2017 and 2022 in GEE. Notably, remarkable overall accuracies ranging from 96% to 100% were achieved across both dry and wet seasons. This unveils surprising seasonal fluctuations, challenging conventional assumptions about water resource availability and advocating for adaptive water resource management strategies that account for such variabilities. Furthermore, the study delves into the impact of LULC alterations on water quality parameters. By integrating in-situ measurements with Sentinel 2 remote sensing data, strong correlations between LULC, spectral bands, water indices, and key water quality variables are revealed. These findings confirm the pollution status of the catchment, accentuating the urgent need for effective land planning and management. This not only challenges conventional notions about water

resource availability but also underscores the necessity of adopting adaptive management approaches and sustainable strategies to address changing climatic conditions and human impacts on water quantity and quality in semi-arid tropical environments.

Keywords: Catchment health; Cloud computing; land use planning, remote sensing; water quality and quantity

Declaration

I declare that the thesis submitted to the University of Limpopo, for the degree of (Doctor of philosophy & Geography and Environmental Science) has not previously been submitted by me for a degree at this or any other university; that it is my work in design and in execution, and that all material contained herein has been duly acknowledged.

Preface

This research study was conducted in the Department of Geography and Environmental Studies, University of Limpopo, South Africa, from April 2021 to December 2023, under the supervision of Prof Timothy Dube, Prof Kingsley Kwabena Ayisi and Marubini Reuben Ramudzuli.

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

Makgabo Johanna Mashala signature

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

Prof Timothy Dube signature……

Prof Kingsley Kwabena Ayisi signature……

Prof Marubini Reuben Ramudzuli signature……

Scientific Publications, manuscripts, and Conferences

The following published papers and manuscripts include my Supervisor. My contribution was greatest and appropriate to be the first author in all cases and in the order that they are presented.

1. **Mashala, M.J.;** Dube, T.; Mudereri, B.T.; Ayisi, K.K.; Ramudzuli, M.R. A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments. Remote Sens.2023, 15, 3926. https://doi.org/10.3390/rs15163926.
2. **Mashala, M.J.,** Dube, T., Ayisi, K.K., and Ramudzuli, M.R., 2023. Using the Google Earth Engine cloud-computing platform to assess the long-term spatial temporal dynamics of land use and land cover within the Letaba watershed, South Africa, Geocarto International, 38:1, 2252781. https://doi.org/10.10101060480/9.2023.2252781.
3. **Mashala, M.J.,** Dube, T. and Ayisi, K.K., 2025. Seasonal and spatial dynamics of surface water resources in the tropical semi-arid of the Letaba catchment: Insights from Google Earth Engine, Landscape Metrics, and Sentinel-2 Imagery**.** *Hydrology* (Hydrology-3468201) (under review).
4. **Mashala, M.J.,** Dube, T., and Ayisi, K.K., 2025. Using Sentinel 2 to understand the effects of land use and land cover on surface water quality in Letaba catchment, South Africa. *GEOMETICA (GEOMAT-D-25-00046.)* (submitted).

Conferences

1. Using the Google Earth Engine cloud-computing platform to assess the long-term spatial temporal dynamics of land use and land cover within the Letaba watershed, South Africa. Presented at the 5th Global Change Conference oral presentation was held from the 30th of January to the 2nd of February 2023, at the University of Free State, South Africa.
2. Using Sentinel 2 to understand the effects of land use and land cover on surface water quality in Letaba catchment, South Africa. Presented at the NRF-SAEON 15th GSN Indibano Conference oral presentation was held from the 23rd to 26th October 2023, SARAO, Cape Town, South Africa.
3. Assessment and monitoring of land use and land cover on surface water quality in Letaba catchment, South Africa. Presented at the 7th Water Institute for South Africa Youth water

professional Conference oral presentation was held from the 8-10 November 2023 at Protea Hotel, Stellenbosch, South Africa.

Dedication

This thesis is devoted to the memory of my late father, Selati Michael Mashala, and my brother Choene Mashala, who departed too soon to witness this accomplishment. They are dearly missed, and I often think of how much they would have loved to see this. I also dedicate this to my mother, Violet Malehu Mashala, and the rest of my family.

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I extend my gratitude to Kabisheng Mabitsela, Mpho Phetla, and Lesetsa Lekgothoane for their assistance in field data collection. I would also like to acknowledge the University of Limpopo, particularly the Geography and Environmental Studies department, for providing the necessary resources.

My family, especially my mother Violet Mashala, my brothers Tshepo Mashala and Mphihla Mashala, and my sister Makoena Mashala, deserve special thanks for their unwavering support, patience, and encouragement throughout my studies.

To my friend Mangana Berel Rampheri and Dr Queen Mogale thank you for words of encouragement, and emotional support and for walking this journey with me you have really been true friends.

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1. CHAPTER ONE

1.1. General introduction

Freshwater, a critical global resource indispensable for ecological balance and socio-economic advancement, faces severe threats due to human-induced activities within watersheds (Liping et al., 2018). Land use practices such as agriculture, mining, industries, and settlement significantly impact the quality and quantity of freshwater resources, raising concerns for both environmental sustainability and human well-being (du Plessis et al 2015; Kibena et al., 2014; Namugize et al., 2018). In particular, the degradation of water quality and quantity resulting from changes in land use and land cover (LULC) poses a substantial challenge, especially in semi-arid and water-scarce regions. LULC, a dynamic interplay of human activities and natural features on the Earth's surface, involves the production of goods and services (Masocha et al., 2018; Tahiru et al., 2020). This study addresses the urgent need to comprehensively understand the intricate relationship between LULC changes and water quality and quantity, specifically in regions grappling with the escalating pressures of population growth and environmental shifts. The implications of these alterations are far-reaching, influencing not only the availability of freshwater resources but also the ecological health of aquatic ecosystems.

The Department of Water Affairs (2011) defines water quality as a complex interplay of chemical, biological, and physical characteristics that determine its suitability for various uses. Disturbances in LULC, including deforestation, urbanization, and agricultural intensification, contribute to shifts in water quality parameters, thereby posing significant challenges to water resource management (Huang et al., 2015; Zhang et al., 2019). Understanding these dynamics becomes paramount as we confront the looming global water scarcity crisis predicted by UN-Water (2011), which projects that 1.8 billion people will face water scarcity by 2025.

In the context of South Africa, a water-scarce nation grappling with the deterioration of 82% of its main river ecosystems (DEAT, 2009), the urgency to address these challenges becomes even more apparent. However, despite the critical importance of understanding the nexus between LULC changes and water quality, there remains a significant research gap. Traditional monitoring approaches, primarily reliant on labor-intensive laboratory analyses, often overlook the role of LULC changes as a substantial source of water pollution. This oversight hampers the development of effective management strategies.

In response to this gap, this study focuses on the adoption of Google Earth Engine (GEE) platforms, presenting a novel approach to address the limitations of traditional monitoring methods of remote sensing softwares. Image processing and mosaicking tasks are time-intensive, especially when dealing with large-scale projects (Gorelick et al., 2017; Kumar and Mutanga, 2018). The cloud-computing platform GEE offers a convenient solution for accessing remote sensing data on desktops, facilitating rapid analysis using sophisticated processing techniques (Hamdi et al., 2018; Sidhu et al., 2018; Mashala et al., 2023a). GEE, a cloud-based platform, offers unprecedented access to vast geospatial datasets and analytical capabilities, presenting an opportunity to enhance the monitoring of LULC changes and their impacts on water quality and quantity at regional and global scales. Despite its potential significance, the need to adopt GEE platforms is not explicitly outlined in the existing literature, marking a critical knowledge gap that this study seeks to address.

Therefore, this research aims to provide a razor-sharp focus on the specific problem of understanding how LULC changes in semi-arid and water-scarce regions impact water quality. It underscores the importance of adopting GEE platforms as an innovative tool to address the limitations of conventional monitoring methods. This study seeks to establish a robust foundation for effective water resource management, emphasizing the necessity of a comprehensive understanding of the intricate interactions between land use dynamics and water quality in the face of global water scarcity challenges.

1.1 Aim and objectives

1.1.1 Aim

The aim of this study is to evaluate LULC dynamics and their effects on water resources from 1990 to 2021 at Letaba catchment South Africa.

1.1.2 Objectives of the study

I. To investigate long-term spatial and temporal changes of LULC within the Letaba catchment.

II. To delineate surface waterbodies found within the Letaba catchment using multi-source remotely sensed data.

III. Estimate the effects of land use and land cover on the water quality using the in-situ and remotely sensed data.

1.2 Description of the study area

The study took place within the Letaba watershed, positioned between longitudes 30°0′ and 31°40′ East and latitudes 23°30′ and 24°0′ South, located in the Limpopo province of South Africa (as depicted in Figure 1.1). Covering an area of 1,451,864 hectares, the Letaba watershed experiences an average annual evapotranspiration ranging from 1100 mm to 1300 mm. The region receives rainfall between 300mm and 400mm, with an annual runoff of 574 million cubic meters. The mean annual temperature ranges from a minimum of 18º C to a maximum of 28º C, differing between the mountainous and lowland areas. The main tributaries of the Groot Letaba River that drain into the catchment include the Klein Letaba, Middle Letaba, Molototsi, and Litsetele rivers (DWAF, 2006). The Letaba catchment has more than 20 constructed dams and weirs, leading to a high degree of regulation within the watershed. The available water resources within this area are overexploited to fulfil both domestic needs and commercial demands, such as afforestation, industrial use, and irrigation. The Groot Letaba, Politsi, Debengeni, Thabina, and Letsitele rivers originate in the Northern Drakensberg Mountains at elevations ranging from 1,100 to 1,800 meters above mean sea level (amsl) and flow northeast, cascading down the steep slopes. The catchment falls within the Limpopo plain ecoregion which has a wide range of different vegetation. This includes sweet and sour bushveld, Mopani bushveld, Soutpansberg Arid Mountain Bushveld and patches of Afromontane Forest, northeastern grassland.

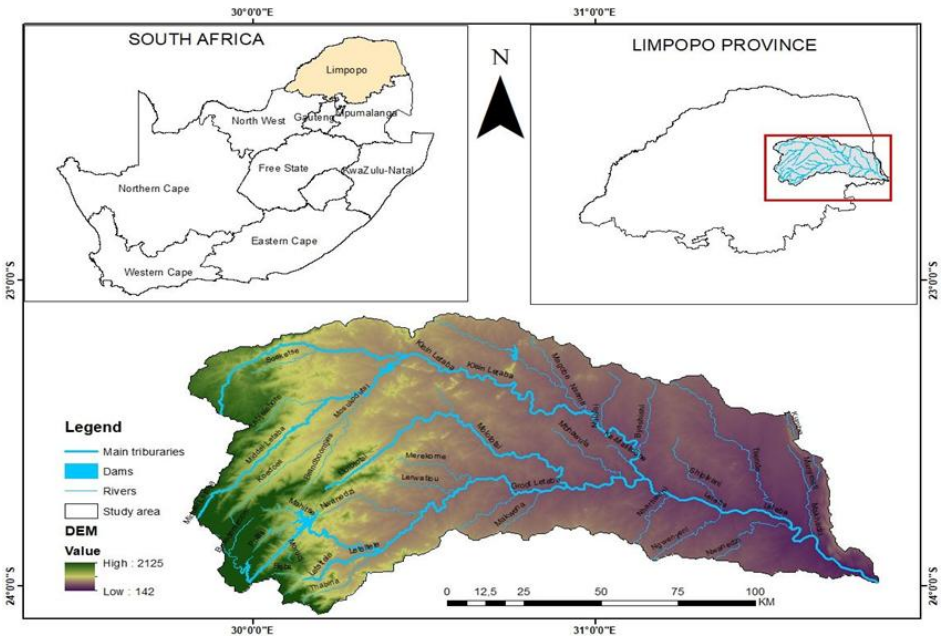

Figure 1.1: Letaba River catchment

1.3 Structure of the research

Chapter 1: The chapter provides an overview of the research background and outlines the objectives as well as the structure of the thesis.

Chapter 2: This chapter provide a systematic review of the advancement in utilizing remote sensing to evaluate the effects of changes in land use and land cover (LULC) on water resources, including both water quantity and quality. It also discusses existing research gaps, challenges, and opportunities linked with using remotely sensed data for assessment and monitoring purposes. The future direction and recommendations are also highlighted.

Chapter 3: This chapter aims to determine the spatial and temporal extent of LULC changes in the Letaba watershed using a machine learning algorithm (Random Forest) in cloud computing Google Earth engine (GEE) platform.

Chapter 4: This chapter aimed to evaluate the efficacy of multi-date Sentinel-2-derived spectral indices, in conjunction with landscape metrics for mapping spatial and seasonal fluctuations of surface water bodies using Google Earth Engine (GEE).

Chapter 5: This chapter aims to understand how alterations in LULC affect water quality parameters using in-situ and remotely sensed data at a catchment scale.

Chapter 6: The chapter offers the findings of the research, discussion, and general conclusions.

2. CHAPTER TWO

A Systematic Review on Advancements in Remote Sensing for Assessing and Monitoring Land Use and Land Cover Changes Impacts on Surface Water Resources in Semi-Arid Tropical Environments

The chapter is published https://doi.org/10.3390/rs15163926

Abstract

This study aimed to provide a systematic overview of the progress made in utilizing remote sensing for assessing the impacts of land use and land cover (LULC) changes on water resources (quality and quantity). This review also addresses research gaps, challenges, and opportunities associated with the use of remotely sensed data in assessment and monitoring. The progress of remote sensing applications in the assessment and monitoring of LULC, along with their impacts on water quality and quantity, has advanced significantly. The availability of high-resolution satellite imagery, the integration of multiple sensors, and advanced classification techniques have improved the accuracy of land cover mapping and change detection. Furthermore, the study highlights the vast potential for providing detailed information on the monitoring and assessment of the relationship between LULC and water resources through advancements in data science analytics, drones, web-based platforms, and balloons. It emphasizes the importance of promoting research efforts, and the integration of remote sensing data with spatial patterns, ecosystem services, and hydrological models to enable a more comprehensive evaluation of water quantity and quality changes. Continued advancements in remote sensing technology and methodologies will further improve our ability to assess and monitor the impacts of LULC changes on water quality and quantity, ultimately leading to more informed decision making and effective water resource management. Such research endeavors are crucial for achieving the effective and sustainable management of water quality and quantity.

Keywords: arid environment; land cover assessment and monitoring; machine learning; satellite data; water quality and quantity; water resources management

2.1 Introduction

Freshwater is a valuable natural resource that sustains biodiversity, carbon and nutrient cycles, food provision, and ecological functions (Chemura et al., 2020). Globally, freshwater resources offer significant socio-economic and ecological benefits, serving industrial, agricultural, and

domestic needs. Semi-arid regions, covering about 15% of the Earth's surface (Leenaars et al., 2014), are characterized by unpredictable weather, long dry seasons, and erratic rainfall (Huang et al., 2013). In the global semi-arid tropical regions, particularly Southern Africa, renewable freshwater resources are estimated to be around 2300 cubic kilometers (Rapholo et al., 2020). Around seventy percent of the available water resources are in transboundary rivers, with the remaining thirty percent distributed between lakes and groundwater (Gan et al., 2016). Any modifications or fluctuations in the water supply can have significant consequences for vital economic sectors, especially agriculture, and the overall natural capital. Scientific research has demonstrated that alterations in seasonal and inter-annual rainfall patterns, climate change effects, droughts, floods, and human activities have collectively influenced water systems, increasing their vulnerability (Gan et al., 2013; Kusangaya et al., 2014).

Thus, it is crucial to manage these delicate freshwater resources carefully. Sub-Saharan African countries heavily rely on freshwater resources for agriculture and residential use, intensifying the pressure on ensuring water security and sustainable management (Tahiru et al., 2020). Uneven rainfall distribution and external influences on water resources highlight the importance of water conservation and effective management. Extensive research had revealed that changes in land use and land cover (LULC), climate change impacts, and the proliferation of invasive alien species make water resources vulnerable (Bilgin, 2015; Fiquepron et al., 2013). The study of LULC change gained prominence in the mid-20th century (Lambin et al., 2013), influencing water resources, human livelihoods, and ecosystem health. Human activities, such as agriculture, mining, and urbanization, significantly drive LULC transformation. These changes affect hydrological processes, climate variability, ecosystem services, drainage systems, and increase vulnerability to floods (Ahearn et al., 2005; Liping et al., 2018; Wu et al., 2013). Consequently, they directly impact the quantity and quality of water resources. For instance, studies have demonstrated how LULC changes contribute to a declining water quality in rivers and lakes, adversely affecting ecology and water quality (Namugize et al., 2018; Rather and Dar, 2020; Tahiru et al., 2020). Therefore, identifying effective methods to assess and monitor the impacts of LULC dynamics on water quality and quantity is vital for efficient water resource management.

Remote sensing has proven to be a cost-effective and efficient tool for providing spatially explicit data on various ecosystems, including surface water resources (Bufebo et al., 2021). Earth

observation techniques, such as modern UAVs, balloons, multispectral, and hyperspectral sensors, can help monitor semi-arid tropical environments and potentially address water scarcity, pollution, and the conservation of water quality. Understanding the relationship between LULC and water resources is essential for effective watershed management, policymaking, future LULC development considerations, and freshwater protection. Giri and Qui (2016) provide a detailed review addressing land use and water quality in the 21st century. The study also provides insights into the factors that contribute to water quality problems, the indices used to evaluate water quality, techniques for identifying suitable explanatory variables for water quality, and the processing methods needed to capture spatial effects. Moreover, the study explores the modelling of water quality, using the identified explanatory variables to gain insights. Ullah et al. (2018) reviewed the impacts of land use on surface water quality using a statistical approach. They indicated that each statistical method has a unique purpose, application and assumptions aimed at providing solutions to different problems. Meanwhile, Ozbay et al. (2017) reviewed the relationship between land use and water quality and its assessment, using hyperspectral remote sensing in the mid-Atlantic estuary. Their main goal was to provide research findings on the application of hyperspectral remote sensing in order to monitor specific LULC and water quality. Meanwhile, previous studies have explored this relationship and the application of remote sensing in monitoring water quality, quantity, and specific LULC changes. However, bibliometric analyses of comprehensive systematic reviews on the use of remote sensing in global semi-arid tropical environments to understand LULC changes and their impacts on water resources are lacking.

This study aims to bridge this research gap by providing a comprehensive systematic overview of the progress, challenges, and opportunities related to the use of remote sensing applications in order to assess and monitor LULC changes and their effects on water quality and quantity in semi-arid tropical environments. This study aims to address the following key questions: (i) Which water quality and quantity parameters can be detected using remote sensing? (ii) What role does remote sensing play in understanding the relationship between LULC changes and water quality and quantity? (iii) Which methods have been utilized to assess and monitor these changes? (iv) What challenges have been encountered in these endeavors? (v) What can be achieved in the future to improve our understanding and monitoring of LULC changes and their impacts on water resources? Through these efforts, the study seeks to offer valuable insights into the potential of

remote sensing technologies and provide suggestions with which to better assess and monitor LULC changes and their impacts on water resources in semi-arid tropical regions.

2.2 Research method and literature search

This study conducted a systematic literature review that aimed to establish progress and identify existing gaps, using remotely sensed data to map and monitor LULC changes and their effects on water quality. This study also aimed to further outline the challenges and opportunities associated with remote sensing applications for assessing and monitoring the impacts of LULC change on surface water resources.

2.2.1 Literature search and data extraction

The literature searches for this study utilized the Google Scholar, Scopus, and Web of Science databases, targeting peer-reviewed international journals related to remote sensing, hydrology, ecology, geographical information systems (GIS), and water resources. The search strategy involved defining appropriate search strings and identifying relevant keywords, phrases, and terms. To identify relevant keywords, phrases, and terms, we used the most cited literature reviews. Initial searches included terms such as “land use and land cover change”, “impacts”, and “water quality and quantity”, resulting in a total of 18,187 publications being retrieved (17,500 from Google Scholar, 411 from Scopus, and 276 from Web of Science).

The retrieved articles underwent further screening using level 2 search criteria, including keywords such as “remote sensing”, “tropical semi-arid”, and the years 2001–2021. This process yielded a total of 1248 articles from Google Scholar, 121 articles from Scopus, and 95 articles from Web of Science. In the level three screening, additional keywords such as “catchment scale”, “sub-catchment scale”, “algorithms”, “riparian buffers”, “land cover land use classifications”, “land use land cover monitoring challenges”, “machine learning”, “freshwater resources”, “deep learning”, “hydrological model”, “spatial pattern”, “ecosystem services”, “change detection”, “multi-spatial scale”, “catchment management”, “buffer zone“ and “water pollution” were used. This resulted in a final compilation of 197 articles in EndNote for further screening, eliminating duplications and excluding non-English papers, gray literature, extended abstracts, conference proceedings, fee articles, and those not published between 2001 and 2021 (Figure 1). The remaining 197 articles were captured in Microsoft Excel and used to comprehensively outline the progress, gaps, challenges, and opportunities related to using remote sensing to assess and monitor land use and

land cover changes and their impacts on surface water resources in semi-arid environments. Bibliometric analysis was employed to assess the published articles and identify key terms related to mapping and monitoring LULC changes and their impacts on surface water quality.

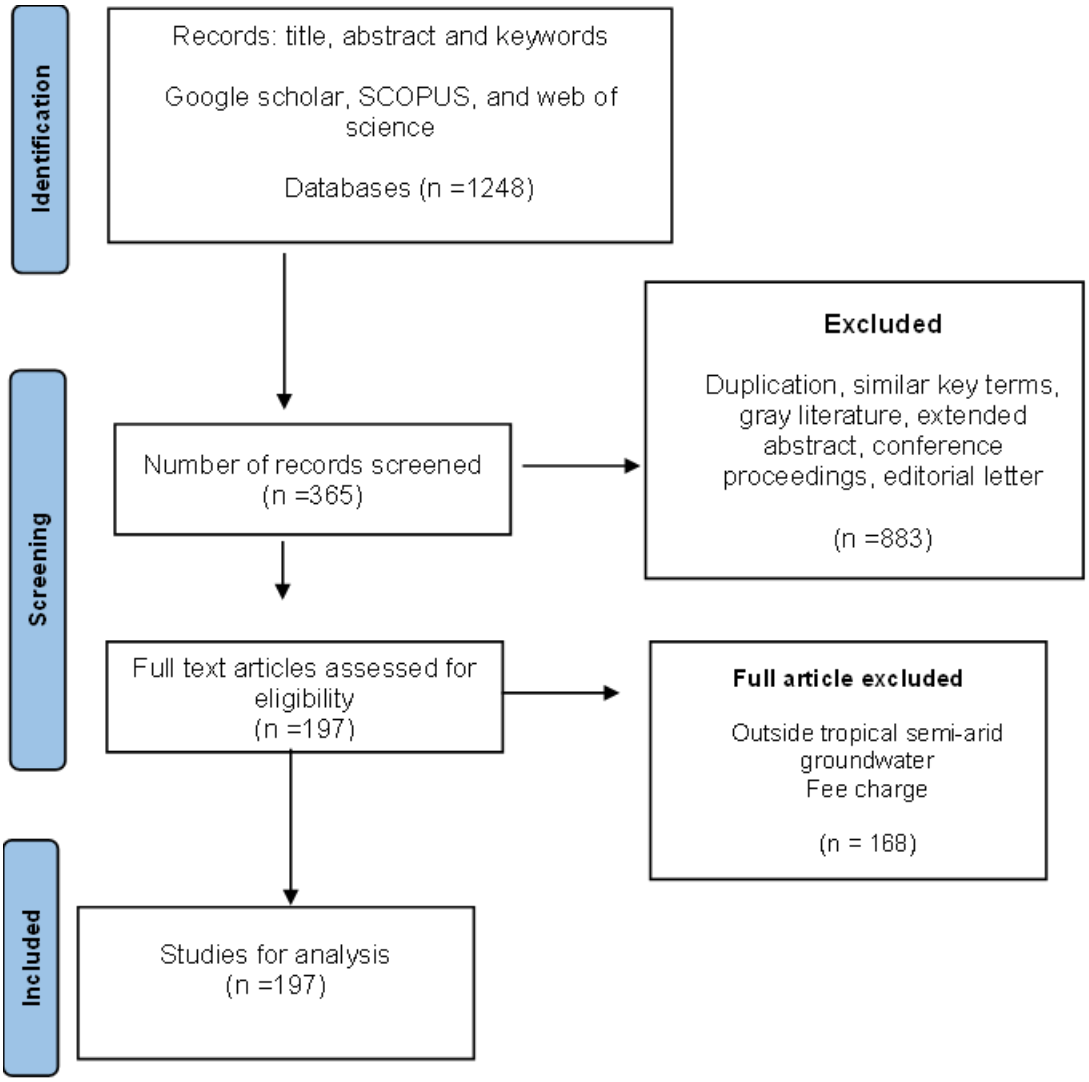

Figure 2.1: Methodology undertaken for selection of articles considered in the review.

2.3 Results

2.3.1 Progress of remote sensing in assessment and monitoring LULC changes

Land use and land cover (LULC) change examines the transformation and alteration of Earth's land surface, including changes in land use patterns and the conversion of natural land cover to human-modified landscapes. The assessment and monitoring of LULC changes using remote

sensing have made significant progress over the years. Remote sensing technologies have advanced in terms of data acquisition, spatial resolution, spectral coverage, and temporal frequency, enabling the more accurate and detailed analysis of LULC dynamics. Some key areas of progress in the remote sensing assessment and monitoring of LULC changes include data availability, fine-scale mapping, the integration of multisource data, classification algorithms, change detection techniques, and web-based platforms and open data initiatives.

2.3.1.1 Data availability and integration of multisource data

The availability of satellite imagery data from platforms such as Landsat, Sentinel, and other commercial satellites has greatly improved. These datasets provide consistent seasonal and long-term coverage, allowing for the analysis of LULC changes over time. Advances in remote sensing have enabled the mapping and monitoring of LULC changes at finer spatial scales. High-resolution imagery and data fusion techniques have enhanced our ability to capture detailed LULC information, including urban areas, agricultural fields, and small-scale changes (Otukei and Blaschke, 2010). The integration of multisource remote sensing data, such as optical, radar, and LiDAR, has expanded the capabilities of LULC change assessment. Combining data from different sensors enhances our understanding of LULC dynamics and provides valuable information regarding vegetation structure, terrain characteristics, and three-dimensional mapping. Remote sensing has progressed in the development of change detection techniques, enabling the identification and quantification of LULC changes. These techniques include image differencing, spectral indices, time series analysis, and object-based change detection, enabling more accurate and efficient change assessment.

2.3.1.2 Classification algorithms

The repetitive practice of using a multi-sensor image system to capture information provides valuable data for managing land-based resources. Remote sensing also offers the standardized data collection procedure, data integration, and analysis within a geographic information system (Mwita et al., 2012; Weng, 2009). Remote sensing satellites have proven valuable in employing various classification techniques to map LULC changes within watersheds such as supervised, unsupervised classification, and object-based image analysis (Table 2.1).

Table 2.1: Classification algorithms for mapping LULC classification.

Algorithm/Techniques	Sensor Used	Performance Range	References
Supervised Classification			
Support Vector Machine (SVM)	Landsat OLI, ETM+, TM, Terra ASTER, Hyperion Hyperspectral imagery and Quickbird Synthetic Aperture Radar (SAR)	88–98%	Jayakumar, 2009; Kadavi and Lee, 2018; Zhou et al., 2016
Random Forest (RF)	Sentinel 2 MSI, Landsat 8, SPOT, RapidEye, LiDAR	88–95	Ghorbanian et al., 2020; Kulithalai et al 2021; Otukei et al., 2010
Convolutional Neural Network (CNN)	Aerial photograph	91–98%	Scott et al., 2017
Classification and Regression Tree (CART)	Sentinel 2 and Landsat OLI, LiDAR	85–90%	Chehata et al 2009; Talukdar et al., 2020
Deep Neural Network (DNN)	Landsat TM and OLI, Sentinel 2	92–95%	Vali et al., 2020
Decision Tree (DT)	Landsat TM and ETM+, Sentinel 2	85–90%	Otukei et al., 2010; Talukdar et al., 2020

Spectral Angle Mapper	Landsat 8, hyperspectral, RapidEye	89–90%	Christovam et al., 2019; Jayakumar, 2009; Makinde et al., 2016
Recurrent Neural Network (RNN)	Very High Spatial Resolution (VHSR)	75–86%	Ienco et al 2017
Artificial Neural Network (ANN)	Landsat ETM+	70–85%	Pal and Mather, 2003
Maximum Likelihood (MLC)	Landsat TM	67–72%	Ktanji and Kielen, 2007; Munthali et al., 2019; Otukei et al., 2010
Unsupervised Classification			
ISODATA	MODIS	54–69%	Kim and Pauleit, 2007
K-Nearest neighbor	Landsat TM and ETM+, Sentinel 2	87–91%	Haapanen et al., 2004
Object-Based Image Analysis			
Object-based image analysis (OBIA)	Lidar, Sentinel 2	87–91%	Zhou, 2013

Unsupervised classification is a computer-automated process that groups pixels that are statistically similar into categories using a clustering algorithm, such as K-means (Chakraborty et

al., 2020) or ISODATA (Haapanen et al., 2004). Unsupervised classification is valuable when the field data are lacking or knowledge about the study area is unavailable (Otukei et al., 2010; Bruzzone and Prieto, 2001). However, the spectral properties change over time with the image data, atmospheric condition, and the sun's angle at the time the image was captured; hence, detailed spectral knowledge of different features may be required. In contrast, supervised classification allows the analyst to select training samples for each land cover class and guide the computer to identify the spectral features of similar areas for each class (Dwarakish and Ganasri, 2015). This is particularly achievable using classification algorithms such as maximum likelihood (MLC), support vector machine (SVM), an artificial neural network (ANN) and random forest (RF), among others. Based on the finding (Figure 2.2), classification techniques such as MLC have been widely employed in studying LULC change in water resources. For example, the study by Ding et al. (2015) derived the LULC change map from the Landsat TM using the MLC algorithm for classification and achieved an overall accuracy of 88% and a Kappa coefficient of 0.85%. Similarly, the study by Tadesse et al. (2017) derived the LULC change from Landsat TM, ETM+ and OLI using MLC and achieved overall accuracies of 87%, 89%, and 93%, respectively, and Kappa coefficients of 0.83, 0.83, and 0.88, respectively. The MLC considers spectral variation within each category and the overlap covering the different classes. However, this method is time-consuming since it requires more pixels in each training dataset to specify each class (Otukei et al., 2010). The MLC technique also produces lower classification accuracy results when compared to other classification techniques such as ANN, SVM, and RF (Arabameri et al., 2020; Otukei et al., 2010; Talukdar et al., 2020).

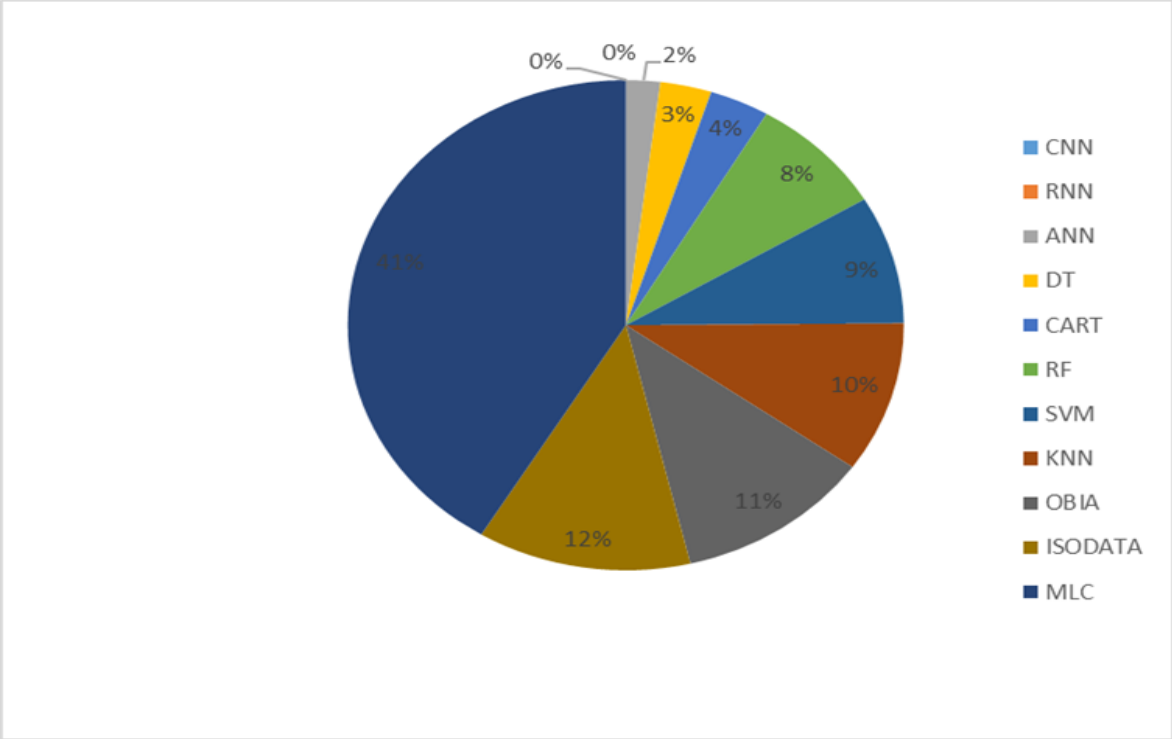

Figure 2.2: Classification algorithms (%) used to detect and map LULC using multi-sensors.

Thus, ANN, SVM, and RF machine learning (ML) algorithms are more robust and effective for classification techniques (Otukei and Blaschke, 2010; Peng et al., 2020; Banerjee et al., 2012). Supervised classification requires labelled training data to learn and understand the patterns associated with each category. Once the training data are labelled, these ML techniques can build models based on the labelled examples and use this knowledge to categorize new, unseen text accurately and efficiently, which is a challenge with MLC. However, the challenges associated with these methods are that they require extensive training (data hungry), require human supervision (expertise), and are computationally extensive when producing accurate LULC change maps (Yuan et al., 2017). Although individual classifiers achieve better accuracy results, they often fail to predict true classes with high accuracy. Therefore, studies have combined different classifiers to boost performance and reduce the classification error (Bullock et al., 2020; Schulz et al., 2021; Shen et al., 2015). However, the ensemble fails on new data when individual classifiers are too complex for the training data present or their training error becomes too large quickly (Tuyakov et al., 2018; Yuan et al., 2017). The problem associated with the ensemble is finding the right balance between the individual models' complexity and their fit to the data. Thereby,

performing more ensemble iterations can reduce the error of the combined classifier on the training data.

Obtaining high-quality and sufficient reference datasets, as is required in most of these machine learning algorithms, is still an enormous task in most of the sub-Saharan African countries (Zhang et al., 2007). Acquiring reference data through field surveys is still challenging due to the inaccessibility of some areas, costs associated with travel and the time investment needed. To counter this limitation, other studies have adopted the migration of reference data from a specific time (year) to another time (target year) in order to address the lack of accurate and reliable current data. Likewise, good training data combined with the high spatial resolution of an image, together with an ensemble ML, often provide a high classification accuracy (Nofallah et al., 2021). For instance, the study by Zhou (2013) used Light Detection and Ranging (LiDAR) to map LULC change using object-based image analysis classification and achieved an overall accuracy of 91% and a Kappa coefficient of 0.87%; additional examples are provided in Table 2.1.

Deep Learning (DL) algorithms have the capacity to extract automatic and hierarchical features from a large dataset, which makes them able to work with remote sensing data (Vali et al., 2020; Witten and Witten, 2019). CNNs is one DL algorithm that are used to solve problems associated with spatial data. CNNs outshine other algorithms when aiming to capture spatial features such LULC patterns, textures, and shapes. They can also handle both multispectral and hyperspectral data. They can automatically learn and extract meaningful representations from the image data, leading to a high classification accuracy (Scott et al., 2017). CNN transfer learning enables the learned features to be leveraged and reduces the need for extensive labelled training data. Meanwhile, RNNs are best at processing temporal and spatial dependencies in sequential remote sensing data, such as time series and spatial data in a sequential structure. RNNs are also able to flexibly work with hyperspectral imagery because they can handle data in which the number of spectral bands may vary across different samples (Ienco et al., 2017). Understanding the different spectral bands can be valuable for the classification of LULC. This provides opportunities to classify complex contextual images and improve the classification accuracy. However, these techniques have never been used to assess and monitor the impacts of LULC on water resources in semi-arid tropical environments. The major drawback of using these algorithms is the requirement for extensive datasets during the training process, particularly when dealing with large

amounts of data. The computation involved in training and testing can be costly. RNNs can struggle to capture long-term dependencies effectively with remote sensing data, especially when analysing time series with a large time lag (Ienco et al., 2017). CNNs are prone to overfitting, where the model becomes excessively specialized to the training data and fails to generalize to unseen data.

2.3.1.3 Spectral classification

2.3.1.3.1 Band based classification

Band-based classification is performed using the individual spectral bands of the remote sensing image (Crossley et al., 2013). This method relies solely on the spectral information captured by the different bands of the remote sensing image. They cannot effectively enhance specific features of interest, as the classification is based on the raw spectral values of each band. The results of band-based classification may be more straightforward to interpret since they directly correspond to the individual spectral bands (Kwam et al., 2020). This method can be more sensitive to atmospheric effects, such as haze or aerosols, which may impact the accuracy of the classification (Crossley et al., 2013; Kwam et al., 2020). It is relatively straightforward and simple to implement, as it involves using each band independently for classification.

2.3.1.3.2 Index Based Classification

Classification using different spectral indices in remote sensing is a common approach used to extract valuable information from satellite imagery. Spectral indices combine specific spectral bands to highlight various land cover characteristics, such as vegetation health, water content, and soil properties. Index-based classification and specific spectral indices, which are combinations of different spectral bands, are used to perform the classification (Dahigamuwa et al., 2016). Instead of using individual bands, index-based classification uses spectral indices that combine bands in specific ways to highlight certain features of interest. By using spectral indices, this method can enhance specific features, such as vegetation, water bodies, or soil, making it more effective in certain applications (Dahigamuwa et al., 2016). Index-based classification can be more robust against atmospheric effects since the spectral indices can mitigate some of the atmospheric influences. Implementing index-based classification may require more pre-processing steps to calculate the spectral indices, adding some complexity to the process. The commonly used indices are the normalized difference vegetation index (NDVI), the normalized difference water index

(NDWI), the normalized difference built-up index (NDBI), and the soil adjusted vegetation index (SAVI). Integrating spectral indices with other data sources, such as ancillary data and ground truth information, can enhance the accuracy and reliability of LULC change classification results.

2.3.1.4 Change detection

Change detection is the process of identifying and quantifying areas of change in the LULC, or other environmental variables over time. Change detection provides a means by which to monitor and understand the dynamics of environmental changes (Verbesselt et al., 2010). It helps identify the magnitude, location, and patterns of changes, enabling researchers and decision makers to gain insights into ecosystem dynamics, urban growth, deforestation, agricultural expansion, and other changes affecting the environment (Kulithalai Shiyam Sundar and Deka, 2021). It facilitates a better understanding of the dynamic nature of the Earth's surface and enables informed decision making for sustainable development and environmental protection. The accuracy of change detection relies on factors such data quality, spatial and temporal resolution, methodology and reference, or ground truth data (Hassan et al., 2016). The accuracy of the quality input data used for change detection plays a significant role. High-quality, well-calibrated data with minimal noise and distortions contribute to better levels of accuracy. Possessing reliable reference data or ground truth information is crucial for evaluating the change detection accuracy. Ground truth data, obtained via field surveys or high-accuracy sources and remote sensing technology, are used to verify the detected changes, and assess the method's performance (Fatima and Javed, 2021; Tewabe and Fentahum, 2020).

Techniques such as pixel-by-pixel differencing, image ratioing, and image thresholding are used to identify and highlight differences between images. Time series analysis involves studying data collected over a period of time to detect patterns or trends. Statistical methods, such as regression analysis, seasonal decomposition, and moving averages, are employed to reveal changes in temporal data (Grifffiths et al., 2012). Remote sensing technologies, including satellite and aerial imagery, play a crucial role in monitoring LULC. Geographic Information Systems (GIS) aid in spatially analyzing and visualizing the detected changes. With the advent of machine learning and artificial intelligence, change detection has seen significant advancements. Supervised and unsupervised learning algorithms, such as SVM, RF, and CNNs, can be trained to automatically detect changes in various data types (Campos-Taberner et al., 2020; Kulithalai Shiyam Sundar and

Deka, 2021). Light Detection and Ranging (LiDAR) technology utilizes laser pulses to measure distances to the Earth's surface and generate high-resolution 3D maps (Chehata et al., 2009). It is especially useful in detecting changes in topography, vegetation, and infrastructure. Radar-based change detection employs microwaves to penetrate clouds and vegetation, making it an all-weather and day-and-night imaging technique. It is useful for monitoring land subsidence, urban growth, and natural disasters. Data mining techniques can be applied to large datasets to discover hidden patterns or anomalies that are indicative of changes. This technology is widely used in fraud detection, network intrusion detection, and more. Time-of-flight cameras use light signals to measure distances, enabling real-time 3D imaging and change detection applications, such as object tracking and gesture recognition (Munthali et al., 2019). The challenges associated with the technique include spatial and temporal resolution, spectral heterogeneity, spectral similarity, radiometric variation, scale and context, computational resources and processing, and data availability.

2.3.1.5 Web-based platforms and open data initiatives

The emergence of web-based platforms, such as Google Earth Engine (GEE) and Sentinel Hub, has facilitated easy access to remote sensing data and analysis tools (Kumar and Mutanga, 2018). Open data initiatives promoted by space agencies and governments have further promoted the sharing of remote sensing datasets, enabling broader participation in LULC change monitoring. These advancements in remote sensing technology and techniques have significantly improved the assessment and monitoring of LULC changes. They provide a more comprehensive understanding of the dynamics and impacts of human activities on the Earth's surface. Continued progress in remote sensing, along with ongoing research and development, will further enhance our ability to monitor and manage LULC changes effectively.

2.3.2 Water quality and quantity

Water quantity refers to the various aspects that contribute to the overall measurement and understanding of water availability and supply. Some common components that can be measured using remote sensing technology include precipitation, evapotranspiration, runoff and streamflow, groundwater, reservoir and lake monitoring, and soil moisture. Remote sensing can estimate precipitation patterns and distribution by measuring cloud properties, rainfall rates, and storm characteristics using sensors such as radar or microwave radiometers (Das et al., 2019; Weng,

2009). Remote sensing can quantify the amount of water lost from the land surface through evaporation and plant transpiration. It involves estimating energy fluxes and vegetation indices using optical or thermal sensors to assess evapotranspiration rates (Becker et al., 2019; Saddique et al., 2020). It can also help to estimate runoff and streamflow by monitoring changes in water levels and river discharge using altimeters, radar sensors, or optical imagery (Beck et al., 2011; Guzha et al., 2018). This enables the water movement in river networks to be assessed. More insights into groundwater resources can be obtained by monitoring changes in the land surface elevation using satellite-based radar interferometry (InSAR) or gravity data from the Gravity Recovery and Climate Experiment (GRACE) mission (Banerjee et al., 2012; Becht et al., 2007). The soil moisture content can be estimated by measuring the microwave radiation emitted or reflected by the Earth's surface (Ahlmer et al., 2018; Das et al., 2019). This information helps to assess water availability in the root zone and supports agricultural water management. In reservoir and lake monitoring, remote sensing enables the monitoring of water levels, surface area, and volume changes in reservoirs and lakes using radar or optical imagery (Tanksali and Soraganvi, 2021). This information is crucial for water supply management and flood control.

Remote sensing data may have limitations regarding its spatial and temporal resolution, sensitivity to atmospheric conditions, calibration and validation, complex terrain and land cover heterogeneity, and limited data accessibility for specific parameters. Therefore, it is important to consider these limitations when using remote sensing for water quantity assessments. Integrating remote sensing with other data sources, utilizing complementary techniques, and incorporating appropriate modelling approaches can help mitigate these limitations and improve the accuracy and reliability of water quantity assessments. In addition, by leveraging remote sensing data, scientists and water resource managers can assess and monitor these components of water quantity on various scales, providing valuable insights into water availability, distribution, and movement.

Water quality refers to the chemical, physical, biological, and radiological characteristics of water that determine its suitability for various uses and its impact on the environment and human health (Scott et al., 2017). The water quality parameters that can be assessed using remote sensing include the chlorophyll-a concentration, water turbidity, dissolved organic matter (DOM), water temperature, total suspended solids (TSS), water pH, and harmful algal blooms (HABs) (Lam et al., 2012). For further details, the study by Gholizadeh et al. (2016) elaborates more on the water

quality parameters and limitations of remote sensing for assessing water quality. However, most studies monitoring water quantity have focused more on water balance (evapotranspiration) and monitoring water (reservoir and lakes), with little attention paid to runoff, ground water recharge and soil moisture. Water quality parameters such as pH, TSS, temperature, and DO are commonly evaluated in water quality assessments (Chen et al., 2021). Meanwhile, HABs and the chlorophyll-a concentration have received little attention.

2.3.3 Impacts of LULC changes on water resources

Rapid population growth, socioeconomic factors and a lack of natural resource conservation policies are major contributing factors to LULC changes worldwide. According to Dwarakish and Ganasri (2015), slope, the distance from the river, soil erosion, altitude, and built-up areas are significant contributing factors to LULC changes. Nonetheless, they are not considered in most studies when assessing and monitoring the impact of LULC on water resources. Changes in LULC can have a wide-ranging impact on various aspects of the environment. These LULC changes can alter landscape patterns, hydrological processes (surface flow), physical factors (stream morphology and temperature increase), biology (biodiversity and ecosystems) and water quality and quantity (nutrients and pollution increase). Semi-arid tropical climates are characterized by erratic climate change. The semi-arid tropical climatic conditions need to be frequently monitored for effective watershed or catchment management, and sustainable water resources. LULC changes, such as agriculture, urbanization, and mining, are likely to improve livelihoods, contribute towards local and national economic development, facilitate food security and advance biofuel energy, making them a priority for the development of countries. Yet, these are the most substantial factors causing negative environmental modification. Agriculture is directly associated with the removal of natural vegetation, increased soil erosion (Ribaudo et al., 2011), algal bloom (Glasgow et al., 2004), increased greenhouse gas emissions and nutrient imbalances. Natural vegetation, such as riparian vegetation, can act as an important habitat for a variety of species and can trap sediments and pollutants in water. Therefore, alterations in the natural vegetation affect the ecosystem services provided by the streams, which are important for reducing flood streams, managing runoff, and preventing erosion (Campos-Taberner et al., 2020; Glasgow et al., 2004; Ribaudo et al., 2011). Ultimately, these changes affect the water storage provided by aquifers, ecological processes, functions and services, and hydrological factors. This will have implications for hydrological factors, thus affecting water supply and availability (Ghorbanian et al., 2020).

This will lead to changes in the drainage network, which is important for surface runoff and drainage patterns. Ecosystem services play an important role in watershed and water management. However, they are often overlooked in water resources management.

Urbanization and mining are associated with impervious surfaces, urban heat islands, the increased susceptibility of areas to floods, the loss of drainage systems and changing hydrological systems (Cai et al., 2016; Yohannes and Elias, 2017). These artificial surfaces often result in increased runoff, and further generate a path for the transportation of pollutants into water bodies (Giri and Qiu, 2018); this reduces the infiltration and storage capacity of water in shallow aquifers and increases the chances of severe floods occurring (Kebede et al., 2014). Urban heat islands can be aggravated by a warming climate, particularly during heat waves, which change the water balance (evapotranspiration) and hydrological factors of the catchment. These changes affect the timing and magnitude of evaporation loss and the water yield, which govern the soil moisture content and the flow patterns of hydrological regimes. In the end, increased streamflow and precipitation occur, and the frequency of large floods and larger sedimentation increases (Schilling et al., 2006). To better manage LULC and water resources effectively, it is important to assess hydrological components by using advanced tools, with which it is very important to attain sustainable water resources at a catchment scale. Land cover changes are located within the spatial representation of the landscape. Modeling LULC patterns offers a better understanding of past and future LULC and its related implications and guides future land use policies. Taking these studies in semi-arid tropical areas into account, will ensure the sustainability of the catchment via the planning and management of the watersheds.

Consequently, these LULC changes have a serious impact on a wide range of ecological processes and result in several global environmental problems, such as land degradation, desertification, biodiversity loss, habitat loss, and species transfer. These impacts affect the water supply, irrigation, fishing, and power generation, reduce food production and land productivity, and decrease many countries' Gross Domestic Products (GDP). Contaminated surface water results in health risks for humans, increases the financial cost of purification, and affects economic development. The impact of LULC on water resources is caused by a lack of proper management strategies and land use planning surrounding water resources. A lack of awareness regarding water pollution, especially in Sub-Saharan African countries, further compromises water quality. The

enforcement of policies and regulations regarding the discharge of pollutants from agricultural sectors, urbanization, waste-water treatments, and industries needs to be strengthened. This will promote sustainable water quality, watershed management and improve global economies.

2.3.4 The role played by remote sensing platforms in assessing and monitoring LULC changes and their impacts on water resources

2.3.4.1 Seasonal and long-term monitoring

The effects of LULC changes on water quality differ spatially and temporarily due to climatic conditions (e.g., temperature and rainfall), and topography (e.g., slope and landscape patterns). The hydrological factors (e.g., flow) also play an important role in the movement and transportation of pollutants into rivers and the degree to which they disrupt ecosystems. Remote sensing platforms, with different image acquisitions (Table 2.2), offer an opportunity for the seasonal and long-term monitoring of the effects of LULC changes on water resources. Long-term monitoring offers the important data needed to measure the changes in natural water resources over time and predict trends; this is in order to implement, plan, monitor and manage water quality. The tabulated information below is helpful in designing an assessment evaluating the effects of LULC changes on water resources and may be used in the selection of appropriate sensors.

Table 2.2: Available sensors that can be applied for assessing and monitoring the effects of LULC changes on water resources.

Sensor/Platform	Resolution (m)	Spectral Bands	Swath Width (km)	Revisit Time (days)	Acquisition Cost
AVHHR	1100	5	2900	1	Free
IKONOS	4	5	11	1–2	High
ASTER	15, 30, 90	144	60	16	Free
GRACE				10	Free
Hyperspectral	<1		>100		Very high
Landsat ETM+	30	8	185	16	Free
Landsat TM	30	7	185	16	Free

Landsat OLI	30	11	185	16	Free
LIDAR	0.45	5	1–2		Very high
MODIS	500, 1000	7	2330	1	Free
MERIS	300	15	1150	3	Free
Radar	0.3, 0.56	2			Very high
Rapid Eye	5	5	77	5.5	High
Sentinel 1 SAR	5, 5 × 20, 20 × 40	4	20, 80, 250, 400	6–12	Free
Sentinel 2 MSI	10, 20, 60	13	290	5	Free
SPOT	10, 20	4	120	26	High
Quickbird	2.4	5	16.5	1–3.5	High
Worldview	<1	8	16.4	1–3.7	Very high

The long-term monitoring of the effects of LULC changes on water resources has used aerial photographs due to their long period of existence. For example, the study by Schilling et al. (2006) used aerial photographs to map LULC, and the results indicated that the change in grassland to row crop increased nitrate levels up from 8.0 to 11.6 mg L in two Squaw creek subbasins in the USA for a period of ten years. Aerial photographs offer a high spatial resolution and are very good for analyzing ground surface events and detecting different LULC (Guo et al., 2017). However, they are limited to a smaller scale compared to satellite data, and the images lack repeatable acquisition. They require qualified and experienced personnel to interpret the image (Gallant, 2015), and interpretating the images is costly and time-consuming.

Landsat ((Thematic Mapper (TM), Multispectral Scanner System (MSS), Enhanced Thematic Mapper (ETM)) multispectral sensors have been widely used to conduct long-term monitoring of the impacts of LULC changes on water quality at regional and local scales. The study by Kibena et al. (2014) used Landsat TM to map the effects of LULC change on water quality from the year 1995 to 2012. They observed that the LULC, namely grassland, forest and bare land, had been

converted into settlement and agricultural land, which had increased pollution in Lake Chevero in Zimbabwe. The results showed that the total phosphorus (TP) increased from 130 to 376 kg/day, the total nitrogen (TN) increased from 290 to 494 kg/day, the DO increased from 0.1 to 6.8 mg/L, the chemical oxygen demand (COD) increased from 11 to 569 mg/L, the biochemical oxygen demand (BOD) increased from 5 to 341 mg/L, Phosphate Phosphorus (PO_4-P) increased from 0.01 to 4.45 mg/L, Ammonia Nitrogen (NH_3-N) increased from 0.001 to 6.800 mg/L and the electrical conductivity (EC) increased from 38 to 642 mg/L. Similarly, Zhang et al. (2021) observed that grassland, forest, water, and bare land were converted into farmland and constructed land from 1990 to 2016, which increased the level of chemical oxygen demand, manganese variant (COD_{MN}) from 0.92 to 1.09 mg/L, BOD from 0.63 to 0.85 mg/L, TP from 0.006 to 0.007 mg/L, and TN from 0.12 to 0.20 mg/L. The temporal range of the Landsat images provided the researchers with the ability to predict the effects of LULC on water quality; however, there are still challenges related to the use of the Thematic Mapper (TM) and Multispectral Scanner (MSS), in that they are no longer operating, and with the Enhanced Thematic Mapper Plus (ETM+) images, which are persistent with the Scan Line Corrector (SLC). The malfunctioning of the sensor's SLC leads to a data loss of approximately 22% of the normal scene area (Dube et al., 2015). Therefore, these medium-resolution sensors (i.e., Landsat TM and MSS) fail to deliver real-time images; in addition, the loss of data for the operational ETM+ sensor has resulted in considerable challenges regarding the estimation of the impacts of LULC change on water quality.

In 1986, the French government launched the Satellite Pour L'Observation de la Terra (SPOT), and it was the first earth resource satellite to have a pointable optic with high resolution, which increases the high opportunity of the imaging areas (Ozemsi and Bauer, 2002). The SPOT sensor has the ability to obtain information every day at any time due to the frequency revisit time, and can map LULC change, ranging from the regional scale to the global scale (Xie et al., 2008). Du Plessis et al. (2014) used Landsat TM and SPOT for classification and successfully predicted the future concentration of the water quality for the years 2015, 2020, 2030 and 2050, which increased with changes in the LULC. However, SPOT imagery is costly, which often hinders the adoption of its products in many studies.

Moderate-Resolution Imaging Spectroradiometer (MODIS) instruments use NASA Aqua and Terra satellites, thus providing nearly daily repeated coverage of the Earth's surface with 36

spectral bands and a swath width of approximately 2330 km (Guo et al., 2017). MODIS plays a significant role in mapping LULC change and dynamics at a coarse spatial resolution (Gallant, 2015). The sensor is freely available and presents an opportunity for the long-term and seasonal monitoring of LULC changes at a large scale due to its long period of existence and its revisit time (Xie et al., 2008). For example, the study by Juma et al. (2014) used MODIS to map LULC change and demonstrated an increase in agriculture and residential growth due to population growth from 1990 to 2008. The results showed that Nitrate Nitrogen (NO_3-N) increased from 10 μg^{-1} to 98 μgL^{-1}, PO_4-P increased from 4 μgL^{-1} to 57 μgmL^{-1} and chlorophyll also increased due to poor practices in agriculture, which resulted in the proliferation of an alien invasive water hyacinth species. However, the limitation of using the MODIS sensor is the difficulty involved in linking the coarse spatial resolution with field data, and the difficulties involved in monitoring small areas using the sensor.

On the other hand, the Advanced Very High-Resolution Radiometer (AVHRR) is freely available and has a high probability of obtaining a cloud-free view of the land surface compared to multispectral sensors (e.g., Landsat) (Van der Meer et al., 2002), and is very useful for long-term monitoring. The coarse spatial resolution of AVHRR can cover large areas and fails to distinguish the earth's features. This makes it difficult to detect or view detailed information about features. However, AVHRR has not been used at a national or global scale because of the difficulties involved in linking coarse spatial resolution data and field measurement (Rothenberger et al., 2009). Still, not all LULC changes affect water quality, as demonstrated by the study by Kaushal et al. 2017. The authors found that the transformation of row crop cover to perennial grassland decreased the amount of NO_3-N. Also, Khare et al. 2012 indicated that between 1974 and 2007, residential areas increased from 10% to 21%, while agriculture decreased from 36% to 19%, and forest decreased from 13% to 8%. This conversion decreased the TN from 2 mg/L to 1.5 mg/L. In addition, the expansion of residential areas may cause an increase in faecal coliform in water bodies since they pave the way for the entry of pollutants into rivers. On the contrary, the expansion of forest cover decreases the number of pollutants entering into rivers, although it increases dissolved oxygen, which is important for the lives of fish and macroinvertebrates (Liao et al., 2011). Therefore, many studies agree that the expansion of forest and grassland cover is an important mitigation strategy for improving water quality (de Mello et al., 2018; Price 2011).

The seasonal monitoring of the river catchment plays a substantial role in evaluating the temporal variations in river pollution due to LULC changes for effective land use management and watershed management. This is important for developing proper management strategies for water resources. The seasonal monitoring of the quality of pollution can further indicate the current, ongoing, and emerging problems. Most studies, for instance those by Tahiru et al. (2020), Namugize et al. (2018), and Beck et al. (2019), have observed that built-up areas are positively correlated with most of the water quality parameters; this is due to increased surface runoff caused by impervious surfaces, which create paths for the transportation of contaminants including TP, TN, NH_3-N. Thus, policies pertaining to land use planning, especially in urban areas, should be implemented and enforced in order to sustain water resources. Forests and grasslands have a relationship with DO and cultivated land/agriculture are positively associated with TN, TP, turbidity, and pH due to various farming practices, such as the use of pesticides, herbicides, and fertilizers. As such, most concentrations of these contaminants are higher during the dry season than in the wet season. However, DO is higher in the wet season than the dry season, while TP and TN are higher in both seasons (dry and wet). The high quantities of contaminants observed in the dry season may be driven by high water discharge and low water retention (Beck et al., 2019).

For instance, Pullanikkatil et al. (2015) seasonally monitored the impacts of LULC on the Likangala river catchment in Malawi and found that turbidity increased in the wet season, with 190.5 NTU downstream in the area dominated by wetland and settlement. Meanwhile, the pH increased during the dry season, with 880.83 mg/L, and decreased by 218.72 mg/L in the wet season downstream, which was dominated by wetland and settlements where people nearby practice fishing. The EC varied from 4 to 466 μs cm^{-1} during the wet season and between 40 and 3520 μs cm^{-1} in the dry season in the upstream and downstream, respectively. The TDS varies from 20 to 1760 mg^{-1} in the dry season and from 2 to 233 mg/L during the wet season. Similarly, the study by Zhang et al. (2021) seasonally monitored the effect of land use on water quality and observed that water quality parameters such NH_3-N and CODmn were higher in the dry season (7.29 mg/L and 7.8 mg/L) and lower in the wet season (0.048 mg/L and 2.2 mg/L) in built-up areas (dominated by urban areas). Meanwhile, the DO was lower in the wet season (3 mg/L) in the built-up area and higher in the dry season (12.9 mg/L) in the forest–grassland area. However, the TP was higher both seasons, with (0.28 mg/L) in the wet season and (0.29 mg/L) in the dry season. The study concluded that the high levels of NH_3-N and COD_{mn} were influenced by urban areas,

which increased the surface runoff of contaminants into the water bodies. Meanwhile, studies such as those by Kaushal et al. (2017) and Rothenberger et al. (2009) found that NO_3-N and NH_4-N, respectively, are higher in the wet season than in the dry season. The high concentration of pollutants in the wet season may be attributed to an increased run-off that washes off the soil, releasing a large amount of sediments, nutrients, and pesticides into surface water. An in-depth understanding of LULC change and seasonal factors can help to implement effective catchment management strategies for the protection of these water resources.

Progress has been noted in detecting, mapping, and monitoring LULC change and its effects on water quality using remotely sensed data over the years (Figure 2.3a). The use of satellite remote sensing in mapping and modelling the impact of LULC change on water quality has recently attracted increased attention, as evidenced in the number of publications between the years 2001 and 2021 (Figure 2.1). According to our analysis, extensive research has been conducted mostly using multispectral sensors; these include a range of Landsat sensors (TM, MSS, ETM+), and a few studies have used Sentinels, SPOT and MODIS (Figure 2.3b).

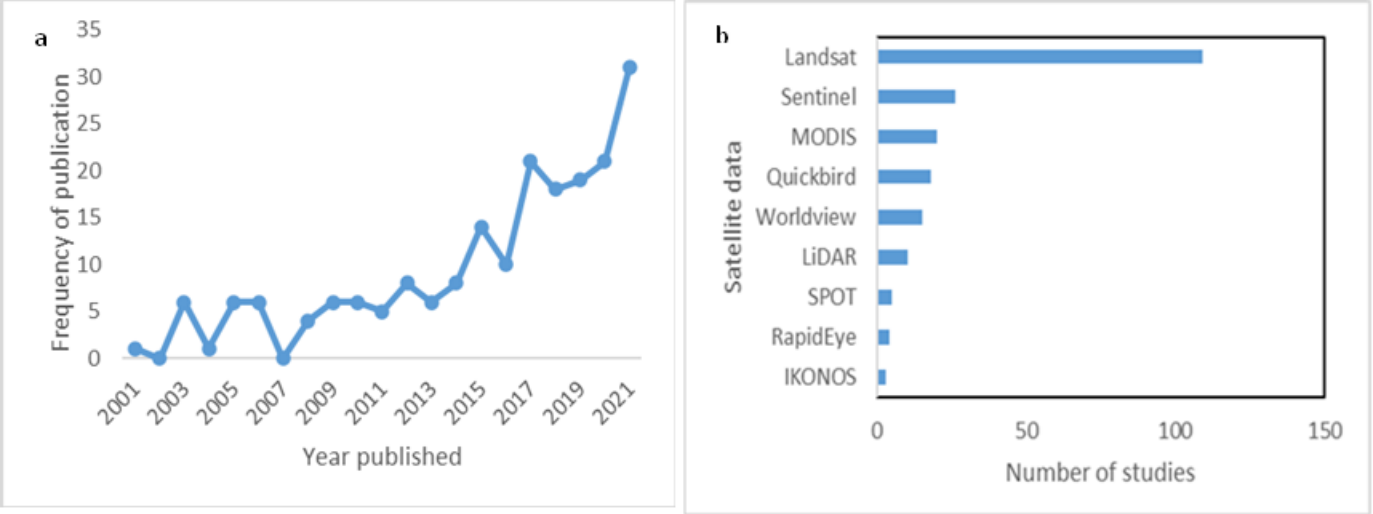

Figure 2.3: (a) Progress of remote sensing publications, and (b) sensors that were used in monitoring the effect of land use and land cover change on water quantity and quality.

The advancement of this research could be attributed to the significant increase in earth observation technologies, their relatively low cost and their time efficiency when managing large areas (Fiquepron et al., 2013). For instance, remote sensing has the ability to perform the spatiotemporal monitoring of LULC change, water quality, and natural resources, which is also important for

assessing water quality and quantity in terms of river pollution. However, Landsat TM, MSS and ETM+ have been the most used sensors [104,105]. This could be attributed to the fact that Landsat is the longest mission (since 1972) that has been supplying remotely sensed data for a wide variety of applications without charges. However, the Landsat sensors have been useful for assessing and monitoring the impacts of LULC change on water quality. It cannot be denied that medium- and low-spatial-resolutions can limit the detection and mapping of LULC and water quality when the area affected is smaller than the pixel size (Dube et al., 2015).

Advances in earth observation technology with improved image acquisition characteristics have progressively expanded our ability to distinguish features of the earth. Platforms such as Sentinel 1, synthetic aperture radar (SAR) provide an opportunity to integrate optical and radar data to improve the mapping capacity on cloudy days (Bullock et al., 2020). This is necessary for monitoring areas such as semi-arid environments, which receive most of their rainfall seasonally (wet season). Therefore, Sentinel 1 uses multiple sensors and sensing periods to accurately map heterogeneous LULC (Schulz et al., 2021). Schulz et al. (2021) and Hu et al. (2021) combined an ensemble Sentinel 1 and 2 Multispectral Instrument (MSI) to map LULC at a local to regional scale and achieved improved results compared to using only the optical sensor exclusively. The water quality parameters that were assessed using Sentinel 1 were TN, TSS, COD and TP. Munthali et al. (2019) and Chen et al., (2021) used Sentinel 2 and normalized the vegetation index to monitor the TSS concentration at various buffer scales and showed that a 300 m scale most effectively explained the variation in TSS concentrations (R^2) of 0.83, $p < 0.001$). Sentinel (SAR and MSI) sensors are freely available and have successfully monitored LULC and water quality separately. However, they have not been used to their full capacity in assessing and monitoring the relationship between LULC and water resources (Gholizadeh et al., 2016). Other studies have used the LULC prototype supplied by the European space agency (ESA) for instance, Copernicus global land cover (100 m × 100 m pixel size) (Teixeira et al., 2014) and Globcover (300 × 300 m pixel size) (Pal and Manther, 2003). Although the LULC prototypes provide useful data, they need to be updated frequently for effective management since the LULC changes over time. The development of hyperspectral sensors presents a unique opportunity for the extraction of the LULC (Sagan et al., 2020), biological and physicochemical parameters of water quality (Gholizadeh et al., 2016; Flores-Anderson et al., 2020). Specifically, hyperspectral remote sensing provides several narrow and quasi contiguous bands that enhance discrimination among different land uses

and land covers. Thus, the narrow band of hyperspectral sensors provides an opportunity to generate spectral reflectance curves for each pixel, which are unique in order to differentiate different classes of LULC, including water and pollutants (Giri and Qiu, 2016; Schilling and Spooner, 2006). Hyperspectral sensors have been reported in the literature to capture unique spectral signatures of water quality indicators, such as salinity, chlorophyll content (chla), turbidity, TSS and colored dissolved organic matter (CDOM) (Mwita et al., 2012). This may help us to understand and quantify the relationships among the spatial, structural, biological, and chemical processes occurring in the natural water ecosystem. The narrow bands of the sensors have allowed researchers to develop and implement water quality indices that have been effective in estimating water quality, thus including the Maximum Chlorophyll Index (MCI), Normalized Difference Turbidity Index (NDTI), and Green Normalized Difference Vegetation Index (GNDVI). The study by Elhag et al. (2019) used water quality parameter indices to estimate water quality, including MCI, NDTI and GNDVI. They achieved an outstanding coefficient of correlation (R) result of 0.96 with MCI, an R of 0.94 with NDTI, and an R of 0.94 with GNDVI. Although water quality indices are effective for monitoring water, they have been widely used in semi-arid tropical environments. The lack of robust and reliable water and quantity data needed to parameterize models remains a challenge.

The optimal spectral and spatial resolution remains a major challenge to the remote sensing community since not all water quality parameters can be detected and monitored using remotely sensed data because they are not optically active. Hyperspectral image analysis has not been fully explored due to its high cost and complex pre-processing procedure (Flores-Anderson et al., 2020). Regardless of their outstanding performance, only a few studies have attempted to use hyperspectral sensors to assess and monitor the relationship between LULC and its associated impacts on water resources. Advanced modern technologies such as Unnamed Aerial Vehicles (UAVs), commonly known as drones, have emerged as a potential alternative for mapping and monitoring LULC and water resources at a local scale (Syifa et al., 2014; Singh et al., 2014). They are flexible, affordable, and offer a very high spatial resolution. However, drones are limited to small areas and many of the affordable drones exclusively cover the true colour (RGB) section, which does not offer sufficient data for extensive application in areas such as characterizing water quality (Sibanda et al., 2021). These have never been fully explored in understanding the relationship between LULC and water quality. Based on the findings of this study, the growing

interest in assessing and mapping the relationship between LULC and its impact on water resources in semi-arid areas has focused on using the Landsat image platform. Meanwhile, advanced earth observation platforms such as Sentinels, UAVs, and hyperspectral technology have not been fully explored in assessing and monitoring the relationship between LULC changes and their impact on water quality and quantity. The use of advanced earth observation could be viable in monitoring the impacts of LULC on water resources in semi-arid tropical environments.

2.3.5 Algorithms used for quantifying the effects of LULC changes on water resources (quality and quantity)

Different algorithms are available for estimating the effects of LULC change on water quality using remotely sensed data. The techniques use different statistical modelling approaches that provide relatively accurate results and are easier to understand when compared to hydrological water quality modelling approaches. Most machine learning (ML) algorithms developed for remotely sensing the effect of LULC changes on water quality can be categorized as parametric or non-parametric. The most frequently used methods by researchers for modelling the relationship between LULC change and water quality parameters are the parametric machine learning algorithm (PMLA), which assumes a linear relationship between variables. Parametric algorithms, such as linear (Verma et al., 2020), multilinear (Tahiru et al., 2020; Silva and Willams, 2001) and Stepwise multilinear (SML) regression (Chen et al., 2014), have shown satisfactory performance. However, PMLA, such as linear and multilinear regression, have the limitations of multicollinearity and the overfitting of large data. Although the SML regression algorithm attempts to reduce the collinearity problems, it also eliminates variables that are ecologically and statistically important (Chen et al., 2014). Seilheimer et al. (2013) used the linear mixed-effect model (LMEM) algorithm approach, which enables the robust simultaneous evaluation of the association and environmental gradient. Meanwhile, it accounts for the repeated measures embedded in the data structure and indicates a better prediction performance when compared to multiple linear regression. The LMEM assumes that observation with the cluster is always positively correlated and that some individuals competing in the cluster for the scarce resources are negatively correlated. Thereby, it ignores a small negative correlation, resulting in a deflated type-1 error, and an invalid standard error and confidence interval in regression analysis (Nielsen et al., 2021).

Researchers have introduced more advanced non-parametric machine learning algorithms (NPMLA), including Partial Least Square Regression (PLSR) and multivariate statistics, which have been reported to be robust and efficient when aiming to overcome the problems of overfitting and multicollinearity with high accuracy. The algorithms include Principal Component Analysis (PCA) (Lee et al., 2010; Chen et al., 2007), Discriminant analysis (DA) (Liu et al., 2018), Cluster analysis (CA), Redundancy Analysis (RDA) (Kändler et al., 2017) and Hierarchical cluster analysis (Liu et al., 2018) (Figure 2.4). The NPMLA works well with large volumes of data. Singh et al. (2004) reported that multivariate statistical techniques (CA, DA, and PCA) are important for evaluating and interpreting large and complex datasets and obtaining better information regarding water quality and the design of monitoring. Besides the robustness of the NPMLA, there are limitations associated with some of the machine learning (ML) algorithms.

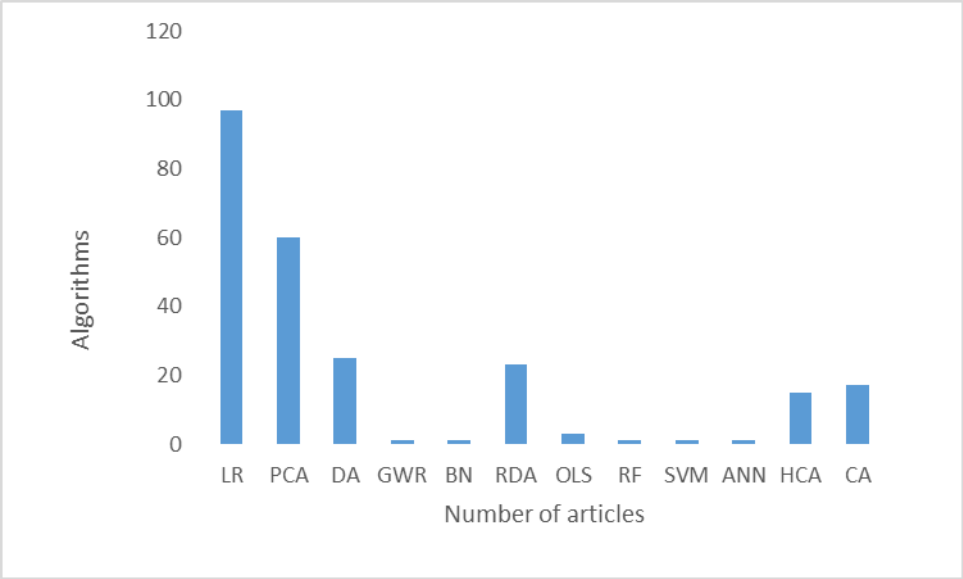

Figure 2.4: Algorithms used to assess and monitor the relationship between impacts of LULC and water quality.

The limitation of these multivariate statistical methods shows an existing relationship between water quality and LULC pattern, which may neglect some of the important spatial characteristics and hide local variation (Brown et al., 2011; de Mello et al., 2018). ML algorithms, including Ordinary Least Squares (OLS) and Geographically Weighted Regression (GWR), were introduced

to address spatial non-stationary issues and to examine spatial autocorrelation, which is neglected by multivariate algorithms (Brown et al., 2011; Liu et al., 2018). OLS is important for developing a relationship between independent LULC and water quality variables at a large scale by selecting the most significant variables in the regression (Ullah et al., 2018). The coefficient from the OLS model provides the most influential parameter of different water quality parameters. However, OLS requires a large dataset to obtain reliable results (Shrestha, 2006). The GWR considers the spatial variation and determines the relationship by incorporating the coordinates of location into the regression equation. The GWR model uses a single land use indicator as the independent variable and excludes the selection model because of the high potential of multicollinearity among different land-use variables; this would result in an invalid GWR model when variables experiencing multicollinearity are selected (Tu et al., 2021). However, GWR statistical analysis is limited to small scales. Therefore, the implementation of models that cover large areas is required. Bayesian Network (BN) is an effective method for spatiotemporal analysis as it enables the interaction of variables in space and time (Ullah et al., 2018) and is suitable for handling missing data prediction (Ullah et al., 2018; Wan et al., 2014). The model is essential for evaluating the complicated LULC change in water quality at various scales. However, the model is too complicated, too difficult to automate, requires specific software to run the model and qualified statistical expertise, and is sensitive to probabilities (Wikle, 2003).

On the other hand, Artificial Intelligence (AI) has gained considerable attention because of its potential to leverage big data and solve the problems faced in traditional techniques (mathematical models). AI refers to the simulation of human intelligence in machines that are programmed to think, reason, learn, and perform tasks that typically require human intelligence (Boukabara et al., 2019). The goal of AI is to create machines or systems that can mimic human cognitive functions, such as problem solving, pattern recognition, language understanding, and decision making (Ashapure et al., 2019). Moreover, AI encompasses a broad range of techniques, algorithms, and methodologies to enable machines to perform intelligent tasks. AI computing technologies are on the edge of becoming the prevalent alternative to conventional data processing techniques (Ashapure et al., 2019). Some of the key subfields of AI that are used in remote sensing include ML and DL. ML developed for earth observation data can support the challenges of spatial and temporal realm adaptations, hyperspectral data, the integration of multisource information and large-volume data analyses (Wang and Xie, 2018; Bhattarai et al., 2021). Advances in ML

technology have created a unique opportunity for the development of accurate large-scale prediction and prescriptive models (Jung et al., 2021). DL is used to improve results due to its accuracy in classification and prediction when trained with extremely big data; in addition, it can extract features from raw data. DL helps to capture the potential relationship between environmental variables for remote sensing retrieval, fusion, downscaling and superiority in multiscale and multilevel feature extraction. However, it is not clear how to best use ML or DL for expanding the range of increasingly accessible satellite data for LULC change research, particularly under environmental and socioeconomic impacts.

2.3.6 Multi-spatial scale relationship between LULC changes and water quality and quantity

Water quality monitoring often relies on the conventional methods of conducting in situ measures using a handheld multiparameter instrument and laboratory analysis. However, the accuracy and precision of collected in situ data may be questionable due to human error in the field and laboratory (Gholizadeth et al., 2016). The use of in situ data provides an accurate measure; therefore, integrating them with remote sensing data provides accurate measurements for the cost- and time-effective management of water pollution. Therefore, remote sensing has been widely used to assess and monitor LULC change on water quality at both the local and global scales (de Mello et al., 2020; Kibena et al., 2014; Song et al., 2020; Xie et al., 2008). However, when determining the relationship between LULC change and water quality, it is important to consider scale (spatial and temporal). Scale plays an important role in reflecting the different impacts of LULC changes on water quality. Therefore, in order to better manage the impacts of LULC changes on water resources, it is essential to consider streams as a complex ecosystem that operate at different spatial and temporal scales (de Mello et al., 2020). Three types of spatial scales, namely the buffer, sub-catchment, and catchment scale, have been used to estimate the impacts of LULC changes on water quality. However, there is no consensus regarding which of the abovementioned spatial scales explains a better relationship between LULC changes and their impacts on water quality and quantity.

Buffer zones are strongly influenced by water from the upslope, which is divided into three categories: surface flow and shallow subsurface flow (Sidle et al., 2007; Tetzlaff et al., 2009). When choosing a buffer scale, one should consider the structure and the function of the catchment, since there are two types of buffer scale; these include a circular and riparian buffer; (Song et al.,

2020). Riparian buffers are determined by the soil, vegetation and hydrology characteristics of the buffer and the interaction with the upslope and downslope. Meanwhile, circular buffers are effective for the diversity of water bodies such as lakes, streams, and dams in the lakeshore areas (Su et al., 2015). Most studies use a riparian buffer rather than a circular buffer to measure the influence of LULC change on water quality and quantity. For example, the study by Su et al. (2015) observed that many impacts came from all land uses, such as constructed land (CL), wetland (WL), original forest (OF), artificial forest (AF), and original land (OL), which reflected TN at 2 km; meanwhile, WL and CL continued to affect TN at the 4 km buffer. Moreover, Song et al. (2020) found that urban areas influenced TN in all buffers from 500 m to 1000 m. Similarly, Li et al. (2009) further indicated that a 300 m buffer is the strongest for the land use type to affect COD. Riparian buffers are storage areas that can be both the source and the sink of pollutants if no degradation process exists in the buffer zone. However, the drawback of using riparian buffers is that there is no uniform way of defining the width of a riparian zone (Kebede et al., 2014). Overcoming this problem requires a wider use of a riparian buffer to maximize its effectiveness in improving the water quality. The other problem with using a riparian buffer is the inability to address all water-related problems, since they are only effective in buffer areas that are not degraded. In the case of a degraded buffer zone, the scale may fail to reflect some of the impacts of land use on water quality and quantity.

Meanwhile, Gyawali et al. (2015) indicated that the sub-catchment scale is more effective in reflecting the impacts of land use on water than the buffer and the whole catchment. Their results indicated that agriculture influenced dissolved oxygen (DO), and that urban and water bodies influenced dissolved solids (DS), biological oxygen demand (BOD), and temperature at the sub-catchment scale. Wan et al. (2014) further revealed that LULC showed varied impacts of the same LULC category over different sub-catchments. However, other LULCs that are not nearby sub-catchments may influence or contribute to impacts on the water quality, because pollutants from LULC in the upper catchment may be transported downstream. The scale of the stream reach might be improper as the pollutants are diluted by the flow or absorbed by plants (Ceballos et al., 2010; Kim and Pauleit, 2007). Other studies propound that the whole catchment plays an important role in influencing the impacts of LULC on the water quality (Ahearn et al., 2005; de Mello et al., 2020; Tanaka et al., 2016). However, it is difficult to sample larger catchments at an appropriate spatial and temporal resolution. In addition, the spatial scale between LULC change and water

quality differs spatially, and the characteristics of the stream, human disturbance and data accuracy all have different degrees of influence in multi-scale studies (Song et al., 2020). Therefore, for the better management of pollution, the application of different spatial scales may provide an effective method by which to understand the relationship between LULC and its impacts on water quality and quantity. Gyawali et al. (2015) revealed that all LULCs, i.e., agriculture, forest, urban, and water bodies, affect temperature, DO, BOD, solid sediments (SS), DS, Faecal Coliform (FC) and EC at all three spatial scales. Similarly, Tanaka et al. (2016) also confirmed that water quality indicators have a different response to LULC patterns when evaluated at different spatial scales.

2.4 Discussion

The findings based on the search keywords indicate that the use of remote sensing in assessing and monitoring land use and land cover (LULC) changes has been significant. Remote sensing techniques have undergone significant advancements, particularly with the introduction of advanced algorithms such as machine learning (ML) and deep learning (DL), which offer increased opportunities to explore and effectively manage environmental issues. Numerous studies (Haapanen et al., 2004; Makinde et al., 2016; Munthali et al., 2019; Saddique et al., 2020) have focused on accurately mapping and detecting LULC changes using remote sensing. However, the utilization of machine learning and deep learning classifiers remains relatively limited compared to the traditional use of methods like maximum likelihood classification (MLC). Over the decades, the assessment and monitoring of LULC changes have extensively employed geographic information systems (GIS) and remote sensing. Earlier methods involved the use of aerial photographs and field observations for the interpretation of LULC to produce maps. With time, there have been notable advancements in LULC classification techniques, leading to improved mapping accuracy facilitated by advanced satellite imagery. Accurate LULC maps play a crucial role in informing decision-making processes for the planning and management of natural land resources.

2.4.1 Challenges in using remote sensing on the effects of LULC changes on water resources

Identifying the non-point source of pollution is still a challenging task due to an ongoing discussion and varying thoughts regarding the scale. Some studies argue that sub-catchment influences can be used (Gyawali et al., 2015), others suggest that the whole catchment would be the most optimum to use (Silva and Williams, 2001), and others have supported that riparian buffer (de Mello et al.,

2018) play an important role in influencing the water quality. Therefore, separating the impacts of LULC on water resources remains problematic, due to the extensive time scale over which impacts from LULC spread through the hydrologic system. The confounding effects of climate and weather, as well as large-scale observation field studies, often lack control, thus making it difficult to assign the temporal changes to causal mechanisms (Stonestrom et al., 2009). Thus far, most of the remote sensing techniques have been applied to LULC changes using a statistical model that links the relationship to in situ water quality parameters. However, the statistical models do not consider physically based hydrologic models, which are important in representing hydrological processes using spatially distributed data such as climate parameters (e.g., precipitation, temperature, and evapotranspiration), vegetation and soil moisture, and slope distribution (Thakur et al., 2017). The data contain crucial information about surface water flow and the integration of surface and ground water and can be used to describe the land surface topography characteristics (Dwarakish and Ganasri, 2015). Hydrological process models, such as the soil and water resources tool (SWAT), have been presented by many reviewers as an effective management tool for watershed models, simulating the stream flow better than other models (Ahlmer et al., 2018; Jordan et al., 2018; Thakur et al., 2017). The integration of these models with remote sensing data will provide effective management for monitoring the impacts of land use on water resources in semi-arid tropical environments. The reviews by Dwarakish and Ganasri (2015), as well as Dong et al. (2018), elaborate more on integrating remotely sensed data and hydrological models in LULC and water resources.

Efficient and accurate LULC using remote sensing therefore requires a high spatial detailed image for the classification method (Brown et al., 2011). However, it is important to note that factors such as image resolution, radiometric conditions, and atmospheric effects can impact the effectiveness and accuracy of classification algorithms in remote sensing. Radiometric and atmospheric corrections play a crucial role in mitigating these challenges. However, performing accurate corrections can be complex, particularly due to the dynamic and spatially varying nature of atmospheric conditions. To address this issue, it is essential for users to have access to suitable atmospheric correction software that aligns with the specific requirements of their study and the chosen approach. Selecting the correct or appropriate atmospheric correction method is crucial in order to ensure reliable and accurate results in remote sensing analyses. By carefully considering the data needs and research objectives, users can make informed decisions and choose the most

suitable atmospheric correction software for their specific study (Sagan et al., 2020). The accurate assessment of LULC change is crucial, particularly when it comes to capturing small classes and heterogenous land use classes with similar spectral class such as roads and built-up areas, as they can have significant impacts on water quality. Achieving precise results for these classes requires the use of sensors with a very high spatial resolution, typically less than 5 m. While sensors like LiDAR, WorldView-2, and Quickbird offer the required level of detail for accurate LULC mapping, their utilization in studies has been limited. The main challenges associated with these sensors are their cost and low temporal resolution. Acquiring data from these sensors for long-term studies can be expensive, and their restricted availability may limit their use to smaller study areas. To conduct the effective long-term monitoring of LULC change, it is necessary to analyse time series of remotely sensed imagery. However, obtaining and analyzing consistent time series data from multiple sensors pose challenges. It is essential to ensure that the acquired images are captured under similar environmental conditions, such as the same time of the year, sun angle, and spectral bands, to minimize errors and maintain data consistency. Overcoming these challenges in acquiring and analyzing time series and multi-sensor data is crucial for improving our understanding of LULC change and its impact on water resources. Efforts should be made to address these limitations and develop methodologies that enable the accurate and consistent analysis of LULC change over time (Verbesselt et al., 2010; Wulder et al., 2008). To minimize errors, the accuracy of a fraction of a pixel must be attained, meaning that variations in solar illumination, atmospheric scattering and absorption and detector performance must be normalized, i.e., the radiometric properties of each image must adjust to those of the reference image (Verbesselt et al., 2010; Wulder et al., 2008).

One drawback of minimizing the issue of radiometric calibration is that any errors identified in the classification maps of individual dates will also be present in the final change detection map. To validate the results, it is important to compare the classified maps with ground-truth data. Researchers often utilize a confusion matrix as the preferred method for validation, which includes metrics such as overall accuracy, user accuracy, producer accuracy, and the Kappa coefficient. However, the Kappa coefficient has been criticized for its limitations in accurately assessing the results. It fails to convert the sample confusion matrix into an estimated population matrix, which can affect the reliability of the assessment (Foody, 2020; Naboureh et al., 2021). To perform this, hardware, software and qualified personnel are required for processing and analyzing the dataset.

This hinders the application of remote sensing in monitoring the effects of LULC on water quality. Moreover, open-source software solutions, such as R-software, QuantumGIS or GRASS (Neteler et al., 2012), are freely available to manipulate remote sensing products. However, these open-source software lack clear documentation and steep learning curves that hinder their adoption and use. Therefore, offering training across the discipline could potentially increase the adoption of these software (Thamaga and Dube, 2018). The lack of reliability in ground-truth data has also inhibited the progress of classification in remote sensing.

Different algorithms have different strengths and require different input parameters (Ullah et al., 2018). Many factors, such as the spatial resolution of the remotely sensed data, the scale of the study area, the availability of software, and the capacity of the analyst skills and knowledge, affect the modelling approach (Naboureh et al., 2021). The developed model from remote sensing data requires adequate calibration and validation using in situ measurement and can only be used in the absence of clouds (Naboureh et al., 2021). ML algorithms rely on a large number of training samples, which are difficult to obtain in the real world. However, remote sensing big data may provide significant solutions to the lack of data, although they often cause computational challenges, for instance, the need for scalable data storage, dynamic workflow management, and flexible computing resource provisioning (Naboureh et al., 2021).

The Google Earth Engine (GEE) (Gorelick et al., 2017), which is a cloud-based semi-automated platform that offers basic calculation functions for both raster and vector data, can successfully handle remote sensing big data on the cloud (Eskandari et al., 2020; Gorelick et al., 2017). These advancements offer new possibilities for integrating and combining techniques to assess and monitor the connection between LULC change and water resources. However, the Google Earth Engine (GEE) platform has its limitations. It does not support the execution of deep learning algorithms due to computational constraints and the unavailability of such algorithms on the platform. Consequently, users can only gather the data on the platform and perform deep learning algorithms outside of the GEE platform. Additionally, using the platform requires a robust internet connection, which can be challenging in developing countries and may result in limited adoption (Gxokwe et al., 2022; Mudereri et al., 2021). GEE can cause an error with large computation complexity because of memory limitation (Jordan et al., 2018). Remote sensing data are often multimodal, which requires the development of a novel ML model to extract joint features from

the heterogeneous spectral, spatial, and temporal information. The integration of hydrologists, statisticians and expert remote sensing analysts is limited, leading to satellite remote sensing data regularly being underutilized and undervalued (Thamaga and Dube, 2018). The limited sharing of data, particularly in Sub-Saharan Africa, significantly hampers our capacity to examine land function changes beyond land use and land cover alterations. Understanding the spatial variability in the land's ability to offer unintended services and identifying the factors influencing it are crucial for regional policy and spatial planning. Despite these challenges, this review emphasizes the need to shift towards adopting satellite data applications in assessing and monitoring the connection between LULC changes and water resources. This shift involves leveraging multiple data sources and employing advanced data processing techniques to enhance our comprehension of these complex systems.

2.4.2 Progress and future direction on remote sensing of LULC changes on water resources

Progress has been made regarding the utility of remote sensing in semi-arid tropical environments, particularly in long-term monitoring, with a limited number of studies on seasonal monitoring. There is still a gap in the real-time use of modern earth observation techniques, such as Sentinels, which are freely available. Sentinels, with improved spectral resolution and revisit time (5 days), bring new opportunities for the biweekly and seasonal monitoring of the effect of LULC on water quantity and quality. The assessment and monitoring of LULC changes and their impacts on water resources using hyperspectral, drones and balloons has not attracted much attention. Only a few studies have attempted nonparametric machine learning algorithms (Eskandari et al., 2020; Naboureh et al., 2021). Numerous researchers have found that LULC change correlates with water quantity and quality; still, there is no clear understanding of how LULC changes affect water quantity and quality. The quantification of the relationship between LULC change and water resources is a complex system. Understanding the relationship between LULC and water resource dynamics cannot be solely based on a single factor. Therefore, factors such as hydrology, spatial patterns and ecosystem services are often overlooked when assessing and monitoring the impact of LULC changes on water resources. Research efforts need to be promoted to evaluate the relationship between LULC and spatial patterns, ecosystem services and hydrological processes, particularly in semi-arid tropical environments that are susceptible to climate variability. This research could be crucial to supporting LULC planning, effective watershed management, and

making informed decisions regarding water resource management in order to ensure the sustainable management of landscape composition and configuration, ecosystem services and hydrological factors.

Multispectral sensors such as Sentinel 2 and Landsat images tend to be limited by clouds and a relatively coarser spatial and temporal resolution (Singh et al., 2014; Syifa et al., 2020). Drone images are not affected by clouds because they are flown at a lower altitude and can be used to collect data over inaccessible and remote areas (Al-Najjar et al., 2019). As the fourth industrial revolution is progressing, the adoption of drones is advised in future studies as an innovative source of near real-time spatial data for mapping and monitoring the relationship between LULC and water resources. Thus far, no studies have been conducted using drones and comparing satellite sensors and drones in monitoring the impacts of LULC change on water quantity and quality in semi-arid tropical environments. Balloons equipped with a digital camera also have capabilities with regard to filling the gap between satellites and aircraft on earth observation platform. Balloons filled with helium gas can be flown at lower altitudes than airplanes when detecting relatively small objects (small rivers, roads) with minimal expense (Kako et al., 2012). The limitations associated with balloons are that they need to be appropriately used to avoid the geometrical distortion of images (Kako et al., 2012). Geometrically distorted images provide false locations for the objects detected. Due to minimal expense, there is a need to also test this platform.

More research is needed to find the best variable and prediction model that can be integrated with a free multispectral dataset (Sagan et al., 2020). Different algorithms have weaknesses and strengths. Thus far, using an ensemble of different individual sensors and classifiers has been the most effective approach regarding the advance of LULC mapping. The use of more advanced non-parametric algorithms in estimating the effects of LULC on water quantity and quality has also been underutilized, despite their higher predictive accuracy, when compared to parametric algorithms, even when using broadband multispectral sensors. The application of the GWR and BN statistical models is robust; therefore, the use of these models should be adopted in future studies since the algorithms alone could not determine the physical processes of water resources. Integrating remotely sensed data with physical-based hydrologic models is recommended in future studies for effective management and decision making in watershed management. More research is needed to develop advanced models using multi-source data, and improved algorithms and

applications are vital and required. The water quality parameter indices also showed effectiveness in estimating water quality; therefore, integrating them with ML algorithms in future might improve the models. There is also a need to assess the spatial pattern since it provides an understanding of the spatial processes underlying the distribution. The use of AI capabilities enables ML approaches to draw the complex nonlinear relationship between the land surfaces variable and water quality parameters (Peng et al., 2020; Yuan et al., 2017). AI has shown much promise for a wide range of physical environmental problems, from identifying critical situations, to aiding human interpretation, and discovering new relationships in large datasets (Yuan et., 2017). This provides new opportunities with which to speed up the analysis process of large datasets, improve models and successfully transform the exploitation of environmental data in the future. In this regard, the use of multispectral sensor and parametric analysis in characterizing the impacts of LULC on surface water is required if the sustainable utilization of water management is to be achieved when aiming to address the rapidly growing population and its water needs. This information holds great importance for water managers, catchment managers, and land planners as it enables them to tailor their land and water management strategies according to the spatial variability and seasonal changes in the impacts of LULC on water quality and quantity. By understanding these relationships, it becomes feasible to implement local to regional framework policies that promote the sustainable utilization of land and water resources, thus facilitating effective land and water management practices.

2.5 Conclusion

The objective of this study was to conduct a systematic review to assess and monitor the progress of remote sensing applications in mapping land use and land cover (LULC) changes and their impacts on surface water quality and quantity. The literature indicates that the use of remote sensing in this field has gained significant attention in recent years. However, most studies have used multispectral Landsat images, while the potential of other sensors with an improved revisit time, a medium spatial resolution, and enhanced radiometric capabilities (e.g., Sentinel 1 and 2) has received less attention. These sensors offer opportunities for seasonal monitoring. Additionally, the integration of multisource remote sensing data, such as Sentinel 1, Worldview, radar, Quickbird, and LiDAR, has expanded our ability to obtain near real world data, although their limitations need to be assessed. Combining data from different sensors enhances our understanding of the impact of LULC dynamics on water resources. Platforms like drones and

helium-filled balloons enable the near-real-time acquisition of fine-resolution data, which can enhance the accuracy of LULC mapping via improved training and validation processes. The use of advanced classification algorithms, namely ML (e.g., SVM, ANN, RF, BN) and DL algorithms (e.g., RNN, CNN, DNN), which improve the accuracy and efficiency of land cover classification, is recommended. Moreover, the underutilization of advanced machine learning and deep learning algorithms in tropical semi-arid regions and globally suggests the potential for adopting these approaches to accurately estimate the effects of LULC changes on water resources. The use of artificial intelligence (AI) technology can enhance the data processing capabilities of big data analysis, thereby improving the quality of outcomes in future studies. The GEE platform, known for its capacity to handle remote sensing big data, could be a valuable and time-efficient tool for mapping LULC changes. To efficiently address water pollution arising from diverse land use and land cover (LULC) patterns and enhance water quality on both local and regional scales, it is imperative to wholeheartedly adopt innovative technologies and methodologies. These cutting-edge advancements significantly augment our capacity to evaluate and monitor the impacts of land use changes on water resources, thereby facilitating more robust planning and management strategies. Consequently, it becomes essential to investigate the efficacy of these technologies, particularly in semi-arid environments, to ensure their adaptability and effectiveness in such specific ecological contexts.

3. CHAPTER THREE

Using the Google Earth Engine cloud-computing platform to assess the long-term spatial temporal dynamics of land use and land cover within the Letaba watershed, South Africa

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Abstract

Population growth and environmental shifts have elevated the pressure on land use and cover (LULC), necessitating vital management and adaptive strategies to preserve the balance between ecosystem services and human well-being in watersheds. It's pivotal to understand the implications of human-induced shifts from natural to human-dominated surroundings. This study utilized Google Earth Engine (GEE) to analyse 31 years of LULC changes in the Letaba watershed. Using GEE's random forest, LULC classes were mapped with 93% to 99% accuracy across four timeframes (1990, 2000, 2010, and 2021). Trends revealed declining water bodies (-4%), bare surfaces (-2%), natural forest (-3%), and grassland (-3%), while shrublands, plantations, and built-up areas increased at annual rates of 41%, 24%, and 47% respectively. This transformation reflects population-driven shifts, necessitating adaptive strategies. Given the importance of plantations for income, embracing climate-smart agriculture could ensure long-term food and environmental security, thus addressing the evolving dynamics in the Letaba watershed.

Keywords: Catchment health; cloud computing; ecosystem system; environmental security; Land resources; population growth.

3.1 Introduction

Land resources form the most important source of livelihoods and pro key ecosystem goods and services globally. They play a vital role in supporting human needs, such as housing, food production, and settlement, as well as ecosystem services like climate regulation, soil formation, nutrient cycling, and supporting natural vegetation (Alemayehu *et al.,* 2009; Amsalu *et al.,* 2007; Mekuriaw, 2017). However, the rapid growth of the population has led to increased pressure on land resources, resulting in changes in Land Use and Land Cover (LULC). Land use refers to how humans utilize and manage the land for various purposes. Land cover, on the other hand, refers to the physical and biological surface characteristics of the land (Jansen and di Gregorio, 2002;

Mendoza *et al.,* 2011). Such changes are the primary cause of global environmental modifications (Liping *et al.,* 2018). For instance, Salazar et al. (2015) found that LULC changes impact land surface climate feedback, altering the exchange of heat, moisture, momentum, trace-gas flux, and albedo, which in turn affected local and regional climate. Additionally, Bufebo and Elias (2021) reported that LULC changes leads to soil and water quality degradation, loss of biodiversity, and reduced ability of watersheds to sustain natural resources and ecosystem services.

To effectively manage LULC, it is crucial to understand the processes driving their changes, the forces transforming natural habitats into human-dominated environments, and their consequences. This understanding will help in implementing appropriate LULC planning practices within watersheds, which play a vital role in managing soil and water resources worldwide (Grecchi *et al.,* 2014; Kerr and Chung, 2002). However, consistent monitoring has been lacking in many sub-Saharan African countries, especially in rural catchments.

Remote sensing technology continues to provide spatial and temporal coverage, and is necessary for monitoring the environment, due to wide observation range (Cui et al., 2022). Globally, numerous studies have been carried out on LULC change monitoring based on remote sensing. Shen *et al.* (2022) used time series Landsat to classify the LULC in the Huangshui River Basin in China from 1987 to 2018 based on Random Forest (RF) and detected bidirectional spatio-temporal changes based on the distribution probabilities. Similarly, Zurqani *et al.* (2018), utilized Landsat 5 and 8 images to map land use changes in the Savanna River basin in the United State of America (USA) from 1999 to 2015 using RF. Pan et al. (2021) classified LULC using Landsat 5 and 8 images in Australia and the USA based on CART and RF. Furthermore, Leta *et al*. (2021) used Landsat to model and predict LULC in the Upper Blue Nile Basin Ethiopia from 1990 to 2019 based on Land change modeler and further predicted future LULC for 2035 and 2050. These studies confirm the effectiveness of remote sensing in extracting LULC changes.

Availability of satellite imagery data from platforms such as Landsat, Sentinel, MODIS, and other commercial satellites has greatly improved. These datasets provide consistent seasonal and long-term coverage, allowing for the analysis of LULC changes over time (Mashala *et al.,* 2023). However, traditional methods of hardware and software are time consuming, as they require much time to perform image processing, and mosaicking when working on a larger scale (Gorelick *et*

al., 2017; Kumar and Mutanga, 2018). This leads to massive challenges in remote sensing data download and low processing efficiency on large scale.

The emergence of remote sensing cloud computing, and cloud storage platform provide new technical for downloading and processing massive remote sensing data. Cloud-computing platform Google Earth Engine (GEE) is convenient for remote sensing data for desktops which enable high speed analysis using advanced processing techniques (Hamdi *et al.,* 2018; Sidhu *et al.,* 2018). The cloud computing can integrate more than 200 remote sensing dataset and provide Python and JavaScript to facilitate users to process data according to their own needs (Shafizadeh-Moghadam *et al.,* 2021). GEE host advanced classification which enables one to run supervised learning algorithms across huge datasets (Lee *et al.,* 2016; Cui *et al.,* 2020). Algorithms that are found in GEE include Random Forest (RF), classification and regression tree (CART), support vector machine (SVM), and Naive Bayes (NB) classifiers can accurately distinguish classes within a heterogeneous watershed.

However, most studies revealed the effectiveness of RF in classifying change by achieving higher accuracy over CART, NB, and SVM (Delaylay *et al.,* 2019; Pan *et al.,* 2022; Loukika *et al.,* 2021). Although RF has proved its capability in differentiating classes, the accuracy of mapping LULC depends on training and validation of data. The common methods that are used for training point in GEE are manual labelling (Yangouliba *et al.,* 2023), semi-automated (Verde *et al.,* 2020) and automated training (Chaves *et al.,* 2023; Zhang *et al.,* 2022). Automated training methods in remote sensing and geospatial analysis offer several advantages that enhance efficiency, scalability, and objectivity in the classification and analysis processes (Chaves *et al.,* 2023). These advantages are particularly valuable when working with large and complex datasets, covering extensive geographic areas or temporal periods (Zhang *et al.,* 2022). However, automated training might struggle with capturing contextual traces and can be limited to spectral information alone (Zhang *et al*., 2021). On the other hand, collected field points data provides ground truth accuracy, contextual insight, and robust validation potential. The semi-automated approach acknowledges that human judgment is crucial for recognizing complex patterns and understanding the context (Xiong *et al.,* 2017).

Researchers have conducted detailed research and analysis and land cover changes focusing on sub-watershed (de Sousa *et al.,* 2021; Sundar and Paresh 2020), urban areas (Lin et al., 2020;

Agariga et al., 2021; Sumari *et al.,* 2020), coastal areas and ecological areas (Abijith and Saravanan, 2021). These studies demonstrated the processing power of using GEE for mapping and monitoring LULC. Besides the high-speed processing power, only a few studies have attempted to use this cloud computing platform in sub-Saharan African countries to monitor and map the spatiotemporal changes of LULC on the watershed (Leta *et al*., 2021; Yangouliba *et al.,* 2023). Therefore, the study aims to determine the spatial and temporal extent of LULC changes in Letaba watershed by achieving the following objectives 1). To determine and select suitable variables for predicting LULC, 2). To evaluate the performance of the RF machine learning algorithm in the GEE platform in detecting and mapping LULC within the Letaba watershed from 1990 to 2021, and 3). To discuss the potential impacts of change in LULC on the watershed.

3.2 Materials and Methods

3.2.1 Field data

Field data collection for land cover types was conducted manually between February and March 2021, using handheld Garmin global positioning systems (GPS). The training dataset consisted of a total of one thousand and fifty ground truth points, with a hundred and fifty points allocated for each individual class. A balanced distribution strategy for class training samples was employed in the study. This approach was adopted to prevent any bias towards specific classes (Mellor *et al.,* 2015). The use of balanced data distribution is associated with enhanced prediction accuracy and reliability across all classes (Mellor et al., 2015). The collected training data was converted into shapefile using ArcGIS, and subsequently imported into the GEE platform for the purpose of model training and validation for the LULC assessment of the Letaba watershed in 2021.

Similarly, high-resolution data from Google Earth was used to generate nine hundred and ninety-three (993) training data points serving as ground truth references for the year 1990. These points were then converted into shapefiles using ArcGIS and integrated into the GEE platform to facilitate the training of the LULC map for 1990. The same training dataset was further utilized for mapping LULC changes in the 2000 and 2010 images. In accordance with established standards in machine learning evaluation criteria, the imported training data areas were partitioned into two distinct sets: 70% for training and 30% for validation (figure 3.2) (Aman et al., 2021). As a result of this methodology, a comprehensive classification of seven distinct land cover types was executed within the confines of the Letaba watershed (Table 3.1)

Table 3.1: Land use and land cover classification description

Classes	Class no	Description
Bare surfaces (BS)	Class 5	Rocks, bare soil
Built-up (BU)	Class 2	Buildings, roads
Grasslands (GL)	Class 6	Rangelands
Natural Forests (NF)	Class 7	Dense, sparse
Plantations (PT)	Class 3	Tropical, pines, citrus
Water bodies (WB)	Class 4	Dams, rivers, streams
Shrublands (SL)	Class 8	Short trees

3.2.2 Data acquisition and processing

The Landsat 5 Top of Atmosphere (TOA) reflectance products, denoted as LT05/C01/T1_TOA, were utilized for the years 1990, 2000, and 2010. Similarly, Landsat 8 TOA reflectance products, identified as LC08/C01/T1_TOA, were employed for the year 2021. These data resources are available within the Google Earth Engine (GEE) cloud database, accessible via this link: https://earthengine.google.com/. Both Landsat 5 and Landsat 8 platforms encompass 7 and 13 spectral bands respectively, each with a spatial resolution of 30 meters. The TOA reflectance values for each spectral band within the GEE database were used in this study. To mitigate the impact of clouds and shadows, the cloud filtering function (QA_PIXEL) was applied, resulting in the removal of these unwanted elements from all filtered images. The process of filtering and creating mosaics was executed using the "*filter"* function. The date parameters (start and end) were set to cover the periods from January 1st to December 31st for all four respective time intervals. Furthermore, the filtered images were cropped to match the boundaries of the study area through the utilization of the *"filter. Bound ()"* function. The resulting stacked images underwent normalization to account for illumination variations and to minimize the presence of clouds. Inclusion criteria for images involved selecting those with less than 20% cloud cover, except for the 2010 image, for which conditions necessitated the use of images with less than 50% cloud cover due to climatic considerations. The images were enhanced and smoothed to produce quality results.

3.2.3 Predictor variables

Within the GEE platform, the random forest (RF) algorithm was employed to identify the most influential spectral bands from Landsat images. This selection process was important for the prediction and mapping of LULC across the Letaba watershed. Utilizing this technique, researchers aimed to reduce the redundancy within explanatory variables (Dube *et al.,* 2014; Mudereri *et al.,* 2020).

3.2.4 Image classification and accuracy assessment

Google Earth Engine (GEE) provides a range of supervised classifiers, including the classification and regression tree (CART), support vector machine (SVM), Naive Bayes (NB), and Random Forest (RF). All four of these classifiers were tested for their effectiveness in categorizing LULC changes within the Letaba watershed. Following testing, the RF classifier emerged as the most superior performer among these options. As a result, it was subsequently utilized to map the dynamics of LULC within the Letaba Watershed. Support for this decision was also drawn from existing literature. The RF classifier available in GEE (*ee.classifier.smileRandomForest*) has consistently demonstrated outstanding performance in LULC classification when compared to CART, SVM, and NB, as attested by Abijith and Saravanan (2021), Gxokwe *et al.* (2021), and Sundar and Deka (2021). Therefore, the algorithm was selected in this study because of its robustness and predictive accuracy even when applied to analyse data with strong noise (Zurqani *et al.,* 2018).

The RF classifier is a non-parametric algorithm that constructs an ensemble model of decision trees from a random subset of features and a bagging randomisation process. RF has a greater processing power for data noise; overfitting and can work well with complex data with high accuracy (Piao *et al.,* 2021). The classifier uses random sample data to generate multiple decision trees independently. The best node of each decision tree relies on a randomly selected subset of input prediction variables (Zhao *et al.,* 2021). The process continues until the samples are similar and splitting no longer occurs. The final class prediction is chosen using the majority voting of the decision tree.

For LULC classification, accuracy assessment is imperative to explain the agreement between the ground truth and the classification outcome. To evaluate the classification accuracy for the year

2021, a subset of four hundred and twenty (420) reference points (representing 30% of the dataset) was used. Similarly, for the year 1990, 2000, and 2010 a total of two hundred and ninety-seven (297) was used for validation of the accuracy. The validation dataset was employed to generate a confusion matrix within GEE for accuracy assessment. The assessment metrics encompass producer accuracy (PA), overall accuracy (OA), and user accuracy (UA), with the exclusion of Kappa due to its criticized suitability for accuracy assessment (Pontius and Milones, 2011).

3.2.5 Land use change detection

The method of post-classification was employed to determine the magnitude trend and rate of LULC change within the Letaba watershed. An analysis of area comparison was conducted by subtracting the total area for each class, resulting in both positive (increasing) and negative (decreasing) values. The percentage and rate of LULC change were calculated using the subsequent formulas:

The proportion of each LULC class type $Ai = Ai/At * 100$

The change for each LULC class type was computed as follows: $Ai = Ait_1 - Ait_2$ and the

Annual rate of change: $Air = ((Ait_1/Ait_2)-1) * 100\%$

In these formulas, *i* represents the particular area of the LULC class type, *At* designates the total study area, and *Ai* % denotes the proportion of each LULC class area. Ait_1 and Ait_2 refers to the total area of LULC class type in specific years $_1$ and $_2$ respectively (Lu *et al.*, 2013; Piao *et al.*, 2021). *Air* refers to the rate of change, which is the magnitude of change between the specified years and the range of change from 1990 to 2021 was analysed (Piao *et al.*, 2021; Tian *et al.*, 2014). Notably, this method offers the advantage of providing insights into both magnitude and direction of change, while also indicating the number of areas that have undergone alterations.

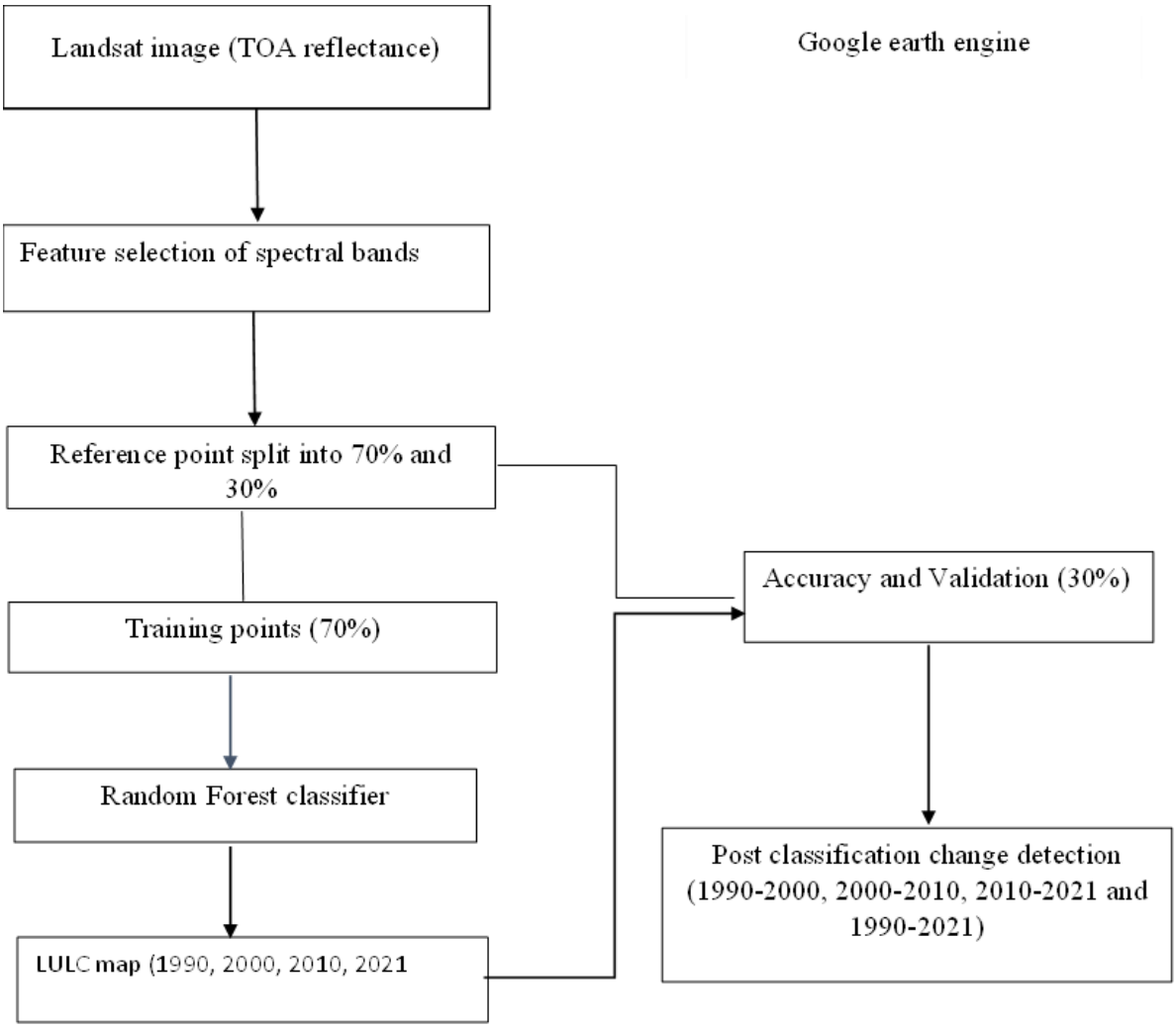

Figure 3.1: The schematic flow chart showing steps performed in GEE to achieve LULC changes.

3.3 Results

3.3.1 Variables of importance

The RF classifier implemented within GEE was used to train the sample with settings of 100 decision trees in mapping LULC in the Letaba watershed. The RF classifier demonstrated a notably overall high level of accuracy in effectively identifying and delineating various LULC categories across the watershed. The spectral bands of Landsat images, specifically band 2 (blue), band 5 (near-infrared or NIR), and band 6 (shortwave-infrared or SWIR), were identified as the most crucial variables for the RF classification process (Figure 3). These specific bands were chosen to predict LULC classes for the years 1990, 2000, 2010, and 2021. This selection served the purpose

of minimizing data redundancy among explanatory variables and enhancing the classification precision.

The cloud-based methodology adopted for this study revealed a notable capability to accurately define LULC classes, offering a visual representation that effectively covered the majority of classes present within the Letaba watershed. In order to optimize the predictive performance, less significant variables were omitted from consideration, as they did not contribute meaningfully to the prediction process. The selection of valuable bands was able to distinguish classes from one another and increased the classification accuracy of the study area.

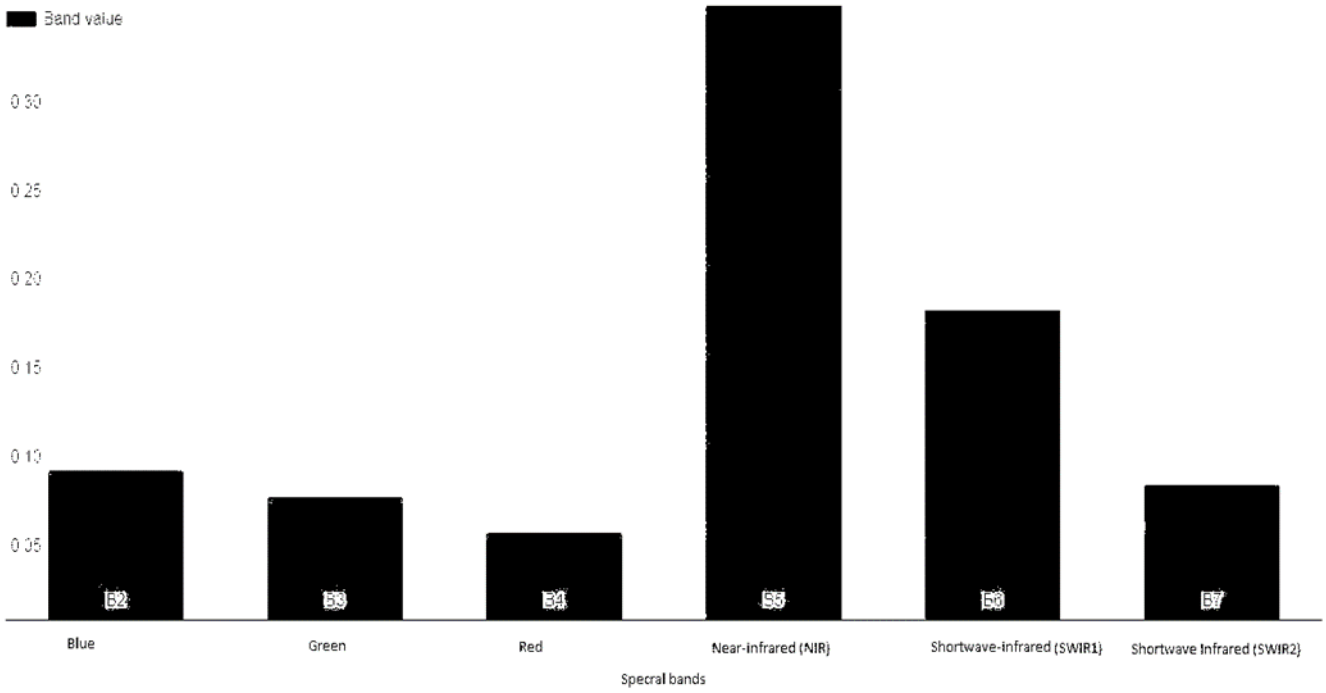

Figure 3.2: Variables of importance percentage derived using the RF variable selection method.

3.3.2 Land cover and land use classification and Accuracy

The RF classifier successfully distinguished LULC classes, achieving OA of 0.95, 0.97, 0.93 and 0.99 for the year 1990, 2000, 2010 and 2021 respectively (Table 3.2). UA and PA values, derived from the confusion matrix, were computed for each class type across all years. Plantations and natural forests occurred in close proximity; however, the RF model effectively captured variations in the upstream area of the Letaba watershed. Notably, the class with the highest accuracy was shrublands, exhibiting a perfect 100% with PAs, and UAs ranging between 93% and 97% across

all time periods. Likewise, water bodies were accurately classified, with PAs ranging from 92% to 98%, and UAs ranging from 95% to 100%. Comparatively, lower classification accuracies were achieved for the Natural Forest class, with PAs varying from 83% to 100% across all time frames. Regarding error assessment, the 2021 classification showcased lower values for error commission (EC) and error of omission (ER), ranging between 0% and 5%. Conversely, the classification for 1990 exhibited higher values of ER (14%) and EO (12%) respectively.

Table 3.2: Derived LULC error matrix for the year 1990, 2000, 2010 and 2021

1990	BS	BU	GL	NF	PT	WB	SL	**Total**	**UA**	**EC**
BS	60	0	0	0	0	0	0	**60**	**100**	**0**
BU	0	60	0	0	0	0	0	**60**	**100**	**0**
GL	1	0	59	0	0	0	0	**60**	**98**	**2**
NF	2	0	0	55	1	2	0	**60**	**92**	**8**
PT	2	0	1	4	53	0	0	**60**	**88**	**12**
WB	2	0	0	1	0	57	0	**60**	**95**	**5**
SL	3	0	0	0	1	0	56	**60**	**93**	**7**
Total	**70**	**60**	**60**	**60**	**55**	**59**	**56**	**420**		
PA	**86**	**100**	**98**	**92**	**96**	**97**	**100.00**			
EO	**14**	**0**	**2**	**8**	**2**	**3**	**0**			
		OA	**95**							

2000	BS	BU	GL	NF	PT	WB	SL	**Total**	**UA**	**EC**
BS	60	0	0	0	0	0	0	**60**	**100**	**0**
BU	1	59	0	0	0	0	0	**60**	**98**	**2**
GL	1	1	56	1	0	1	0	**60**	**93**	**7**
NF	0	0	0	60	0	0	0	**60**	**100**	**0**
PT	2	0	0	3	55	0	0	**60**	**92**	**8**
WB	0	0	0	1	0	59	0	**60**	**98**	**2**
SL	1	0	0	1	0	0	58	**60**	**97**	**3**
Total	**65**	**60**	**56**	**66**	**55**	**60**	**58**	**420**		
PA	**92.31**	**98.33**	**100.0**	**90.91**	**100.0**	**98.33**	**100.00**			

EO	**8**	**2**	**0**	**9**	**0**	**2**	**0**			
		OA	**97**							

2010	BS	BU	GL	NF	PT	WB	SL	**Total**	**UA**	**EC**
BS	59	0	0	0	0	1	0	**60**	**98**	**2**
BU	4	56	0	0	0	0	0	**60**	**93**	**7**
GL	0	0	56	2	0	2	0	**60**	**93**	**7**
NF	0	0	0	57	1	2	0	**60**	**95**	**5**
PT	3	0	0	7	50	0	0	**60**	**83**	**17**
WB	0	0	0	3	0	57	0	**60**	**95**	**5**
SL	0	0	2	0	1	0	57	**60**	**95**	**5**
Total	**66**	**56**	**58**	**69**	**52**	**62**	**57**	**420**		
PA	**89.39**	**100.00**	**96.55**	**82.61**	**96.15**	**91.94**	**100**			
EO	**11**	**0**	**3**	**7**	**4**	**5**	**0**			
		OA	**93**							

2021	BS	BU	GL	NF	PT	WB	SL	**Total**	**UA**	**EC**
BS	57	3	0	0	0	0	0	**60**	**95**	**5**
BU	0	60	0	0	0	0	0	**60**	**100**	**0**
GL	0	0	60	0	0	0	0	**60**	**100**	**0**
NF	0	0	0	60	0	0	0	**60**	**100**	**0**
PT	0	0	0	0	60	0	0	**60**	**100**	**0**
WB	0	0	0	0	0	60	0	**60**	**100**	**0**
SL	2	0	0	0	0	0	58	**60**	**97**	**3**
Total	**61**	**65**	**60**	**60**	**60**	**60**	**58**	**420**		
PA	**96.72**	**92.31**	**100.0**	**100.0**	**100.00**	**100.0**	**100**			
EO	**3**	**5**	**0**	**0**	**0**	**0**	**0**			
		OA	**99**							

3.3.3 The spatiotemporal changes of the Letaba watershed in 31 years

Over the past 31 years, significant shifts in land use and land cover (LULC) have been observed within the Letaba watershed (Figure 3.4, Table 3.3). By the year 2021, there has been a noteworthy

transformation in the LULC composition. Particularly, the natural forests and grasslands have undergone deforestation and degradation, resulting in a decline in their respective percentage covers from 13% and 23% in 1990 to 6% and 9% in 2021. Furthermore, there has been a reduction in the percentage cover of bare surfaces and water bodies, which decreased from 44% and 13% in 1990 to 29% and 1% in 2021, respectively. In contrast, there has been a considerable increase in the percentage covers of plantations, shrublands, and built-up areas. These categories have seen their coverage expand from 4%, 2%, and 2% in 1990 to 24%, 15%, and 16% in 2021, respectively.

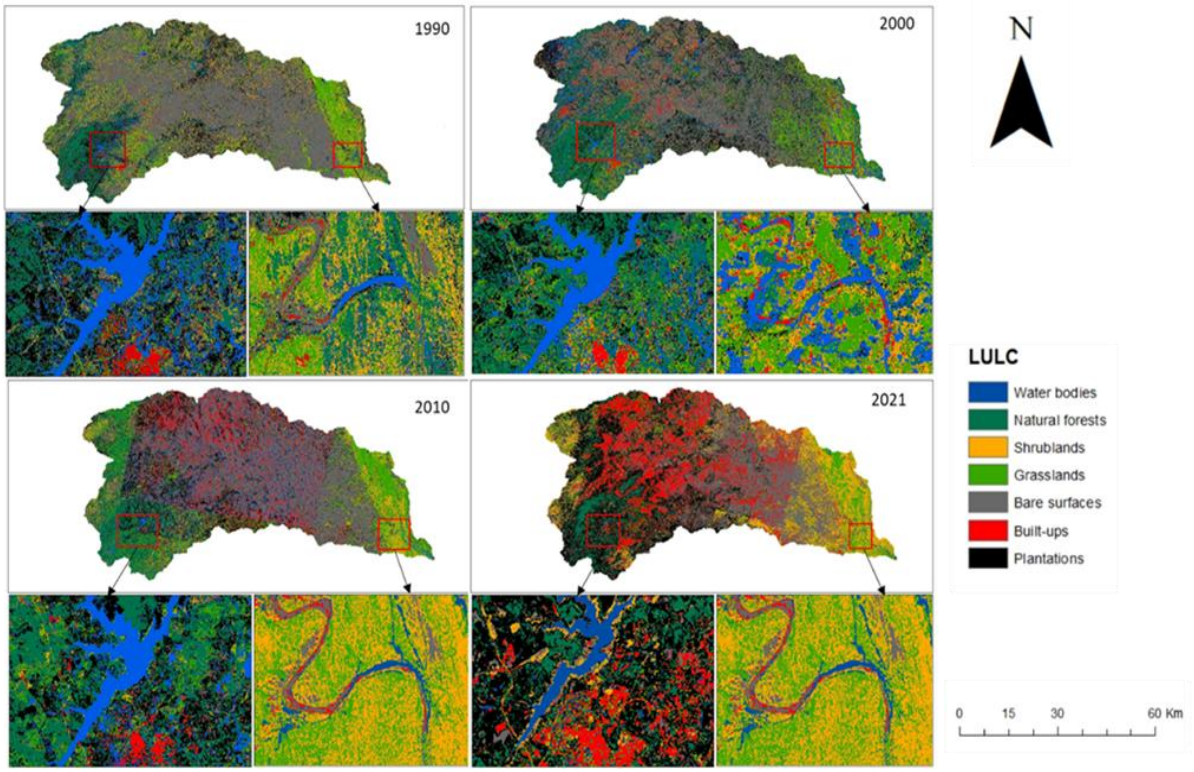

Figure 3.3: Spatiotemporal pattern of LULC at Letaba watershed

Table 3.4: Area covered by each class type for four-time period.

	1990		2000		2010		2021	
Classes	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**	**Area (ha)**	**Area (%)**
Bare surfaces	645894	44	581998	40	560638	39	418694	29
Built-up	22068	2	47395	3	140123	10	238994	16
Grasslands	335100	23	193814	13	194121	13	134894	9
Water bodies	184736	13	99332	7	106812	7	15595	1
Natural forests	184049	13	170381	12	142161	10	84325	6
Plantations	57514	4	277227	19	216961	15	343700	24
Shrublands	22503	2	81717	6	91048	6	215662	15
Total	**1451864**	**100**	**1451864**	**100**	**1451864**	**100**	**1451864**	**100**

The rate of change presented in Table 3.4 revealed different changing progression for each class category from 1990 to 2021. Bare surfaces, water bodies, natural forest and grasslands areas reduced trend at a rate of -2%, -4%, -3% and -3% respectively whereby plantations area increased at rate of 24%. However, built-up and shrublands showed a clear extension trend which significantly increased from the year 1990 to 2021 with a rate of 47% and 41% respectively. The highest intensity of built-up areas, plantations and shrublands occurred between 2010 and 2021 (Figure 3.5). Conversely, the highest decline intensity of water bodies, natural forests and bare surfaces occurred between 2010 and 2021, and grassland occurred in two time periods between the year 2000 and 2010 and 1990 and 2021.

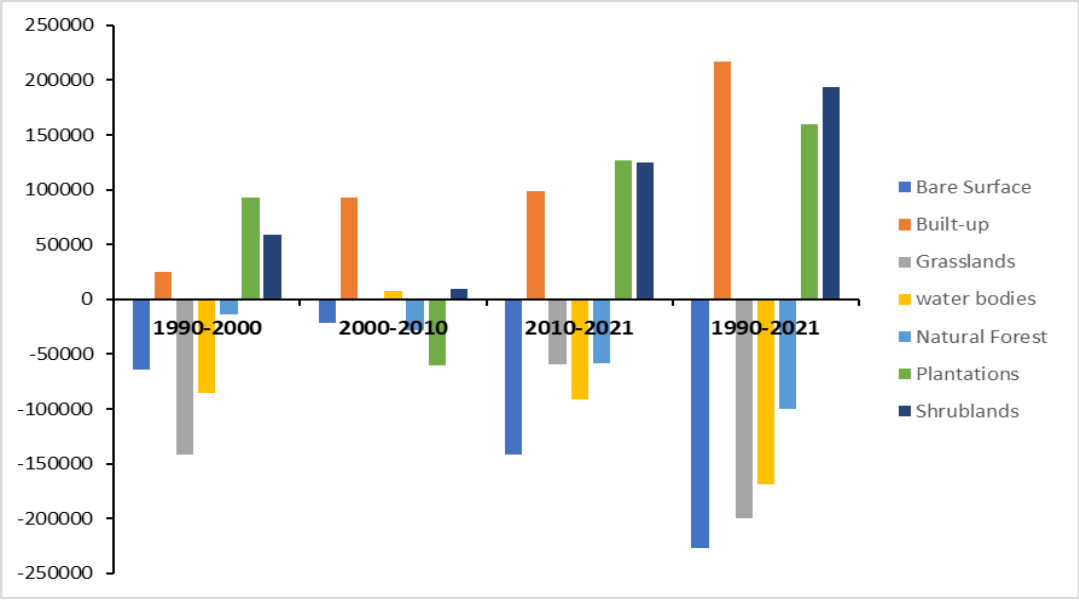

Figure 3.4: Representation of total area LULC change (gains and loss) in the Letaba watershed for the time period 1990, 2000, 2010 and 2021

Table 3.5: The rate of change in LULC classes from the year 1990 to 2021

Class	1990 Area %	2021 Area %	1990-2021 rate of change %
Bare surfaces	**44**	**29**	**-2**
Built-up	**2**	**16**	**47**
Grasslands	**23**	**9**	**-3**
Water bodies	**13**	**1**	**-4**
Natural forests	**13**	**6**	**-3**
Plantations	**4**	**24**	**24**
Shrublands	**2**	**15**	**41**

Moreover, the study revealed a reduction in the area covered by natural forest to plantations in the upstream of the watershed. Whereas grasslands are hastily replaced by shrublands downstream of the watershed. The bare surfaces are swiftly substituted by built-up and plantations in the middle stream of the watershed. Although bare surface areas are decreasing, they are still the most dominating land cover in the watershed. The water bodies are diminished by plantations and construction of dams alongside the streams in the middle and upper streams which prevents the flow of the water downstream of the watershed. Additionally, water bodies downstream of the watershed are becoming drier and converted into bare surfaces.

3.4 Discussion

Accurate detection and mapping of LULC are important for understanding the drivers that results in change of the natural environment into human dominant. Advanced data analytics and remote sensing application has improved fast monitoring of LULC changes in Letaba watershed. The implementation of GEE has been effective for leveraging big data in remote sensing technology. This technology allows users from other regions to adapt and customize the existing analysis scripts or create new ones that cater to the specific characteristics of the new region (Huang *et al.*,

2017). This may include modifying classification algorithms, adjusting parameters, and thresholds based on the unique land cover types, climate, and land use patterns (Azzari and Lobell, 2017).

The aim of this study was to determine the spatiotemporal changes in LULC within the Letaba watershed from 1990 to 2021 using GEE. The scalability and flexibility of GEE's platform demonstrated the capabilities in continuous monitoring LULC changes and support targeted management and conservation strategies across diverse landscapes and regions (Pan, *et al.*, 2022). The limitations of GEE include spatial and temporal resolutions of satellite image, which may not be adequate for capturing fine-scale changes in a heterogeneous landscape. This can lead to challenges in accurately identifying and classifying different land cover types, in areas with complex and mixed land use patterns. Cloud cover can be a significant issue in tropical regions, this can limit the availability of cloud-free imagery, which affects the temporal consistency and reliability of LULC change detection (Delalay *et al.*, 2019). Additionally, GEE's algorithms and processing methods might not be optimized for the specific characteristics and challenges of mapping LULC changes in watersheds. GEE might perform well in certain regions but may lack accuracy and generalization when applied to complex and heterogeneous semi-arid landscapes (Gxokwe *et al.*, 2022). The interpretation of LULC changes requires careful consideration of local socio-economic and cultural factors. GEE's remote sensing approach might not fully capture the drivers and underlying reasons for LULC changes, limiting the understanding of the complexities involved.

Based on the analysis using the GEE, the use of RF for classification provided useful information in detecting and mapping spatiotemporal changes of the Letaba watershed. The results from the RF analysis demonstrated the efficacy of utilizing specific spectral band values to differentiate various land cover classes present in the watershed. Notably, the Blue, Near-Infrared (NIR), and Shortwave Infrared 1 (SWIR1) bands exhibited significant discriminatory power among these classes (Mudereri *et al.*, 2020). Among these bands, the NIR band emerged as the most pivotal due to its sensitivity to factors like vegetation type, water content, density, and overall vegetation health (Forkuor *et al.*, 2018; Kyere *et al.*, 2019). Likewise, the SWIR1 band's sensitivity to moisture levels and shades in the forest stand structure proved valuable in the classification process (Izadi and Sohrabi, 2021). Additionally, the blue band played a crucial role in distinguishing

between soil and vegetation, as well as differentiating deciduous trees from coniferous vegetation (Acharya *et al.,* 2015; Zeferino *et al.,* 2020).

The study's findings also suggested that a strategic selection of a few informative bands could potentially outperform the classification achieved using the entire set of wavebands (Cai *et al.,* 2018; Dube and Mutanga, 2014; Mudereri *et al.,* 2020). While the spectral bands alone demonstrated the capability to differentiate land cover, the incorporation of indices such as the Normalized Difference Vegetation Index (NDVI), Modified Normalized Difference Water Index (NDWI), Normalized Difference Built-Up Index (NDBI), and slope could potentially provide additional value in the prediction and mapping of LULC. Despite RF's success in effectively mapping LULC within the Letaba area, it's important to acknowledge certain limitations associated with the classifier. When dealing with datasets characterized by imbalanced class distributions, RF might exhibit a bias towards the majority class, potentially resulting in decreased accuracy for minority classes and the risk of overfitting (Pan *et al.,* 2022).

The information regarding precision and accuracy presented in the classified map outcomes holds significant importance for users aiming to effectively utilize the generated maps (Munthali *et al.,* 2019). Therefore, conducting accuracy assessment remains a pivotal step in image classification, and this study demonstrated commendable accuracy results, even though some errors arose from spectral confusion among natural forests, bare surfaces, and plantations. The established standard level for overall classification accuracy typically stands at 85% (Yesuph and Dagnew, 2019; Witkowska *et al.,* 2021). However, the outcomes of this study outperformed this standard, achieving remarkable overall accuracy rates of 95%, 97%, 93%, and 99% for the years 1990, 2000, 2010, and 2021 respectively. This achievement indicates that the classification results were both rational and dependable, enabling subsequent post-classification change detection comparisons. The high overall accuracy achieved can be due to the implementation of the RF classifier, which effectively minimize errors as the number of decision trees increases (Abijith and Saravanan, 2021), and the selection of variable importance reduces the redundancy of correlated variables. It is essential to note that the accuracy of LULC classification within the GEE depends on the availability of high-quality training data.

Utilizing ground truth data has proven to be effective in achieving high classification accuracy within the Letaba watershed. Nonetheless, the challenges associated with acquiring ground truth data for validation can be difficult in remote and inaccessible areas. This can result in potential inaccuracies during the classification procedure and minimize confidence in the outcomes. Xiong *et al.* (2017) and Verde et al., (2020), used automated crop mapping in GEE, this method can quickly generate training data, enabling rapid response to changing land cover conditions, and provide consistent training samples across the study area, reducing potential bias. Automated methods are useful and work well in situations where ground truth data are scarce or when capturing rapid changes is crucial. Although automated methods in GEE provides an impressive computational infrastructure; it still relies on remote sensing data and may not be a substitute for detailed on-the-ground surveys and local knowledge (Pan *et al.,* 2022). Field-based data collection and ground-truthing are essential for validating and improving the accuracy of LULC maps generated through GEE (Kander *et al.,* 2021; Pande *et al.,* 2021). Automated and field-based data collection methods share the common objective of enhancing accuracy in land cover analysis. Both approaches contribute to reliable classification outcomes by providing representative training samples. Automated methods leverage algorithms to rapidly generate training points from spectral properties, enabling efficient processing of large datasets (Zhang et al., 2021). In contrast, field-based data collection involves on-site observations, capturing contextual details that algorithms might miss (Pande *et al.,* 2018).

The process and rate of change over the 31 years were analysed using four time periods with rapid increase in shrublands and built-up from 2% and 2% in 1990 to 15% and 16% in 2021 respectively. The increase rate (47%) in the built-up areas (residential, commercial, roads, and industries) could be attributed to increasing demand for land by growing population rate and development of commercial infrastructure that are taking place in the Letaba watershed (DWAF, 2004; Querner *et al.,* 2016). Such expansion of buildings transforms natural landscape which emerge to cause severe environmental degradation such as loss of natural habitat. This disrupts the connectivity between ecosystems, isolating populations of plants and animals and reducing genetic diversity, making species more vulnerable to extinction (Hailu *et al,* 2021). The increased impervious surface such as pavements, reduce natural water infiltration, leading to increased surface runoff during rainfall events. This can result in water pollution as runoff carries pollutants from urban areas into nearby

water bodies, negatively impacting aquatic ecosystems and biodiversity (Du Plessis *et al.,* 2015; Namugize *et al.,* 2018).

Moreover, the plantations also increased from 4% in 1990 to 24% in 2021, which indicates that plantations are the main source of income within the watershed. The increase rate (24%) of plantations in the Letaba watershed can be attributed to rapid growth in demand for arable land (Marks-Bielska and Witkowska-Dąbrowska, 2021). The expansion of uncontrollable plantation lands often results in deforestation, wetland conversion, or the draining of natural habitats to make way for crops or livestock. This leads to habitat loss and fragmentation, disrupting ecosystems and reducing biodiversity as native species struggle to adapt or face displacement. The intensification of plantations using agrochemicals, irrigation, and monoculture practices can lead to soil degradation, erosion, and loss of fertility (Uniyal et al., 2021). This do not only affect agricultural productivity but also impacts nearby water bodies through runoff of pesticides and fertilizers, leading to water pollution and harming aquatic life (Chen *et al.,* 2014; Uniyal *et al.,* 2020). The population increase has resulted in conversion of bare surfaces and grasslands into built-up areas from the year 1990 to 2021.

The decrease rate (-3%) of grassland could be attributed to overgrazing, encroaching invasive tree species which suppress the growth of grasslands and the effects of climate change. The decreasing grassland will have implications on the functioning of ecosystems in the area, climate regulation and depletion of species (Ceballos *et al,* 2010; Zavaleta and Havley, 2004). Grasslands play a crucial role in providing ecosystem services such as carbon sequestration, water filtration, and soil conservation. Their destruction can release stored carbon into the atmosphere, reduce water quality due to increased runoff, and lead to soil erosion (Wang *et al*., 2022).

The bushes are encroaching the grasslands with an increase rate of 41%. The invasion of bushes could be attributed to veld fires and climate change effects downstream of the Letaba watershed. The invasion will also alter the vegetation structure and water use characteristics in ways which can reduce the runoff or decrease the groundwater recharge and results in loss of biodiversity (Le Maitre *et al.,* 2020). The findings of grassland being converted to bushlands correspond with the study by Yesuph and Dagnew (2019) at the Beshilo Catchment in Ethiopia. The increased rate of shrub encroachment can fragment and disrupt natural ecosystems. The formation of dense shrub

patches may act as barriers to the movement of wildlife, making it difficult for some species to access food, water, or breeding sites (Shiferaw *et al.,* 2019). This fragmentation can reduce gene flow and genetic diversity within populations, potentially leading to inbreeding and reduced resilience to environmental changes (Wang *et al.,* 2022).

Comparatively, the decline rate (- 4%) of water bodies can be attributed to the significant increase in the plantations along the river and streams banks, invasive species and lots of constructed dams and weirs within the watershed which is becoming problematic (Pullanikkatil *et al.,* 2016; Munthali *et al.,* 2019). This relates with the study by Munthali *et al.* (2019) in Dedza district of Malawi where they observed an increase in plantation alongside the stream at the expense of the water bodies. The reduction of water bodies leads to degraded water quality, loss of critical ecosystem services like water purification and flood regulation, and increased vulnerability to climate change impacts. This threatens the livelihoods of local communities' dependent on fisheries and agriculture, while also impacting the overall health and resilience of surrounding terrestrial ecosystems (Rotich *et al* 2022).

The study also revealed natural forests deteriorated from (13%) in 1990 to (6%) in 2021 in the upper watershed. The declining rate (-3%) of natural forest cover could be attributed to the rapid population growth in demand for arable land for food production as it is mostly converted into plantations. The result corresponds with the finding by Agariga *et al.* (2021) where they observed conversion of forest to agriculture between 1986 and 2020. The decline in natural forest also reduces the size of the carbon sinks, thereby contributing to greenhouse gas emissions (Berry *et al.,* 2010). Bare surface decreased from 44% in 1990 to 29% in 2021 with a decreased rate of -2 %. Most of the bare surfaces were converted into built-up and plantations.

The changes in LULC within the Letaba are driven by lack of regulations, policies, and socioeconomic factors. Therefore, it is essential to understand these drivers and policy contexts behind LULC changes to develop effective strategies for sustainable land management, biodiversity conservation, and environmental protection. Integrating environmental considerations into policy-making processes can help balance human development needs with conservation goals and foster sustainable land use practices (Rotich *et al.,* 2022). The information gathered from this study can be used to develop targeted management strategies to address challenges such declined

water bodies, grasslands, and natural forest and promote sustainable land use practices. To manage the socioeconomic implications of LULC changes in Letaba watershed effectively, it is crucial to integrate social considerations into land use planning and decision-making processes. Community engagement, participatory approaches, and consideration of local knowledge can help ensure that the interests and well-being of the local population are considered in development and conservation initiatives. Moreover, balancing economic development with environmental sustainability is essential for promoting the long-term prosperity and resilience of local communities.

3.5 Conclusion

With the right set of variables, the GEE's RF classifier can accurately map and predict the extent and rate of LULC dynamics. The findings revealed that the Letaba watershed experienced significant LULC change between 1990 and 2021. During these years, the watershed has lost bare surfaces, water bodies, grassland, and natural forest. While built-up, shrublands and plantations are on the rise. Built-up, plantations and shrublands are likely to continue growing due to the growing population's demand for settlement and arable land to meet human needs, as well as climate change variability favouring invasive shrubland. Water bodies, natural forests, bare surfaces, and grassland are also expected to decline further as a result of overexploitation of water for irrigation of commercial farming within the Letaba watershed, rapidly increasing population, and invasive shrub species. The lack of enforced regulations and policies to protect natural resources within the Letaba watershed is the primary driver of the large LULC transition. The majority of natural forest conversion to plantation areas will result in deforestation, which will have consequences for ecosystems, human livelihoods, climate regulation, and biodiversity. Grasslands, on the other hand, are being converted to shrublands, built-up areas, and plantations, which has implications for the extinction of uncounted populations and species, as well as biodiversity and climate. As a result, environmentalists, watershed managers, forest managers, decision makers, and stakeholders must act quickly to address issues of environmental degradation. To avoid land degradation, the study recommends that appropriate measures be taken to protect and restore natural resources such as grasslands, natural forests, water bodies, and eradicate invasive shrubs in the Letaba watershed.

4. CHAPTER FOUR

Using Google Earth Engine to monitor the spatial and seasonal dynamics of surface water quantity in tropical semi-arid of the Letaba catchment

Abstract

Understanding the spatial and seasonal dynamics of surface water bodies is imperative for addressing water security challenges, particularly in water scarcity regions. This study aimed to evaluate the efficacy of multi-date Sentinel-2-derived spectral indices, specifically normalized difference water index (NDWI), modified normalized differences water index (MNDWI), and Sentinel 2 water index (SWI), in conjunction with landscape metrics for mapping spatial and seasonal fluctuations of surface water bodies. Google Earth Engine (GEE) was employed for this assessment. The research consistently achieved impressive overall accuracies ranging from 96% to 100% for both dry and wet seasons, showcasing the robustness of the methodology. The study revealed significant differences in water bodies in terms of size and coverage between dry and wet seasons. Surprisingly, the dry season exhibited a higher prevalence of water bodies, indicating unexpected patterns of water availability in the region, and substantial heterogeneity in water bodies. Whereas the wet season was characterized by extensive coverage. These findings challenge conventional assumptions about water resource availability during different seasons. Based on the finding, it is recommended that water resource management strategies in semi-arid regions consider the observed seasonal variability in water bodies. Policymakers and stakeholders should adopt adaptive management approaches to address the unique challenges posed by differing water body dynamics in dry and wet seasons. Future research endeavors should explore deeper into the underlying factors driving these seasonal fluctuations and assess their potential long-term impacts on water availability. This can help to develop more resilient and sustainable water security strategies to cope with changing climate conditions in semi-arid tropical environments.

Keywords: landscape pattern; watershed, remote sensing; semi-arid

4.1 Introduction

Surface water is the most accessible and irreplaceable natural resource that sustains most organisms on the planet (Khalid *et al.,* 2021; Rokni *et al.,* 2014) including livelihoods, socio-economic development, ecosystem services, and circulation and exchange of earth energy (Khalid *et al.,* 2021; Verpoorter *et al.,* 2012). Tropical semi-arid regions are characterized by unpredictable

weather, long dry season, and inconsistent rainfall (Haas *et al.,* 2009). The surface water availability in these regions is subjected to complex interplay of climatic, geological, ecological, and anthropogenic factors (Feyisa *et al.,* 2 013; Tulbure and Broich, 2014). As global temperature rises, these regions are experiencing alterations in precipitation patterns, intensification of droughts, and increased evapotranspiration rates, further exacerbating water scarcity issues (Gan *et al.,* 2016; Kusangaya *et al.,* 2014). Moreover, rapid population growth and urbanization are putting immense pressure on already limited water resources, making it imperative to explore effective water management strategies to avoid environmental casualties (Bhangale *et al.,* 2020).

Accurate and up to date information on the distribution of surface water are important indicators of climate change, demarcation and prediction of floods, the assessment of actual driving forces, and quantifying their decline (Klein *et al,* 2013; Khalid *et al.,* 2021). Tropical semi-arid regions are particularly vulnerable to fluctuation in surface water availability due to their arid nature and irregular rainfall patterns. Understanding the spatial and seasonal dynamics of surface water bodies is crucial for enhancing water security, especially during dry periods when water scarcity becomes a pressing concern. Furthermore, this will contribute to water management strategies, and allow decision-makers to allocate water resources efficiently and sustainably.

Remote sensing offers a powerful and efficient means of collecting data over large areas, enabling comprehensive assessment of water resources and their spatial patterns. Several studies have demonstrated the effectiveness of remote sensing in long-term monitoring surface water resources. Zou *et al., (*2017) used Landsat 5 and 7 to map open surface water bodies in Oklahoma from 1984 to 2015 based on modified normalized difference water index (MNDWI) and normalized difference water index (NDWI). Similarly, Sarp and Ozcelik (2017) used Landsat 5 and 7 to extract water bodies in Lake Burdur, Turkey from 1987 to 2011 based on support vector machines (SVM), NDWI, MNDWI, and automated water extraction index (AWEI). Khandelwal *et al.* (2017) also monitored the surface water extent using MODIS in USA, Egypt, Ukraine, Brazil, and Canada based SVM. The abovementioned studies observed high inter and intra annual variability of surface water resources. However, temporary water bodies are missed in the annual monitoring studies due to their short and erratic appearance. Seasonal surface water can show the strong variation between the wet and the dry season, even shifting geographically (Haas et al., 2009).

There are limited studies that focus on seasonal variation of surface water bodies. Majority of these studies have used Landsat satellites for long-term monitoring of water bodies (Pickens *et al.* 2020; Feyisa *et al.,* 2014).

Availability of free satellite imagery data from platforms such as Sentinels satellites has greatly improved spatial resolution (10m) and revisit time (days) (Mashala *et al.,* 2023). Yet only few studies have attempted to use these satellites for mapping and monitoring water bodies (Jiang et al., 2021; Yang et al., 2017). These datasets provide consistent seasonal and long-term coverage, allowing for the analysis of water bodies changes over time. Water indices such as NDWI, and MNDWI, have been frequently used to extract water bodies using spectral bands from Landsat series. This is due to their effectiveness for delineating water bodies with accuracy. Although these indices have good effects for water extraction from Landsat series satellites, slight change in the spectral range of the corresponding wavebands for different sensors may lead to a change in the water extraction results (Jiang *et al.,* 2021).

Sentinel-2 is a state-of-the-art satellite system developed by the European Space Agency (ESA), designed for Earth observation with a particular focus on monitoring land and water resources. The spatial resolution of 10m of the satellite offers a set of unique characteristics that make it ideal for mapping water bodies (Jiang et al., 2021; Yang et al., 2017). Due to the multispectral advantage of Sentinel, researchers have introduced the use of different bands such SWIR, red edge, optical bands, spatial resampling to calculate water indices that can achieve feasible water extraction performance (Jiang *et al.,* 2021; Yang *et al.,* 2017). The process involving desktops proved to be time-intensive to perform tasks like mosaicking, image retrieval, and cloud filtering. This leads to massive challenges in remote sensing. Therefore, platforms such as Google Earth Engine (GEE) with power processing speed provide a need for monitoring and mapping surface water bodies within the study area. Cloud computing can integrate more than two hundred remote sensing datasets and provide python and JavaScript to facilitate users to process data according to their own needs (Shafizadeh-Moghadam *et al.,* 2021). Besides, no studies attempted to use it in monitoring water resources especially in tropical semi-arid southern Africa.

Therefore, the study aims to test Sentinel 2 derived spectral indices in mapping spatial and seasonal variability of surface water bodies of the Letaba catchment in tropical semi-arid southern Africa

using GEE. The Letaba catchment has experienced a booming agriculture over the past years yet the data on variability of and trends in water availability, pollution and scarcity is still lacking. Therefore, the study aims to achieve the following objectives: (i). to seasonally detect and map spatial surface water bodies of the Letaba catchment through GEE platform using Sentinel 2 derived spectral indices, (ii) to quantify the seasonal spatial configuration of surface water bodies landscape metrics.

4.2 Materials and methods

4.2.1 Data acquisition and analysis

The study was conducted between the years 2017 to 2022 and divided into seasons. The seasons were categorized into two main periods: wet and dry. The wet season extended from mid-September to March, while the dry season covered the period from April to mid-September. Additionally, a wet season was defined from mid-September of the previous year to March of the current year. For example, the wet season for 2017 was considered from mid-September 2016 to March 2017 etc. The research utilized Sentinel 2 satellite images between 2017 and 2021 to cover the study area. The GEE platform was employed to gather images by filtering for scenes with cloud ratios of under 10% (indicating no clouds).

4.2.2 Extraction of surface water bodies

Various water indices were tested in Letaba catchment for the years 2017 to 2022 to distinguish water bodies from non-water bodies. The method of water indices in water extraction were chosen based on their competence of using several reflectivity variations in the spectrum that differentiate water from non-water classes (Acharya *et al.,* 2018; Zhai *et al.,* 2015). Moreover, they have been successfully used to extract water bodies due to their accuracy and they can capture significant information on inter and intra seasonal variation of surface water bodies (Zhou *et al.,* 2017; Serban *et al.,* 2022). However, in this case water indices such as the normalized difference water index (NDWI), Sentinel water Index (SWI) and the modified normalized water index (MNDWI) were assessed as the most appropriate algorithms for outlining water bodies. These indices were compared against each other for delineating surface water bodies within the Letaba Catchment. Table 4.1 presents the spectral indices applied to surface water bodies using imagery from the Sentinel 2 Multispectral Instrument (MSI) within the Letaba catchment.

Table 4.1: Spectral water indices used to extract surface water bodies of the Letaba Catchment from Sentinel 2.

Water indices	Formulae	Threshold	Reference
Normalized difference water index (NDWI)	NDWI = (Green- NIR)/(Green + NIR)	NDWI > 0	Mcfeeters, 1996
Modified normalized difference water index (MNDWI)	MNDWI = (Green- SWIR2)/(Green + SWIR2)	MNDWI > 0	Xu, 2006
Sentinel 2 water index (SWI	SWI = (Red edge -SWIR2)/(Red edge+ SWIR2)	SWI > 0	Jiang et al., 2021

4.2.3 Validation

A total of three hundred referenced random points of water bodies were generated and digitized using high spatial resolution imagery in Google earth (GE) and imported into the GEE cloud computing platform. The points were compared with the points generated using water indices maps produced in google earth engine to confirm if they relate to those collected in GE. Then a confusion matrix was performed to quantify the producer, user, and overall accuracy by means of identifying four variables of pixels:

True positive (TP): number of accurate extracted water pixel points.

False negative (FN): number of undetected water pixel points.

False positive (FP): number of erroneously extracted water pixel points.

True Negative (TN): number of non-water pixel points.

Overall accuracy (%) = (TP+TN) x 100/Total number of pixel (T)

Table 4.2: Confusion matrix

Class	Reference data	
	Water	Non-water

Classified data	Water	TP	FP
	Non-water	FN	TN

Producer, user, and overall accuracy reflect correct predictions and have a range of 0 to 100%, with the value close to one hundred showing perfect accuracy (Albarqouni et al., 2022).

4.2.4 Spatial configuration

To assess the spatial arrangement of water bodies in terms of landscape characteristics, it is essential to define and quantify landscape complexity (Tulbure and Broich, 2013). Four landscape metrics were chosen and employed to capture distinctive attributes of various water body levels. These metrics were selected to illustrate changes and enable comparative analysis, facilitating an evaluation of water body complexity within the Letaba catchment. The metrics utilized are as follows:

(i). Number of Water Bodies (NW): This metric represents the count of water bodies within a specific area. (ii). Mean Area of Water Bodies (MAW): Calculated by dividing the total sum of all water body areas by the total number of water bodies: MAW = Xi / NW, where Xi corresponds to the surface water bodies within a given landscape, and NW represents the count of water bodies in that landscape. (iii). Total Area of Water Bodies (TAW): This metric quantifies the cumulative area covered by water bodies within a landscape. (iv). Coefficient of Variation (CV): Derived from the standard deviation of MAW divided by MAW, multiplied by one hundred. This metric indicates the extent of variability in water body sizes within a landscape. All these calculations were performed using Microsoft Excel to generate tables and graphs, providing a comprehensive understanding of the landscape's water body configuration and complexity.

4.3 Results

4.3.1 Water indices and validation

The calculated water indices were able to detect and map surface water bodies within Letaba catchment with accuracy. However, NDWI performed better than MNDWI and SWI in delineating water bodies in tropical semi-arid Southern Africa**.** Figure 4.1a and 4.1b shows the extent and seasonal variation of the Letaba catchment surface water bodies.

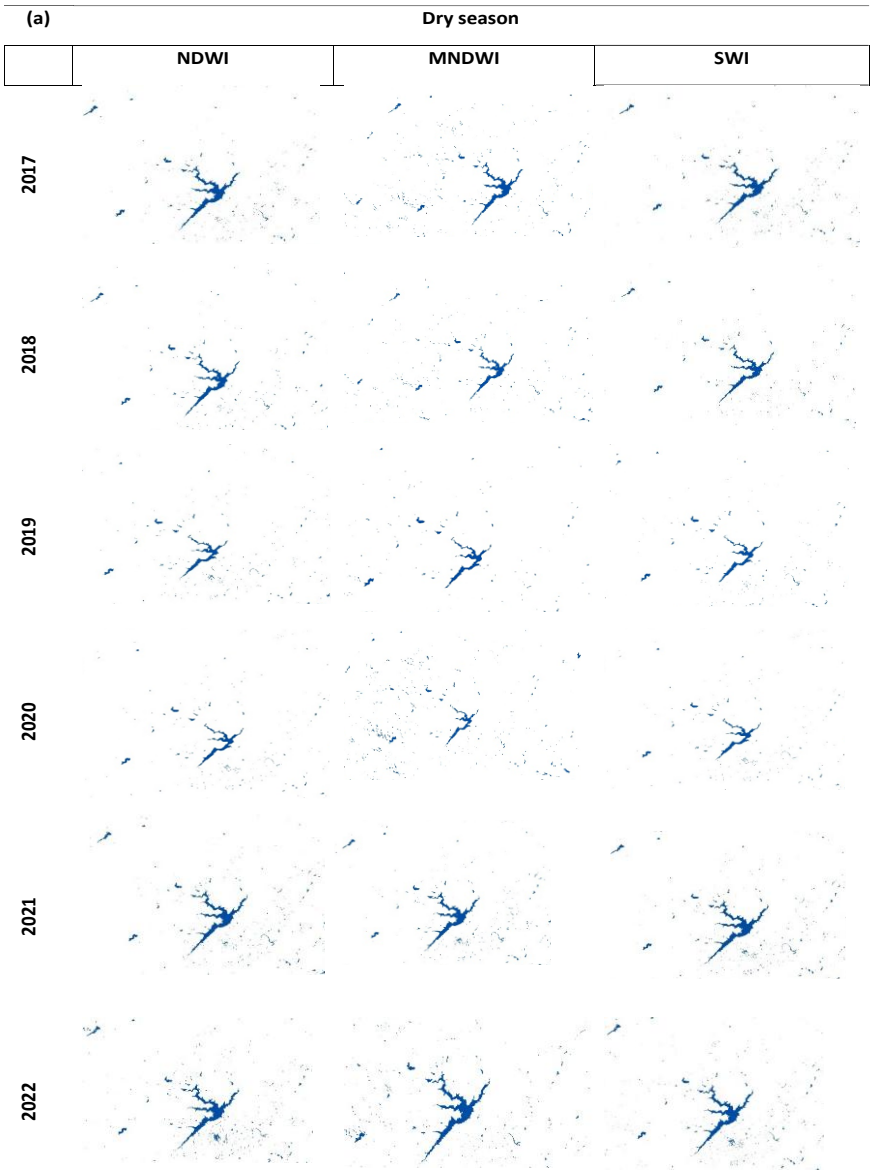

Figure 4.1a: Extracted water bodies using NDWI, MNDWI, and SWI in dry season.

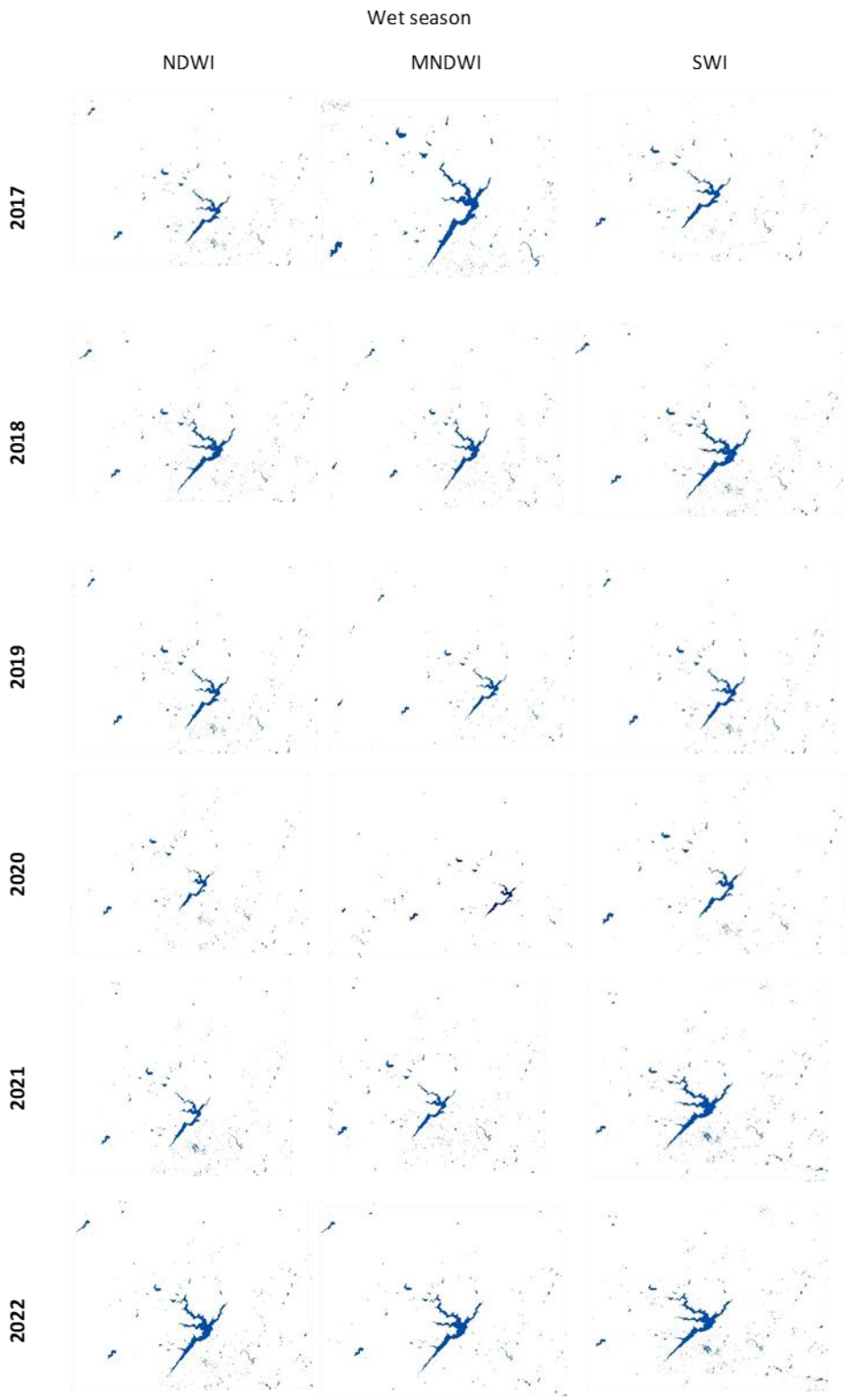

Figure 4.1b: Extracted surface water bodies in wet season.

The results also proved that NDWI, SWI, and MNDWI can seasonally extract temporary and permanent small water bodies. All indices have achieved an overall accuracy of over 85% recommended perfect score (Table 4.3).

Table 4.3: The accuracy assessment results of extracted pixel with NDWI, MNDWI, and SWI in (a) dry season and (b) wet season.

(a)	**Dry season**								
	NDWI			**MNDWI**			**SWI**		
	OA%	UA%	PA%	OA%	UA%	PA%	OA%	UA%	PA%
2017	99	99	100	94	92	99	99	99	100
2018	98	98	100	96	95	99	98	98	100
2019	99	98	100	96	96	99	99	98	100
2020	96	94	99	92	92	99	98	97	99
2021	99	96	100	98	97	99	99	99	100
2022	100	100	100	99	99	100	98	97	100

(b)	**Wet season**								
	NDWI			**MNDWI**			**SWI**		
	OA%	UA%	PA%	OA%	UA%	PA%	OA%	UA%	PA%
2017	99	99	100	99	99	100	99	98	100
2018	98	98	100	98	98	99	98	98	100
2019	99	98	100	96	95	100	99	98	100
2020	96	95	99	92	90	99	95	94	99
2021	99	98	100	99	98	99	99	99	100
2022	100	100	100	98	80	100	98	97	100

OA- overall accuracy, UA-user accuracy, and PA- producer accuracy

4.3.2 Intra and inter-seasonal dynamics of surface water bodies

The Letaba catchment displayed varying quantities of water bodies extracted through spectral water indices. For instance, the minimum count was 2514 for MNDWI in the year 2020, whereas other indices such as NDWI, and SWI recorded 4948, and 3922 respectively in 2018 wet season. Notably, the maximum numbers of water bodies were observed in 2022 during the wet season, reaching 8012 for MNDWI, 28973 for NDWI, and 25594 for SWI (Figure 4.2(a) and (b)).

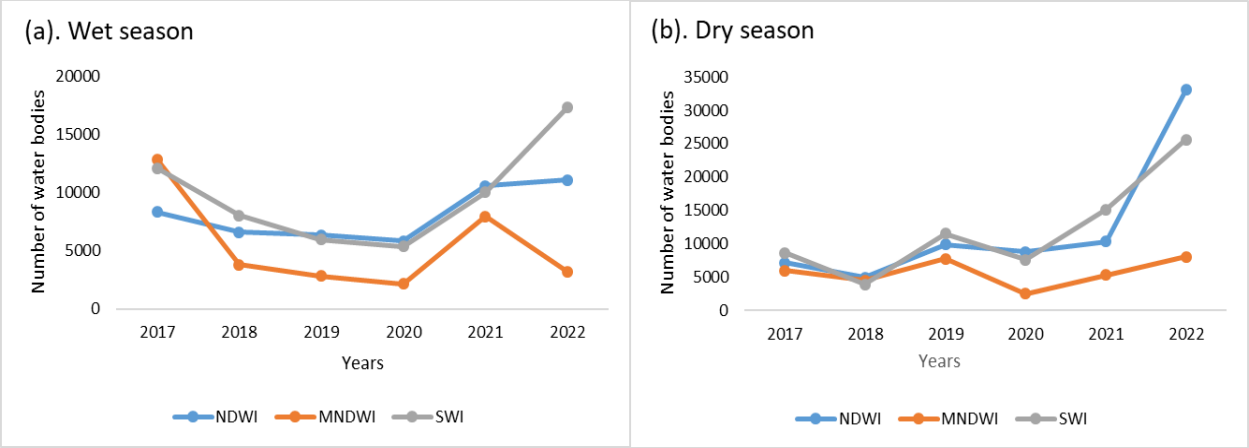

Figure 4.2: The number of water bodies within a landscape in (a) wet season, and (b) dry season.

Throughout the dry season, the minimum counts of water bodies ranged from 2124 for MNDWI in 2020 to 5527 for NDWI, and 7649 for SWI in 2017. Conversely, the maximum counts during this period reached 8022 for MNDWI, 25594 for SWI, and 33029 for NDWI in 2022 (as shown in the figure 4.2a and 4.2b). The number of water bodies exhibited significant seasonal variation, peaking during the dry season when more surface water was present within the landscape, and decreasing during the wet season when the water bodies were fewer.

Furthermore, the average size of water bodies displayed fluctuations, being larger in the dry season and smaller in the wet season. This indicated that water bodies exhibited greater heterogeneity during the dry season and were generally larger in size during the wet season. This trend is evident from the results (figure 4.3b), showing more water bodies during the dry season compared to the wet season.

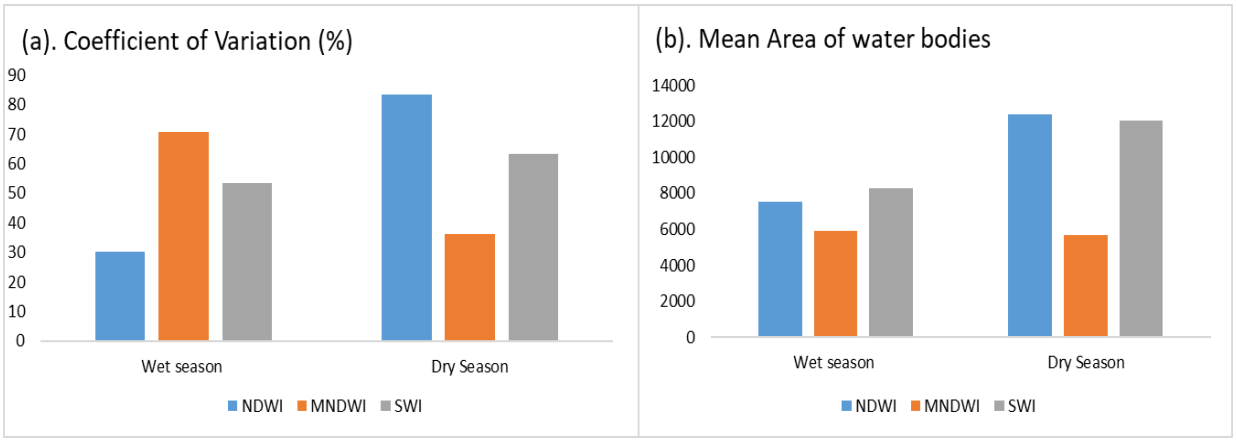

Figure 4.3: (a) coefficient of variation of the mean area of number of water bodies on a landscape, (b) Mean area of water bodies in a landscape.

In terms of the total area covered by water bodies, the landscape exhibited a range from a minimum of 1795 to 2527 ha during the wet season, and from 2592 to 6809 ha during the dry season across different years (figure 4.4a and b). Both seasons exhibited variability in terms of both the number and size of water bodies. Notably, there was a gradual increase in the number of water bodies during the dry season from 2019 onwards, followed by a decline in 2018. The mean area of water bodies also increased during the dry season. All four-landscape metrics demonstrated both intra and inter-seasonal changes in the distribution of surface water bodies.

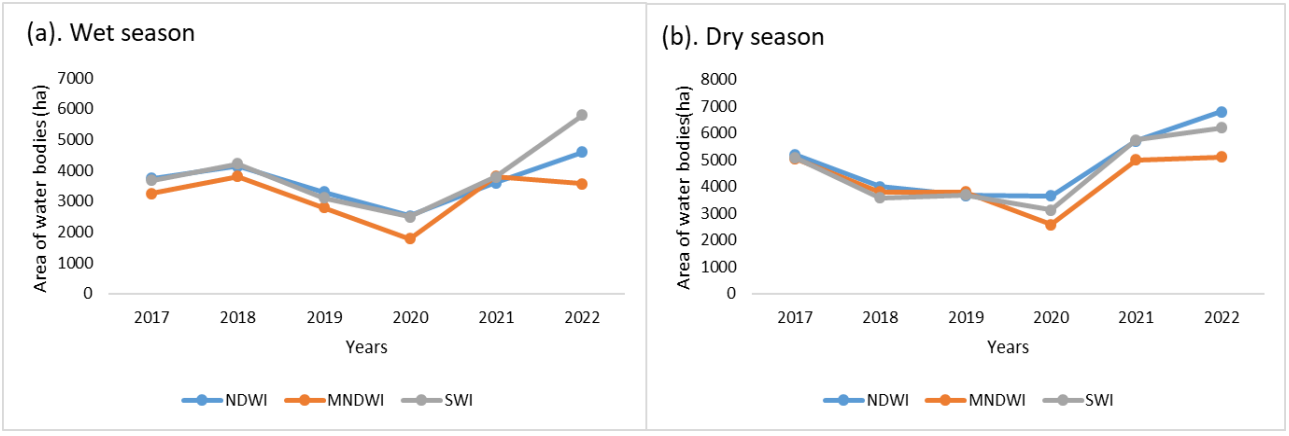

Figure 4.4: Total area of water bodies in (a) wet season, and (b) dry season within a landscape from 2017 to 2022.

4.4 Discussion

The work aimed at testing the utility of derived spectral indices obtained from Sentinel 2 imagery integrated with landscape metric to map the spatial and seasonal fluctuations of surface water bodies within the Letaba catchment situated in tropical semi-arid of southern Africa. The geospatial analysis was conducted using GEE. Although certain months presented difficulties in obtaining cloud-free images, GEE's approach of consolidating images from the different months into a single stack proved to be advantageous. This method effectively reduced the proportion of the area covered by clouds and offered a solution to the challenge of cloud-free imagery. Although GEE was effective in monitoring water bodies in Letaba catchment, there are limitations associated with the cloud computing platform. The limitations of GEE include spatial and temporal resolutions of satellite image, which may not be adequate for capturing fine-scale changes in a heterogeneous landscape. Cloud cover can be a significant issue in tropical regions, this can limit the availability of cloud-free imagery, which affects the temporal consistency and reliability of LULC change detection (Delalay et al., 2019).

Sentinel-2 has proven to be an effective tool for detecting and mapping water bodies in the Letaba catchment. The advantages include the ability to capture imagery at regular intervals, allowing for near-real-time monitoring of changes in water bodies, and facilitating accurate water body detection (Lombana and Martinez-Graña, 2022). Moreover, Sentinel-2's wide swath coverage helps capture large areas efficiently, making it suitable for assessing the extent of water bodies in the Letaba catchment. However, there are several challenges associated with using Sentinel-2 for this purpose. One major challenge is the influence of cloud cover on data acquisition. In regions like the Letaba catchment, which may experience frequent cloud cover, obtaining cloud-free imagery can be difficult, leading to data gaps and hindering the ability to monitor water bodies consistently. However, studies by Marzi and Gamba, (2021); Musa et al. (2015) have shown that synthetic aperture radars (SAR) are able to deal with clouds since they are not affected by clouds.

The accomplishment of consistently high overall accuracy levels, ranging from 96% to a perfect 100% over the five-year period in both wet and dry seasons (2017-2022), in the detection and mapping of water bodies within the Letaba catchment using Sentinel-2 derived spectral indices NDWI, SWI and MNDWI is remarkable (Table 3). The study's ability to maintain such precision across seasons speaks to the robustness and reliability of the chosen methodology and the

effectiveness of these spectral indices in capturing variations in water bodies in a dynamic environment (Feyisa et al., 2014; Masocha et al., 2018). The significance of these findings cannot be understated, as they have direct implications for water resource management, land-use planning, and ecological conservation in the region, particularly in an area like Letaba where seasonal fluctuations in water availability can be significant. However, it is essential to look deeper into the factors contributing to the observed variations within the accuracy range, which could be influenced by seasonal changes, water quality dynamics, or even differences in image acquisition conditions (Feyisa et al., 2014; Zhang et al., 2010). Additionally, the study's validation and ground-truthing efforts should be discussed to provide a comprehensive understanding of the accuracy assessment's credibility. The sustained high accuracy in mapping water bodies using NDWI, SWI and MNDWI throughout both wet and dry seasons in the Letaba catchment demonstrates the robustness of the chosen methodology and its potential to address critical water-related challenges in the region across different climatic conditions. Similar results were obtained by Jiang et al. (2021) which stipulated the effectiveness of spectral derived indices from Sentinel 2 in extracting water bodies in China.

Application of landscape metrics integrated with derived spectral indices accuracy and precision is important for effective management of water resources in tropical semi-arid environments. The total number of water bodies showed high seasonality with a high number of water bodies in the dry season and lower in wet season in the study area. The areas receive much rainfall during the wet season, whereas the study observed a lower number of water bodies. This could be attributed to high temperatures that dries up the landscape. Similar results were found by Tulbure and Broich, 2013, where they observed a lower number of water bodies during summer in the southern hemisphere. The increased number of water bodies in the dry season could be attributed to a lot of constructed dams or reservoirs that are found in the Letaba catchment. The increasing number of water bodies from 2021 to 2022 could be due to high rainfall. Similar results were obtained by Amusha et al., 2022, which observed an increasing number of water bodies from 2000 to 2020 with increased rainfall. Conversely, in 2020 there was a decrease in surface water bodies within the study area in both dry and wet season. This may be because of lower rainfall received by the area. The mean of water bodies of water bodies was with coefficient of variation of 87%, 36% and 63% for NDWI, MNDWI, and SWI respectively in dry season, than in wet season.

4.5 Conclusion

The study of the Letaba Catchment has showed a significant variability in water bodies within this semi-arid tropical environment. The findings of this study highlight the remarkable utility of Sentinel 2-derived spectral indices, specifically NDWI, SWI and MNDWI, in effectively extracting and monitoring seasonal surface water bodies within the region, employing the power of Google Earth Engine (GEE). The findings of the study observed seasonal variation, where dry season exhibited a higher abundance of water bodies, both in terms of quantity and surface area, compared to the wet season. These results demonstrate immense significance for semi-arid tropical environments like the Letaba Catchment. They challenge existing patterns of water resource management, urging a re-evaluation of strategies and policies. By using the insights gained from this study, stakeholders and policymakers can make informed decisions regarding water allocation, conservation, and sustainable use in regions facing similar climatic challenges. This information will further enhance water security, agricultural practices, and ecosystem sustainability in the Letaba Catchment. Furthermore, the capability of remote sensing and geospatial technologies in this study underscores their potential as essential tools for real-time monitoring and adaptive management of water resources in semi-arid tropical landscapes, ultimately contributing to greater resilience and sustainability in climate change and increasing water scarcity. The study recommends the use of integrated sentinel 1 and 2 or only sentinel in monitoring water bodies in semi-arid environment.

5. CHAPTER FIVE

Using Sentinel 2 to understand the effects of land use and land covers dynamics on surface water quality in Letaba catchment, South Africa

Abstract

This study examines the effects of land use and land cover (LULC) changes on water quality in the Letaba Catchment by combining in-situ measurements and remote sensing data. Water samples were analyzed for temperature, pH, dissolved oxygen (DO), electrical conductivity (EC), total dissolved solids (TDS), and salinity (SAL) using a multi-probe. Sentinel 2 MSI bands were utilized to compute water indices (WI), exploring their correlation with water quality and LULC through Pearson's correlation coefficient, Spearman coefficient and stepwise multiple linear regression. The findings highlight significant correlations (ranging from -0.50 to 0.89) between certain spectral bands, particularly in the visible and red-edge regions, and in-situ water quality parameters. Water indices such as Normalized difference turbidity Index (NDTI), land surface water index (LSWI), and AWEIsh1 showed strong correlations with these parameters. EC and TDS were most accurately modelled using Sentinel 2 data, with high coefficient determination (R^2 of 0.84 and 0.87, respectively) and low RMSE, indicating reliable predictions of these parameters. However, models for DO, SAL, temperature, and pH showed varied success, with some achieving lower R^2 values. The analysis confirmed the pollution (eutrophic and organic matter) status in the catchment. The study, further highlights the significant impact of LULC changes on water quality, stressing the need for meticulous land planning by local and regional authorities, and regional institutions to mitigate pollution and protect freshwater ecosystems.

Keywords: remote sensing; water quality spectral indices; Sentinel 2; catchment health

5.1 Introduction

The world's population continues to grow at an unprecedented rate, exerting enormous pressure on natural resources and ecosystems (Juma et al., 2014; Mashala et al., 2023a). Consequently, land use (LU) changes, characterized by urban expansion, deforestation, agriculture intensification, and industrial development, have become increasingly prevalent (Elhag et al., 2019; Umwali et al., 2021). Simultaneously, these alterations in land use are linked to changes in land cover (LC), as natural landscapes are transformed into built environments (Kibena et al., 2014). These

transformations have substantial implications for the environment, particularly in terms of water quality. Runoff from urban areas loaded with pollutants, deforestation leading to soil erosion, and agricultural practices involving chemical fertilizers and pesticides all contribute to the degradation of water quality in rivers, lakes, and aquifers (Chotpantarat and Boonkaewwan, 2018; de Mello et al., 2018; Mashala et al., 2023).

Several studies have been conducted on assessing the impacts of LULC on water quality. For instance, Namugize et al. (2018), observed that the change in LULC has caused a decline in the water quality of the uMngeni river catchment in South Africa, which indicated the high level of Escherichia coli (E. coli) exceeding the recommended guideline. Again, Tahiru et al. (2020) reported that the change in LULC of the Nawuni catchment in Ghana has contributed to a massive change in water quality, which increased turbidity and ammonia in rivers. Similarly, Rather and Dar (2020) also confirmed that the change in LULC of the Dal Lake catchment in India resulted in the deterioration of ecology and water quality.

Given the complexity of factors affecting water quality in semi-arid tropical environments, a comprehensive approach is required to understand the relationship between LULC changes and water quality (Abdelmalik, 2018). Traditional ground-based monitoring techniques face limitations in spatial and temporal coverage, often missing the full scope of LULC dynamics and their impacts on water quality. Remote sensing has emerged as a crucial alternative, providing extensive coverage and detailed data through satellites, aircraft, and drones, as outlined by Dhaouadi et al. (2020) and Khattab and Merkel (2014). This technology, combined with advanced statistical methods (Ullah et al., 2018), has proven effective in mapping and analyzing water quality indicators like turbidity, salinity, and temperature (Kibena et al., 2014; Ding et al., 2015). Despite the wealth of research, the Letaba catchment, an area significantly influenced by commercial forestry, agriculture, and industrial activities, has been relatively overlooked. This study aims to employ Sentinel 2 satellite data to fill this gap by identifying LULC in the Letaba catchment, mapping water quality parameters, and analyzing the relationship between LULC and water quality. Sentinel 2 satellites, with their high resolution and frequent revisits, offer a promising tool for detailed monitoring of LULC changes and their impacts on water quality, underscoring the potential for more targeted and effective environmental management practices (Elhag et al., 2019; Peterson et al., 2020).

5.2 Materials and Methods

5.2.1 Field data collection

Fieldwork took place in the rainy season between October 1st, 2020, and February 2021. During the field visit, Garmin GPS devices were used to record various LULC types and water quality sampling locations. This recorded data served as the basis for training and validating our LULC results. Field data for water quality was conducted in February 2021, using a handheld YSI Model 554 Data Logger multiprobe equipment to measure physicochemical water parameters. This device facilitated the real-time measurement of parameters such as electrical conductivity (EC; µS/cm;), pH, dissolved oxygen (DO; mg/L), water temperature (Temp;°C), salinity (ppt), and total dissolved solids (TDS) within the catchment. A total of 48 data points were sampled from the upper, middle, and lower region of the catchment. Specifically, we obtained sixteen samples from the upper reaches, sixteen from the middle reaches, and sixteen from the lower reaches of the catchment.

5.2.2 Satellite image acquisition and processing

Sentinel 2 MSI satellite images corresponding to the month (e.g. February 2021) of fieldwork were acquired, whereas cloud cover was corrected and filtered in Google Earth Engine (GEE) platform. Sentinel-2 mission include twin satellites in the same orbit and carries a push-broom Multi-Spectral Instrument (MSI) payload with the aim of land cover change detection, agricultural applications, coastal zone, inland water, and Glacier monitoring. The sensor is characterised by a swath-width of 290 km Field of View (FOV), Multispectral data with 13 bands (443-2190 nm) from VNIR to SWIR. Furthermore, the sensor has the spatial resolution at 10m (visible and near-infrared bands), 20m (six red-edge and shortwave infrared bands) and 60 m (three atmospheric correction bands), 5 days' revisit, and 12-bit radiometric resolution. These unique sensing characteristics allows for catchment scale water quality monitoring and assessment over time with a reasonable accuracy a previously challenging task with broadband multispectral; sensors together with non-routine in-situ measurements (Soomets et al., 2020).

5.2.3 Land use and land cover mapping

Land use and land cover map for the Letaba catchment was drawn up from a Sentinel 2 image. The map was created following random forest classification in google earth engine (GEE) platform. Image processing and acquisition were performed using filtering functions such as cloud

and shadows, date, and cropping were computed in google earth engine (GEE). Seven classes of land cover and land use were identified within the Letaba catchment refer-to (Table 5.1) for more details.

Table 5.1: Land use and land cover classification description within the catchment

Classes	Description
Bare surfaces	Rocks, bare soil
Built-up	Buildings, roads
Grasslands	Rangelands
Natural Forests	Dense, sparse
Plantations	Tropical, pines, citrus
Water bodies	Dams, rivers, streams
Shrublands	Short trees

5.2.4 Water quality physicochemical parameters

5.2.4.1 Statistical analyses of physicochemical water parameter data

Following the observed changes in LULC within the catchment, then the catchment was subdivided into three distinct categories (Figure 5.4). This categorization informed the design of the sampling framework. The initial step involved a statistical comparison of water quality concentrations among these three categories, aiming to identify the catchment or river sections exhibiting higher pollution levels. Water Quality An analysis of variance (ANOVA) was used to determine whether there was spatial variation of the physicochemical parameters by calculating the mean and standard deviation of the parameters using Statistica (Version 10, 2007).

5.2.4.2 Modelling and validating water quality parameters

5.2.4.2.1 Water quality spatial data analysis

A point map of the water sampling areas was created using the field data and GPS readings. The points were superimposed on the Sentinel 2 MSI image, and then band values or image spectra

were extracted to points using ArcGIS 10.3 software. The extracted image spectra were then averaged for each river catchment and saved on a Microsoft Excel Spreadsheet for analysis. The commonly used water indices such as the Normalized Difference Water index (McFeeters, 1995); The Normalized Difference Turbidity Index (NDTI) (Lacaux et al., 2007) and the Modified Normalized Difference Water Index (MNDWI) (Xu, 2006) were calculated in this study to map water quality. Water indices have proven to accurately map water bodies, for instance MNDWI uses green and SWIR bands for the enhancement of open water features (Xu, 2006). It also diminishes built-up area features that are often correlated with open water in other indices (Xu, 2006). Table 2 shows the list of other water indices that were tested to identify the best index for estimating water quality with Sentinel 2 MSI.

Table 5.2: Summary detail of spectral water indices used for water quality mapping.

Index	**Formula**	**Reference**
NDWI	NDWI = (Bgreen - BNIR)/ (Bgreen + BNIR)	McFeeters (1995)
mNDWI	mNDWI = (Bgreen - BSWIR-1)/ (Bgreen + BSWIR-1	Xu (2006)
NDWI plus VI	EVI = 2.5 * (BNIR-Bred)/ (BNIR + 6.0 * Bred - 7.5 * Bblue+1)	Menarguez (2015)
mNDWI plus VI	NDVI = (BNIR - Bred)/ (BNIR + Bred)	Menarguez (2015)
LSWI plus VI	LSWI = (BNIR - BSWIR-1)/ (BNIR + BSWIR-1)	Menarguez (2015)
LSWI plus VI7099	AWEIsh=Bblue+2.5 *Bgreen - 1.5 *(BNIR+BSWIR-1) - 0.25 * BSWIR-2	Feyisa et al. (2014)
AWEInsh	AWEInsh = 4 * (Bgreen-BSWIR-1) - (0.25 * BNIR-2 + 2.75 * BSWIR-1)	Feyisa et al. (2014
GNDVI	GNDVI = (NIR - Green)/ (NIR + Green)	Gitelson et al. (1996)
NDTI	NDTI = (Red - Green) / (Red + Green)	Lacaux et al. (2007)

Spectral indices from table 2 were selected because normally water bodies have low reflectance or high absorption in the optical regions of the electromagnetic spectrum when compared to other materials of the earth's surface, therefore this helped to accurately discriminate water from data (Masocha et al., 2018; Zhou et al. 2017). To determine the relationship between spectral bands, water indices, and water quality parameters, Pearson's correlation coefficient (r) was used. The correlation coefficient (r) was analysed at $\alpha = 0.05$ measuring the strength of the linear relationship between selected water quality parameters (DO, EC, Salinity, TDS, pH, and Water temperature), individual bands and indices. Furthermore, stepwise multiple linear regression (R^2) was used to

estimate water quality using remote sensing data and in-situ field measurements. The subsequent linear relationship was assumed as follows:

$$Y = \beta_0 + \beta_{1.} * X_1 + \varepsilon \qquad \text{Eq. 1}$$

Where Y is the in-situ water quality parameter, X_1 is variable vectors corresponding to Sentinel 2 MSI data derived spectral and water indices, β_0 and β_1 are the coefficients that characterise the model and the ε is the additive bias (Corona et al., 1998). The novelty behind performing the regression analyses is to predict the regression potentials between the actual and the remotely sensed estimated water quality parameters. To quantitatively evaluate the results of the models, the coefficient of determination (R^2) was calculated as:

$$R^2 = 1 - \left(\frac{SS_{res}}{SS_{tot}} \right) \qquad \text{Eq. 2}$$

where SS_{res} is the residual sum of squares and SS_{tot} is the total sum of squares (Draper and Smith, 1981). Then the actual parameters were plotted against the estimated parameters and root mean square error (RMSE) values were used to obtain the best fit. RMSE is obtained as follows.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (p_i - O_i)^2}{n}} \qquad \text{Eq. 3}$$

Where *P* is the predicted value; *O* is the observed values. Mean absolute percentage error (MAPE) is the average of absolute errors divided by actual observation values (Draper and Smith, 1981). MAPE was also calculated to evaluate model performance. MAPE is calculated as:

$$MAPE = \frac{\sum_{i-1}^{n} \frac{| y_i - y_i |}{y}}{n} x100$$

5.2.4.2.2 Water quality model validation

A complete Leave-One-Out Cross-Validation (LOOCV) method was used to calculate root means square error (RMSE) of the models used to map water quality in the study (Singh et al., 2007). LOOCV was selected over other methods of validation because there were no statistical

significances to split the in-situ water samples data for validation, since the samples collected were few (n = 48) across the catchment area. The cross-validation has a single hyper-parameter "k" that controls the number of subsets that a dataset is split into. Once split, each subset is given the opportunity to be used as a test set while all other subsets together are used as training dataset (Singh et al., 2007).

5.2.4.2.3 Mapping water quality

An algorithm generated through the regression method was used to make spatial prediction for water quality parameter. The algorithm ($Y = \beta_0 + \beta_{1.} * X_1 + \varepsilon$) was applied to the Sentinel 2 MSI images of Letaba river catchment using a raster calculator tool in ArcGIS environment to get a spatial distribution map of water quality parameters (Dube et al., 2015). Water quantity information was extracted from data generated on LULC and was presented in the form of tables.

5.2.5 Relationship between LULC and water quality

Since there was no normal distribution of the data, Spearman correlation was used to determine the relationship between LULC and water quality. This rank-based method evaluates the monotonic relationships between variables, focusing on the order or trend rather than precise values, which is particularly beneficial. Furthermore, Spearman correlation is less sensitive to outliers, a common occurrence in environmental data, thus providing a more robust analysis compared to other methods like Pearson correlation.

5.3 Results and discussion

5.3.1 Land use and land cover classes

The most dominant land cover type is built-up areas found in the middle of the catchment, accounting for 37.2% of the land. This high percentage indicates significant urbanization or development, possibly including residential, commercial, and industrial zones (Kibena et al., 2014). The prevalence of built-up areas reflects human activity and its profound impact on the landscape. Shrublands cover about 17.6% of the area, suggesting the presence of low-lying woody vegetation. This type of land cover is often found in semi-arid regions and can be indicative of certain climatic or ecological conditions which are mostly dominant in lower catchment (Mashala et al., 2023a). Bare surfaces, making up 13.9% of the area, likely represents regions with little to

no vegetation, which could be due to natural factors like soil type or human activities such as construction or mining. Natural forests cover 12.8% of the area, indicating regions with native tree species and diverse ecosystems is dominate in the upper catchment. These areas are crucial for biodiversity, carbon sequestration, and maintaining ecological balance (de Mello et al., 2018). Plantations, which include areas used for agricultural or commercial cultivation, constitute approximately 10.5% of the land cover. This reflects the region's agricultural activity and its role in the local economy and land use. Grasslands account for 7.6% of the land cover, suggesting open, grassy areas that could be natural or used for grazing and agriculture. Water bodies, though constituting a small fraction (0.47%), are critical for the region's hydrology and ecology. They include lakes, rivers, and other water features., particularly in terms of water resources and biodiversity.

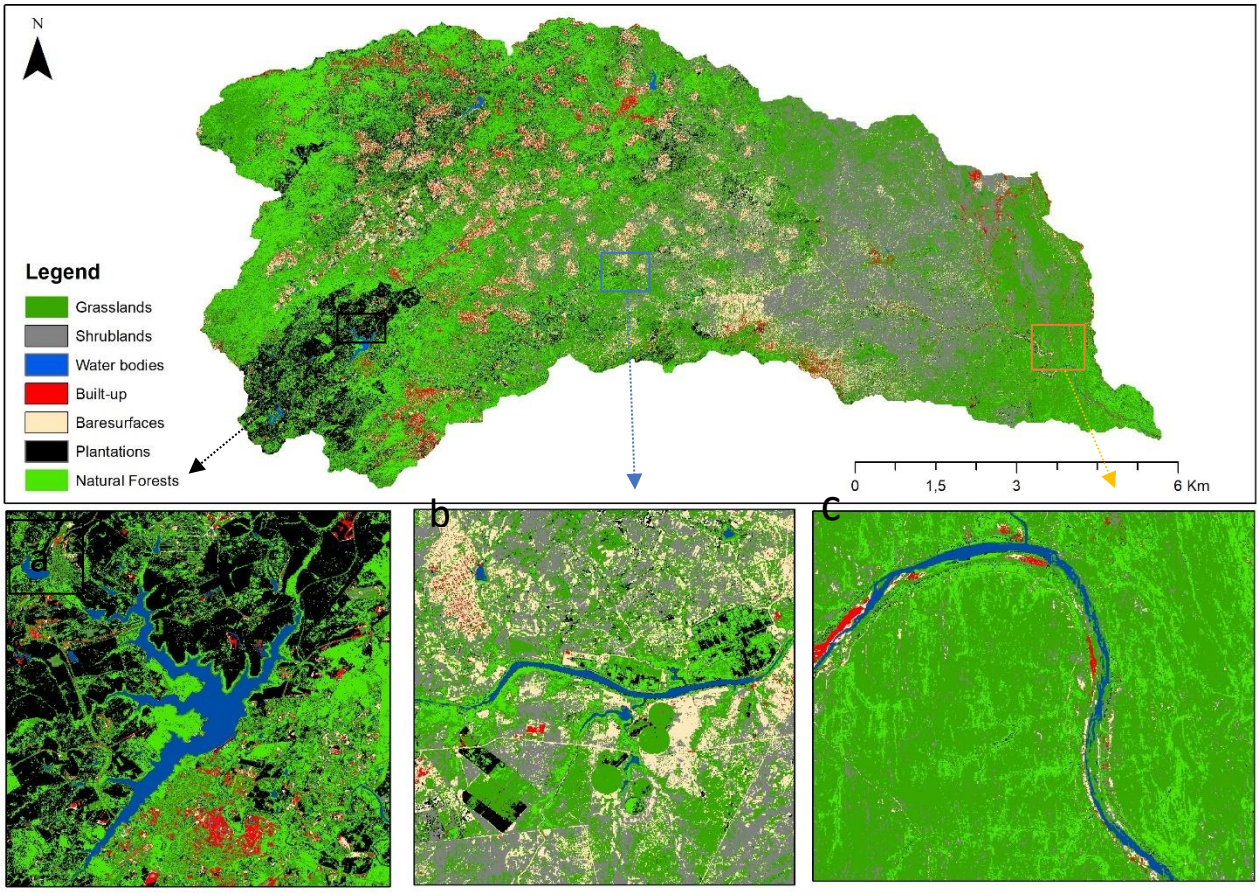

Figure 5.1: Satellite-derived Land cover map for Letaba catchment for the year 2021. (a) indicates the sampled upper catchment section, (b) middle catchment sampled area and (c sample) Lower catchment

5.3.2. Physicochemical parameters

Physicochemical parameters, including dissolved oxygen (DO), pH, temperature, total dissolved solids (TDS), and electrical conductivity (EC), were measured in Letaba using a multi-probe system (see Table 5.3 and Figure 5.2). The findings show that the higher concentrations of the six examined parameters were predominantly observed in the lower sections of the catchments, in contrast to the middle and upper parts of the catchment.

Within the catchment area, water temperatures varied between 21.36°C and 26.57°C. The analysis revealed highly significant differences ($p < 0.000$) across the three sections of the river catchment, with the most pronounced temperature variations found in the lower reaches (refer to Table 5.3). Conversely, the lowest temperatures were recorded in the upper reaches of the Letaba catchment (see Figure 5.2). The temperature of river water plays a crucial role in affecting photosynthetic activities, the rate of gas diffusion, and the solubility of oxygen, among other factors. According to Kale (2016), colder water has the capacity to dissolve more gases compared to warmer water. This indicates the significant impact of temperature on the ecological and physicochemical dynamics within a river system, influencing the distribution of aquatic life and the overall health of the ecosystem.

The study highlighted significant variations in dissolved oxygen (DO) levels across the catchments 'sections, with a statistical significance ($p < 0.000$) noted in the differences (refer to Figures 5.2 and 5.3). DO levels were found to range from 1.66 mg/L in the upper reaches to 4.04 mg/L in the lower reaches. Dissolved oxygen is essential for all aquatic life, as it supports metabolic processes and is replenished through mechanisms such as direct diffusion from the atmosphere, agitation by wind and waves, and photosynthesis (Trivedi et al. 2009; Kale, 2016). The Department of Water Affairs and Forestry (DWAF) of South Africa's 1996 and World health Organization (WHO) guidelines suggest that DO levels in freshwater should be approximately 10 mg/L, indicating that the observed values within the Letaba catchment were considerably lower. This discrepancy in DO levels could be attributed to various factors, including the impact of catchment discharge, possibly exacerbated by flooding during the study period. Moreover, the consumption rate of oxygen by aquatic organisms and the accelerated decomposition of organic matter during the warmer summer months could further deplete DO levels. The lower DO levels observed in the study suggest potential risks to aquatic health, affecting species dependent on higher oxygen

concentrations and possibly leading to a decrease in biodiversity. For human health, although direct implications of low DO are less pronounced, the overall health of the ecosystem can impact water quality indirectly, affecting its suitability for consumption, recreational use, and other purposes.

The study found that the variations in mean TDS (64.05 to 109.44) and EC (41.23 174.48) values were significantly different across all sections of the catchment area, with a high level of significance ($p < 0.001$) noted (Table 5.2 and Figure 5.3). The highest concentrations of EC and TDS were detected in the lower reaches of the rivers, suggesting a substantial presence of electrolytes and ions in the water. This phenomenon is likely due to the leaching of dissolved organic compounds, metals, and salts from the catchment area. Moreover, the increased TDS levels might also be linked to phytoplankton blooms, which have been known to contribute to reduced Dissolved Oxygen (DO) levels. High levels of TDS and EC can indicate pollution and affect water's taste.

The study observed alkaline water conditions within the Letaba catchment, with pH values ranging from 8.38 to 8.58 (see Table 5.2), indicating a generally high pH level across the area. Despite these overall alkaline conditions, the study found no significant differences in pH levels among the different reaches of the catchment. Contradictorily, it was noted that the upper reaches exhibited significantly higher pH levels than the middle and lower reaches. Water pH is a critical factor that affects the solubility and bioavailability of various chemical components, including nutrients like phosphorus, nitrogen, and carbon, as well as heavy metals such as lead, copper, and cadmium. According to Kale (2016), heavy metals become more soluble and toxic at lower pH levels. Additionally, salinity was found to be higher in the lower reaches of the catchment when compared to the upper and middle reaches, with no significant differences observed between the middle and lower reaches.

High salinity and extreme pH levels can adversely affect aquatic life, altering the availability of nutrients and the toxicity of pollutants. These conditions can also impact water usability for drinking, agricultural, and recreational purposes, underscoring the need for careful monitoring and management to adhere to established health and environmental standards. However, the Letaba catchment concentrations was within the recommended range according to WHO and DWAF guidelines.

Table 5.3: Physicochemical parameters of the Upper, Middle, and Lower reaches of the Letaba

		Parameter					
Site	**Reaches**	**DO**	**EC**	**TDS**	**SAL**	**PH**	**Temperature**
Letaba	Lower	4.04	174.48	109.44	0.220	8.58	25.46
	Middle	3.90	121.14	84.37	0.065	8.46	24.11
	Upper	1.66	64.05	41.23	0.029	8.38	21.53
	p value	***0.0001***	***0.0001***	***0.0001***	***0.0002***	***0.170***	***0.0001***

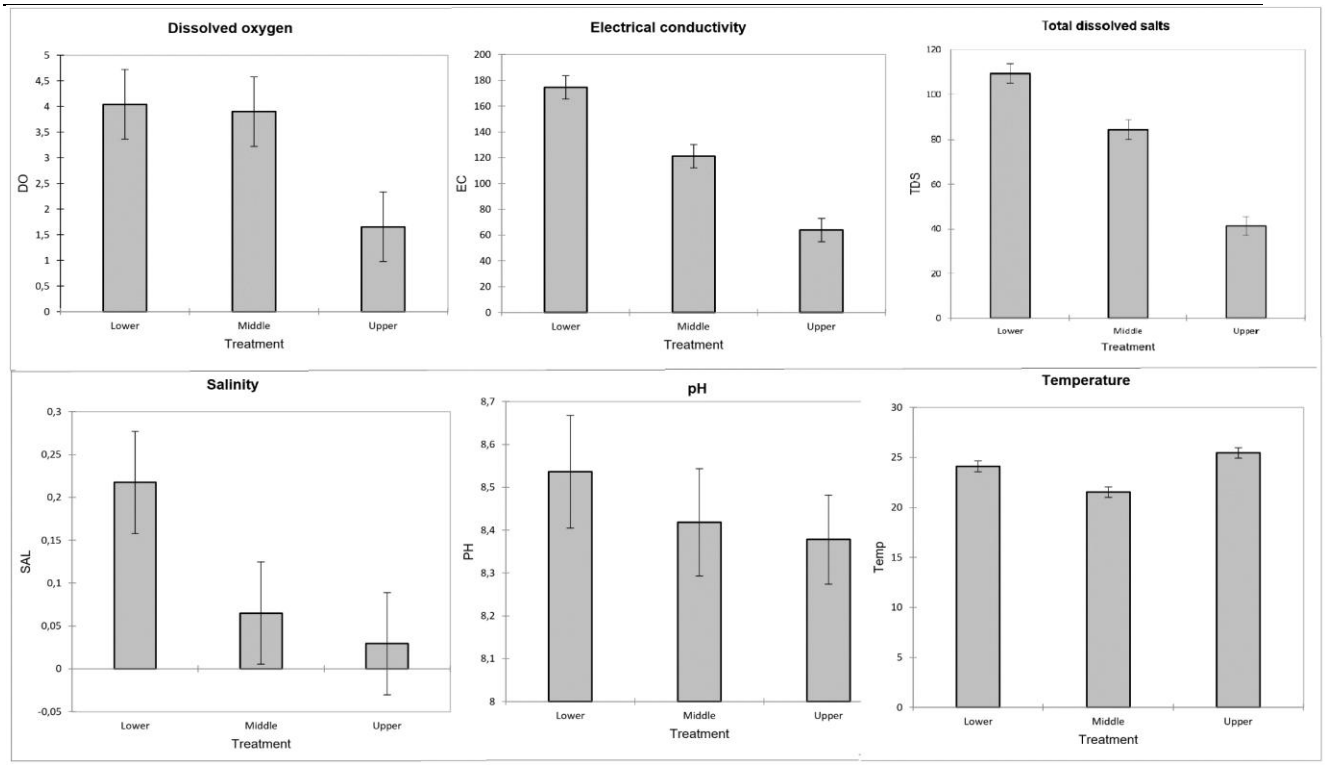

Figure 5.2: Physicochemical properties of the Letaba river

5.3.2 The relationship between *in-situ* water quality parameters, bands, and indices

The relationships between *in-situ* measurements and satellite derived spectral bands and indices were established (Table 5.4). The findings reveal robust correlations primarily within the visible and red-edge regions of the electromagnetic spectrum (bands 2, 3, 4, 5) and in-situ water quality parameters such as dissolved oxygen (DO), electrical conductivity (EC), total dissolved solids (TDS), salinity (SAL), and pH. For instance, the results exhibited high correlations ($\alpha = 0.05$) in these cases. However, the Near Infrared (NIR - 6, 7, 8, 8A) and Shortwave Infrared (SWIR - 11, 12) regions demonstrated notably weak correlations with in-situ water quality parameters.

Temperature displayed very weak correlations when associated with all water quality variables, with correlation coefficients (r) ranging from -0.15 to 0.26. Similarly, all the indices assessed in this study exhibited subpar performance when correlated with in-situ water quality parameters, except for the Normalized Difference Turbidity Index (NDTI), which demonstrated correlations with all field-observed water quality parameters ($-0.4 < r > 0.89$).

Table 5.4: The correlation coefficient between water quality parameters, bands, and indices for Letaba river catchment.

Variables	DO	EC	TDS	SAL	PH	Temp
B02	**0,518**	**0,627**	**0,561**	**0,727**	**-0,450**	0,049
B03	**0,587**	**0,713**	**0,651**	**0,767**	**-0,484**	0,010
B04	**0,643**	**0,797**	**0,750**	**0,764**	**-0,502**	-0,073
B05	**0,565**	**0,684**	**0,632**	**0,684**	**-0,458**	0,022
B06	0,147	-0,020	-0,013	0,080	0,003	-0,094
B07	0,128	-0,057	-0,042	0,019	0,038	-0,121
B08	0,048	-0,012	-0,066	0,194	-0,088	0,229
B8A	0,056	-0,154	-0,134	-0,052	0,085	-0,118
B11	0,004	-0,168	-0,173	0,008	0,000	-0,002
B12	0,039	-0,116	-0,146	0,119	-0,114	0,104
NDWI	0,052	0,096	0,123	-0,011	0,000	-0,156
mNDWI	0,038	0,251	0,218	0,175	-0,082	0,154
NDWI plus VI	**-0,333**	**-0,478**	**-0,501**	-0,267	0,212	0,266
mNDWI plus VI	-0,177	-0,258	**-0,288**	-0,091	0,081	0,223
LSWI plus VI	0,128	**0,432**	**0,345**	**0,407**	-0,207	**0,400**
AWEIsh1	**0,350**	**0,543**	**0,533**	**0,391**	-0,264	-0,113
AWEInsh	0,232	**0,449**	**0,431**	**0,295**	-0,192	-0,004
GNDVI	-0,052	-0,096	-0,123	0,011	0,000	0,156
NDTI	**0,649**	**0,859**	**0,890**	**0,506**	**-0,411**	**-0,403**

Values in bold are different from 0 with a significance level alpha= 0.05

In situ measurement values were effectively subjected to regression analysis using various band combinations and indices, as outlined in Table 5.5, which have been previously employed in the

literature for different sensor systems. The adoption of a stepwise approach was pivotal in this analysis, primarily because it serves to reduce the number of predictors, thus mitigating the issue of multicollinearity and addressing overfitting, as suggested by Hocking 1976. Multiple band combinations and indices were incorporated into models to forecast water quality, and their performance was assessed using metrics such as R^2, MSE, RMSE, and MAPE. The findings presented in Table 5.5 indicate that the prediction of dissolved oxygen (DO) was accomplished through the utilization of Sentinel 2 band 4 and the Normalized Difference Turbidity Index, yielding a coefficient of determination (R^2) of 0.47 and an RMSE of 1.28 mg/L. The DO model was also deemed highly significant, with a p-value of less than 0.0015. Conversely, for the estimation of electrical conductivity (EC), band 4, AWEInsh, and NDTI were employed, as other variables were eliminated via the stepwise approach.

The EC model exhibited a high level of significance at alpha=0.05, with a p-value less than 0.0001, an R^2 of 0.84, and an RMSE of 12.09 S/m. Notably, the total dissolved oxygen (DO) model achieved the highest coefficient of determination (R^2 = 0.86) when compared to other models assessed in this study. However, it relied solely on band 7, AWEInsh, and NDTI for modeling DO, resulting in an RMSE of 11.62 mg/L and a p-value of less than 0.0001. In the context of predicting water salinity (SAL) and pH, the Sentinel 2 MSI Green (Band 3) and Red (Band 4) bands were identified as useful. The SAL model yielded a moderately significant R^2 of 0.59, with an RMSE of 0.09. Conversely, the pH model performed less satisfactorily in comparison to other models tested in this study, exhibiting the lowest R^2 of 0.25 and an RMSE of 3.14, with a p-value below 0.000. Additionally, the water temperature model achieved moderate success, achieving an R^2 of 0.66 using a combination of bands located in the red edge and near-infrared region (band 5 and 8), along with mNDWI, LSWI, VI, and NDTI. This model exhibited significance at alpha=0.05, with a p-value less than 0.0001 and an RMSE of 1.19°C. These optimal models were subsequently employed to generate water quality maps within the catchment area.

Table 5.5: Water Quality estimates derived using Sentinel 2 MSI spectral bands and indices through stepwise multiple linear regression models. R^2, MSE, RMSE and MAPE of each model are included to evaluate overall model performance.

WQ	Model	R^2	MSE	RMSE	MAPE	Pr > F

DO	**DO** = 2,4896+14,5231*B04+8,5241*NDTI	0,47	1,63	1,28	40,94	<0,0001
EC	**EC** = 141,7760+265,6664*B08+70,4027*AWEInsh+470,7626*NDTI	0,84	412,29	20,31	12,09	<0,0001
TDS	**TDS** = 83,1879+178,4408*B07+51,4416*AWEInsh+275,5208*NDTI	0,86	134,95	11,62	10,69	<0,0001
SAL	**SA**L = -0,2524+3,2901*B03	0,59	0,009	0,09	65,36	<0,0001
PH	**PH** = 10,6670-43,4249*B04	0,25	9,84	3,14	17,29	0,000
Temp	**Temp** = 17,3726+92,8243*B05-51,9519*B08+5,7187*mNDWI plus VI+4,4594*LSWI plus VI-37,8944*NDTI	0,66	1,43	1,196	3,638	<0,0001

5.3.4. Satellite-derived water quality for Letaba Catchment

Sentinel 2 corrected images were employed to create spatial maps of water quality parameters using optimal regression models (refer to Table 5.5). The water quality maps produced in this study are illustrated in Figures 5.3 through 5.7. Figure 5.3 displays the spatial distribution of dissolved oxygen (DO) in the upper, middle, and lower regions of the Letaba Catchment. For example, Figure 5.3(a) reveals that DO concentrations were notably high in the middle of Tzaneen Dam in the upper catchment. The findings indicate a decrease in DO levels as one moves away from the center of the dam. The maps also indicate that the highest predicted DO values ranged from 4.98 to 5.42 mg/L in the upper catchment (Figure 5.3-a), followed by 4.89 to 5.79 mg/L in the middle catchment (Figure 5.3-b), and 5.85 to 9.70 mg/L in the lower catchment (Figure 5.3c).

Similarly, figure 5.3(d) shows a high concentration of electrical conductivity (EC) at the center of Tzaneen Dam in the upper catchment of the Letaba River, with a noticeable decrease in EC from the upper catchment to the lower catchment, as depicted in Figures 5.3(e) and 5.3(f). The lowest EC values (55.35 - 161.59 S/m) were estimated in the upper and lower regions of the Letaba River catchment, in contrast to the middle region with EC values ranging from 116.80 to 178.23

S/m.Figure 5.4 (g, h, and i) displays the salinity distribution in the upper, middle, and lower catchment regions of Letaba. In the upper catchment (Figure 5.4g), Tzaneen Dam exhibited evenly distributed salts, with higher concentrations observed in the southern tip of the dam. Conversely, the Letsitele portion of the Letaba River in the middle catchment displayed relatively uniform salinity levels (Figure 5.4h). In the lower catchment, there were relatively high salinity concentrations, with maximum salinity levels ranging from 0.49 to 1.15, which was the highest across the entire catchment.

Figures 5.4 (j-l) illustrate the distribution of total dissolved solids (TDS) in the Letaba catchment. The middle (Figure 5.4k) and lower (Figure 5.4l) catchment regions exhibited higher TDS values (ranging from 3.65 to 174 mg/L) compared to the upper catchment (Figure 5.4j) with TDS values ranging from 22.15 to 169.14 mg/L. Figure 5.4 (n-p) shows that pH levels were relatively evenly distributed across the catchment area, with the lower catchment (Figure 5.5p) having relatively lower pH values. Additionally, the model predicted abnormal surface temperatures in the Letaba River catchment (Figure 5.5 q-s), especially in the northern part of the upper catchment (Tzaneen Dam – Figure 5.5q) with temperatures ranging from 27.70 to 37.83°C, and in the lower catchment (Figure 5.5s) with temperatures ranging from 28 to 38°C. These temperature anomalies may be attributed to model errors that overpredicted surface water temperatures, whereas the middle catchment exhibited lower average temperatures, ranging from approximately 18 to 27°C.

Upper **Middle** **Lower**

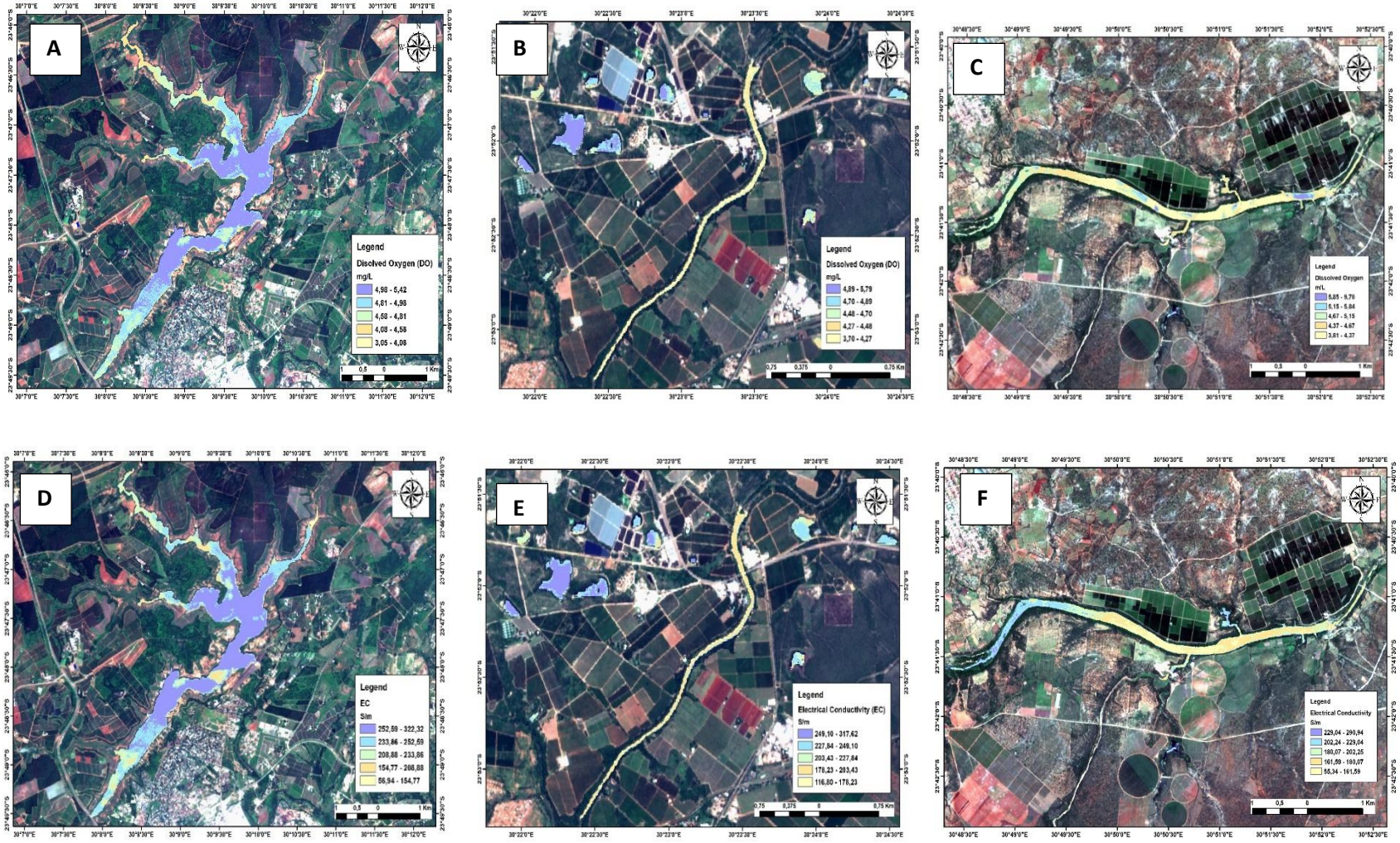

Figure 5.3: Sentinel 2 derived distribution map of Dissolved Oxygen (DO) (a-c) and Electrical conductivity (d-f) in the Letaba river catchment.

Upper **Middle** **Lower**

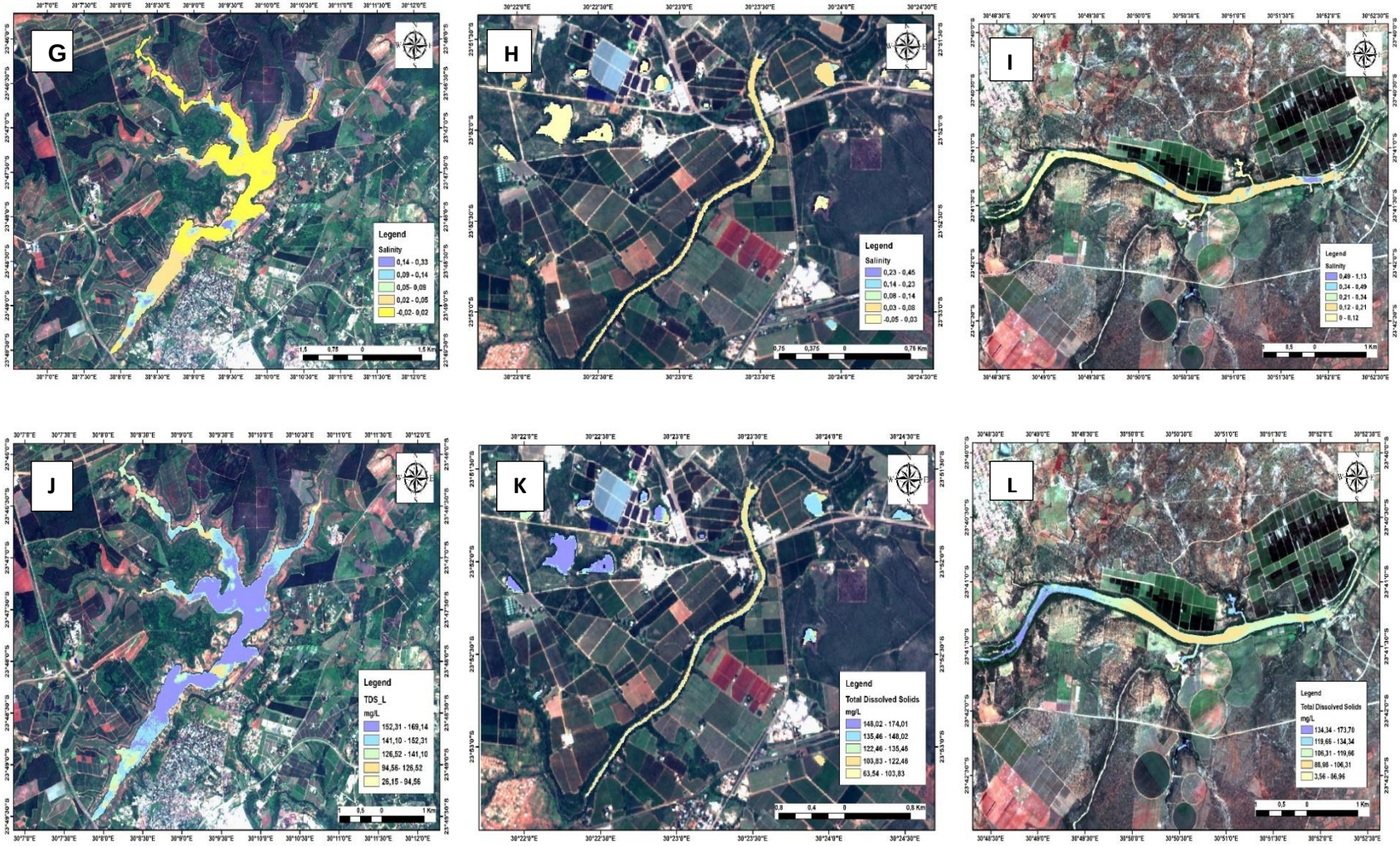

Figure 5.4: Sentinel 2 derived distribution map of Salinity (g-i) and Total Dissolved Solids (j-l) in the Letaba river catchment.

Upper **Middle** **Lower**

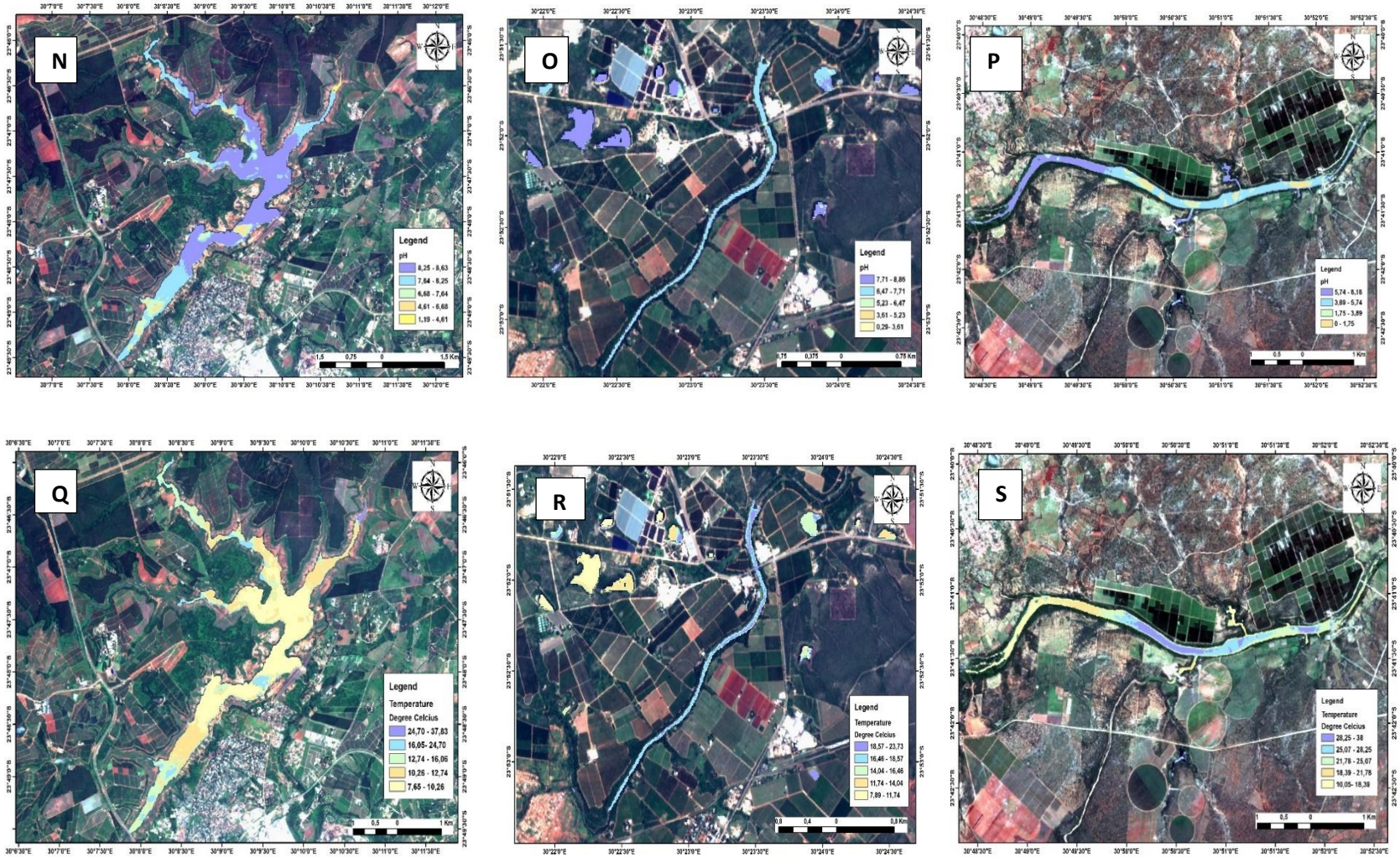

Figure 5.5: Distribution map of pH (n-p) and Temperature (q-s) in the Letaba river catchment.

5.3.3 Relationship between LULC and their effect on water quality

Natural forests show a positive correlation, suggesting that areas with natural forests might have higher DO levels (Table 5.6). Similar studies were observed by Ding et al. (2014) whereas forest areas were highly and positively related to DO. This could be due to natural forests aiding in maintaining water quality, perhaps due to less pollution or better ecological balance (Huang et al., 2016; Mello et al, 2020; Nkwanda et al., 2021). Water bodies show a negative correlation, which indicated lower DO levels in water bodies possibly due to factors like stagnation or pollution. Since it was rainy (summer) season abstraction and precipitation have strong influence or river discharge, runoff, change in sediments and nutrients concentration (Gani et al., 2023; Waturu et al., 2023). Both EC and TDS show a positive correlation but not significant with natural forests (Table 5.6). This might imply higher mineral content in these areas, but not necessarily poorer water quality, as some minerals are natural and harmless.

Shrublands and water bodies also show positive correlations with EC and TDS, possibly due to natural soil content or human activities impacting these areas. The uniform correlation across all LULC categories might suggest a general characteristic of the region's water, rather than a specific impact of land use (Karikari and Ansa-Asare, 2006; Obubu et al., 2021). pH has a positive correlation with bare land, built-up areas, grasslands, and shrublands could be influenced by soil composition and human activities. For example, urban runoff or agricultural practices might alter the pH. The negative correlation of pH with natural forests suggests a potential for more acidic conditions, possibly due to natural organic matter (Table 6.6). Natural forests showing a positive correlation with temperature might relate to water sources being shaded or less exposed, affecting temperature dynamics (Baltodano et al., 2022). Negative correlations in some LULC types with temperature could be influenced by exposure to sunlight, air temperature, and other environmental factors.

These finding should be approached with caution. While they offer hypothetical insights into how different land uses might be associated with water quality, the lack of statistical significance on other relationships means these trends are not confirmed by this dataset. They could serve as starting points for more detailed investigations, considering other factors and a larger or different sample for more conclusive results.

Table 5.5: The correlation coefficient between LULC and water quality parameters

LULC	DO	EC	TDS	SAL	pH	Temp
Bare Surfaces	-0,08	0,09	0,09	0,09	**0,24**	0,03
Built-up	-0,04	0,08	0,08	0,09	**0,23**	0,02
Grasslands	-0,07	0,13	0,12	0,09	0,2	0,02
Natural forest	**0,22**	0,25	0,25	0,19	-0,2	0,13
Plantations	0,01	0,11	0,1	0,09	0,2	-0,01
Shrublands	-0,06	0,14	0,12	0,09	0,19	-0,2
Water bodies	-0,17	0,15	0,12	0,09	0,22	0,03

Bold numbers indicate correlation coefficient (r); $p<0.05$.

5.3.4 Limitations of the study

There are numerous constraints associated with researching the effects of LULC on water quality, most notably financial and material related. The fieldwork, essential for such studies, often involves substantial costs, including travel to multiple and possibly remote locations, procurement and maintenance of specialized equipment, and the need for skilled personnel to conduct accurate and reliable data collection (Ding et al., 2014). These financial and logistical challenges can limit the scale and frequency of data collection, potentially affecting the study's comprehensiveness and representativeness. Additionally, once samples are collected, laboratory analysis is required to assess various water quality parameters. This process incurs additional costs for laboratory use, reagents, and the need for trained laboratory technicians (Obubu et al., 2022). Moreover, the handling of collected materials presents its own set of challenges. Samples must be carefully preserved and transported under controlled conditions to prevent contamination or degradation, which could compromise the accuracy of the results The necessity of adhering to stringent protocols for sample handling and storage further adds to the complexity and cost of these studies. Thus, while LULC change impact studies are crucial for understanding and managing environmental health, they are often constrained by financial, logistical, and technical limitations related to fieldwork and laboratory analysis.

5.4. Conclusion

The assessment and monitoring of water quality closely followed the observed changes in LULC within the catchment area. The results revealed significant variations in water quality throughout

the catchments. In general, the study's findings indicated a notable concentration of water quality parameters in the lower regions of the catchments. Specifically, physicochemical parameters such as dissolved oxygen, pH, temperature, total dissolved solids, and electrical conductivity exhibited elevated levels in the lower reaches of the Letaba catchment. The water quality maps derived from satellite data displayed visible spatial variability for all these parameters within the catchment. The results were compared to the South African Water Quality and World Health Organization recommended standards for drinking water and agriculture to assess whether these systems are heavily polluted. The study's findings emphasize that LULC changes have directly and indirectly influenced the water quality within the catchment. These findings underscore the importance of utilizing spatially explicit remote sensing methodologies to assess the impacts of LULC changes on water quality. However, future investigations should also consider the potential impacts of climate change and variability on surface water resources. It's worth noting that the water quality assessment in this report primarily relies on the analysis of physicochemical parameters. Nevertheless, laboratory analysis results further corroborated the observed trends in water quality within the catchment.

6. CHAPTER SIX

SYNTHESIS OF THE RESULTS

6.1 Introduction

Water resources play an important role in human livelihoods, socio economic development and ecosystem services (Kibena et al., 2014; Ding et al., 2015). However, the quality and quantity of surface water resources are increasingly under threat due to various factors. Among these, changes in LULC have been identified as major contributing factors. These changes alter the natural landscapes through urbanization, agriculture, deforestation, and industrial activities have profound impacts on the hydrological cycle (Masocha et al., 2018; de Mello et al., 2020). These changes can lead to significant variation in water yield, flow patterns and pollution levels in surface water bodies (Mashala et al., 2023b).

Traditional methods of monitoring water resources are often time-consuming, expensive, and may not provide comprehensive coverage (Elhag et al., 2019). Consequently, there is a need for more efficient and effective methods to evaluate the impacts of LULC changes on water quality and quantity. Remote sensing offers a solution due to its ability to provide large scale, continuously and timely data. This can greatly enhance our understanding of the spatial and temporal dynamics of surface water resources in response to LULC changes. Therefore, it is important for the development of sustainable management practices. By identifying the key LULC factors influencing water quality and quantity, effective strategies can be formulated to mitigate negative impacts (Obubu et al., 2020). More particularly in regions facing water scarcity or pollution issues, where the management of surface water resources is critical for sustaining both human populations and ecosystems.

Although remote sensing has been effective for monitoring the water resources, satellite such as Landsat has been widely used for monitoring. Whereas sensors such as Sentinel has never been used into their full capabilities (Soomets et al., 2020). The sensor offers more spectral bands with improved resolution of 10m when compared to Landsat. The presence of red-edge bands offers more opportunities for monitoring water quality and quantity especially in tropical and subtropical regions. Due to advance technology cloud computing platform such as GEE has also been used to monitor LULC. This study aimed to utilize remote sensing to assess the impact of LULC changes

on the quality and quantity of surface water resources, a critical step in developing sustainable water management strategies.

6.2 The objectives of the study were:

1. To map long-term spatial and temporal changes of LULC within the Letaba watershed.

2. To map surface waterbodies found within the Letaba catchment using multi-source remotely sensed data.

3. Estimate the effects of land use/cover on the water quality using the in-situ and remotely sensed data.

6.2.1 To map long-term spatial and temporal changes of LULC within the Letaba watershed

The study utilized GEE to analyse 31 years of LULC changes in Letaba watershed. Using GEE's random forest, LULC classes were mapped with 93% to 99% accuracy across four timeframes (1990, 2000, 2010, and 2021). Trends revealed declining water bodies (-4%), bare surfaces (-2%), natural forest (-3%), and grassland (-3%), while shrublands, plantations, and built-up areas increased at annual rates of 41%, 24%, and 47% respectively. This transformation reflects population-driven shifts, necessitating adaptive strategies. Given the importance of plantations for income, embracing climate-smart agriculture could ensure long-term food and environmental security, thus addressing the evolving dynamics in Letaba watershed. The study also revealed the efficacy of using GEE and reference data for mapping LULC.

6.2.2 To delineate surface waterbodies found within the Letaba catchment using multi-source remotely sensed data

The multi-date Sentinel-2-derived spectral indices, specifically normalized difference water index (NDWI), modified normalized differences water index (MNDWI), and SWI, in conjunction with landscape metrics was used for mapping spatial and seasonal fluctuations of surface water bodies. Google Earth Engine (GEE) was employed for this assessment and the research consistently achieved impressive overall accuracies ranging from 96% to 100% for both dry and wet seasons, showcasing the robustness of the methodology. The study revealed significant differences in water bodies in terms of size and coverage between dry and wet seasons. Surprisingly, the dry season exhibited a higher prevalence of water bodies, indicating unexpected patterns of water availability

in the region, and substantial heterogeneity in water bodies. Whereas the wet season was characterized by extensive coverage. These findings challenge conventional assumptions about water resource availability during different seasons in semi-arid tropical regions.

6.2.3 Estimate the effects of land use/cover on the water quality using the in-situ and remotely sensed data

The in-situ multi-probe instrument was used to measure six physicochemical variables include temperature (Temp), pH, dissolved oxygen (DO), electrical conductivity (EC), total dissolved solids (TDS) and salinity (SAL) in the field whereas Sentinel 2 MSI bands values were extracted to calculate water indices (WI) of the Letaba Catchment. To determine the relationship between spectral bands and WI and water quality parameters, Pearson's correlation coefficient (r) was used. Stepwise multiple linear regression was used to model water quality using the Sentinel 2 data and in-situ field measurements. The results indicate a strong correlation (-0,50;0,79) between the bands mainly in the visible and red-edge region of the electromagnetic spectrum (band 2,3,4,5) and in-situ water quality parameters such as DO, EC, TDS, SAL pH. WI such as NDTI, LSWI, and AWEIsh1 portrayed strong correlations (-0,50; 0,89) with water quality parameters. Furthermore, EC and TDS yielded the best strong regression models using Sentinel 2 band 7, band 8, NDTI, AWEIsh with coefficient determination (R^2) of 0,84 and 0,87 and RMSE of 20,31 µS/cm and 11,62, respectively. Whereas DO, SAL, T and pH models produced lower striking results with R^2 lower than 0,5 (DO and PH) and as high or better than > 0. 55 (SAL and Temp). The analysis confirmed the pollution (eutrophic and organic matter) status in the catchment. As a result, Sentinel 2 showed its capability for mapping water quality variables. Spearman was used to determine the relationship between LULC and Water quality.

6.3 Conclusions

The aim of this study was to evaluate LULC dynamics and their effects on water resources at Letaba catchment, South Africa. The outcomes of the study indicated the efficacy of GEE platform for monitoring the LULC and water bodies with accuracy within the Letaba catchment. Satellite such as Sentinel 2 and Landsat images have also shown the capabilities for monitoring LULC and water resource. Based on the findings of the study, the following conclusions were drawn:

- Over a period of 31 years, the Letaba watershed has undergone substantial LULC changes, including decreases in natural forests, grasslands, and water bodies, and increases in shrublands, plantations, and built-up areas, reflecting the impact of population growth and environmental shifts.
- There is a significant difference in the size and prevalence of water bodies between dry and wet seasons. Contrary to conventional expectations, the dry season exhibited a higher prevalence of water bodies, indicating complex and unexpected patterns of water availability.
- The use of multi-date Sentinel-2-derived spectral indices and landscape metrics demonstrated high accuracy (96% to 100%) in mapping surface water bodies, proving the effectiveness of these methods in environmental monitoring.
- The study identified strong correlations between LULC changes and key water quality parameters, such as electrical conductivity and total dissolved solids. This correlation confirms the pollution status in the catchment, emphasizing the impact of human activities on freshwater ecosystems.

6.4 Contribution to new Knowledge

Using Google Earth Engine (GEE) to map land use and land cover (LULC) impacts on water quality represents a significant advancement in environmental monitoring and management. GEE's powerful cloud computing capabilities and access to extensive satellite imagery enable detailed, large-scale analyses of LULC changes and their effects on water bodies. By integrating remote sensing data with in-situ water quality measurements, researchers can identify critical areas where land use practices contribute to water pollution, eutrophication, or sedimentation. This approach aligns with Sustainable Development Goals (SDGs), particularly SDG 6 (Clean Water and Sanitation) and SDG 15 (Life on Land), by providing actionable insights for sustainable land management and conservation efforts. Furthermore, it supports SDG 13 (Climate Action) by facilitating the assessment of how climate-related land use changes impact water resources. Through these contributions, GEE enhances our ability to monitor, understand, and mitigate the environmental impacts of human activities on vital water resources, promoting a more sustainable and resilient future.

6.5 Recommendations

Based on the findings of this study, the following recommendations are proposed:

Policymakers and stakeholders should adopt adaptive management approaches to address the unique challenges posed by the varying dynamics of water bodies in different seasons, especially in semi-arid regions. Local authorities, regional agencies, and institutions should engage in careful land planning to mitigate the impacts of LULC changes on water quality and quantity. This includes implementing policies to control deforestation and urban expansion in sensitive areas. To address the challenges in regions like the Letaba catchment, embracing climate-smart agriculture and nature-based adaptation practices is crucial. This approach will help in balancing the need for plantation expansion for income generation with the preservation of environmental and water resources. Future research should delve deeper into understanding the underlying factors driving seasonal fluctuations in water bodies and assess their potential long-term impacts. This is vital for developing more resilient water security strategies, particularly in the face of changing climate conditions. Increasing public awareness and education about the importance of sustainable land use practices and their impact on water resources is essential. Communities should be engaged in conservation efforts and informed decision-making processes. Through these recommendations, the study aims to contribute towards the development of more sustainable and resilient strategies for water resource management in the face of evolving environmental challenges.

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