



University of the Witwatersrand

Faculty of Science

School of Geography, Archaeology and Environmental Studies

**MULTITEMPORAL ANALYSIS OF LAND COVER AND
EVALUATION OF LANDSCAPE INFLUENCES ON VEGETATION
DYNAMICS USING REMOTE SENSING DATA AND MACHINE
LEARNING IN A KARST ENVIRONMENT: A CASE STUDY OF THE
CRADLE NATURE RESERVE**

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A thesis submitted to the Faculty of Science, University of the Witwatersrand, Johannesburg,
in fulfilment of the requirements for the degree of Doctor of Philosophy Supervisor

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September 2024

DECLARATION

I declare that this thesis is my own, unaided work. It is being submitted for the Degree of Doctor of Philosophy at the University of the Witwatersrand, Johannesburg. It has not been submitted before for any degree or examination at any other University.



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LIST OF OUTPUTS OF THE THESIS

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I declare that I had a maximum contribution (i.e., >80%) in each of the abovementioned research outputs. _ I declare that I had a maximum contribution (i.e., >80%) in each of the

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ABSTRACT

Monitoring vegetation dynamics and ecosystem processes is crucial for understanding and managing natural environments, particularly in sensitive regions such as protected heritage sites in karst landscapes prone to land degradation. Geospatial science and technology, especially remote sensing, have revolutionised environmental monitoring by providing unparalleled insights into complex ecological processes and land cover dynamics. Despite their immense potential, these advanced technologies remain underutilised in sensitive ecological archaeological sites, particularly within South African contexts. The Cradle of Humankind, a protected World Heritage site, is confronting a myriad of environmental problems, such as land degradation, invasion by alien plants, bush thickening, loss of native vegetation cover, increased soil erosion, and habitat loss, threatening its ecological integrity, biodiversity and archaeological significance. Furthermore, there is a notable paucity of research focusing on land degradation and land cover changes in protected heritage sites in Africa and other parts of the world, even though geospatial technologies capable of accurately mapping and tracking these changes have proliferated. Addressing this research gap is critical for developing effective conservation strategies and ensuring the preservation of sensitive ecological and archaeological areas. This study aims to demonstrate the significant value of integrating geospatial technology and machine learning in environmental monitoring by identifying and addressing research gaps in the application of these technologies, particularly remote sensing, for vegetation mapping. Through a detailed case study of the Cradle Nature Reserve in South Africa, the study employs novel machine learning classification algorithms and advanced geospatial analytical methods to assess land cover change, landscape fragmentation, multitemporal analysis of vegetation trends, topographic influences on vegetation vigour, biomass estimation, and impacts of land cover change on evapotranspiration using multisource satellite, drone, and field geospatial datasets.

The study utilised a systematic review and scientometric analysis using the Scopus database to investigate the application and trends of geospatial technologies in archaeology and cultural heritage in South Africa from 1990 to 2022, employing VOSviewer for visualising bibliometric data. Additionally, the study employed a systematic review and scientometric analysis using the Scopus database to examine the growth and trends in the application of remote sensing and machine learning techniques for vegetation mapping from 2000 to 2024, using VOSviewer for visualising relationships and trends in the collected data. The research also utilised Google Earth Engine (GEE) to download and preprocess satellite imagery, employing the XGBoost and Naïve Bayes classifiers for land cover classification and accuracy assessment, followed by applying landscape metrics for fragmentation analysis using QGIS. Further, Sentinel-2 multispectral imagery was processed using QGIS and ArcGIS software to compute the Enhanced Vegetation Index (EVI) and analyse vegetation dynamics through Principal Component Analysis (PCA) and multilinear regression, examining the relationships between EVI and climatic factors such as rainfall, temperature, and soil moisture. The study also utilised RGB drone imagery and various vegetation indices (BGVI, ExG, GBVI, GRBI, NGRDI, RBVI) combined with nDSM and chlorophyll concentration measurements to estimate above-ground biomass (AGB) in riparian and non-riparian zones of the Cradle Nature Reserve. High-resolution satellite imagery from Sentinel-2A and the Shuttle Radar Topography Mission

Digital Elevation Model (SRTM DEM) was used to calculate the Enhanced Vegetation Index (EVI) and various topographic indices such as the Topographic Position Index (TPI), Topographic Ruggedness Index (TRI), and Topographic Wetness Index (TWI), with the data analysed using QGIS and ArcGIS software to model the relationship between topography and vegetation vigour in the Cradle Nature Reserve. Finally, the study employed MODIS data and XGBoost classification to analyse the impacts of land use change on annual evapotranspiration (ET) in the Cradle Nature Reserve from 2000 to 2023, incorporating statistical analysis and regression models to explore the relationship between ET and different land cover types.

The research identified significant gaps in the application of advanced geospatial technologies, noting that only 12% of global research output is attributed to South African studies despite an increase in publications from 2018 to 2022. Key research gaps identified include the limited use of virtual and augmented reality applications, aerial photography, optical radar, and UAVs, which remain underexplored and present opportunities for future research. The analysis revealed a significant increase in research publications, particularly from 2018 to 2023, with the number of articles rising from 6 in 2018 to 48 in 2023, highlighting the critical role of advanced machine learning algorithms and remote sensing technologies in enhancing vegetation mapping accuracy and depth. China led in research output, followed by the United States and India. However, we identified significant research gaps, such as the need for more comprehensive studies on evapotranspiration and above-ground biomass estimation and the integration of climate change data with remote sensing technologies. The study showed that between 1990 and 2020, the Cradle Nature Reserve's landscape became much more fragmented. There was a 39% rise in bare ground or rock outcrop and a 26% and 12% decrease in native forest and natural grassland, respectively. This was mostly caused by human activities and the introduction of alien plant species. The analysis revealed that the EVI exhibited strong positive correlations with rainfall ($r = 0.71$), temperature ($r = 0.62$), and soil moisture ($r = 0.76$), highlighting the significant influence of these climatic factors on vegetation health. The PCA revealed that the first two principal components accounted for 90.08% of the data variability, underscoring the combined impact of these environmental factors on vegetation vigour. The riparian vegetation model had an R^2 value of 0.42 (adjusted $R^2 = 0.34$), which means that chlorophyll and BGVI were important factors. Conversely, the non-riparian model had a higher R -value of 0.66 (adjusted $R^2 = 0.64$), which meant that nDSM and RBVI were important predictors. This shows how important vegetation height, and stress indicators are in estimating biomass. The analysis revealed strong correlations between EVI and topographic indices, with EVI showing a significant negative correlation with TPI ($R^2 = 0.95$) and TRI ($R^2 = 0.94$) and a strong positive correlation with percentage slope gradient ($R^2 = 0.85$), highlighting how terrain features like sinkholes and depressions impact vegetation health. The research identified significant ecological changes in the Cradle Nature Reserve, with ET values showing substantial fluctuations across different land cover types. Notably, the mean ET increased from 47.115 mm in 2000 to 57.316 mm in 2020, reflecting overall improvement in vegetation health and water availability, while the Indigenous Forest area saw an increase in ET from 45.59 mm in 2000 to 59.89 mm in 2020, underscoring the impact of land use changes and climatic factors on the reserve's ecosystem.

This study equips researchers and conservationists focused on the Cradle Nature Reserve with advanced tools to enhance the precision of monitoring ecosystem changes and detecting land degradation. These insights facilitate targeted conservation efforts and informed management

strategies tailored to the reserve's unique ecological needs, contributing significantly to the global understanding of sustainable land management and conservation practices.

Keywords: geospatial technologies, remote sensing, machine learning, vegetation mapping, land cover change, Cradle Nature Reserve, evapotranspiration

DEDICATION

I dedicate this work to my family, mum and dad

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ABBREVIATIONS

AGB: Above-Ground Biomass
APCs: Article Processing Charges
BGVI: Blue-Green Vegetation Index
CAS: Chinese Academy of Sciences
CHMs: Canopy Height Models
CNN: Convolutional Neural Networks
COH: Cradle of Humankind
COHWH: Cradle of Humankind World Heritage Site
CSV: Comma-Separated Value
DEA: Department of Environmental Affairs
DEM: Digital Elevation Model
DSM: Digital Surface Models
DTM: Digital Terrain Models
ESA: European Space Agency
ET: Evapotranspiration
EVI: Enhanced vegetation index
ExG: Excess Green Index
GBVI: Green-Blue Vegetation Index
GCPs: Ground Control Points
GEE: Google Earth Engine
GIS: Geographic Information Systems
GMAO: Global Modeling and Assimilation Office
GNSS: Global Navigation Satellite Systems
GRBI: Green-Red Vegetation Index
IGARSS: International Geoscience and Remote Sensing Symposium
ISRO: Indian Space Research Organisation
LAI: Leaf Area Index
LC: Land Cover
LecoS: Landscape Ecology Statistics
LiDAR: Light Detection and Ranging
LOS: Length of the growing season
LPI: Largest patch index
LULCC: Land use and land cover changes
M3T: Mavic 3 Thermal
MDPI: Multidisciplinary Digital Publishing Institute
MERRA-2: Modern-Era Retrospective Analysis for Research and Applications, Version 2
METRIC: Mapping Evapotranspiration with Internalized Calibration
MODIS: Moderate Resolution Imaging Spectroradiometer
MPS: Mean patch size
MSI: Multispectral Instrument
NASA: National Aeronautics and Space Administration
nDSM: normalised Digital surface model
NDVI: Normalized Difference Vegetation Index

NGRDI: Normalised green-red difference index
NIR: Near-infrared
NP: Number of patches
PCA: Principal Component Analysis
PCs: Principal components
PD: Patch density
PLAND: Percentage of Landscape
RBVI: Red-Blue Vegetation Index
RF: Rainfall
RGB: Red, Green, and Blue
ROI: Region of interest
RS: Remote Sensing
SAGA: System for Automated Geoscientific Analyses
SAR: Synthetic Aperture Radar
SAVI: Soil Adjusted Vegetation Index
SfM: Structure from motion
SH: Shrub
SHDI: Shannon's diversity index
SNAP: Sentinel's Application Platform
SOS: Start of the season
SRTM: Shuttle Radar Topography Mission
SVM: Support Vector Machines
TEMP: Temperature
TITLE-ABS-KEY: Title-Abstract-Keywords
TPI: Topographic position index
TRI: Topographic ruggedness index
TWI: Topographic wetness index
UAV: Unmanned aerial vehicle
UNESCO: United Nations Educational, Scientific and Cultural Organisation
USGS: United States Geological Survey
VIF: Variance inflation factor
WHS: World Heritage Site
XGBClassification: Extreme Gradient Boost Classification
XGBRFClassification: Extreme gradient boost Random Forest Classification

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Chapter 1 INTRODUCTION

1.1 Background

Geospatial technologies have become essential tools in archaeological research and environmental monitoring, particularly at sites with dual designations like game reserves. These technologies facilitate archaeological site identification, mapping, and analysis, supporting ecosystem management and vegetation monitoring (Ahmad & Umar, 2024; DiBiase et al., 2010). Over the years, the deployment of these technologies across various fields, including archaeology, has significantly increased, resulting in a rich body of literature (Ahmad & Umar, 2024; DiBiase et al., 2010; Y. Huang, 2024). Geospatial technology is variably defined as a science, a group of tools used in various professional fields, or a profession with specific competence standards (Kamraju, 2023; Malloy Nicolas R., 2024). It encompasses land surveying, remote sensing, mapping, geographic information systems (GIS), geodesy, and global navigation systems, collectively forming a geospatial industry (Aina, 2012; DiBiase et al., 2010). Historically, geospatial technologies in archaeology have evolved from producing hand-drawn maps to using advanced tools for visualising geometric structures and detecting settlement patterns. Robust geospatial technologies, capable of handling high volumes of spatial data, are responsible for this growth (Wheatley & Gillings, 2013). Modern applications of these technologies, including remote sensing, GIS, and 3D modelling, have become integral to archaeological investigations (Feder, 2016a; Hester, 2016b).

Similarly, remote sensing technologies, a crucial subset of geospatial technologies, have become essential tools for environmental management and monitoring at archaeological sites and game reserves (Elfadaly et al., 2018; Lindsay & Mkrtchyan, 2023). These technologies enable the assessment of vegetation cover, condition, and temporal changes without compromising the archaeological integrity of the site (Elfadaly et al., 2018; Lindsay & Mkrtchyan, 2023). Advancements in sensor technology, satellite platforms, and UAVs have made it much easier to collect accurate environmental data at these dual-purpose sites, which is crucial for understanding how ecosystems work (Cui et al., 2023; Vidican et al., 2023). Continuous observation and detailed analysis facilitated by remote sensing are vital for efficient decision-making in conservation, land use planning, and resource management, ensuring that archaeological sites remain undisturbed while supporting the ecological health of the game reserve (Rocchini, 2014; Szpakowski & Jensen, 2019).

Improvements in satellite imaging technology, particularly the enhanced spatial and spectral resolution of sensors like Landsat, Sentinel, and MODIS, have markedly increased the accuracy and reliability of vegetation maps at archaeological sites within game reserves (Hansen et al., 2013; Morell-Monzó et al., 2020; Pastick et al., 2018, 2020). Additionally, vegetation indices like the NDVI have become robust tools for assessing vegetation health and productivity without impacting the archaeological integrity of the site (Benhizia et al., 2024; Niyonsenga et al., 2024). Integrating advanced machine learning algorithms with remote sensing data has improved vegetation analysis. It is now easier to track plant growth, spot changes in land cover, measure land degradation and fragmentation, figure out how terrain affects plant health, and estimate biomass and evapotranspiration at these one-of-a-kind sites (Bauer et al., 2024; Mullissa et al., 2024; Pettorelli et al., 2005). These technological advancements are critical for managing and researching complex environments like the Cradle Nature Reserve. Understanding the complex interrelationships among vegetation dynamics, hydrology, and topography within this karst environment can significantly benefit from machine learning algorithms and advanced modelling techniques (Chang et al., 2022; Loehman et al., 2020).

Understanding and addressing the intricate interrelationships among vegetation dynamics, hydrology, and topography are crucial in the Cradle Nature Reserve. This ecosystem is characterised by its intricate topography, where variables such as moisture distribution, vegetation condition, and terrain ruggedness significantly impact ecological processes (Berhanu & Bisrat, 2018; Kopecký et al., 2021). Key metrics like the TWI and EVI provide essential information about vegetation distribution and moisture availability (Cantón et al., 2004; Talebi & Mostafazadeh, 2022). Slope gradients also play a crucial role in influencing habitat suitability, water runoff, and soil erosion, further complicating ecosystem management (Talebi & Mostafazadeh, 2022; M. Wu et al., 2018). Other topographic indices, such as the TPI and TRI provide critical insights into hydrological processes and landscape features (Al-Sababhah, 2023; Dilts et al., 2022; K. B. Jones et al., 2000; Rózycka et al., 2017). Understanding the synergies and trade-offs among these indicators is essential for developing effective conservation and management strategies that ensure the long-term viability and resilience of the dual-purpose site's fragile karst ecosystem (Berhanu & Bisrat, 2018; Kopecký et al., 2021). This comprehensive approach is particularly beneficial in studying ET, a critical hydrological process in such environments.

ET, a key component of the hydrological cycle, encompasses the processes of water evaporation from soil and water surfaces and plants' release of water vapour (U.S. Geological Survey, 2023a). At dual-purpose sites, such as those that are both archaeological and game reserves, understanding ET trends is essential for managing water resources, supporting vegetation health, and maintaining ecosystem balance without disrupting the archaeological sites. Efficient water resource management ensures that the flora and fauna within the reserve are sustained, which is vital for the habitat's ecological health and biodiversity (Durán-Sánchez et al., 2018; Stephenson et al., 2022). Simultaneously, maintaining the water cycle supports the preservation of archaeological artefacts by preventing erosion and other water-related damages. Traditional methods for determining ET include hydrological, meteorological, and micro-meteorological techniques, such as the Penman-Monteith equation and eddy covariance systems (Food and Agriculture Organization of the United Nations, 2024; Shoko et al., 2015). However, these methods are often limited by their spatial and temporal resolution (Derardja et al., 2024; Tan et al., 2021). Remote sensing technology has revolutionised ET estimation by providing extensive, continuous, and replicable data on a large scale (Derardja et al., 2024). There are full and ongoing ET observations in the MODIS data, especially in the MODIS/061/MOD16A2GF dataset, which lets us study changes over time from 2000 to 2023 (LP DAAC 2024). Additionally, advancements in remote sensing technologies have facilitated more accurate and extensive monitoring of ET, which is essential for managing water resources and studying climate change effects (Derardja et al., 2024; L. Jin et al., 2024). Machine learning algorithms, like the XGBRFCClassifier, have improved land cover classification by making it easier to analyse big, complicated datasets more accurately and quickly (Talukdar et al., 2020a). Recent developments in Landsat sensor technology, especially with Landsat 8 and 9, have further enhanced the accuracy and reliability of land cover classifications (Phiri & Morgenroth, 2017).

Balancing the dual roles of archaeological preservation and ecosystem management in game reserves requires careful planning and the use of advanced geospatial technologies. These technologies protect archaeological sites from anthropogenic and natural disturbances while enabling sustainable management of the game reserve's ecosystem. These sites make a

significant economic contribution to the nation and surrounding communities, providing tourism revenue, job opportunities, and community development. By integrating geospatial technologies, we can preserve cultural heritage and natural resources for future generations.

1.2 Problem Statement

The application of geospatial technologies in archaeology has made significant advancements, but a systematic review of the existing literature is lacking, leading to a fragmented understanding of trends and gaps in research (Klehm, 2023a). The use of geospatial technologies in archaeology has been shown to enhance the accuracy and efficiency of site identification, mapping, and monitoring (Wheatley & Gillings, 2013). However, despite the growing interest in remote sensing and machine learning technologies for vegetation mapping, there is a notable lack of comprehensive literature reviews synthesising the existing research in this field, particularly in the context of the Cradle Nature Reserve, a unique site that combines both archaeological significance and game reserve conservation efforts, presenting a complex dual configuration that warrants specialised attention (Brembs, 2018; Whig et al., 2024a; Y. Xie et al., 2008a). Vegetation mapping is a critical component of archaeological site management, as it provides valuable insights into site formation processes and human-environment interactions (Pettorelli et al., 2005). Moreover, vegetation mapping is essential for understanding ecosystem dynamics, biodiversity conservation, and land degradation assessment (Deb et al. 2022). The Cradle Nature Reserve, a UNESCO World Heritage Site, is an ideal location for applying remote sensing techniques in vegetation mapping due to its unique geological and ecological features, including its location in the Cradle of Humankind, a region of high archaeological significance (Bauer et al. 2024). The reserve's diverse vegetation cover, ranging from grasslands to forests, also presents an opportunity to test the efficacy of remote sensing techniques in different environments (Mullissa et al. 2024). Therefore, a literature review on geospatial technologies in archaeology should be followed by a focused literature review on the application of remote sensing and machine learning in vegetation mapping in the Cradle Nature Reserve to further explore the potential of these technologies in this specific context and identify areas for future research and application

The Cradle Nature Reserve experiences significant challenges in maintaining ecological health due to the complex interplay between topography, vegetation dynamics, and hydrology. These challenges are exacerbated by the rugged terrain and varying moisture distribution, which affect plant health and ecological processes. The existing body of research highlights the need for comprehensive studies integrating topographic indices such as TWI, EVI, TPI, and TRI to understand these interactions better (Berhanu & Bistrat, 2018; Kopecký et al., 2021). Despite the availability of various geospatial tools and indices, there remains a gap in the application of these tools to fully capture and analyse the intricate details of the karst environment. This gap underscores the need for more detailed and scale-appropriate studies to provide actionable insights for sustainable land management and conservation efforts (Cantón et al., 2004; Kopecký et al., 2021).

Additionally, the Cradle Nature Reserve faces challenges from varying climatic conditions and land management practices, affecting ET patterns and vegetation health—critical indicators of the reserve's ecological state (Mccollum et al., 2017; Pedrinho et al., 2024). Previous studies have identified fluctuations in ET due to climate variability and human activities, but a comprehensive understanding of these trends over an extended period remains incomplete (Arnell et al., 2019; Gerten et al., 2013). The relationship between ET and topographical

features, such as elevation, requires a thorough investigation to develop adaptive management practices that consider both climatic and biophysical factors in the game reserve (Nakileza & Nedala, 2020; Q. Yang et al., 2022). Even though remote sensing and machine learning have come a long way, the Cradle Nature Reserve still needs constant monitoring and accurate land cover classification to support good conservation strategies and ecological management (Manandhar et al., 2009; Phiri & Morgenroth, 2017).

Land cover degradation is evident in the Cradle Nature Reserve, marked by a significant increase in bare ground and a reduction in indigenous forests and natural grasslands (L. Berger & Maduwa, 2023). This degradation leads to habitat loss, biodiversity decline, soil erosion, and ecosystem alterations, negatively impacting the area's aesthetic and tourism value (Adepoju & Salami, 2017; Martinez del Castillo et al., 2015). The invasion of alien plant species, particularly pompom weed, exacerbates this degradation, reducing the vegetation's productivity and the area's grazing capacity (O'Connor & van Wilgen, 2020). There have been improvements in machine learning algorithms, but there hasn't been a comparison of the parametric Naïve Bayes and non-parametric XGBRF classifiers for LULC classification in this region. This means that more research is needed to find the best classifier for tracking changes in land cover and figuring out how much landscape fragmentation is caused by humans and climate change.

Advancements in remote sensing technology exist, but the variability and interactions of environmental factors, such as temperature, rainfall, and soil moisture, that collectively influence the health and productivity of vegetation in grassland ecosystems in archaeological settings such as the Cradle Nature Reserve are outstanding (Mashala et al., 2023; Ogungbuyi et al., 2023a). These factors exhibit complex and often non-linear relationships, making it challenging to develop accurate and reliable models for ecological monitoring and decision-making (Jobson, 1991). The inherent seasonality of these environmental factors can further complicate the analysis, potentially leading to misleading conclusions if not properly accounted for (Helali et al. 2022). Multilinear regression models, commonly used in these kinds of studies, do not always show all of these complex relationships because the independent variables aren't always linear, and seasonality is not considered (Jobson, 1991; Rebecca Bevans, 2023). According to (Fatima et al., 2022) and (Marukatat, 2023), Principal Component Analysis (PCA) is a better way to deal with these kinds of problems because it reduces the number of dimensions in the data and turns correlated variables into uncorrelated components. This makes it easier to see the patterns and relationships that lie beneath the surface.

The Cradle Nature Reserve, a unique site combining archaeological significance and game reserve conservation efforts, requires accurate biomass estimation for effective vegetation management and conservation. However, the use of drone technology for biomass estimation in this context faces challenges, including reduced precision during early growth stages and varying vegetation types (Bareth et al., 2015; Possoch et al., 2016). While vegetation indices derived from RGB drone imagery can provide insights into plant health and characteristics, integrating additional data sources, such as field-measured chlorophyll concentrations, is essential for improving biomass estimate accuracy (Agapiou, 2020). The lack of research addressing these challenges in the Cradle Nature Reserve's dual configuration setting hinders the development of effective vegetation management strategies, emphasising the need for targeted investigations to overcome these knowledge gaps and improve biomass estimation accuracy in this unique environment.

1.3 Research questions

The following research questions were addressed in this study:

- What are the key concepts and themes shaping the use of geospatial technologies in archaeology, and which potential research gaps and underexplored areas remain in this field, both globally and in South Africa?
- What are the key applications of remote sensing in monitoring vegetation, detecting land cover changes, assessing degradation, evaluating topography's impact, and estimating biomass and evapotranspiration?
- Which classifier, Naïve Bayes or Extreme Gradient Boosting Random Forest, demonstrates higher accuracy for LULC classification in the Cradle Nature Reserve in 2020, and what are the land use and land cover changes from 1990 to 2020?
- What are the spatio-temporal trends of EVI and environmental factors, and how do their statistical associations with climatic factors inform sustainable grassland management using remote sensing, multilinear correlation, and PCA in the Cradle Nature Reserve?
- What factors influence above-ground biomass in the Cradle Nature Reserve, using RGB drone photos, nDSM vegetation heights, and field-measured chlorophyll analysed with PCA and stepwise regression?
- Which topographic factors, TWI, EVI, TRI, TPI, and percentage slope gradient, collectively affect vegetation growth and changes, moisture distribution, terrain roughness, and habitat suitability in the Cradle Nature Reserve's karst environment?
- What are ET's yearly patterns and spatial distribution, and how does ET correlate with DEM data and land cover changes in the Cradle Nature Reserve?

1.4 Aims and objectives of the study

- To investigate the key concepts and themes shaping the use of geospatial technologies in archaeology and to identify potential research gaps and underexplored areas in this field, both globally and in South Africa.
- To investigate the key applications of remote sensing in monitoring vegetation, detecting land cover changes, assessing degradation, evaluating topography's impact, and estimating biomass and evapotranspiration.
- To investigate which classifier, Naïve Bayes or Extreme Gradient Boosting Random Forest, demonstrates higher accuracy for LULC classification in the Cradle Nature Reserve in 2020 and to determine the land use and land cover changes from 1990 to 2020.
- To investigate the spatio-temporal trends of EVI and environmental factors and examine their statistical associations with climatic factors to inform sustainable grassland management using remote sensing, multilinear correlation, and PCA in the Cradle Nature Reserve.

- To investigate the factors influencing above-ground biomass in the Cradle Nature Reserve, using RGB drone photos, nDSM vegetation heights, and field-measured chlorophyll analysed with PCA and stepwise regression.
- To investigate how topographic factors, TWI, EVI, TRI, TPI, and percentage slope gradient collectively affect vegetation growth and changes, moisture distribution, terrain roughness, and habitat suitability in the Cradle Nature Reserve's karst environment.
- To investigate ET's yearly patterns and spatial distribution and to explore how ET correlates with DEM data and land cover changes in the Cradle Nature Reserve.

1.5 Study area

The Cradle Nature Reserve, encompassing approximately 8,000 hectares within the Cradle of Humankind World Heritage Site (COHWHHS), is situated in the Sterkfontein Valley, about 50 kilometres northwest of Johannesburg, South Africa, and 10 kilometres north of Krugersdorp (Lelliott, 2016; Rogerson & van der Merwe, 2016). The geographical coordinates of the reserve are between longitudes 27°42'58" and 27°52'57" and latitudes 25°51'13" and 25°51'19" (see Figure 1). This location was designated a World Heritage Site by UNESCO in 1999 due to its profound significance in the study of paleoanthropology (Rogerson & van der Merwe, 2016). The reserve is renowned for its diverse plant species, particularly those that bloom and hosts over 200 bird species alongside various other animals (Braga et al., 2016; Rogerson & van der Merwe, 2016). Vegetation in the reserve is influenced by key climatic factors such as temperature and precipitation, with annual rainfall ranging from 650 to 750 mm, summer temperatures reaching up to 39°C, and winter temperatures dropping as low as -12°C, creating a dynamic environment conducive to plant growth (FLOW Communications, 2022). The Rocky Highveld Grassland climatic area, characterised by fire, significantly impacts the plant structure. Additionally, natural springs, watercourses, streams, and tributaries to the Magalies and Crocodile Rivers provide essential moisture, supporting the area's wide range of plant species (Caruana & Stratford, 2019; Lelliott, 2016). Historically, both subsistence and commercial farming practices have significantly impacted plant distribution within the reserve; additionally, the reintroduction of wild animal species, which exhibit distinct grazing patterns compared to domesticated animals, has further influenced these alterations (Makokotlele, 2009). Unique geological characteristics, such as dolomitic sinkholes that protect tree species from forest fires and the chemical weathering of limestone and dolomitic rocks forming karst landforms, contribute to the distinct patterns of plant growth in the area (Bradley et al., 2010; Eloff, 2010).

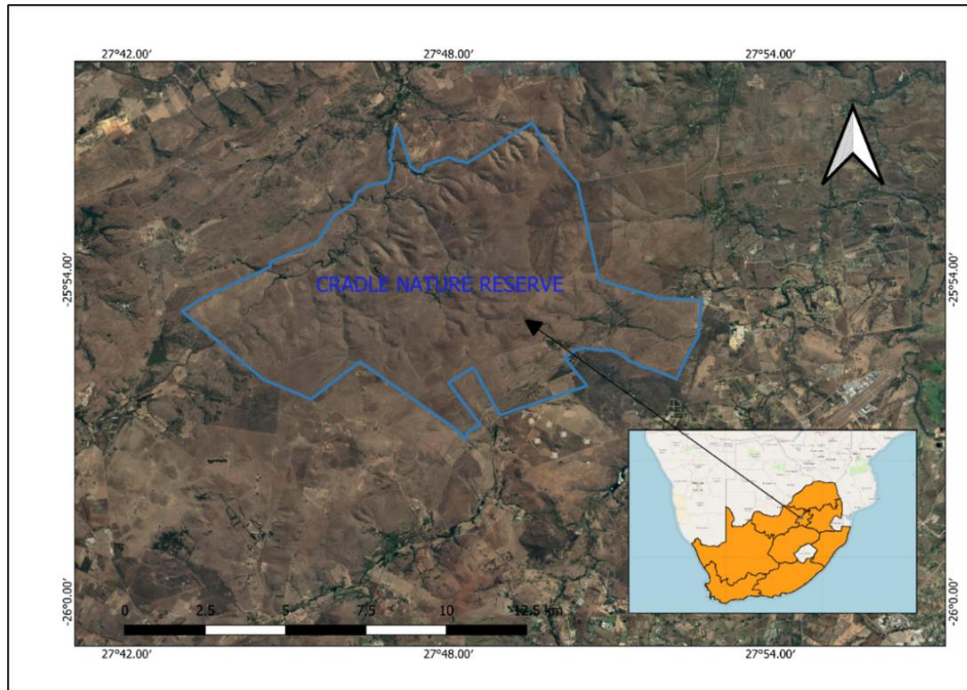


Figure 1- 1: Study Area—Cradle Nature Reserve in South Africa with overview of the Google Earth Pro Imagery in UTM/WGS84 plane coordinate.

1.6 Significance of the study

This study aims to illuminate trends and advancements in geospatial technologies for archaeological investigations, specifically focusing on South Africa. By identifying research gaps and showcasing recent developments in affordable geospatial tools, the study underscores their significance within the broader academic landscape. Encouraging the adoption of these methods in South African archaeology and fostering interdisciplinary collaboration will enhance spatial technology applications, ultimately advancing the field and contributing to global archaeological practices.

Furthermore, the study aims to enhance vegetation mapping by integrating remote sensing technologies with machine learning algorithms. Through a comprehensive literature review using Scopus and employing VOSviewer for bibliometric analysis, the research will highlight key trends and advancements in the utilisation of remote sensing techniques such as Random Forest, Support Vector Machines (SVM), neural networks and XGBRFCClassifier for improving vegetation map accuracy. These insights are crucial for identifying areas where research is lacking, facilitating more accurate environmental management, and aiding in creating successful conservation programs and sustainable development practices. Conducting ongoing studies in these specific areas of deficiency will improve our capacity to reduce the effects of climate change and other environmental pressures.

Additionally, this study will provide critical insights into land use and land cover changes (LULCC) in the Cradle Nature Reserve from 1990 to 2020 using satellite imagery and the

XGBRFClassifier. By classifying the landscape, the research will reveal trends in environmental degradation and landscape fragmentation. These changes, driven by both natural dynamics and anthropogenic factors like invasive species, underscore the need for effective conservation strategies. The study will support the Cradle Nature Reserve's efforts to eradicate invasive species, restore degraded landscapes, and maintain ecological integrity. The study will assist in developing evidence-based policies and management plans that will contribute to the sustainable preservation of this important ecological and historic site through comprehensive analysis.

Furthermore, the study will enhance ecological decision-making and sustainable land management in the Cradle Nature Reserve through PCA and correlation analysis. By understanding environmental factors, the research will support evidence-based policies to maintain grassland ecosystems, ensuring the health of vegetation and dependent wildlife. The study will guide policymakers in promoting healthy vegetation, creating seasonal plans, allocating resources to stressed areas, and formulating climate adaptation strategies. Continuous monitoring will assess policy effectiveness and adapt strategies as needed. By identifying key environmental variables, managers can prioritise climatic factors in conservation efforts and implement targeted interventions. The research aims to simplify complex ecological data into actionable insights, guiding grassland management strategies to maintain ecological health and sustainable use of these ecosystems.

This study's significance also lies in its potential to support informed conservation policies, sustainable land management, and biodiversity preservation by uncovering significant variations in water availability and vegetation health due to climate variability and land management practices. By examining the relationship between evapotranspiration (ET) and elevation, the study will provide insights into the influence of biophysical and climatic factors, emphasising the need for adaptive management to maintain ecosystem health. The findings will underscore the importance of continuous monitoring and effective management strategies to sustain the reserve's health and biodiversity amidst climate change impacts.

Additionally, this study's significance lies in addressing the complex interactions between vegetation dynamics, hydrology, and topography in the Cradle Nature Reserve. By integrating topographic indices such as TWI, EVI, TPI, and TRI, the study will comprehensively analyse how these factors collectively impact vegetation health, moisture distribution, terrain ruggedness, and habitat suitability, which is crucial for effective conservation and sustainable land management. The research will utilise advanced remote sensing technologies and machine learning algorithms to ensure robust and reliable findings, informing adaptive management practices amidst climate variability and human activities. This contribution to environmental science emphasises the importance of continuous monitoring and diverse geospatial tools, providing practical solutions for global biodiversity conservation and ecological balance.

In summary, this study aims to provide critical data and insights to support informed decision-making in environmental management and conservation efforts, contributing significantly to the fields of environmental science and ecological management.

1.7 Outline of the thesis

This is a thesis that utilises a paper-based technique. The thesis consisted of nine chapters, of which seven chapters detailed the achievement of the given objectives:

Chapter 1 provides the background, problem statement, objectives, and outline of the research.

Chapter 2 provides a scientometric review of the advancements in the application of geospatial technology in archaeology and cultural heritage in South Africa. The scientometric review highlights significant research growth and technological integration, emphasising global collaboration, key academic platforms, multidisciplinary contributions, and the need for ongoing research to enhance data accuracy and develop innovative solutions for environmental sustainability amidst climate change and degradation challenges.

Chapter 3 provides a scientometric review of advances in vegetation mapping through remote sensing and machine learning techniques. The study revealed that the main drivers that propel research in vegetation mapping using remote sensing are advancements in machine learning algorithms and prominent academic platforms such as major journals and conferences.

Chapter 4 assessed changes in land cover and landscape structure by applying extreme gradient boosting random forest and fragmentation analysis. The study found that the XGBRFCClassifier excels in land cover classification, revealing significant land cover changes and increased fragmentation from 1990-2020

Chapter 5 investigated vegetation growth dynamics using EVI and PCA in the karst environment of the Cradle Nature Reserve. The study found that climatic conditions significantly influence vegetation health, with PCA effectively revealing the combined and individual impacts of the environmental factors

Chapter 6 investigated the use of RGB Drone Imagery and vegetation indices for accurate above-ground biomass estimation. The study identified nDSM and RBVI as key predictors of AGB in non-riparian areas, while chlorophyll content and BGVI played important roles in riparian areas.

Chapter 7 investigates the impact of topographic parameters TWI, EVI, TRI, TPI, and % slope gradient on plant development, moisture distribution, terrain roughness, and habitat compatibility in the Cradle Nature Reserve. The study found that vegetation health in the Cradle Nature Reserve is significantly influenced by topographic variables, with healthier vegetation typically found on steeper slopes and poorer vegetation in elevated and rugged terrains.

Chapter 8 investigated the effects of land use change on annual evapotranspiration in the Cradle Nature Reserve (2000-2023) using MODIS data and XGBoost classification. The study identified fluctuations in evapotranspiration and land cover from 2000 to 2023.

Chapter 9 concludes the thesis by highlighting the primary results attained for each target, the research's value to the remote sensing field, and suggestions for future investigations.

Chapter 2 ADVANCEMENT IN THE APPLICATION OF GEOSPATIAL TECHNOLOGY IN ARCHAEOLOGY AND CULTURAL HERITAGE IN SOUTH AFRICA: A SCIENTOMETRIC REVIEW

This Chapter is based on the following manuscript

Matyukira, C., & Mhangara, P. (2023). Advancement in the application of geospatial technology in archaeology and cultural heritage in South Africa: A scientometric review. *Remote Sensing (Basel)*, 15(19), Article 4781. <https://doi.org/10.3390/rs15194781>

Abstract: Geospatial technologies have become an essential component of archaeological research, aiding in the identification, mapping, and analysis of archaeological sites. Several journals have published existing narratives on the development and impact of geospatial technologies in the study of archaeology and cultural heritage. However, this has not been supported by a systematic review of articles and papers, where meticulously collected evidence is methodically analysed. This article systematically reviews the trends in the use of geospatial technologies in archaeology and cultural heritage through the search for keywords or terms associated with geospatial technologies used in the two fields on the Scopus database from 1990 to 2022. Bibliometric analysis using Scopus Analyse tool and analysis of bibliometric networks using VOSviewer visualisations, reveals how modern archaeological studies are now a significant discipline of spatial sciences and how the discipline enjoys the tools of geomatics engineering for establishing temporal and spatial controls on the material being studied and observing patterns in the archaeological records. The key concepts or themes or distinct knowledge domains that shape research in the use of geospatial technologies in archaeology and cultural heritage, according to the Scopus database (1990–2022), are cultural heritage, archaeology, geographic information systems, remote sensing, virtual reality, and spatial analysis. Augmented reality, 3D scanning, 3D modelling, 3D reconstruction, lidar, digital elevation modelling, artificial intelligence, spatiotemporal analysis, ground penetrating radar, optical radar, aerial photography, and unmanned aerial vehicle (UAV) are some of the geospatial technology tools and research themes that are less explored or less interconnected concepts that have potential gaps in research or underexplored topics that might be worth investigating in archaeology and cultural heritage.

Keywords: geospatial technologies, geographic information systems, lidar, remote sensing, South Africa, virtual reality

2.1 Introduction

The application of geospatial technology in a broad spectrum of fields is gaining momentum worldwide. The widespread application of geospatial technology has resulted in a multiplicity of definitions owing to the distinct perspectives of the stakeholders. Some denote this application as a science, while others consider geospatial technology a group of tools used in various professional fields. Geospatial technology is also recognised as a profession with codes of ethics and specific competence standards (DiBiase et al., 2010). As a profession, geospatial technology, also referred to as geomatics, is a growing multidisciplinary academic field with diverse applications encompassing land surveying, remote sensing, mapping, geographic information systems (GIS), geodesy, and global navigation systems (Aina, 2012). This multidisciplinary academic field constitutes a geospatial industry defined by the United States Department of Labour as “an information technology field of practice that acquires, manages, interprets, integrates, displays, analyses, or otherwise uses data focusing on the context” (Klinkenberg, 2007). From this definition, (Klinkenberg, 2007) deduced that geospatial technologies should be classified as GIS, global navigation satellite systems (GNSS), photogrammetry, remote sensing, cartography, surveying, and other related fields. Aina (Aina,

2012) concurred with Klinkenberg (Klinkenberg, 2007) on the definitions. She added devices such as cellular phones, RFID (radio frequency identification) tags and surveillance cameras with embedded technologies that use locational information to the list of geospatial technologies. The fields in which geospatial technologies have been implemented are wide-ranging, including facilities management, precision farming, urban planning, business geographics, security and intelligence, telecommunication, automated mapping, and civil engineering. Archaeology is a further field where such technology has been applied (Aina, 2012). There is an established deep link between geospatial technologies and information communication systems, which has benefitted geomatics fields such as GIS (Aina, 2012). The above discussion elucidates what this literature review refers to as geospatial technologies.

As early as the 18th century, archaeologists had grasped the importance of spatial data accompanying archaeological recordings, ranging from relative locations with varying scales to data depicting individual artefacts with excavation contexts (Wheatley & Gillings, 2013). Over the years, the deployment of geospatial technology in archaeology has been used to expound on different spatial phenomena. Such phenomena include seasonal hunter-gatherer camps within a landscape, the hierarchy of settlements within a region, the location of artisanal mines in an area, and many others that exploit spatial links, patterns, and relationships (Wheatley & Gillings, 2013). According to Aina, (2012), and Wheatley & Gillings, (2013), growth in the study of spatial archaeological data has grown from descriptive (tabulated and plotted on simple flat maps) to explanatory (explanation of spatial patterns and relations). Wheatley & Gillings, (2013) further attributed this development to emerging robust geospatial technologies capable of handling high volumes of spatial data with high resolutions and processing speeds.

According to Nsanziyera and three other authors (Nsanziyera et al., 2018), the tremendous growth in remotely sensed spatial data has created new horizons and possibilities for archaeological research, such as creating predictive models that are becoming standard tools for investigation in GIS mapping. Further, these advancements in geospatial technologies have created new territories for research in archaeology and many documents in journals of different rankings. Although several journals have published existing narratives on the development and impact of geospatial technologies in the study of archaeology, as noted in this review and others, this has not been supported by a systematic review of articles and papers (Linnenluecke et al., 2020). In a systematic review, evidence is assembled, identified, and critically analysed through systematic procedure so that readers are constantly updated about current literature on the subject (Carrera-Rivera, Larrinaga, et al., 2022). According to Linnenluecke et al., (2020), the world is witnessing an exponential growth of poor-quality scholarly articles, often in open-access formats in predatory journals and good scholarly articles in ranked journals. However, according to Brembs, (2018), the reliability of even exceptionally high-ranking journals could be better, but these journals are currently the only source of credible information on geospatial technologies. This review aims to establish the trend in using and applying geospatial technologies in archaeology globally and in South Africa using the Scopus database. Scopus is an extensive database that provides fully referenced scholarly documents in social sciences, arts, humanities, science, technology, and medicine (Burnham, 2006). The following section gives a framework of the goals and objectives of using geospatial technologies in archaeology.

2.1.1 Geospatial Technology in Archaeology

Before reviewing the goals and objectives of geospatial technology in archaeology, it is necessary to first look at the field of archaeology itself. The latter has undergone many changes over the past century. Each change attracts a new purpose or modification of the existing ones (Trigger, 1989, p. 370-411, as cited in (Shafer, 2016a)). Establishing temporal and spatial controls on the material being studied and observing patterns in the archaeological records forms the backbone of modern archaeology; however, some aspects have been retained from the older versions of archaeology, such as in archaeologies defined as cultural/historical, new, and or postprocessual (Shafer, 2016a). Historically, the usage of geospatial technologies in archaeology aimed to produce archaeological maps (primarily hand-drawn) meant to record/document site progress and archaeological investigations (Feder, 2016a, 2016b). For instance, the objective of traditional sketch maps was to record the in-situ context or geometrical descriptions of uncovered material evidence (Garrison et al., 2011; Kruger et al., 2016; Reilly, 1991; Shafer, 2016a, 2016b). With advanced geospatial technologies, modern complex maps aim to visualise geometric structures, taphonomic associations and linkages between in-situ and ex-situ fossils to illuminate a landscape signature and detect comprehensive settlement patterns. In this context, the settlement pattern represents how people relate and interact with a landscape, which archaeologists call the landscape signature (Ainsworth et al., 2017; Kruger et al., 2016; Reilly, 1991; Shafer, 2016a). The phenomenal growth in geospatial technologies over the past century has revolutionised archaeological maps, particularly those used for site surveying and more changes are envisaged in the foreseeable future (Ainsworth et al., 2017; Garrison et al., 2011; Kruger et al., 2016; Reilly, 1991; Shafer, 2016a, 2016b).

According to Feder, (2016a), archaeological sites are analogous to extinct animal fossils; a fossil is more than the sum of its parts. However, the juxtaposition and spatial positioning of the bones provide valuable information for palaeontology. Similarly, the juxtaposition and spatial distribution of archaeological remains provide insightful information about the habits of people using the site (Feder, 2016a, 2016b; Lazo, 2005). Archaeological and paleontological excavations, by nature, are destructive; remains left behind by historic and prehistoric people, which inherently are the archaeological source of knowledge, are removed or destroyed in the process of understanding our past (David, 2006; Feder, 2016a; Latham et al., 1999). Artefacts are removed from their original contexts and sent to the laboratory; in the process, spatial relationships are destroyed (Hester, 2016a, 2016b), so how do archaeologists capture and preserve the spatial relationships of the artefacts during site surveys? The answer is to carry out in situ recording (in a reference coordinate system) of the exact horizontal and vertical positions of artefacts. These same positions constitute recorded coordinates of the original location of an artefact, referred to in archaeological terms as provenience (Thomas, 2021). For instance, many items are left in situ to take proveniences before the excavation procedures destroy material evidence when excavating a site (Hester, 2016b). Irrespective of the survey methods employed, the exact location of these proveniences is the subject of geospatial technologies, be they pedestrian walking, subsurface survey, or remote sensing (Feder, 2016a)

The following sections are dedicated to expounding these technologies, first by defining form, space, and place, the essential ingredients when defining a spatial location, linking geospatial technologies to spatial archaeology, and tracking the development of these technologies globally and in South Africa.

2.1.2 Understanding Space and Place

Before turning to the intricate issues surrounding the development of spatial technologies and how they have revolutionised archaeology in South Africa, a detour to understand the meaning of spatial archaeology is essential. Understanding the recursive linkages between spatial structure and social relations has been the subject of archaeology for years; of primary concern is the interpretation of the meaning of space and place regarding spatial structure in archaeological records (Ashmore, 2002). Albert Spaulding (1954, p. 161-162, as cited in (Ashmore, 2002)) defined space in archaeology as the dimensions used in empirical data operations to characterise and analyse artefacts and assemblages codified as forms with temporal and spatial locus. The description and classification of material evidence archaeologists uncover during their site investigations are called form (Shafer, 2016a). This definition shows that material evidence is diachronic because it has temporal and spatial characteristics (Shafer, 2016a). According to Ashmore, (2002), archaeological studies define a place as a plotted episode on a map through which the past becomes visible. From these definitions, space contains a place, and form exists in place boundaries. On the significance of place, Lewis Binford (1982, p. 5, as cited in (Ashmore, 2002)) implored archaeologists to acknowledge the subtle importance of place; he argued that in understanding the organisation of past cultural systems, it is paramount that archaeologists understand temporal and spatial relations among places which were used differentially during the operation of past systems. He reiterated these sentiments by adding that repeated human actions were essential in forming individual places and constructing social memories; a single place had multiple and mutable roles in society, and past social interactions are essayed thoroughly by understanding space and place. Wherever space and place are defined, (Holdaway et al., 1998) added that archaeologists should analyse artefacts by finding patterns that represent behaviours repeated in common temporal and spatial locus. An average picture of past behaviours is reconstructed from the abandoned artefacts in one location by past individuals (Holdaway et al., 1998). According to Simek, (1984), a conventional approach to intra-site spatial analysis should identify where the pre-historical or historical activity used to happen (place), the spatial distribution of the places, and the tool kit used to perform the actions. Hodder, Jochim and Zimmerman (1978, 1976, 1977, as cited in (Shafer, 2016a)) added that “Just as behaviour itself is not random, human beings do not behave randomly in space; that is, they do not use the landscape randomly”. Trigger and Clarke also lauded the importance of defining space; they argued that the past is illuminated by studying the spatial distribution and relative sizes of sites (place) and linking them with relevant evidence, such as political boundaries and regions of influence (Trigger & Clarke, 1977).

2.1.3 Development of Geospatial Technologies in South Africa

The use of rudimentary geospatial technology for the documentation of fossil deposits in South Africa north of the Vaal River (formerly the Transvaal Province from 1910-1994) can be traced

back to the lime-mining activities in the calcitic speleothem caves at Sterkfontein by G Martinaglia in the mid-1890s and David Draper of the Geological Society of South Africa in 1895 (Kuykendall & Štrkalj, 2007). However, the documentation of the fossils in those inception years of archaeology as a discipline lacked accuracy and precision. Most discoveries were from the works of amateur archaeologists, and some of the documented historical fossils had no provenience and no precise spatial context other than a reference to a deposit or member (Kuykendall, 2007; Kuykendall & Štrkalj, 2007). In addition, a significant challenge existed when the fossils were in close contact, and mixing fossil deposits of different ages became inevitable (Armstrong et al., 2018). Furthermore, the apparent disconnection between the provenience of some fossils and museums created misinterpretation of the archaeological record; for instance, in the past, different deposits or samples were grouped as if they came from the same assemblage (Armstrong et al., 2018).

An example is in the archaeological documentation of fossils in Sterkfontein, which were referenced as coming from Makapansgat or Taung. However, these prominent localities contain multiple sites spanning millions of years of deposition (Armstrong et al., 2018). Therefore, archaeologists needed to embrace geospatial technologies for detailed recording of all demolished during excavations and exhumations. This is a necessary step in archaeological investigations as it enables future reinterpretation of similar results or for the future archaeologist to experience the site as it was in the first place, arguably making the excavation process virtually reversible (Armstrong et al., 2018; Feder, 2016a; Hester, 2016a).

2.2 Materials and Methods

2.2.1 Overview

Systematic reviews are qualitative research methods that follow a predefined protocol such as that provided by Systematic reviews and Meta-Analysis PRISMA statement of 2020, which aim to establish an unbiased and comprehensive summary of available evidence in a particular subject area from existing research studies on some specific topic (Higgins & Green, 2011). Systematic reviews are often conducted to answer specific research questions (Higgins & Green, 2011; Ozturk & Ozen, 2020) and be undertaken in a replicable, scientific, and transparent process with minimum bias from including or excluding studies in the literature review process (Carrera-Rivera, Ochoa-Agurto, et al., 2022). This study aims to reveal the trend in using geospatial technologies in archaeology and cultural heritage from 1990 to 2022 and be insightful in understanding paradigms in archaeological investigations using geospatial technology. Systematic reviews are qualitative analyses often employed with scientometric and bibliometric analyses. The scientometric analysis is a quantitative study of science and scientific research focusing on broader trends across disciplines, research, and the evolution of scientific fields (Bornmann & Marx, 2014). At the same time, bibliometric analysis is a subset of scientometric analysis that mainly focuses on evaluating the performance of researchers, institutions, and journals with specific fields of study (Bornmann & Marx, 2014). This study uses the Scopus search engine to search for scholarly articles containing keywords or terms fundamental to understanding the use of geospatial technology in archaeology and cultural heritage, as listed in Table 2-1. Scopus was launched in 2004 and uses Boolean Syntax to perform bibliometric searches; it combines keywords and operators to yield consolidated and

relevant results for a given search criterion (Ozturk & Ozen, 2020). The Scopus database has more information for literature searches than other databases, such as the Web of Science (WOS) (Carrera-Rivera, Larrinaga, et al., 2022; Carrera-Rivera, Ochoa-Agurto, et al., 2022; Ozturk & Ozen, 2020).

Table 2- 1: Scopus search engine and queries used for the scope of this study.

Search Engine	Website	Technology	Query
Scopus	scopus.com	<i>WORLD GEOSPATIAL</i>	(TITLE-ABS-KEY("geospatial technology") OR TITLE-ABS-KEY(GIS) OR TITLE-ABS-KEY("remote sensing") OR TITLE-ABS-KEY(LiDAR) OR TITLE-ABS-KEY("3D scanning") OR TITLE-ABS-KEY("spatial analysis") OR TITLE-ABS-KEY("web mapping applications") OR TITLE-ABS-KEY("augmented reality") OR TITLE-ABS-KEY("virtual reality") OR TITLE-ABS-KEY("geospatial data processing") OR TITLE-ABS-KEY("archaeological predictive modeling") OR TITLE-ABS-KEY("archaeological site mapping") OR TITLE-ABS-KEY("geospatial data integration") OR TITLE-ABS-KEY("geospatial data visualisation") OR TITLE-ABS-KEY("geodetic techniques") OR TITLE-ABS-KEY("satellite remote sensing") OR TITLE-ABS-KEY("geospatial heritage management") OR TITLE-ABS-KEY("GIS-based excavation planning")) AND TITLE-ABS-KEY(archaeology OR "cultural heritage" OR "cultural resource management") AND PUBYEAR > 1989 AND PUBYEAR < 2023 AND PUBYEAR AND (LIMIT-TO (DOCTYPE, "ar")) AND (EXCLUDE (PREFNAMEAUID, "Undefined")) AND (LIMIT-TO (LANGUAGE, "English"))

<i>SOUTH AFRICA</i>	(TITLE-ABS-KEY("geospatial technology") OR TITLE-ABS-KEY(GIS) OR TITLE-ABS- KEY("remote sensing") OR TITLE-ABS- KEY(LiDAR) OR TITLE-ABS-KEY("3D scanning") OR TITLE-ABS-KEY("spatial analysis") OR TITLE-ABS-KEY("web mapping applications") OR TITLE-ABS-KEY("augmented reality") OR TITLE-ABS-KEY("virtual reality") OR TITLE-ABS-KEY("geospatial data processing") OR TITLE-ABS-KEY("archaeological predictive modeling") OR TITLE-ABS- KEY("archaeological site mapping") OR TITLE- ABS-KEY("geospatial data integration") OR TITLE-ABS-KEY("geospatial data visualization") OR TITLE-ABS-KEY("geodetic techniques") OR TITLE-ABS-KEY("satellite remote sensing") OR TITLE-ABS-KEY("geospatial heritage management") OR TITLE-ABS-KEY("GIS-based excavation planning")) AND TITLE-ABS- KEY(archaeology OR "cultural heritage" OR "cultural resource management") AND PUBYEAR > 1989 AND PUBYEAR < 2023 AND PUBYEAR > 1989 AND PUBYEAR < 2023 AND (LIMIT-TO (AFFILCOUNTRY,"South Africa")) AND (LIMIT-TO (DOCTYPE,"ar")) AND (EXCLUDE (PREFNAMEAUID,"Undefined")) AND (LIMIT-TO (LANGUAGE,"English"))
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The bibliometric analysis uses document types such as books, conference papers, patents, and others; this study elects scholarly articles mainly because their level of detail allows for more nuanced analysis and a deeper understanding of our research landscape. Scholarly articles undergo rigorous peer-reviewing, papers reveal vivid citation patterns, and scholarly articles are available in most bibliometric databases like Scopus and follow a standardised format; they contain time-stamped information (Kadam et al., 2020; Ozturk & Ozen, 2020). Among several software for visualisation and analysing bibliometric networks, such as co-authorship, co-citation, and co-occurrence networks, is VOSviewer (Jan van Eck & Waltman, 2023). VOSviewer is widely used in scientometric and bibliometrics analysis to explore and understand relationships between authors, publications, and research topics. In this study, VOSviewer allows the analysis of geospatial technologies in archaeology and cultural heritage by visualising and exploring relationships between different articles, authors, and keywords in the field (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). The unit

of analysis in this study is the keywords or terms related to geospatial technologies, archaeology, and cultural heritage like “GIS”, “remote sensing”, “spatial analysis”, “archaeological site”, “satellite imagery”, and more.

VOSviewer uses keywords or terms to visualise the keyword co-occurrence network, where the size and proximity of keywords in the visualisation indicate their relationships (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). There are different types of analysis in VOSviewer, and this study elects co-occurrence, bibliographic coupling analysis, and keyword analysis. With co-occurrence analysis, co-occurrence of keywords or terms related to geospatial technologies are identified in the set of documents obtained from the Scopus dataset, and these will help the review to explore the relationship between different geospatial technologies and their application areas and visualise the thematic clusters (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). The bibliographic coupling analysis focuses on the shared references between articles and creates clusters of related articles based on their shared geospatial technology keywords or terms and applications (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). While keyword analysis involves analysing the occurrence and co-occurrence of keywords or phrases related to geospatial technologies in archaeology, this will help the researcher understand the main topics and trends in using geospatial technologies in archaeology and cultural heritage (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). VOSviewer utilises clustering, link strength, and total link strength to visualise and analyse the relationships and patterns within bibliometric networks, providing valuable insights into the structure and dynamics of scholarly information (Centre for Science and Technology Studies, 2023). A cluster refers to a group of related items within a bibliometric network; in this study, clusters represent different thematic areas and keywords or terms related to geospatial technologies used in archaeology and cultural heritage (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). In a co-occurrence network visualisation created using VOSviewer, keywords are represented as nodes, and the links between these nodes represent how often those keywords appear together within the same documents or context. The "Weight" or "Total Link Strength" associated with a link between two keywords signifies the strength of their co-occurrence relationship. This strength is typically determined by the frequency of co-occurrence, meaning how often those two keywords appear together in the analysed dataset (Centre for Science and Technology Studies, 2023).

VOSviewer uses three visualisations: network, layout, and density (Centre for Science and Technology Studies, 2023). The purpose of network visualisation is like layout visualisation; both are graphical representations of the relationship between keywords based on their co-occurrence in the same articles collected (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). Each keyword is represented by a node (point), and the connection between keywords by lines, the frequency of co-occurrence determines the strength of the relationship (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). In this review, network visualisation allows for identifying clusters of related keywords, which represent thematic areas or topics within geospatial technologies in archaeology and cultural heritage. In addition, visualisation provides a high-level overview of the key concepts and connections that will help identify trends, central themes, and potential focus areas for further

investigations (Ozturk & Ozen, 2020). The size of a node in the co-occurrence network indicates the frequency of a keyword's appearance in the analysed literature (Centre for Science and Technology Studies, 2023). Larger nodes represent keywords that occur more frequently in association with other keywords. Density visualisations help to identify clusters of keywords that are tightly connected and often appear together (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023). In VOSviewer's density visualisation, both high and low density and colour gradients provide valuable insights into the relationships and interactions within a network (Centre for Science and Technology Studies, 2023; Ozturk & Ozen, 2020). In the context of geospatial technologies in archaeology and cultural heritage, high-density and dark colours represent established topics with solid connections within the field. In contrast, low-density, lighter colours represent less explored or less interconnected concepts with weaker links (Centre for Science and Technology Studies, 2023). Findings from these visualisations will focus on the specific clusters or thematic areas with high keyword co-occurrence that are closely related and frequently discussed within geospatial technologies in archaeology and cultural heritage. Further, the information gained guides further research directions, informs collaborations and helps identify gaps in literature.

Although VOSviewer makes it easier for researchers to identify research trends, key authors, and influential papers in their fields of interest, it requires external intervention to deal with synonyms in bibliometric data. Handling synonyms and similar terms in VOSviewer is crucial for creating meaningful visualisations and analyses. There are several ways of addressing this issue in VOSviewer to make visualisations more intuitive. These include preprocessing the data by either creating consistent terminology and manually cleaning the data to identify and merge synonyms, by creating a synonym list and manually linking the synonyms together in VOSviewer, or by creating thesaurus files and importing these files into VOSviewer or post-processing the results by grouping nodes or terms that represent the synonyms into a single category (Centre for Science and Technology Studies, 2023; Jan van Eck & Waltman, 2023).

2.2.2 Design/methodology/approach

2.2.2.1 Scopus Database Search

The bibliographic data of the journal articles published over the past thirty-three years (1990 to 2022) were extracted from Scopus (www.scopus.com). Figure 2-1 shows the workflow diagram for this study. The search queries in the English language using search strings where Boolean operators separate the synonyms “OR” and “AND” (Carrera-Rivera, Larrinaga, et al., 2022) are shown in Table 2-1 based on keywords from the geospatial technologies as essayed in the introduction. The search was limited to articles for reasons given in section 2.1; it is also limited to documents between the years 1990 and 2022 because the archaeological history of South Africa is intertwined with the history of apartheid, which came to an end in the early 1990s (Shepherd, 2019); therefore, most documents covering South Africa only feature in the late 20th century on the database. The search was split into two; one was limited to South Africa, and the other was global. This was done so that trends in geospatial technology development in South Africa could be compared with the rest of the world. The first round of Scopus database search results was exported to a comma-separated value (CSV) format file and opened in an Excel spreadsheet. Using conditional format command in Excel, duplicate document titles

and documents with unidentified authors were noted for exclusion in the Scopus bibliometric analysis and export files to VOSviewer. Figures 2-4 were generated using the inbuilt function of Scopus bibliometric analysis tools. Bibliographic data consisting of the author, year of publication, document title, source title, citation count, abstract, author keywords and indexed keywords were exported as CSV files for use in VOSviewer.

2.2.2.2 VOSviewer visualisation and analysis of bibliometric networks

The bibliographic data exported from Scopus data was imported into VOSviewer, and the type of analysis was set to co-occurrence with a total count of all keywords or terms related to the use and application of geospatial technology in archaeology and cultural heritage. The minimum number of occurrences of a keyword was set to 10 worldwide and was lowered to 5 for South Africa because of the relatively small database. The keywords on verification were set to exclude names of continents, countries, and the word “article” so that the obtained network, overlay and density visualisation could show only the relationships between the spatial technologies, applications, archaeology, and cultural heritage. However, after running VOSviewer with the bibliographic data from the Scopus database, we realised synonyms were an issue. We then created a thesaurus file in a text format, where synonyms for keywords or terms related to geospatial technology tools and applications were grouped. For instance, keywords related to the laser were grouped as laser technology, lidar as lidar technology, laser as laser technology and “3D modeling”, “3D modelling” etc., as three-dimensional modeling. The thesaurus was imported to VOSviewer to resolve the issue. The VOSviewer program network and density visualisation maps were generated where the size and proximity of keywords in the visualisation indicate their relationships. VOSviewer network files were saved as text files for bibliometric analysis in Excel spreadsheets, Tables 2 -(5-6).

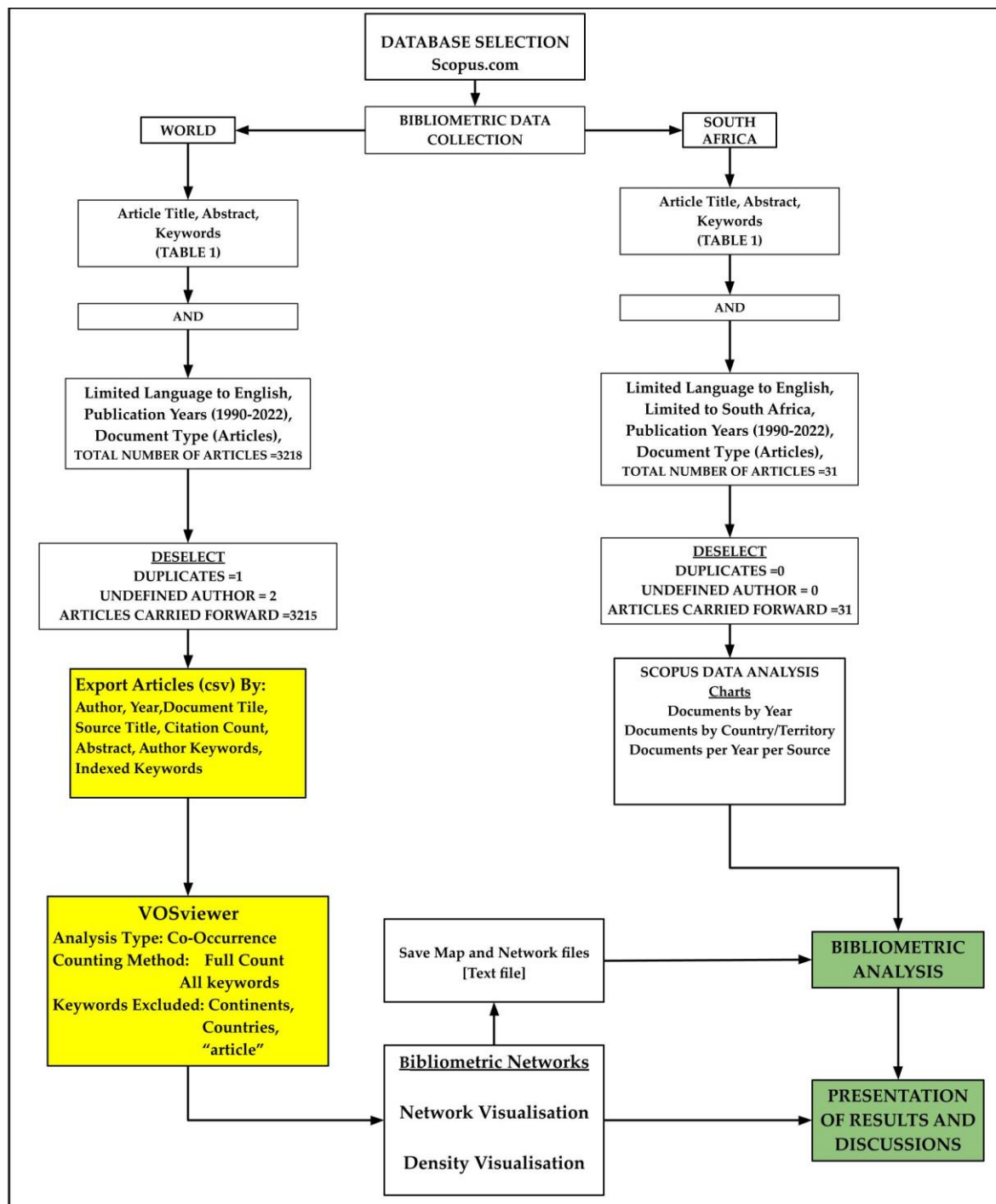


Figure 2- 1: Schematic workflow for Scopus Document Search and the Bibliometrics Using VOS Viewer and Scopus Analysis Tool.

2.3 Results and Discussion

2.3.1 Trend in worldwide documents published per year

This study has revealed that geospatial technology is an essential component of archaeological research, aiding in identifying, mapping, and analysing archaeological sites via articles containing keywords or terms associated with the technological tools from 1990 to 2022. Figure 2-2 and Table 2-2 are the worldwide Scopus bibliometric analysis results. Figure 2-2 shows the impetus for geospatial technologies use in archaeology and cultural heritage, as demonstrated by the growth of articles containing the keywords or terms from 7 in 1990 to 406 in 2022. As noted in the literature review, Figures 2-2 and Table 2-2 are testimony to the burgeoning number of archaeological investigations that employ geospatial technologies and are revolutionising the archaeological recording of proveniences of artefacts (Schneider & Panich, 2008). The worldwide rise in the use of geospatial technologies Figure 2-2 can be explained by rapid advancements in geospatial technology tools that are more accessible, affordable, and user-friendly, such as GIS, remote sensing, LiDAR, 3D scanning, and related software that have encouraged the integration of the tools in archaeological research and heritage management (Comer et al., 2013; Lock, 2000). Other reasons for the worldwide rise are that geospatial technologies offer efficient and accurate data collection methods that enable archaeologists to collect detailed spatial information about sites, artefacts, and landscapes (Lock, 2000). In addition, geospatial technologies offer enhanced visualisation, advanced spatial analysis, and data integration tools for a better understanding of spatial relationships, patterns and distributions that are very helpful to archaeologists and other researchers (Vereenooghe, 2006). Further, the growth is also explained by the ability of geospatial technology tools to assist in interdisciplinary collaboration, allow for digital documentation and preservation, assist in heritage management by providing data-driven insights into site conditions and potential threats, and offer educational opportunities for students and the public who would like to explore archaeological sites and artefacts virtually (Comer et al., 2013; Ellenberger, 2017).

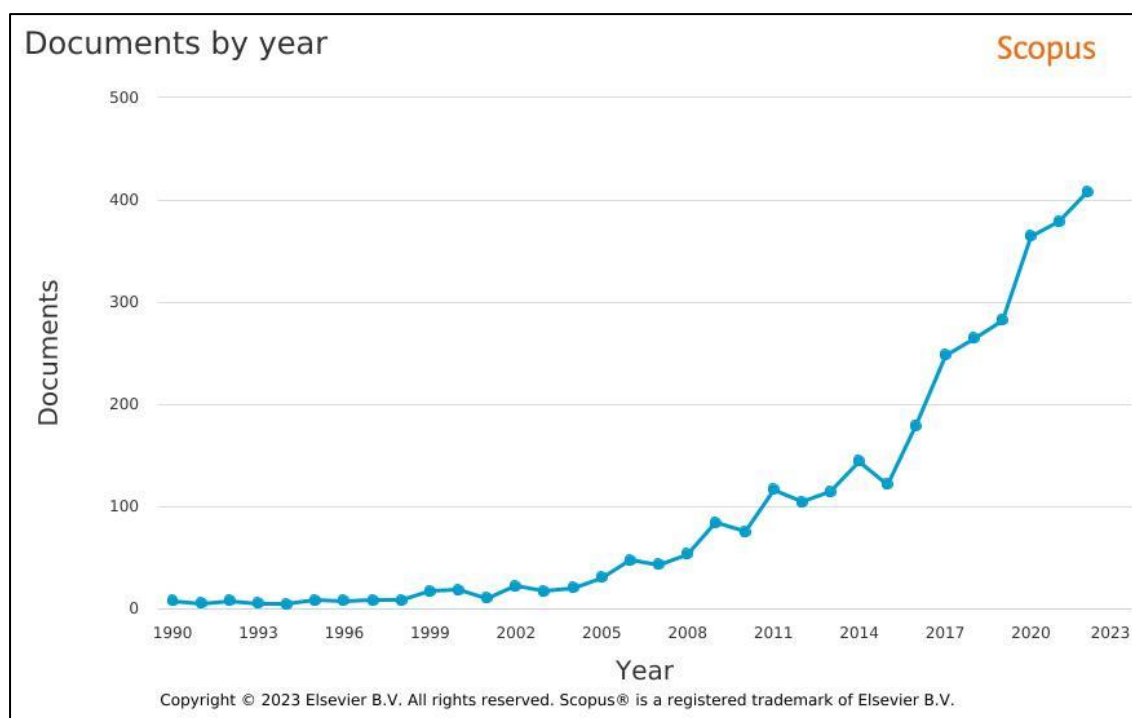


Figure 2- 2: World Articles per Year from Scopus Database from 1990 to 2022

Table 2- 2: Worldwide Articles per Year from Scopus Database from 1990 to 2022

YEAR	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
No. Articles	7	5	7	5	4	8	7	8	8	17	18	10	22
YEAR	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
No. Articles	17	20	30	47	43	53	84	75	116	104	114	144	121
YEAR	2016	2017	2018	2019	2020	2021	2022	Total					
No. Articles	179	248	264	282	364	378	406	3215					

2.3.2 Trend in South Africa documents published per year

Figure 2-3: and Table 2-3: depict the trend in the growth of archaeological investigations employing geospatial technologies. The worldwide rise in the use of geospatial technologies is not shown in South African space in Figure 2-3. Only 31 articles were found in the Scopus database from 1990 to 2022. There was a peak of 5 articles in 2019, which dropped to 3 in 2021; this could be explained by the same worldwide restrictions on outdoor archaeological investigations brought by the COVID-19 pandemic restrictions.

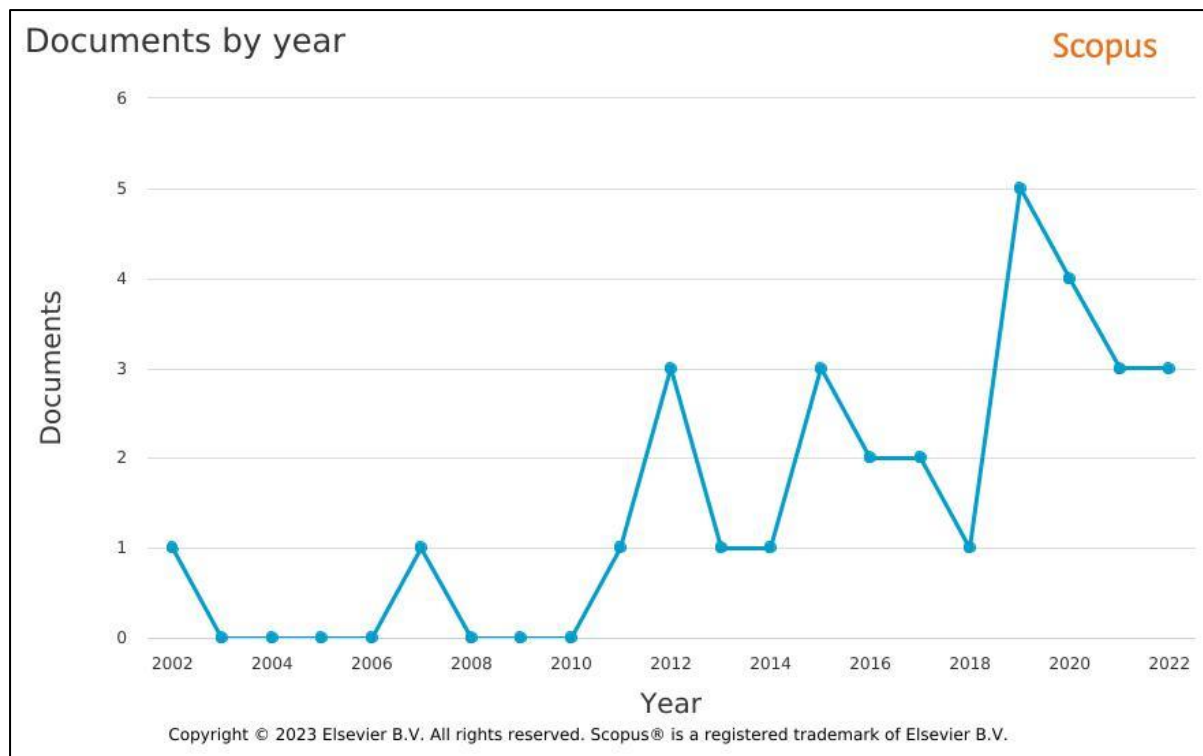


Figure 2- 3: South Africa Articles per Year from Scopus Database from 1990 to 2022

Table 2- 3: World Articles per Year from Scopus Database from 1990 to 2022

YEAR	1990	1991	1992	1993	1994	1995	1996	1997	1998	1999	2000	2001	2002
South Africa	0	0	0	0	0	0	0	0	0	0	0	0	1
YEAR	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
South Africa	0	0	0	0	1	0	0	0	1	3	1	1	3
YEAR	2016	2017	2018	2019	2020	2021	2022	Total					
South Africa	2	2	1	5	4	3	3	31					

The slow growth or limited adoption of geospatial technologies in archaeology and cultural heritage in South Africa could be influenced by a range of factors. Below are some potential reasons:

- **Lack of Awareness:** Many archaeology and cultural heritage practitioners might be unaware of geospatial technologies' potential benefits and applications (Earley-Spadoni, 2017; McCoy & Ladefoged, 2009). Awareness campaigns and educational initiatives are needed to showcase how these technologies can enhance research and preservation efforts.
- **Limited Training:** Geospatial technologies require specialised skills in GIS, remote sensing, photogrammetry, and LiDAR (Klehm, 2023b). If archaeologists and cultural heritage professionals lack access to training programs and workshops, they may hesitate to adopt these technologies.

- **Resource Constraints:** Acquiring the necessary hardware, software, and data for geospatial technologies can be costly (Klehm, 2023b; Klehm et al., 2019). Archaeological and cultural heritage projects often have limited budgets, making it difficult to invest in the technology and expertise required.
- **Data Accessibility:** The availability of accurate and high-quality spatial data is crucial for geospatial analysis (Klehm, 2023b). If relevant data is not easily accessible or is lacking, it can hinder the effective use of these technologies.
- **Integration Challenges:** Incorporating geospatial technologies into existing archaeological and cultural heritage workflows might require changes in methodologies and practices (McCoy & Ladefoged, 2009). This transition can be perceived as challenging and time-consuming.
- **Cultural Sensitivity:** In cultural heritage preservation, there can be concerns about using advanced technologies that may disturb or damage fragile artefacts or sites (De La Porte & Higgs, 2019). Overcoming these concerns requires careful planning and understanding of the technology's impact.
- **Regulatory Hurdles:** Archaeological and heritage sites often have legal protections and regulations to prevent damage or destruction (De La Porte & Higgs, 2019). Using geospatial technologies might require approvals, permits, or compliance with specific guidelines, which can slow down adoption.
- **Perceived Complexity:** Geospatial technologies can be perceived as complex, especially for professionals who do not have a background in technology or geography (McCoy & Ladefoged, 2009). This perception can deter individuals from attempting to integrate these tools.
- **Institutional Support:** Institutional support from archaeological and cultural heritage organisations and government bodies plays a crucial role. Adopting may be slower if there is a lack of encouragement or incentives for using geospatial technologies.
- **Collaboration Gaps:** Effective use of geospatial technologies often involves collaboration between archaeologists, cultural heritage experts, geographers, and technologists (Earley-Spadoni, 2017; Klehm, 2023b). Limited cross-disciplinary collaboration can hinder progress.
- **Educational Curriculum:** Including geospatial technologies in archaeological and cultural heritage educational curricula might be limited. Graduates entering the field might lack exposure to these tools.

To address these challenges, efforts should be made to provide training opportunities, raise awareness about the benefits, develop funding sources for technology adoption, promote cross-disciplinary collaboration, and advocate for policies that support integrating geospatial technologies into archaeological and cultural heritage work in South Africa.

2.3.3 Trends in worldwide published articles per journal results and discussion

According to the Scopus database, the results and discussion are based on the first top 5 journals. The assumption is that the trends established represent the general trend in publishing articles related to geospatial technologies, archaeology, and cultural heritage. Figure 2-4 depicts the trend in the publications of articles containing keywords or terms relating to archaeology and cultural heritage. Although the *Journal of Archaeological Science* has been the journal of choice and the dominant journal from 1996 to 2022, with a peak of 26 articles in 2011, it lost its dominance to *Remote Sensing Journal* Figure 2-4 and Table 2-4. The *Journal of Archaeological Science* is subscription-based and interdisciplinary, implying that articles must combine archaeological methods and scientific techniques. Therefore, manuscripts submitted must demonstrate a strong integration of both disciplines. The emergence of other journals with a singular field focus, like *Remote Sensing Journal*, with its first publication in 2010, Table 2-4, took over the dominance because authors' supposed preference could have shifted to journals with relaxed adherence to an interdisciplinary approach. Another reason for the supremacy of the *Remote Sensing Journal*, which started with 1 article in 2010 and rose to 36 articles in 2020, is attributed to the journal's niche focus, which is closely aligned with the intersection of new geospatial technologies, archaeology, and cultural heritage. In addition, the COVID epidemic, which restricted archaeological investigations to indoor activities, favoured remote sensing technologies worldwide. The pandemic contributed to the boom in the number of articles published in the *Remote Sensing Journal*; there was a peak of 36 articles in 2020 during the height of the COVID restrictions. The loss in the dominance of the subscription-based journal, the *Journal of Archaeological Science*, is also attributed to the emergence of open-access journals like the *Journal of Archaeological Science, Reports*, the *Journal of Cultural Heritage*, and the *Sustainability Switzerland*. These open-access journals offer freely accessible articles to readers and promote broader dissemination of research findings. With the worldwide boom in internet access, these journals have increased visibility, leading to more citations. Therefore, researchers and institutions from various economic backgrounds tend to favour them because they can access research without facing paywalls.

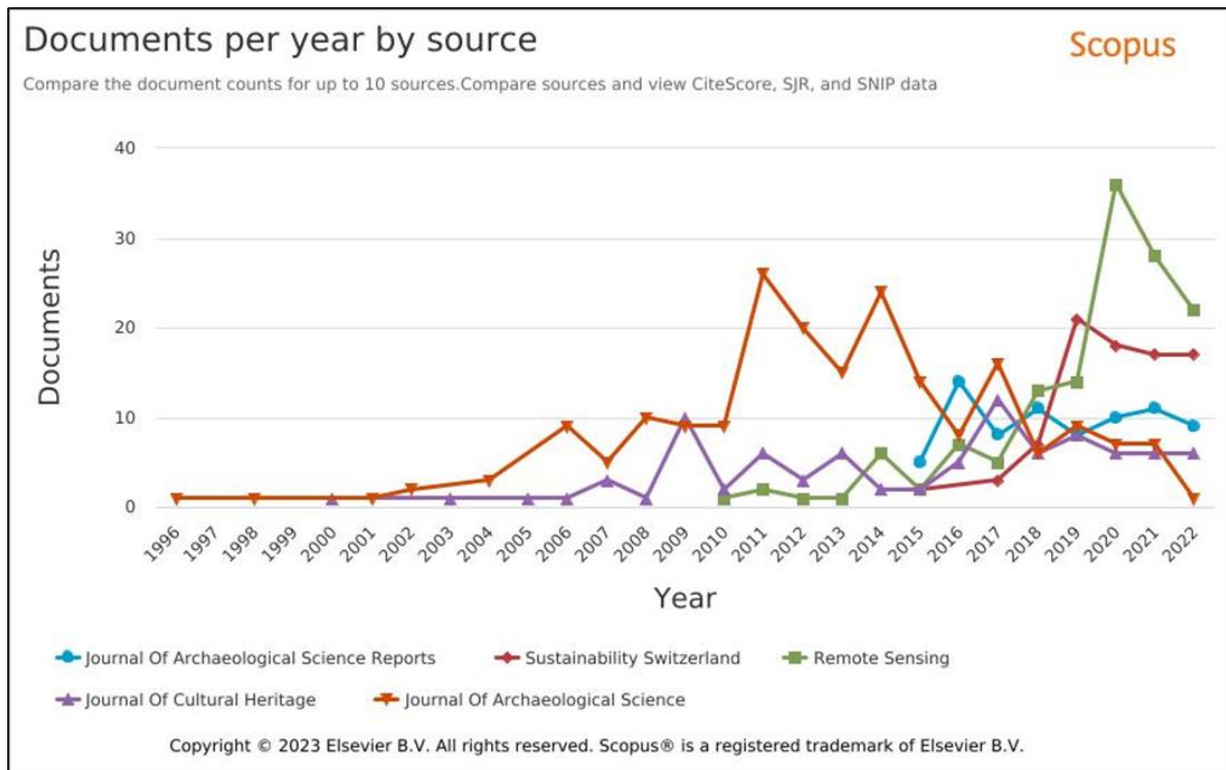


Figure 2- 4: World Articles per year per Source from Scopus Database from 1990 to 2022

Table 2- 4: Top 5 Worldwide articles per journal from Scopus Database from 1990 to 2022

YEAR	1996	1997	1998	1999	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
Journal Of Archaeological Science	1	0	1	0	0	1	2	0	3	0	6	5	10	10
Remote Sensing	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Journal of Cultural Heritage	0	0	0	0	1	0	0	1	0	1	1	3	1	10
Journal Of Archaeological Science Reports	0	0	0	0	0	0	0	0	0	0	0	0	0	0
Sustainability Switzerland	0	0	0	0	0	0	0	0	0	0	0	0	0	0
YEAR	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022	
Journal Of Archaeological Science	9	26	20	15	24	14	8	16	6	9	7	7	1	
Remote Sensing	1	2	1	1	6	2	7	5	13	14	36	28	22	
Journal of Cultural Heritage	2	6	3	6	2	2	5	12	6	8	6	6	6	
Journal Of Archaeological Science Reports	0	0	0	0	0	5	14	8	11	8	10	11	9	
Sustainability Switzerland	0	0	0	0	0	2	0	3	7	21	18	17	17	

South Africa has significantly low numbers in the top worldwide publications or journals with keywords or terms related to geospatial technology, archaeology, and cultural heritage, as shown in Figure 2-3, Table 2-3, and Table 2-5. From Table 2-5, it can be deduced that South African-based researchers and institutions favour subscription-based journals. Even though open-access journals offer a variety of advantages, such as broader accessibility, increased visibility, and reduced access barriers, they require Article Processing Charges (APCs). They can be prohibitive to researchers without funding. Some of them are predatory journals and are perceived by some researchers as of lower prestige and, therefore, shunned. Some well-established subscription-based journals, like the Journals of Archaeological Sciences and Remote Sensing Journal, are considered prestigious due to their long history and rigorous peer-review processes. They, therefore, become the first choice for some researchers in South Africa. In addition, authors are not required to pay for APCs to publish in subscription-based journals, which can benefit researchers without funding for publication fees.

Table 2- 5: Common Source Articles

Common Source Title		Articles	
	Access	World	South Africa
Journal of Archaeological Science	Subscription	203	3
Remote Sensing	Open	138	3
Quaternary International	Subscription	70	2
Plos One	Open	44	2
Journal of Field Archaeology	Subscription	40	2
American Antiquity	Subscription	18	1
Archaeological And Anthropological Sciences	Open	18	1
Proceedings of The National Academy of Sciences of The United States of America	Subscription	15	1
Journal of Cultural Heritage Management and Sustainable Development	Subscription	14	1
Journal of Human Evolution	Subscription	14	1
Science of The Total Environment	Subscription	10	1
Quaternary Science Reviews	Subscription	9	3
Forensic Science International	Subscription	8	1
Photogrammetric Engineering and Remote Sensing	Subscription	5	1
African Archaeological Review	Subscription	4	1

2.3.4 Density Visualisation and analysing bibliometric networks

Co-occurrence analysis in VOSviewer was used to visualise the keyword or term network used in geospatial technologies, archaeology, and cultural heritage co-occurrence networks. The aim was to explore the relationships between these keywords or terms in geospatial technology,

archaeology, and cultural heritage and to visualise thematic clusters. The size and proximity of keywords in the visualisation indicated their relationships. As discussed, VOSviewer uses a colour gradient to represent different density levels. In the Viridis colour scale, Figures 2-5 and 2-6, the pale colours indicate low density and the intense colour (yellow) indicates high density. In Figure 2-5, the high-density clusters are archaeology, cultural heritage, geographic information system and remote sensing; these keywords and themes are closely related and frequently discussed. In addition, these high-density clusters represent contemporary, traditional disciplines that have established interdisciplinary connections and collaborations. Areas with relatively lower density (light yellow), Figure 2-5, such as virtual and augmented reality, three-dimensional modelling and spatial analysis, represent geospatial technology tools and themes already and still being explored. While lower density areas such as radar technology, lidar technology, laser technology, artificial intelligence, visual analysis, and others in Figure 2-5 represent geospatial technology tools and research themes that are less explored or less interconnected concepts that have potential gaps in research or underexplored topics that might be worth investigating in archaeology and cultural heritage. For South Africa, density visualisation, Figure 2-6, shows three geospatial technology tools: geographic information systems, spatial analysis, and remote sensing, and one application, archaeology. However, the absence of the density visualisation of various geospatial technologies and applications, as presented in Figure 2-5, suggests gaps in research and underexplored topics worth investigating in South Africa. Density visualisation, when used to analyse the trend in the use of geospatial technologies in archaeology and cultural heritage, serves the purpose of highlighting and understanding the evolving thematic clusters and research focus over time. In both Worldwide and South Africa-based density visualisation, this review analysed a static period from 1990 to 2022, and the results could be more comprehensive regarding tracking changes over time and visualising research evolution; however, these would require density visualisation at different periods. Finally, it should be noted that as trends and research priorities evolve, other clusters may gain or lose prominence.

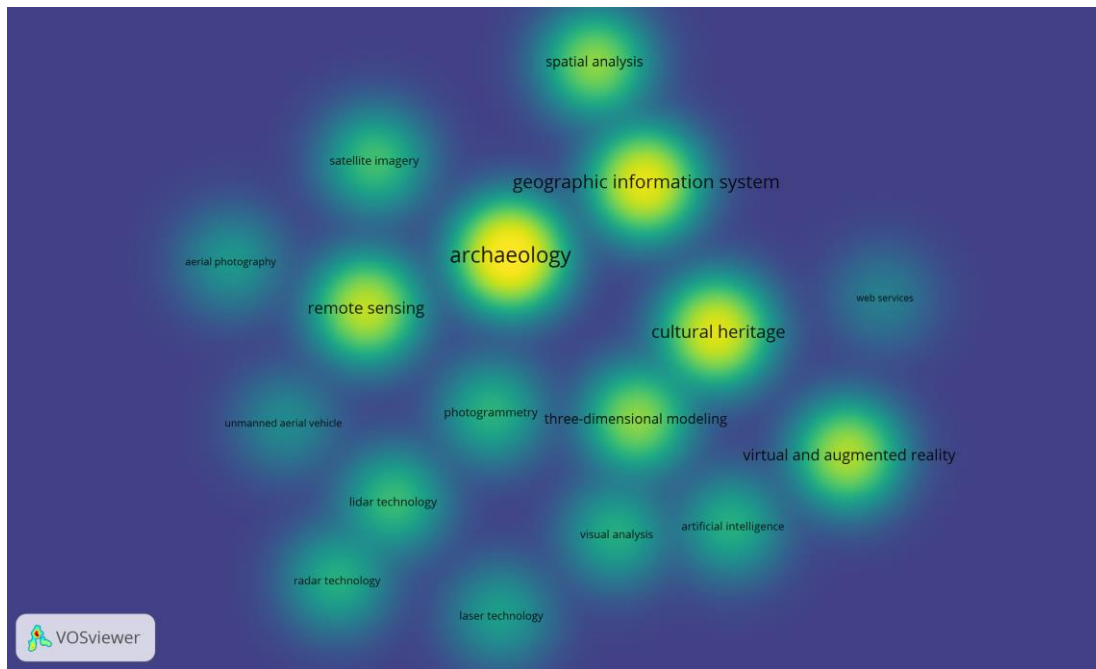


Figure 2- 5: Worldwide Density Visualisation-Scopus database 1990 to 2022

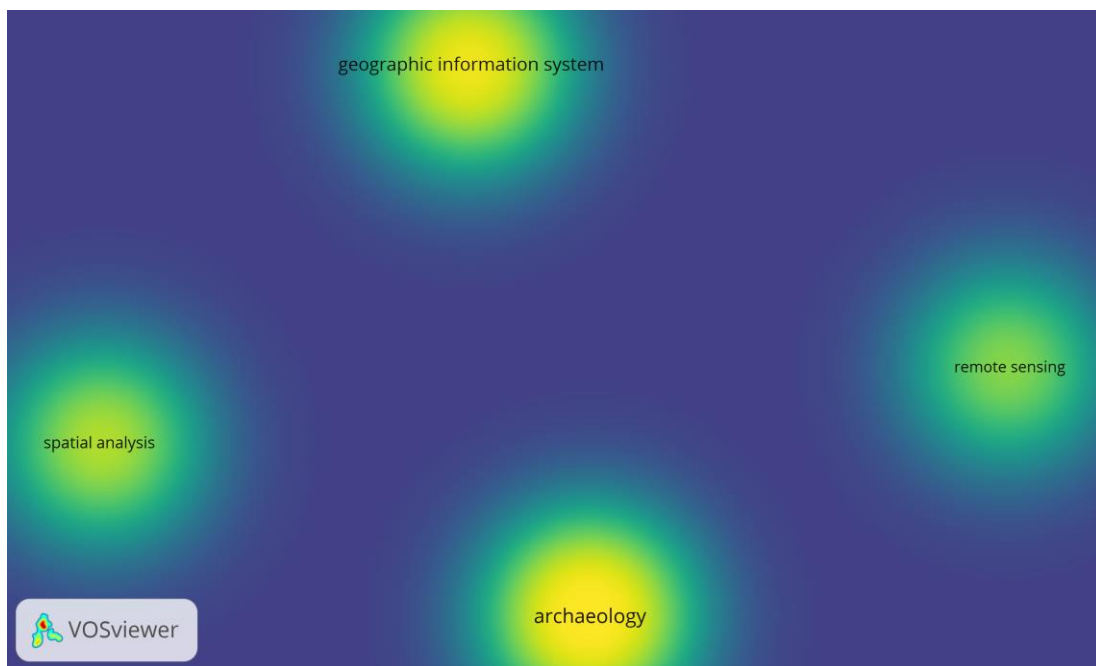


Figure 2- 6: South Africa Density Visualisation-Scopus database 1990 to 2022

2.3.5 Network Visualisation and analysing bibliometric networks

Figures 2 (7–10) and Table 2-6 show the network visualisation maps and the obtained map structural information related to the geospatial technology tools for the keywords or terms used Worldwide and South Africa related to geospatial technologies and cultural heritage in the literature review. In this review, three clusters (related keywords, which represent thematic areas or topics within geospatial technologies in archaeology and cultural heritage) were identified. Cluster 1 with 8 items (red), cluster 2 with 6 items (green) and cluster 3 with 3 items (blue), as shown in Figure 2-7. The key concepts that shape research in the use of geospatial

technologies in archaeology and cultural heritage, according to the Scopus database 1990–2020, are shown as central hubs (large nodes) and network weighted strengths within the network. These significant hubs represent the focus or theme or distinct knowledge domains within the World Wide Web are shown in Figure 2-7 as cultural heritage (green), archaeology (blue), geographic information systems (blue), remote sensing (red), virtual and augmented reality (green), and spatial analysis (blue). As discussed in the preview, the link length between two nodes represents the strength or degree of co-occurrence between the corresponding keywords. Shorter links indicate stronger relationships, while longer links suggest weaker connections. From Figure 2-7, the central themes of research that use geospatial tools are archaeology, cultural heritage and spatial analysis. The prominent geospatial tools are remote sensing, geographic information systems and virtual and augmented reality.

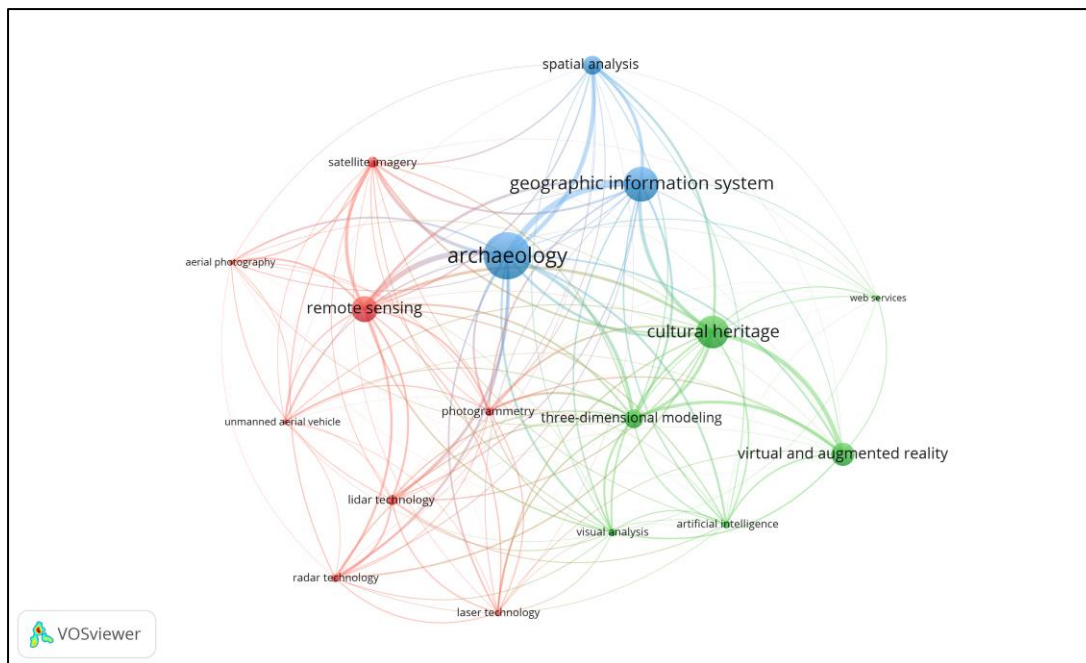


Figure 2- 7: Worldwide Network Visualisation—Scopus database 1990 to 2022, cluster 1 = red, cluster 2 = green, cluster 3 = blue

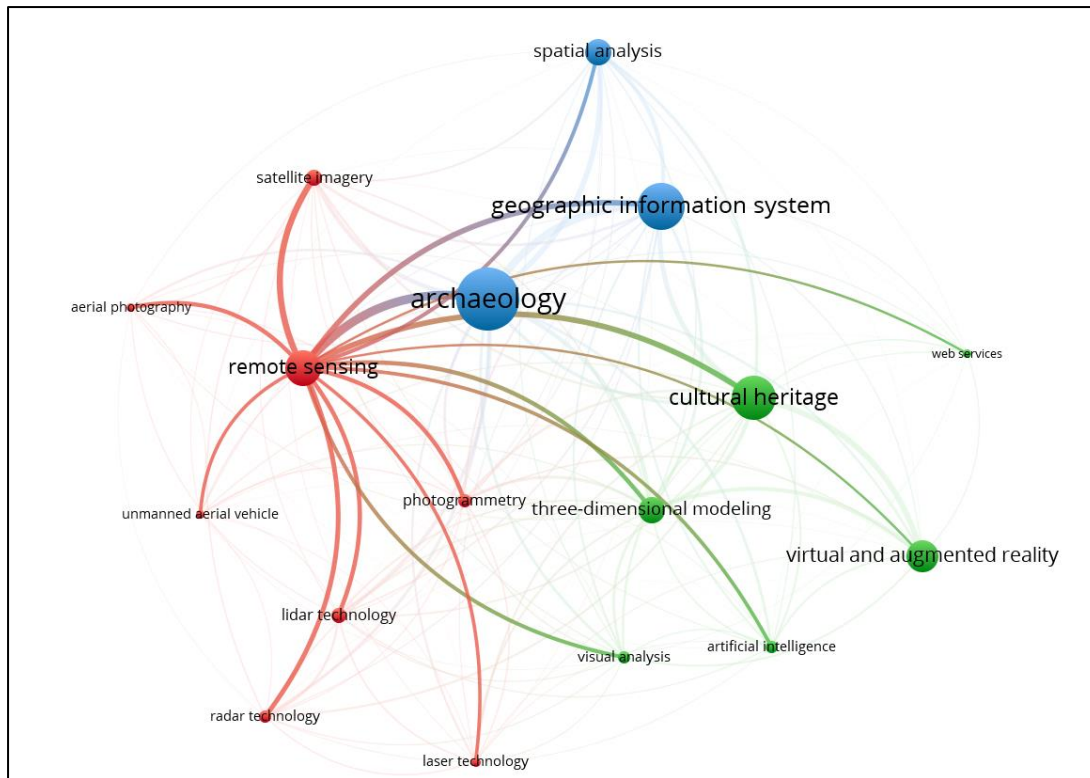


Figure 2- 8: Worldwide remote sensing and associated technologies 1990 to 2022, cluster 1 = red, cluster 2 = green, cluster 3 = blue

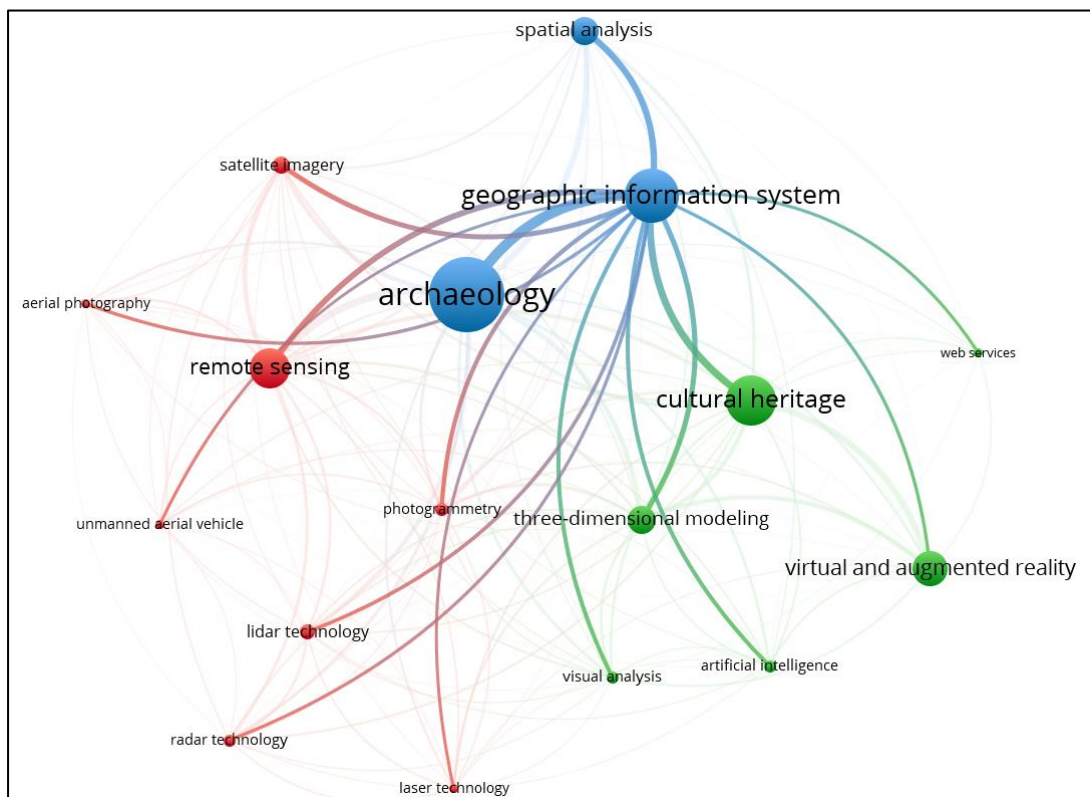


Figure 2- 9: Worldwide geographic information systems and associated technologies 1990 to 2022, cluster 1 = red, cluster 2 = green, cluster 3 = blue.

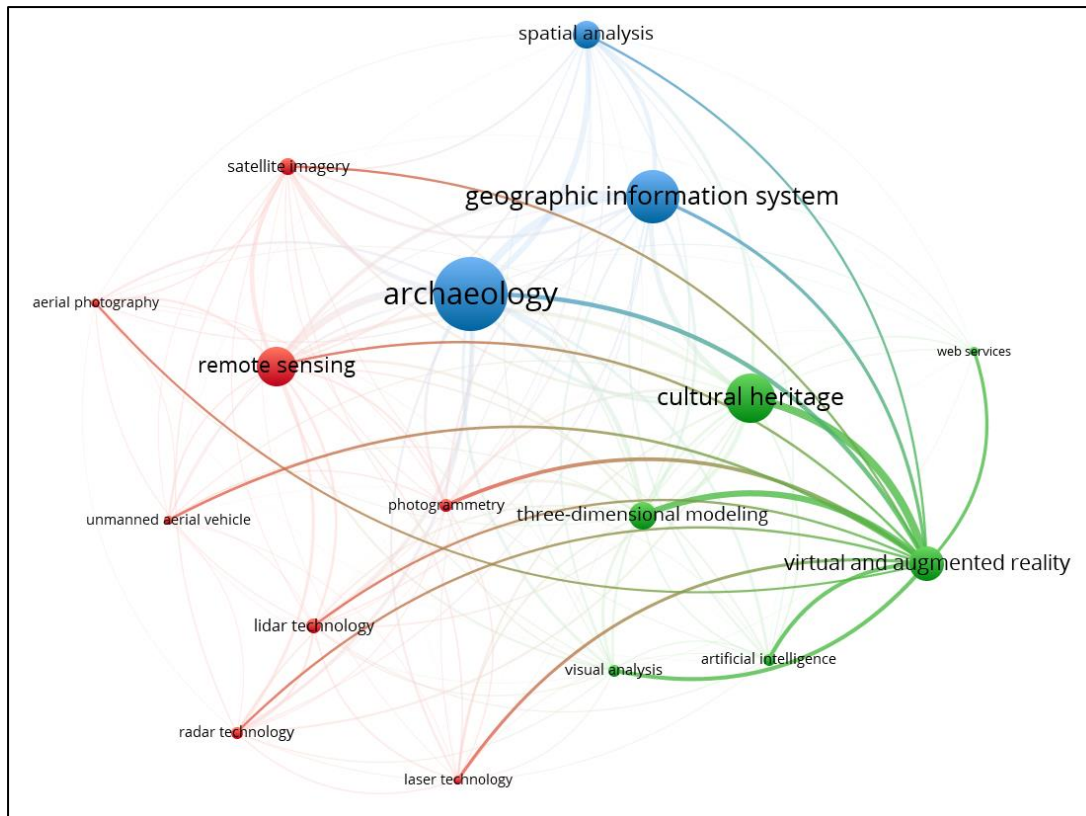


Figure 2- 10: Worldwide Virtual Reality and associated technologies 1990 to 2022, cluster 1 = red, cluster 2 = green, cluster 3 = blue

Table 2- 6: Worldwide network visualisation map structural information

Archaeology	3	16	2324	1248
Geographic Information System	3	16	1450	889
Cultural heritage	2	16	1438	833
Remote Sensing	1	16	1397	649
Three-Dimensional Modeling	2	16	1120	460
Spatial Analysis	3	16	763	458
Satellite Imagery	1	16	744	261
Virtual and Augmented Reality	2	16	710	576
Photogrammetry	1	16	588	197
Visual Analysis	2	16	555	175
Lidar Technology	1	16	544	238
Radar Technology	1	16	501	182
Artificial Intelligence	2	16	432	183
Laser Technology	1	16	361	126
Aerial Photography	1	15	288	105
Unmanned Aerial Vehicle	1	15	237	75
Web Services	2	14	130	50

Table 2-6 shows the top 20 keywords or terms ranked in order of the weighted total link strength; it can be deduced that the geospatial technology tools highlighted in red are leading

research in archaeology and cultural heritage and follow that ranking according to the searched Scopus database from 1990 to 2022.

Remote sensing technologies Figure 2-8, prominent tools (large dots) in the review period are lidar, satellite imagery and optical radar. Examples from the Scopus database are *Modern flint mining landscapes and flint knapping evidence from the Kraków Gunflint Production Centre—What we know from LiDAR and field survey* (Szubski et al., 2022), *Airborne LiDAR-derived digital elevation model for archaeology* (Štular et al., 2021), *Documentation of archaeology-specific workflow for airborne LiDAR data processing* (Lozić & Štular, 2021), *New developments in the use of spatial technology in archaeology* (McCoy & Ladefoged, 2009) and several others. These are identified as the significant contributors of information in remote sensing that help identify and document archaeological features (archaeology is the closest application to remote sensing Figure 2-8 that are not easily visible from the ground. Cultural heritage and spatial analysis tend to be distant from remote sensing in Figure 2-8, implying these terms are infrequently used with remote sensing and, therefore, potential research areas to be pursued using the technology tool. In addition, in remote sensing cluster two, Figure 2-8, geospatial technologies such as radar technology, aerial photography, and unmanned aerial vehicle (UAV) represented by the small dots and low-weighted total link strengths present gaps or unexplored research areas in remote sensing and novel application in archaeology and cultural heritage.

Geographic Information Systems (GIS) are software that allows archaeologists to capture, store, manipulate, analyse, and visualise geospatial data, including maps, satellite imagery, and various layers of archaeological information. In Figure 2-9, the major application areas of the software are archaeology, cultural heritage, and spatial analysis. Examples from the Scopus database are *A GIS-based Methodology to Explore and Manage the Historical Heritage of Rabat City (Morocco)* (Simou et al., 2022), *a GIS-based precise predictive model of mountain beacon sites in Wenzhou, China* (Tan et al., 2022), *ACTA IMEKO Photogrammetry and GIS to investigate modern landscape change in an early Roman colonial territory in Molise (Italy)* (Peters & Stek, 2022) and several others. Remote sensing is the prominent tool that is used to gather information for use by GIS applications. According to Figure 2-9, applications of GIS software in conjunction with spatial analysis, lidar technology, visual analysis, artificial intelligence, laser technology, three-dimensional modelling, etc. (small dots) represent gaps and potential research areas.

Virtual and Augmented Reality applications are technologies that enable the visualisation and exploration of archaeological sites and reconstructions in immersive and interactive ways. Figure 2-10 shows these as the significant geospatial tools used in cultural heritage; they also provide information to GIS and archaeology in the review period 1990 to 2022. Notable examples from the Scopus database are *Digital Creativity and the Regional Museum: Experimental Collaboration at the Convergence of Immersive Media and Exhibition Design* (Beale et al., 2022), *3D Documentation and Visualisation of Cultural Heritage Buildings through the Application of Geospatial Technologies* (Stylianidis et al., 2022), *Developing Augmented Reality Lontar Prasi Bali as an E-learning Material to Preserve Balinese Culture* (Sudipa et al., 2022), *Accurate 3D models in both geometry and texture: An archaeological*

application (Polo et al., 2022) and several others. Web services, visual analysis, artificial intelligence, photogrammetry, etc., Figure 2-10 (small dots) need to be explored and present gaps for research in cultural heritage studies.

2.4. Findings

From the systematic review of literature containing keywords or terms related to geospatial technologies used in archaeology and cultural heritage, this review reinforces what is already essayed in some non-systematics reviews about geospatial technology tools. These tools are an essential component of archaeological research.

- Geospatial technology aids in identifying, mapping, and analysing archaeological and cultural heritage sites.
- Geographic Information System, Figure 2-9, is the prominent software that allows archaeologists to capture, store, manipulate, analyse, and visualise geospatial data, including maps, satellite imagery, and various layers of archaeological information. Growth in GIS could also be attributed to the proliferation of open-source GIS software and the development of machine learning algorithms. Web mapping services will impact the future growth of geospatial applications in archaeology
- These tools provide specialised spatial analysis functions that help archaeologists understand patterns, relationships, and trends in archaeological data. The dot size in Figure 2-9 shows that they are relatively less explored concepts in archaeology and cultural heritage and present gaps worth investigating.
- Spatiotemporal analysis and spatial modelling tools are subsets of spatial analysis tools, Figure 2-9. These are often synchronised or integrated with GIS; this review shows that they are less explored or less interconnected with concepts in archaeological and cultural heritage studies and, therefore, present potential research gaps that might be worth investigating.
- Spatial Databases (data set), Figure 2-9, are databases designed for storing and managing geospatial information. The dot size in Figure 2-9 shows that they are relatively less explored concepts in archaeology and cultural heritage and present gaps worth investigating. Innovation in data structures and data architecture for extensive data handling and storage will impact the future growth of applications in archaeology.
- Remote sensing technologies, Figure 2-8, are primary geospatial technology tools in archaeology and cultural heritage for identifying and documenting archaeological features that are not easily visible from the ground. However, in this review period, tools such as aerial photography, optical radar, and unmanned aerial vehicle (UAV) show that they are relatively less explored tools in remote sensing technologies for archaeology and cultural heritage and present gaps worth investigating. Lidar and satellite imagery are already well-explored tools in remote sensing applications; however, they are distant from archaeology and cultural heritage as stand-alone tools Figure 2-7, and, therefore, present opportunities for novel applications. Open, free, and accessible data from earth observation missions such as Landsat and Sentinel satellite series may be driving the growth in remote sensing. Cloud computing platforms such as Google Earth Engine and Digital Earth Africa will likely drive future growth.

- Virtual Reality and Augmented Reality applications, Figure 2-10, are emerging and prominent technologies in cultural heritages; they enable the visualisation and exploitation of archaeological sites and reconstructions in immersive and interactive ways. Associated tools or concepts such as 3D modelling, 3D computer graphics, 3D reconstruction, photogrammetry and artificial intelligence are less explored and present potential research gaps worth investigating in archaeology and cultural heritage.
- Geographic information systems and spatial analysis are the primary geospatial technology tools used in South Africa for archaeological and cultural heritage investigations in the review period.

If national funds permit, all the research growth areas established in this review are worth investigating.

2.5 Conclusions

This study aimed to reveal the trends in the use of geospatial technologies in archaeological investigations via the search engine Scopus that support the literature review on advancement in the application of geospatial technology in archaeology in South Africa. Overall, there has been growth in digital technologies since the beginning of the twenty-first century that supports spatial archaeology. The search for keywords associated with geospatial technologies on the Scopus database reveals how modern archaeological studies are now a significant discipline of spatial sciences and how the discipline enjoys the tools of geomatics engineering for establishing temporal and spatial controls on the material being studied and observing patterns in the archaeological records. While total stations and GNSS technologies revolutionised the practice of archaeological investigations, as seen by the florescence of application areas that, in one way or another, support the goals and objectives of the archaeology discipline, they cannot match remote sensing technologies. This study exposed the new synthesis in archaeological studies, which has a new paradigm that uses geospatial technologies. However, South Africa needs to catch up, as judged by the number of published documents on the Scopus database, despite having many sites that house archaeological phenomena features, such as the Cradle of Humankind. As alluded to by different reviews on geospatial technologies, the most comprehensible reason for the limited uptake of these advanced technologies is the low-budget research projects that cannot afford the high-end technologies. However, recent advancements in new technologies and methods in archaeological prospecting have seen the deployment of portable, low-cost geospatial technologies with high-quality results that are reliable, detailed, accurate and precise, which might introduce changes in the statistics of studies that employ geospatial technologies. One assumption might be that South Africa still has conservative archaeologists who feel geospatial technologies are intrusive in archaeological methodologies and might introduce bias in archaeology. If it is true, then positive discussions in the discipline should shift to the theoretical understanding of spatial technologies or functionalist approaches in archaeology. In addition, interdisciplinary collaboration should be encouraged between archaeologists and technologies specialists

Chapter 3 ADVANCES IN VEGETATION MAPPING THROUGH REMOTE SENSING AND MACHINE LEARNING TECHNIQUES: A SCIENTOMETRIC REVIEW

This Chapter is based on the following manuscript

Matyukira, C., & Mhangara, P. (2024). Advances in vegetation mapping through remote sensing and machine learning techniques: A scientometric review. *European Journal of Remote Sensing* (In review).

Abstract- This study investigates the rapid growth and rising interest in remote sensing technologies for vegetation mapping, emphasising the integration of advanced machine learning techniques. An analysis of publication trends from Scopus reveals significant growth in this field, particularly from 2019 to 2023, reflecting technological advancements and increased accessibility. Integrating remote sensing with machine learning algorithms such as Random Forest, Support Vector Machines, neural networks, and XGBRFCClassifier has substantially improved the ability to monitor, analyse, and understand vegetation dynamics across various scales. This growth underscores the critical importance of continued research to address global environmental challenges, such as climate change and environmental degradation, by providing timely data for conservation and management strategies. China leads in research publications, followed closely by the United States and India, highlighting remote sensing research's global significance and collaborative nature. Major journals like "Remote Sensing" and conferences such as IGARSS play crucial roles in disseminating research findings. The study also shows that most publications are research articles, underscoring the field's reliance on original research and empirical data. The multidisciplinary nature of this field is evident, with significant contributions from Earth and Planetary Sciences, Agricultural and Biological Sciences, Environmental Science, and Computer Science. Visualisations using VOSviewer illustrate interconnected research themes, emphasising the importance of topics such as land use, climate change, evapotranspiration, and aboveground biomass. These visualisations highlight the necessity of advanced machine learning algorithms to enhance remote sensing methods for effective vegetation monitoring. The findings underscore the urgent need for continued research and international collaboration to develop innovative solutions for environmental sustainability.

Keywords- vegetation mapping, remote sensing, machine learning, climate change, environmental monitoring

Highlights

- Remote sensing and vegetation mapping research has grown, notably using Random Forest, Support Vector Machines, neural networks, and XGBRFCClassifier.
- Chinese researchers publish the most, followed by the USA and India, suggesting worldwide interest and investment in remote sensing and vegetation mapping.
- More research papers are published in key journals like "Remote Sensing" and "Remote Sensing of Environment" and at significant conferences like IGARSS.
- Vegetation mapping, remote sensing, and machine learning are strongly linked in the VOSviewer network and density visualisations

3.1 Introduction

The capacity of remote sensing technologies to create detailed vegetation maps has made them vital for environmental management and monitoring. These technologies enable the assessment of vegetation covering, condition, and temporal changes, offering crucial insights into the dynamics of ecosystems. Advanced sensors, satellite platforms, and unmanned aerial vehicles (UAVs) have recently improved the precision and breadth of environmental data gathering. These advancements make it easier to monitor and evaluate a wide range of environmental

data, and they also allow for multiscale studies (Cui et al., 2023; Marques et al., 2024; Szpakowski & Jensen, 2019; Timilsina et al., 2020; Vidican et al., 2023). Remote sensing facilitates efficient decision-making in conservation, land use planning, and resource management by offering continuous observation and thorough analysis (Rocchini, 2014; Szpakowski & Jensen, 2019). Advances in satellite imaging technology, such as the increased spectral and geographic resolution of sensors like Landsat, Sentinel, and MODIS, have significantly enhanced the precision and reliability of vegetation maps (Hansen et al., 2013; Morell-Monzó et al., 2020; Pastick et al., 2018, 2020).

Machine learning in the field of vegetation mapping has made significant advancements, greatly enhancing the accuracy, efficiency, and detail of vegetation classification and monitoring. Integrating advanced machine learning algorithms with remote sensing data has further improved the accuracy and depth of vegetation analysis. Algorithms such as Random Forest (RF), Support Vector Machines (SVM), neural networks, and gradient boosting classifiers have facilitated the accurate grouping of different vegetation types and the detection of changes over time (Jozdani et al. 2019). These algorithms can process large volumes of multi-source data, including spectral, spatial, and temporal information, to differentiate between vegetation types, assess health conditions, and monitor changes over time. Deep learning, particularly through Convolutional Neural Networks (CNNs), has enabled sophisticated image analysis, such as the automated extraction of vegetation features and high-resolution mapping of plant communities (Corbane et al., 2021; Maxwell et al., 2021; Timilsina et al., 2020). Integration with advanced sensors and cloud-based platforms like Google Earth Engine allows for large-scale, real-time analysis, making machine learning an indispensable tool in biodiversity conservation, land management, and ecological research (Google Earth Engine Team, 2024b).

However, machine learning in the domain of vegetation mapping faces several challenges. One of the primary issues is the need for high-quality labelled training data. Accurate vegetation mapping often requires large, well-labelled datasets, which are time-consuming and costly to collect, particularly for diverse or remote regions (Kaiser et al., 2017; Liang et al., 2020; Stanimirova et al., 2023). Additionally, model performance can be hindered by the quality and resolution of remote sensing data. Factors such as cloud cover, atmospheric conditions, and sensor limitations can affect data quality, leading to potential inaccuracies in vegetation classification. Spectral and spatial resolutions are also critical; lower spectral resolution can limit the differentiation of vegetation types, while lower spatial resolution can obscure fine-scale patterns in heterogeneous landscapes (Di & Yu, 2023a; Dou et al., 2024; Lin et al., 2022; Wilson & Jetz, 2016). Sensors like Landsat, Sentinel, and MODIS offer varying levels of spectral and spatial resolution, which may not always meet the requirements for detailed vegetation analysis. Recent advances, such as hyperspectral imaging and the use of finer spatial resolution sensors like WorldView-3 and PlanetScope, have begun to address these limitations by providing richer spectral information and finer spatial details (Liu et al., 2020; Satellite Imaging Corporation, 2024; Whig et al., 2024; Xie et al., 2008b). These advances allow machine learning models to capture more subtle differences in vegetation characteristics, improving classification accuracy and the detection of small-scale changes. However, integrating such high-resolution data still poses challenges in terms of data processing and

storage, requiring further advancements in computational methods (Ayhan et al., 2020; Lu et al., 2022).

Furthermore, despite the effectiveness of machine learning models, they often function as "black boxes," making it difficult to interpret their decisions and understand the ecological processes they detect. This lack of interpretability can be a barrier to their acceptance in ecological research and management practices (Shams et al., 2024; Welchowski et al., 2022). Additionally, the generalisation of models across different regions and conditions is another challenge, as models trained in one area may not perform well in other regions with different vegetation types, climate conditions, or spectral characteristics. This necessitates ongoing model tuning and adaptation to ensure accuracy across diverse landscapes (Ayhan et al., 2020; B. M. Turner et al., 2019; J. Yang et al., 2022). Despite these challenges, the advancements in machine learning, combined with evolving remote sensing technologies, continue to push the boundaries of vegetation mapping, offering increasingly precise and scalable tools for ecological analysis.

The aim of this research is twofold: first, to conduct a comprehensive literature review exploring the applications of remote sensing in monitoring vegetation growth patterns, detecting land cover changes, assessing land degradation and fragmentation, evaluating the impact of topography on vegetation health, and estimating biomass and evapotranspiration. This research seeks to contribute to the field by highlighting the advancements in combining remote sensing technologies with machine learning algorithms, which offer significant improvements in the accuracy, depth, and scale of vegetation analysis. These methods can better track environmental changes, support biodiversity conservation, and enhance land management practices (Bauer et al., 2024; Matyukira & Mhangara, 2023b; Mullissa et al., 2024; Pettorelli et al., 2005). Additionally, this paper aims to offer insights into the evolving techniques that allow more precise assessment of ecosystem health and changes in vegetation over time, thereby contributing to the body of knowledge essential for sustainable environmental monitoring and management. By systematically reviewing the literature, this research identifies critical themes and advancements that highlight the growing potential of remote sensing and machine learning in tackling environmental challenges.

3.2 Approaches to Vegetation Mapping and Analysis Using Remote Sensing Technologies

3.2.1 Advancements in Machine Learning Algorithms for Vegetation Classification

Remote sensing and machine learning have evolved significantly over the past few decades, each contributing to vegetation mapping and classification advancements. The use of remote sensing to map vegetation began in the 1960s with the advent of aerial photography and early satellite imaging, marking the start of widespread remote sensing applications. During this initial phase, these technologies facilitated the visual evaluation of vegetation patterns across vast territories, initiating the first phase of remote sensing applications in environmental

monitoring (NASA Earth Observatory, 2023; U.S. Geological Survey, 2023b). The launch of the Landsat program in 1972 was a pivotal event, producing the first multi-spectral satellite images capable of efficiently studying vegetation. Early studies utilised these images to classify various types of vegetation and monitor changes in land cover (Cohen & Goward, 2004; Tucker, 1979a) demonstrating the potential of satellite imagery for comprehensive environmental monitoring.

In parallel, the field of machine learning began to take shape. In the mid-20th century, early machine learning efforts focused on pattern recognition and statistical learning, laying the groundwork for more sophisticated algorithms. The development of decision trees, neural networks, and support vector machines (SVM) in the 1980s and 1990s marked significant milestones (Breiman, 2001; Cortes & Vapnik, 1995). These advancements allowed for better handling of complex datasets and improved predictive accuracy. As machine learning techniques became more advanced, they began to be applied to remote sensing data, enhancing vegetation classification accuracy (Chaves et al., 2020; Maxwell et al., 2018). The technical advancements in digital image processing throughout the 1990s significantly improved the analysis of data obtained from remote sensing. The precision of vegetation maps increased due to the development of algorithms for image classification, such as the Maximum Likelihood Classifier (MLC), providing environmental scientists with more accurate tools. Additionally, the development of vegetation indices, such as the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI), enabled quantitative analysis of vegetation health and productivity (Arifeen et al., 2021; Lillesand et al., 2004; M. T. Rahman et al., 2017; Rani et al., 2023). These indices became widespread for analysing environmental impacts and monitoring vegetation growth and are directly related to machine learning as they serve as key input features for various models. By incorporating vegetation indices into machine learning algorithms like decision trees, neural networks, and SVM, researchers can enhance the accuracy and efficiency of vegetation classification and monitoring tasks. Machine learning models leverage these indices to identify patterns, distinguish between different vegetation types, assess vegetation health, and predict changes over time (Pan et al., 2023; Turhal, 2022; Xie et al., 2019). Furthermore, the availability of higher-resolution satellite images from sensors like SPOT and the continuous enhancements of Landsat sensors significantly improved spatial resolution and spectral capabilities, facilitating more detailed and accurate vegetation analysis (Hansen et al., 2013; Morell-Monzó et al., 2020; Qarallah et al., 2023; Radoux et al., 2016; Townshend et al., 2000; U.S. Geological Survey, 2023b).

Since its first use, vegetation mapping has advanced significantly with the integration of remote sensing data into Geographic Information Systems (GIS) in the 2000s. This combination allowed for comprehensive geographical analysis, enabling the mapping of vegetation patterns in relation to other environmental factors such as topography, soil types, and climate (Brown et al., 2016; Foody, 2002; Lv et al., 2019). GIS technology facilitated the management and analysis of large datasets, enhancing the ability to monitor changes in land cover and assess their impacts on ecosystems (Arifeen et al., 2021; Brown et al., 2016; Foody, 2002; Rouse et al., 1974). Platforms like Google Earth Engine further revolutionised the field with cloud-based

processing capabilities and access to a vast library of satellite images, making large-scale environmental assessments more accessible and efficient (Gorelick et al., 2017).

In recent years, the integration of machine learning techniques with remote sensing data has become increasingly important to tackle the complexities and scale of environmental data. Advanced algorithms, particularly deep learning and neural networks, have greatly enhanced image classification tasks. Convolutional Neural Networks (CNNs) have demonstrated superior performance by automatically learning hierarchical features from raw satellite imagery, significantly improving the accuracy and comprehensiveness of vegetation mapping (Ma et al., 2019; Zhu et al., 2017). Additionally, machine learning algorithms such as Random Forest (RF) and Support Vector Machine (SVM) have been widely used for classification tasks. RF employs an ensemble of decision trees to manage high-dimensional data and identify key features, aiding in differentiating vegetation types based on their spectral signatures while minimising overfitting (Berhane et al., 2018; Dobrinić et al., 2021; Q. Wang et al., 2018). SVM, on the other hand, finds an optimal hyperplane in a high-dimensional space to classify vegetation using spectral and spatial features, making it particularly useful in scenarios with limited training data (Fu et al., 2017; Hasan et al., 2019; Xie et al., 2019). Unsupervised learning methods like K-means clustering also play a valuable role in grouping similar spectral signatures, helping to identify various vegetation zones without labelled training samples (Cohn & Holm, 2021; Tavallali et al., 2021).

The integration of remote sensing with machine learning is thus crucial for facilitating more precise, detailed, and scalable ecological research. For example, a study by (Kluczek et al., 2024) demonstrates this integration by combining multitemporal optical and radar satellite data to enhance vegetation mapping accuracy, account for seasonal variability, and provide a robust methodology for biodiversity conservation, land management, and ecological monitoring in mountainous regions. Similarly, (Bartold & Kluczek, 2024) show that augmenting deep neural networks with metadata significantly improves wild animal classification accuracy, offering valuable tools for biodiversity conservation, wildlife management, and ecological research. Furthermore, Sharma (2022) highlights the practical applications and successes of integrating machine learning with multispectral data, achieving detailed, high-resolution (10-meter) countrywide mapping of plant ecological communities using CNNs, thereby enhancing land management, biodiversity conservation, and ecological research. By integrating these advanced machine learning algorithms with remote sensing platforms such as Google Earth Engine, researchers can process and analyse satellite imagery in real-time, leading to further advancements in the field of environmental monitoring and ecosystem assessment (Gorelick et al., 2017).

Another significant advancement in the application of machine learning to remote sensing is the introduction of extreme gradient-boosting algorithms, such as XGBoost and its variants (Chen & Guestrin, 2016a). These algorithms have complemented traditional machine learning techniques by offering superior performance in handling large datasets and high-dimensional features, which are common in remote sensing data (Chen & Guestrin, 2016; Matyukira & Mhangara, 2023b). Extreme gradient boosting combines the strengths of decision trees and

gradient boosting, providing robust and efficient classification results. Its ability to handle missing values and its scalability have made it a popular choice for vegetation classification tasks, further enhancing the accuracy and efficiency of remote sensing analyses (Pham et al., 2020; Zhang et al., 2020).

3.2.2 Vegetation Growth Dynamics Using Remote Sensing Technologies

Remote sensing technologies have become indispensable for environmental monitoring and management due to their ability to map vegetation comprehensively. These technologies enable the evaluation of vegetation coverage, condition, and temporal fluctuations, providing crucial insights into ecosystem dynamics (Knauer et al., 2014). The continuous advancements in satellite remote sensing, such as the development of high-resolution sensors and sophisticated data processing algorithms, have significantly enhanced researchers' ability to monitor vegetation health, productivity, and changes over time (Li et al., 2023; Pradhan et al., 2024a).

Time-series analysis of remote sensing data is a crucial technique for monitoring temporal changes in vegetation phenology and growth patterns (Kooistra et al., 2024). Common methods for assessing vegetation health and productivity include using NDVI, EVI, and other vegetation indices that provide accurate measurements of plant greenness, which are closely correlated with photosynthetic activity and biomass (Li et al., 2023; Pradhan et al., 2024a). These indices are instrumental in detecting seasonal variations, identifying periods of maximum growth, and evaluating long-term trends in vegetation dynamics. By analysing temporal changes through remote sensing data, researchers can better understand vegetation's response to climate fluctuations, human activities, and natural disturbances (Nyamjav et al., 2024; Obuchowicz et al., 2024; Pettoirelli et al., 2005). Furthermore, phenological metrics derived from remote sensing data, such as the start of the season (SOS), end of the season (EOS), and length of the growing season (LOS), provide essential information about plant growth over time (White et al., 2009). These measures help detect changes in phenological events due to climate change and other environmental variables. For instance, higher temperatures often result in an earlier onset of SOS and a longer duration of LOS. By observing these changes, scientists can more accurately predict the effects of climate change on ecosystems, adjust agricultural practices, and conserve biodiversity (Chen & Zhang, 2023; Fang et al., 2023a).

In addition to vegetation indices, several advanced methods are employed for assessing vegetation health and analysing time-series data. One of the most common approaches is the use of radiative transfer models such as PROSPECT + SAIL models, which simulate light interaction with vegetation to estimate biophysical parameters like leaf area index (LAI) and chlorophyll content (K. Berger et al., 2018; Gupta & Pandey, 2022; Jacquemoud et al., 2009). A recent study utilised PROSAIL model inversion on Google Earth Engine to estimate aboveground biomass continuously over time on the Tibetan Plateau (Xie et al., 2022). This method provided detailed insights into vegetation structure and function, highlighting the benefits of combining biophysical models with remote sensing data for comprehensive vegetation analysis. Additionally, LiDAR and radar technologies are increasingly being used to measure vegetation height and biomass, offering information that cannot be captured by optical sensors alone (Edson & Wing, 2011; Maesano et al., 2020).

However, despite these advancements, several challenges remain in analysing vegetation growth dynamics using remote sensing data. One of the major challenges is the data quality and resolution. While temporal resolution has improved, there are still limitations in capturing rapid vegetation changes, especially in areas with high variability due to seasonal or anthropogenic factors (Fan et al., 2022; Li et al., 2023). In regions with frequent cloud cover, optical data collection can be interrupted, necessitating the use of radar or LiDAR technologies. Additionally, lower spectral resolution may hinder the differentiation between various vegetation types in heterogeneous landscapes, making it difficult to capture subtle vegetation characteristics (Ougahi et al., 2022; Wegehenkel, 2009).

Moreover, vegetation indices such as NDVI, while widely used, have limitations in areas of dense vegetation where they tend to saturate, reducing sensitivity to biomass changes (Fu et al., 2022; Hassan et al., 2023). To overcome these challenges, alternative approaches such as data fusion techniques—which combine optical, radar, and LiDAR data—are being developed to offer a more comprehensive assessment of vegetation health (Illarionova et al., 2024; J. Tian et al., 2024). Furthermore, the analysis of vegetation dynamics is complicated by the variability in environmental factors, such as climate variability and human-induced changes. Phenological shifts, for instance, may vary significantly across ecosystems, making it difficult to create generalisable models for predicting vegetation responses (Hassan et al., 2023; Roberts et al., 2015).

Finally, integrating environmental variables like temperature, precipitation, and soil moisture into remote sensing data remains a complex task. Although studies have demonstrated correlations between these factors and vegetation indices (Tsai & Yang, 2016; Zhong et al., 2010a), predicting vegetation dynamics accurately requires sophisticated models capable of capturing these intricate interactions. Additionally, the increasing occurrence of extreme weather events adds further complexity, making it essential to develop robust models that integrate remote sensing data with in-situ measurements. These advancements are crucial for improving predictions of vegetation responses and guiding ecosystem management practices (Fang et al., 2023b).

3.2.3 Analysis of Land Cover and Land Use Change Utilising Remote Sensing Technologies

Remote sensing technologies are crucial in identifying and examining changes in land cover and land use. These changes are essential for comprehending environmental shifts and guiding sustainable land management strategies. Monitoring these changes over time allows for valuable observations of the effects of human activities and natural processes on landscapes. Researchers use various remote sensing methods to obtain precise information on the evolution of land cover and land use. This knowledge is invaluable for developing effective conservation strategies and informing policy decisions (Fang et al., 2023a; Knauer et al., 2014; Pradhan et al., 2024b). Change detection methods, such as post-classification comparison, image differencing, and principal component analysis (PCA), are often used to detect changes in land cover using multi-temporal remote sensing data. Post-classification comparison is the separate categorisation of images from various periods, followed by comparing the outcomes to identify any alterations (Liu & Zhou, 2004). Image differencing is a process where the pixel values of

one date are subtracted from the pixel values of another date, which helps to identify places where there have been substantial changes (Panuju et al., 2020a). Principal Component Analysis (PCA) decreases the number of dimensions in the data, improving the ratio of useful signal to unwanted noise and increasing the efficiency of detecting changes (Li et al., 2024; Wu et al., 2015). These tools have shown efficacy in monitoring several land cover changes, such as urbanisation, deforestation, and agricultural development (Asokan & Anitha, 2019; Cheng et al., 2023; Marukatat, 2023; Y. Yu et al., 2023).

Remote sensing technology has been instrumental in tracking urbanisation and deforestation, key drivers of environmental transformation. High-resolution satellite imagery facilitates detailed mapping of land cover changes, revealing the extent and patterns of urban growth and forest clearance (Panuju et al. 2020). By analysing remote sensing data, researchers can observe the impact of urban development on natural environments, such as the proliferation of impervious surfaces and built-up areas. Similarly, deforestation activities can be scrutinised to ascertain the pace and spatial pattern of forest depletion. These insights are vital for understanding the consequences of land-use changes and formulating interventions to mitigate their adverse effects (Joseph & Jaya, 2019; Kumar, 2011).

Building on this understanding, evaluating the effects of changes in land cover and land use on ecosystems and biodiversity becomes a critical next step for implementing sustainable management practices (Kumar, 2011). Remote sensing data provide significant information for estimating the impacts of these changes on habitat fragmentation, species distribution, and ecosystem services (Matyukira & Mhangara, 2023b). One such impact is habitat fragmentation, often a result of urbanisation or deforestation. To understand its effects on biodiversity, researchers can analyse landscape metrics derived from remote sensing data (Musetsho et al., 2021; Rong & Fu, 2023). In addition, remote sensing may be used to observe changes in land use patterns, such as the transformation of forests into agricultural areas, which has substantial consequences for carbon sequestration, water cycles, and soil quality (Assede et al., 2023; Cheng et al., 2023). Researchers may create complete models to forecast future land use scenarios and their possible effects by combining remote sensing with ecological and socio-economic data. This integration helps formulate policies for sustainable development and conservation (Jiang et al., 2021; Vitale & Salvo, 2024).

While remote sensing technologies have greatly enhanced the examination of land cover and land use changes, specific limitations intrinsic to these tools must be acknowledged. A significant difficulty is the accessibility and quality of remote sensing data. High-resolution satellite imagery, essential for comprehensive monitoring, may be inaccessible due to expense, cloud cover interference, or limited satellite revisit time, especially in tropical areas susceptible to persistent cloud cover (Breunig et al., 2023). Furthermore, the validation of remote sensing data necessitates access to accurate ground truth data, which can be costly and logistically difficult to acquire, particularly in distant or politically dangerous areas. The absence of dependable validation data may undermine the accuracy of land cover classifications, resulting in inaccuracies in identifying land use changes (Olofsson et al., 2014; Stehman & Foody, 2019).

The classification algorithms employed in remote sensing are frequently constrained by their sensitivity to spectral similarities among various land cover types. For instance, differentiating between specific vegetation types or urban areas might be challenging when their spectral signatures overlap, potentially resulting in misclassification (Gündüz & Orman, 2024; Mehmood et al., 2022). The intricacy of data processing and the substantial computational expenses linked to managing extensive multi-temporal remote sensing data may be prohibitive for certain researchers or organizations. These challenges, including the time and resources required for data preprocessing and analysis, must be balanced against the powerful insights that remote sensing offers in understanding land cover and land use dynamics (Di & Yu, 2023b; Southworth & Muir, 2021; X. Yao et al., 2020). Consequently, although remote sensing is an invaluable instrument, these constraints must be recognized to guarantee precise monitoring and informed decision-making in land management.

3.2.4 Utilising Remote Sensing Technologies to Monitor Land Degradation and Fragmentation

Remote sensing technologies are efficient tools for monitoring land degradation and fragmentation, which are significant environmental concerns impacting ecosystem health and species diversity. These technologies provide detailed, multi-temporal data that are essential for the ongoing evaluation of land degradation indicators such as soil erosion, loss of plant cover, and desertification (Tejaswi., 2007; Reddy et al., 2018; Shange, 2020; Symeonakis, 2022). Spectral indices like the NDVI and the Soil Adjusted Vegetation Index (SAVI) are instrumental in measuring the extent and condition of vegetation, offering valuable insights into the health of the land (Reddy et al., 2018). By aiding in detecting regions undergoing deterioration and assessing the magnitude of these changes over time, NDVI and SAVI enhance our ability to monitor and address the critical issue of land degradation. The integration of remote sensing data with spectral indices allows for a more comprehensive understanding and management of environmental changes, ensuring the preservation of ecosystems and biodiversity (Tejaswi Rome 2007; Lu et al. 2015; Mambo & Archer 2007; Yengoh et al. 2016).

Various remote sensing methods are key for effectively monitoring land cover changes, which in turn can indicate land degradation. Supervised and unsupervised classification techniques are commonly used for categorising land cover types. Supervised classification utilises predefined training datasets, enabling the algorithm to classify images according to known land cover categories. In contrast, unsupervised classification relies on the spectral properties of pixels to group them into clusters without prior knowledge of land types (Parashar, 2023). Object-Based Image Analysis (OBIA) is another important method that segments high-resolution satellite images into objects and classifies them based on both spectral and spatial properties such as texture and shape, improving classification accuracy in complex landscapes (Dronova, 2015; Kumar et al., 2020).

Additionally, change detection techniques such as post-classification comparison, image differencing, and NDVI differencing play a vital role in identifying land cover transitions over time. These techniques allow for detecting changes like deforestation, urbanization, and agricultural expansion, which often contribute to land degradation (Asokan & Anitha, 2019; Cheng et al., 2023; Parelus, 2023). Incorporating these methods into land monitoring systems

enhances the detection of subtle changes in land cover and provides better insights into ongoing degradation processes.

Similarly, fragmentation analysis is an essential application of remote sensing in environmental monitoring. It addresses habitat fragmentation—dividing continuous habitats into smaller, isolated patches. Metrics such as patch size, edge density, and connectedness, derived from remote sensing data, provide insights into habitats' spatial arrangement and integrity (S. K. Singh et al., 2014). Analysing these metrics helps researchers understand fragmentation's extent and impact on ecosystems. This knowledge is vital for conservation efforts and land-use planning to mitigate negative effects on biodiversity and ecosystem services (Dupin et al., 2013; Mambo & Archer, 2007; S. K. Singh et al., 2014; Zlinszky et al., 2015).

In parallel, monitoring desertification is crucial for evaluating land deterioration, especially in dry and semi-dry regions. Remote sensing approaches, including the Land Degradation Neutrality (LDN) frameworks, leverage satellite data to track changes in land cover and soil characteristics over time (Kust et al. 2023). Such monitoring is key to identifying areas vulnerable to desertification. The data obtained from these tools are essential for mapping and observing desertification trends, which in turn supports the development of policies aimed at combating land degradation. By integrating remote sensing data with ground-based observations and climate factors, researchers can create comprehensive models to predict and manage desertification, thereby helping to maintain land productivity and ecological balance in susceptible areas (Dharumarajan et al., 2022; Hassan, 2004; Hill & Helldén, 2005; Xu, 2023).

3.2.5 Assessing the Impact of Terrain on Plant Health Using Remote Sensing Technologies

Topography is crucial in influencing vegetation distribution and vitality because variations in elevation, slope, and aspect create a diversity of microhabitats (Xun et al. 2023). Remote sensing technologies, including Digital Elevation Models (DEMs), facilitate a comprehensive analysis of topographic factors on vegetation. DEMs derived from remote sensing data offer detailed topographical information, allowing researchers to explore the effects of elevation gradients on vegetation patterns (Guth et al., 2021). Remote sensing data such as those derived from radar (e.g., SRTM – Shuttle Radar Topography Mission, or TanDEM-X) and LiDAR (Light Detection and Ranging) can be used to directly obtain ground elevation information through the generation of Digital Elevation Models (DEMs). These datasets provide detailed topographical information at various resolutions. SRTM, for example, provides global elevation data at a 30-meter resolution, while LiDAR offers even more precise elevation data, typically down to meter or sub-meter accuracy (Guth et al., 2021, 2024; Wei & Bartels, 2012). These remote sensing methods invert elevation data directly from satellite or aerial observations, allowing researchers to analyse terrain features like slope, aspect, and elevation, which are critical for understanding vegetation patterns. For instance, elevation can significantly influence plant growth and health by affecting temperature and moisture availability, which are vital factors. By examining these elevation-related factors, scientists can gain a deeper understanding of the spatial distribution of various plant species and their

responses to topographic changes (Brocard et al., 2023; Khalaf et al., 2021; Matsuura & Suzuki, 2013; Odgaard et al., 2014).

In tandem with the analysis provided by DEMs, remote sensing is also instrumental in evaluating vegetation vigour through topographic correction. Since remote sensing data frequently requires modifications to account for topographic impacts such as slope and aspect on reflectance measurements, topographic correction techniques are employed to alter the reflectance data (Zhang, 2011). This process ensures that vegetation indices like the NDVI are more accurate. Precise vegetation indices are critical for assessing vegetation health and productivity because they provide reliable assessments of plant biomass and photosynthetic activity. Therefore, topographic correction not only complements the insights gained from DEMs but also enhances the accuracy and relevance of vegetation vigour evaluations by removing the impact of the underlying topography (Gao & Zhang, 2009; S. Ma et al., 2021; Riaño et al., 2003; Yao et al., 2022).

Furthermore, topography-induced microclimates significantly impact vegetation vigour in the Southern Hemisphere, as differences in terrain may generate localised climatic conditions that affect plant development. North-facing slopes in the Southern Hemisphere receive more sunshine, resulting in higher temperatures and less moisture, while south-facing slopes are colder and have more moisture (Barry and Blanken 2016). These microclimatic differences impact the species makeup, growth rates, and general health of plants. By combining remote sensing data with topography information, researchers can examine microclimates' influence on plants' distribution and health (Jucker et al., 2018). Such assessments are crucial for forecasting the impact of climate change on vegetation patterns since variations in temperature and precipitation patterns may modify the microclimatic conditions that plants rely on for their survival and development. Understanding these relationships enables scientists to formulate more efficient conservation and land management techniques (Bramer et al., 2018; Chen et al., 2013; De Frenne et al., 2013; Jung et al., 2016).

In addition to topography, vegetation growth and health are also influenced by both environmental factors and human activities, which can be monitored using remote sensing technologies. Environmental factors such as temperature, precipitation, and soil moisture can be captured using satellite data from missions like MODIS (Moderate Resolution Imaging Spectroradiometer) and Sentinel-2, which track climate variables over time (Dhillon et al., 2023; Lange et al., 2017). Similarly, human activities such as land use changes, deforestation, and urbanization can be monitored through remote sensing, using methods such as land cover classification and change detection. These factors significantly impact vegetation by altering local climates and soil conditions, affecting plant growth and health (Abebe et al., 2022; Nedd et al., 2021). For example, a study using the CCDC algorithm with optical and SAR images investigated marsh vegetation phenology in the Honghe National Nature Reserve, China, and found that hydro-meteorological factors significantly drive phenological changes (Fu, et al., 2022). Additionally, another study in the same reserve employed the LandTrendr algorithm and Google Earth Engine to analyse the dynamic relationship between marsh vegetation and hydrological changes over a 35-year period, further demonstrating how remote sensing can be used to monitor complex environmental interactions over time (Fu et al. 2022). Integrating data

on climate and human-induced changes, alongside topographic information, provides a more holistic understanding of the drivers affecting vegetation patterns

3.2.6 Remote sensing technologies for estimating biomass and evapotranspiration

Estimating biomass and quantifying evapotranspiration are crucial for comprehending ecosystem production and water use, which are fundamental environmental and resource management aspects (Khan et al., 2019; G. Zhou et al., 2008). Remote sensing technologies are used to estimate biomass, using many sophisticated approaches such as vegetation indices, radar, LiDAR, and UAVs. Vegetation indices, such as the NDVI, are commonly used for biomass estimation by correlating the reflectance of vegetation to biomass levels. Radar data, particularly from Synthetic Aperture Radar (SAR), provides structural information by penetrating vegetation canopies, enabling biomass estimation. LiDAR offers a precise 3D measurement of plant structures, including height, which is essential for biomass calculations (Borsah et al., 2023; Kumar et al., 2015; Sinha et al., 2015).

The use of UAVs equipped with advanced RGB, and multispectral sensors has significantly enhanced the precision and spatial resolution of biomass estimation. These drones, as highlighted by Tait et al. (2019) and Bazrafkan et al. (2023), are capable of capturing high-resolution images across various spectral bands, enabling precise spatial and spectral vegetation analysis. RGB sensors offer insights into the visible spectrum for visual assessments, while multispectral sensors provide critical data at specific wavelengths like near-infrared for in-depth vegetation studies. The detailed imagery from UAVs is particularly beneficial for monitoring minute changes in plant structure, proving invaluable in hard-to-reach areas or when high-detail information is required (Lussem et al., 2019; Nex & Remondino, 2014). However, despite their high resolution and flexibility, UAVs face challenges in covering large spatial scales due to their limited flight range, data volume constraints, and regulatory restrictions. For larger areas, satellite-based methods such as synthetic aperture radar (SAR) and LiDAR remain more effective (Nedd et al., 2021; Saadatseresht et al., 2015)

Advancements in remote sensing techniques for measuring evapotranspiration have been marked by the sophisticated use of thermal infrared data and energy balance models. Thermal infrared sensors, which Holmes (2019) elaborates on, are instrumental in gauging vegetation surface temperatures to estimate rates of water transpiration and soil evaporation. Energy balance models like SEBAL and METRIC, discussed by Allen et al. (2007) and Elhag et al. (2011), leverage this thermal data alongside meteorological and environmental factors to precisely calculate evapotranspiration rates. These models are particularly suited for large-scale applications where satellite-based remote sensing can efficiently capture vast areas, a task where UAVs often struggle due to their operational limitations. Such large-scale, accurate evapotranspiration data are crucial for managing water resources effectively, particularly in arid and semi-arid regions, where efficient water use is critical for the sustainability of agriculture and ecosystem health (Gxokwe et al., 2020; Nedd et al., 2021; Saadatseresht et al., 2015).

Furthermore, the combination of biomass estimation and evapotranspiration data with carbon and water flow measurements enriches our understanding of ecosystem dynamics. Remote sensing is pivotal in providing spatially accurate data for modelling carbon and water movements on various scales, assisting in assessing the impact of different plant types on the carbon cycle, as noted by (Allen et al., 2007; H. Huang et al., 2024; Srinet et al., 2022). UAVs, as Bendig et al. (2014) suggest augmenting these capabilities with their flexible and immediate data collection, adapting them to specific research needs and schedules. These models are essential for appraising climate change effects on ecosystem services and formulating mitigation strategies. Integrating remote sensing data with terrestrial observations and other environmental variables offers researchers a deeper understanding of carbon-water cycle interactions, leading to the development of comprehensive models that enhance environmental management practices, as highlighted by (Initiative, 2016; Niu et al., 2021) and Niu et al. (2021).

3.3 Materials and Method

3.3.1 Employing Scopus and Excel for Targeted Literature Review in Vegetation Mapping

Scopus is a comprehensive, multidisciplinary bibliographic database that indexes various peer-reviewed literature, including journals, conference proceedings, and patents, across diverse science, technology, medicine, social sciences, and arts and humanities fields (Burnham, 2006). Its extensive coverage and robust search capabilities make it an invaluable resource for conducting thorough literature reviews (Kadam et al., 2020). Scopus provides advanced search functionalities that allow for the precise construction of queries using logical operators and field-specific filters, which are essential for refining searches and retrieving highly relevant studies (Burnham, 2006; Kadam et al., 2020). Additionally, its analytical tools enable detailed examination of citation patterns, authorship networks, and research trends, offering insights into the impact and progression of specific fields. These features make Scopus particularly well-suited for our research on vegetation mapping through remote sensing, as it ensures access to high-quality, peer-reviewed articles and facilitates the identification of key contributions and emerging trends in the intersection of remote sensing technologies and advanced machine learning techniques (Burnham, 2006; Kadam et al., 2020; Matyukira & Mhangara, 2023a).

Leveraging the extensive coverage and advanced search capabilities of Scopus, our research on vegetation mapping through remote sensing was able to tap into a rich repository of high-quality, peer-reviewed articles. By utilising Scopus's precise query construction using logical operators and field-specific filters, we were able to define the research scope clearly and identify key terminologies as detailed in Table 3-1. These included terms related to both vegetation mapping and remote sensing, as well as advanced machine learning techniques such as "random forest," "support vector machine," "neural networks," "deep learning," and "XGBRFCclassifier." The additional search terms related to specific applications further honed our exploration, ensuring a targeted yet comprehensive review of the subject matter.

The construction of the Scopus query was meticulously executed, incorporating both primary and secondary keywords. Logical operators such as AND, OR, and NOT were employed to

interconnect relevant concepts, as demonstrated in Table 3-1. This systematic strategy expedited the retrieval of studies pertinent to vegetation mapping and remote sensing. The search was further refined by focusing on specific research disciplines listed in Table 3-1, including earth and planetary sciences, environmental science, agricultural and biological sciences, computer science, engineering, geography, planning, and development. This refinement was instrumental in aligning the search results with the study's objectives by concentrating on the intersection of vegetation mapping, remote sensing, sophisticated computational methods, and interdisciplinary environmental applications.

To enhance the precision of our search outcomes, we strategically excluded generic or unrelated terms that could yield irrelevant or overly broad information for our inquiry. As indicated in Table (3-1), terms such as “Antennas,” “Artificial Intelligence” (in a broader context), “China,” “Crops,” “Engines,” “Forestry,” “Image Analysis,” “Image Enhancement,” “Image Processing,” “India,” “Procedures,” “Satellite Data,” “Soils,” and “United States” were omitted. This exclusionary tactic ensured a focused aggregation of literature pertinent to vegetation mapping via remote sensing and machine learning techniques. By judiciously selecting and excluding keywords while honing in on essential subject areas, our methodology not only streamlined the literature collection process but also guaranteed the incorporation of high-calibre research directly relevant to our study goals.

Incorporating visual tools such as Scopus’s export function alongside Excel’s conditional formatting and filtering features enabled us to effectively identify and eliminate duplicate document titles. After deactivating these duplicates, we harnessed Scopus’s analytical tools to scrutinise the data based on various parameters like country of origin and authorship. This analysis facilitated the distillation of key findings into succinct summary tables and graphical representations, including bar charts, line charts, pie charts, and global maps. The creation of an array of tables and figures was pivotal in providing a structured synthesis of the literature review findings. Visualising the geographical distribution of research efforts highlighted the global scope of scholarly activities in this domain. Author contribution analysis was employed to pinpoint leading researchers and their collaborative networks within this specialised field. The trend analysis of publications over time underscored the growing scholarly interest in common machine-learning approaches applied to vegetation mapping through remote sensing.

Table 3- 1: Scopus search engine and queries used for the scope of this study

Search Engine	Website	Query
Scopus	scopus.com	TITLE-ABS-KEY ("vegetation mapping" AND "remote sensing" AND ("machine learning" OR "Random Forest" OR "Support Vector Machine" OR "neural networks" OR "deep learning" OR "XGBRFCClassifier")) AND ("vegetation classification" OR "vegetation growth dynamics" OR "land cover change" OR "land degradation" OR "fragmentation" OR "topographic influences" OR "vegetation vigor" OR "biomass estimation" OR "evapotranspiration")) AND (LIMIT-TO (SUBJAREA , "EART") OR LIMIT-TO (SUBJAREA , "ENVI") OR LIMIT-TO (SUBJAREA , "AGRI") OR LIMIT-TO (SUBJAREA , "COMP") OR LIMIT-TO (SUBJAREA , "ENGI") OR LIMIT-TO (SUBJAREA , "GEOG")) AND (EXCLUDE (DOCTYPE , "le") OR EXCLUDE (DOCTYPE , "re")) AND (LIMIT-TO (LANGUAGE , "English")) AND (EXCLUDE (EXACTKEYWORD , "China") OR EXCLUDE (EXACTKEYWORD , "Antennas") OR EXCLUDE (EXACTKEYWORD , "Crops") OR EXCLUDE (EXACTKEYWORD , "Times Series") OR EXCLUDE (EXACTKEYWORD , "Soils") OR EXCLUDE (EXACTKEYWORD , "Time Series") OR EXCLUDE (EXACTKEYWORD , "Article") OR EXCLUDE (EXACTKEYWORD , "India") OR EXCLUDE (EXACTKEYWORD , "United States") OR EXCLUDE (EXACTKEYWORD , "Engines") OR EXCLUDE (EXACTKEYWORD , "Image Enhancement") OR EXCLUDE (EXACTKEYWORD , "Image Processing") OR EXCLUDE (EXACTKEYWORD , "United Kingdom") OR EXCLUDE (EXACTKEYWORD , "Study Areas"))

3.3.1 Bibliometric Visualisation and Analysing of Data in VOSviewer

VOSviewer is a powerful software tool designed for constructing and visualising bibliometric networks, offering an intuitive interface for analysing relationships within large datasets derived from academic publications (Jan van Eck & Waltman, 2023). Its primary advantages include handling extensive bibliographic data and generating detailed visual maps that illustrate complex networks of authorship, co-citation, and keyword co-occurrence (Centre for Science and Technology Studies, 2023). VOSviewer supports the use of thesaurus files to manage synonyms and term variations, ensuring consistency in data analysis (Centre for Science and Technology Studies, 2023). Its visualisation capabilities are particularly robust, allowing

researchers to create both network and density visualisations that reveal underlying patterns and trends in the data (Jan van Eck & Waltman, 2023). These features make VOSviewer an indispensable tool for our research, as it enables the effective synthesis and interpretation of vast amounts of bibliometric data, facilitating a deeper understanding of the research landscape in vegetation mapping through remote sensing and advanced machine learning techniques (Matyukira & Mhangara, 2023a).

Building on VOSviewer's robust capabilities for constructing and visualising bibliometric networks, our research methodology involved seamless integration of this tool with our Scopus-derived bibliometric data. By importing data in CSV format, we captured essential details such as authors, titles, sources, and citation counts, which laid the foundation for our subsequent analysis. The creation of a thesaurus file was a critical step in managing synonyms and term variations, ensuring consistency across our dataset.

With VOSviewer's intuitive interface, we generated a map using this bibliographic data, applying the thesaurus file during import to standardise terms. Both computational efficiency and expert judgment guided our systematic approach to determining criteria for item inclusion. This allowed us to focus on cluster formation that was relevant to our research topic, creating a clear and informative visualisation that highlighted key patterns and relationships within the field of vegetation mapping through remote sensing and advanced machine learning techniques.

This meticulous process resulted in a network visualisation that effectively displayed nodes and edges representing elements such as authors or keywords and their connections. Transitioning to density visualisation mode enabled us to analyse item distribution and identify areas of high concentration, discern clusters, and detect trends that emphasised significant themes or authors. After conducting a systematic study, we exported our visualisations as image files for presentation purposes and optionally extracted the raw data for further detailed analysis. This methodical approach enhanced our understanding of the research landscape and provided us with valuable insights into the progression of vegetation mapping through remote sensing.

3.4 Results and Analysis

3.4.1 Publication Trends in Remote Sensing and Vegetation Mapping

Table 3- 2: Worldwide Articles per Year from Scopus Database from 2000 to 2024.

Year	2002	2004	2006	2007	2008	2009	2010	2011	2012	2013	2014
No. Articles	1	1	1	3	1	1	3	2	2	1	4
Year	2015	2016	2018	2019	2020	2021	2022	2023	2024	Total	
No. Articles	2	2	6	6	6	11	35	48	26	162	

The analysis of the publication trend from Scopus, as illustrated in Figure 3-1 (a) and Table 3-2, highlights the dynamic growth and increasing interest in applying remote sensing for vegetation mapping, particularly with integrating advanced machine learning techniques. The

number of articles published yearly has notably increased, particularly recently. For instance, starting with a modest count of 1 article per year from 2002 to 2004 and sporadic increases thereafter, the trend significantly accelerated from 2018 onwards. The number of publications rose from 6 articles in 2018 and 2019 to a remarkable 48 articles in 2023. This upward trend underscores the critical importance and necessity of continuing research in this field, reflecting the growing recognition of the value of combining remote sensing technologies with advanced analytical methods to enhance vegetation mapping efforts. The total number of articles reaching 162 by 2024 further emphasises this research area's expanding scope and relevance.

Remote sensing technologies, coupled with machine learning algorithms such as Random Forest, Support Vector Machines, neural networks, and XGBRFCClassifier, have significantly enhanced our ability to monitor, analyse, and understand vegetation dynamics across various spatial and temporal scales (Belgiu & Drăgu, 2016; Hansen et al., 2013; Maxwell et al., 2018; X. Song et al., 2016). The sharp rise in publications from 2019 to 2023 reflects the technological advancements and increased accessibility of these tools, making conducting more precise and comprehensive vegetation studies possible (Maxwell et al., 2018).

Continuing research in this area is essential for several reasons. Firstly, ongoing climate change and environmental degradation pose significant challenges to global ecosystems. Advanced remote sensing and machine learning techniques are crucial for monitoring these changes, providing timely data that can inform conservation and management strategies (Joshi et al., 2016; L. T. H. Pham et al., 2019; Wulder et al., 2004). Secondly, integrating these technologies facilitates the detection of subtle changes in vegetation health and distribution, which are vital for early warning systems and disaster management, such as in the case of forest fires, pest infestations, and drought conditions (Hansen et al., 2013). Lastly, continuous improvement and adaptation of these methods will drive innovation in environmental research, allowing for more accurate predictions and effective interventions. As global environmental challenges become more complex, the need for advanced tools to monitor and mitigate their impacts becomes increasingly urgent, making sustained research in remote sensing and vegetation mapping not just necessary but imperative for future sustainability (Bhandari et al., 2012; L. Jiang et al., 2007).

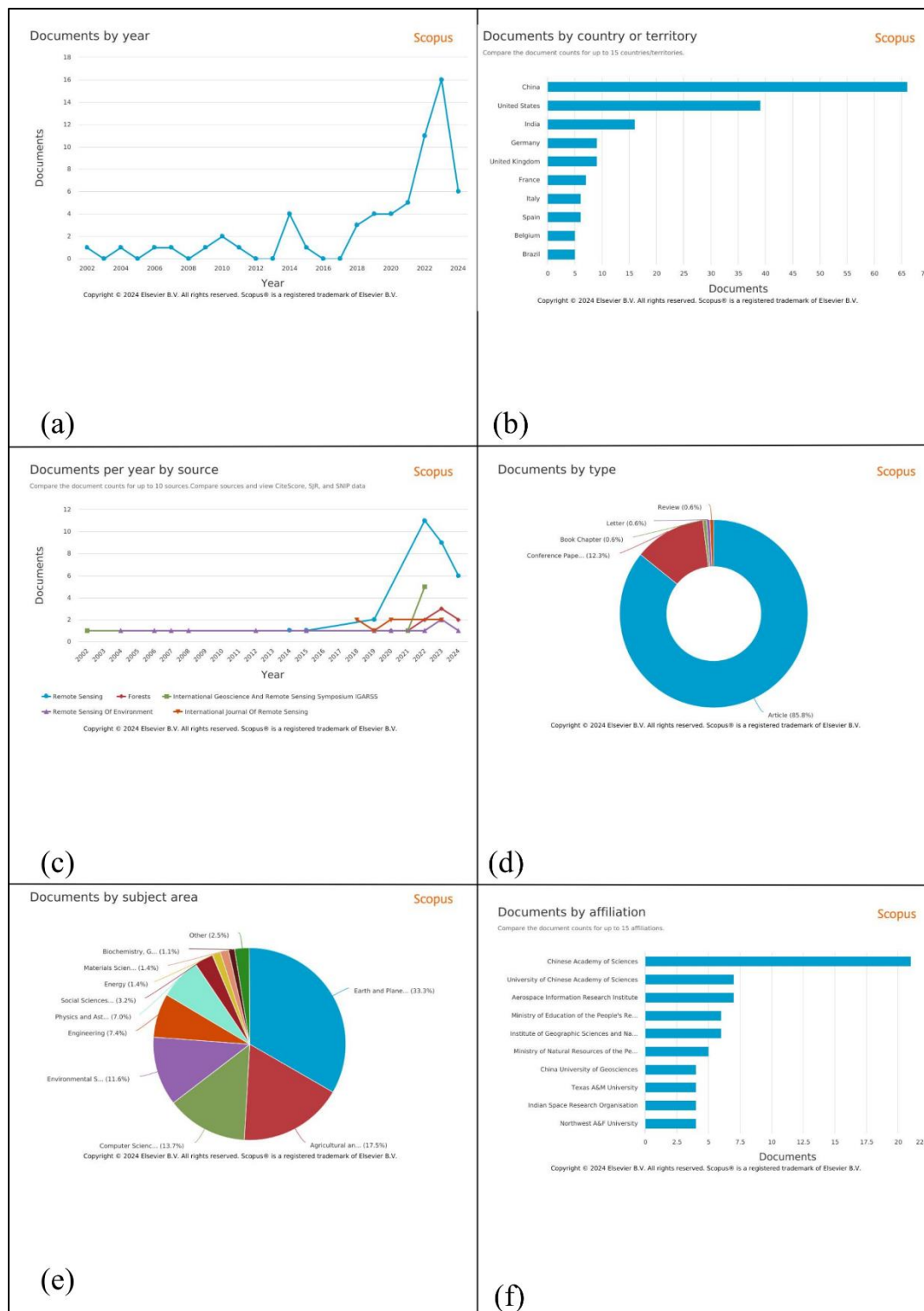


Figure 3- 1: Examination of Research Publications in Remote Sensing and Vegetation Mapping

3.4.2 Geographical breakdown of research on remote sensing and vegetation mapping

China has the highest number of research publications as shown in Figure 3-1 (b), in the field of remote sensing and vegetation mapping, indicating its leadership in this area. The United

States closely follows China, also making significant contributions and showing leadership in this research field. India's ranking as the third-largest contributor underscores its increasing emphasis on using remote sensing technology for the purpose of environmental monitoring and vegetation analysis. Germany, the United Kingdom, France, Italy, Spain, Belgium, and Brazil, among other European nations, demonstrate significant contributions, indicating a broad international interest in this topic. Many geographical locations emphasise the worldwide significance and cooperative character of research in remote sensing and vegetation mapping.

The reason for China's significant role in remote sensing research is its huge investment in satellite technology and environmental monitoring programs. The United States' robust position results from its enduring leadership in technology innovation and environmental research. Both nations have developed comprehensive remote sensing infrastructure and research institutes, which have facilitated progress in this domain (Chen & Chen, 2018; Wulder et al., 2018). India's rising production is probably fueled by its focus on sustainable agriculture and forest management, bolstered by national efforts such as the Indian Space Research Organisation's remote sensing projects (P. S. Roy et al., 2015). The European nations have made noteworthy advances in comprehending and tackling environmental difficulties by using improved remote sensing methods, as shown by the studies conducted by (Anjos et al., 2015), Dalouman et al. (2023) and de Soler & Verburg, (2010). The worldwide dissemination of research emphasises the significance of international cooperation and information sharing in promoting remote sensing for vegetation mapping and environmental sustainability.

3.4.3 Distribution of publications in remote sensing and vegetation mapping by source

Table 3- 3: Top 5 articles per journal from Scopus database from 2000 to 2024

Year	2002	2004	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015
Remote Sensing											1	1
Remote Sensing of Environment		1	1	1	1				1			1
Forests												
International Geoscience and Remote Sensing Symposium IGARSS	1											
International Journal of Remote Sensing												
Year	2016	2018	2019	2020	2021	2022	2023	2024				
Remote Sensing			2			11	9	6				
Remote Sensing of Environment			1	1		1	2	1				
Forests				1	1	2	3	2				
International Geoscience and Remote Sensing Symposium IGARSS					1	5						
International Journal of Remote Sensing		2		1		2	2					

The analysis of remote sensing and vegetation mapping research conducted between 2002 and 2024 reveals a substantial rise in publications, particularly from 2018 onwards, as depicted in Figure 3-1 (c) and Table 3-3, reaching a prominent peak in 2023. The journal "Remote Sensing" has the largest number of articles, especially from 2019 onwards, highlighting its significant role in sharing research on this subject. This increase in publications may be credited to the rapid progress in remote sensing technology and the expanding use of machine learning methods in vegetation research. Publications such as "Remote Sensing of Environment" and "International Journal of Remote Sensing," as well as conferences like the "International Geoscience and Remote Sensing Symposium (IGARSS)," also make significant contributions to the field of remote sensing in environmental monitoring and management. The journal "Remote Sensing" showed a notable increase in articles, especially from 2019 onwards, with 11 articles in 2021 and 9 in 2022, Tables 3(2-3). Similarly, "Remote Sensing of Environment" maintained a consistent presence, contributing significantly to the field. The "International Journal of Remote Sensing" and "IGARSS" conferences also played pivotal roles, with a notable increase in their contributions in the latter years of the study period sources reflect the diverse interests and wide range of applications of remote sensing (Hansen et al., 2013; Maxwell et al., 2018).

The significant rise in publications in the journal "Remote Sensing" corresponds to the wider pattern of incorporating sophisticated analytical techniques, such as deep learning and neural networks, in vegetation mapping research. This tendency emphasises the crucial significance of the journal in advancing groundbreaking approaches and applications in the discipline. The ongoing contributions from "Remote Sensing of Environment" and the "International Journal of Remote Sensing" underscore the well-established venues these publications provide for impactful research (Belgiu & Drăgu, 2016; Wulder et al., 2018). Moreover, the inclusion of IGARSS in the publishing landscape indicates the significance of conference proceedings in spreading advanced research and promoting cooperation among scientists and practitioners. The increase in publications from these sources highlights the growing research community and the urgent need for more investigation and advancement in remote sensing technologies to tackle intricate environmental issues (Joshi et al., 2016; Matyukira & Mhangara, 2023a; L. T. H. Pham et al., 2019; P. S. Roy et al., 2015).

3.4.4 Types of Documents in Remote Sensing and Vegetation Mapping Research

The distribution of various remote sensing and vegetation mapping publications, Figure 3-1 (d), demonstrates that a substantial majority, 85.8%, of the papers are research articles, highlighting a strong emphasis on original research and experimental discoveries in this discipline. Conference papers account for 12.3% of the publications, underscoring the significance of academic conferences in sharing recent progress and promoting dialogue among scholars. The other categories, such as book chapters, letters, and reviews, account for just 0.6% of the total publications. This indicates that these publication platforms are less often used in this field of study. The prevalence of research publications highlights the field's dependence on comprehensive experimental investigations and empirical data to progress knowledge and innovate new technologies. Research publications include in-depth analysis of

methodology, findings, and debates, which are crucial for the scientific community to expand on previous research and foster innovation (Hansen et al., 2013; Maxwell et al., 2018). The significant percentage of conference papers demonstrates the ever-changing nature of this field of research, where quick technological progress and the implementation of novel methods require frequent sharing of knowledge and collaboration, which is facilitated by conferences like the International Geoscience and Remote Sensing Symposium (IGARSS) (Joshi et al., 2016; P. S. Roy et al., 2015). The limited quantity of reviews and book chapters suggests that although these formats are useful for consolidating existing knowledge and offering a broader perspective, they are not the main means of presenting innovative research findings in remote sensing and vegetation mapping (Pham et al., 2019).

3.4.5 Subject Area Distribution of Research in Remote Sensing and Vegetation Mapping

The extensive array of fields involved in remote sensing and vegetation mapping indicates that the majority of papers, Figure 3-1 (e), namely 33.3%, pertain to Earth and Planetary Sciences, highlighting the essential relevance of geospatial science in this particular study domain. The prevalence of this dominance underscores the need to comprehend the Earth's surface and atmosphere since they are pivotal for precise vegetation mapping and environmental monitoring (Chen & Chen, 2018; Wulder et al., 2018). Agricultural and Biological Sciences represent 17.5% of the published works, emphasising the practical use of remote sensing in agriculture. This includes activities such as monitoring crops, estimating yields, and implementing sustainable land management practices (P. S. Roy et al., 2015; Shoko et al., 2015, 2016; Wulder et al., 2018). The substantial contributions from Environmental Science (11.6%) and Computer Science (13.7%) emphasise the multidisciplinary character of this subject, combining environmental monitoring with sophisticated computational tools and data analysis methodologies (Maxwell et al., 2018, 2021; Pham et al., 2019).

The inclusion of other disciplines, Figure 3-1 (e), such as Engineering (7.4%), Physics and Astronomy (7.0%), and Social Sciences (3.2%), underscores the diverse range of applications and research interests in remote sensing. Engineering plays a crucial role in advancing the development of novel remote sensing devices and platforms, including unmanned aerial vehicles (UAVs) and satellites. These technologies are vital for collecting data (Hansen et al., 2013; Matyukira & Mhangara, 2023a). Physics and Astronomy are essential in remote sensing technologies since they include physical concepts to comprehend how the electromagnetic spectrum interacts with plants. Incorporating Social Sciences indicates a desire to explore the social consequences and policy dimensions of environmental monitoring and land use management. The wide range of subject areas covered in remote sensing and vegetation mapping research demonstrates this field's extensive practicality and interdisciplinary character. This emphasises the importance of ongoing collaboration among different scientific disciplines to tackle complex environmental issues effectively ((Dalouman et al., 2023; de Soler & Verburg, 2010; Joshi et al., 2016; Roy et al., 2015).

3.4.6 Analysis of Research Affiliations in Remote Sensing and Vegetation Mapping

According to the prominent research institutes in remote sensing and vegetation mapping, the Chinese Academy of Sciences (CAS) stands out as the institution with the most publications, Figure 3-1 (f), surpassing other affiliations by a substantial margin. China's dominant position in scientific research and environmental monitoring may be linked to its significant investment and strategic focus on remote sensing technology (Chen, 2018). Chinese universities, such as the University of Chinese Academy of Sciences and the Aerospace Information Research Institute, part of the CAS network, play a significant role in promoting remote sensing research. These institutions are well-known for their thorough research programs and large cooperation networks, which enable them to produce influential research results (Dalouman et al., 2023; de Soler & Verburg, 2010b; Liu & Zhang, 2024; Rakhmankulova et al., 2024; Xu & Bai, 2024).

Additional significant associations include the Ministry of Education and the Institute of Geographic Sciences and Natural Resources Research, both of the People's Republic of China and the Ministry of Natural Resources. These organisations represent the Chinese government's comprehensive scientific research strategy to enhance environmental management and policy development (Wulder et al., 2018). Notable international collaborators include Texas A&M University and the Indian Space Research Organisation (ISRO). Texas A&M University is renowned for its strong research programs in geospatial science and engineering, while ISRO's proficiency in satellite technology and remote sensing applications showcases India's increasing focus on sustainable agriculture and natural resource management (P. S. Roy et al., 2015). The wide range of these associations demonstrates the worldwide cooperation and multidisciplinary character of remote sensing and vegetation mapping research, highlighting the significance of multinational alliances in tackling intricate environmental issues (Anjos et al., 2015; Bhandari et al., 2012; Dalouman et al., 2023; Chen, 2018; de Soler & Verburg, 2010; Jiang et al., 2007; Roy et al., 2015; Wulder et al., 2018).

3.4.7 Summary of the significance and need of remote sensing and vegetation mapping research using the Scopus database.

The analysis of the Scopus database reveals a substantial increase in publications related to remote sensing and vegetation mapping. This development may be attributed to technological improvements and machine learning methods like Random Forest and neural networks. The data shows a steady increase in the number of articles from 2002 to 2016, followed by a significant surge from 2018 to 2023, with the number of articles peaking at 48 in 2023. This substantial growth highlights the urgent need for continuous research to tackle climate change and environmental difficulties.

China and the United States are at the forefront regarding publication volume, indicating significant expenditures in satellite technology and environmental monitoring. Well-known publications such as "Remote Sensing" and "Remote Sensing of Environment" are crucial in spreading new approaches, as evidenced by their consistent and increasing contributions to the field. For instance, "Remote Sensing" saw a notable rise in articles, particularly from 2019 onwards, while "Remote Sensing of Environment" has maintained a consistent presence. The

significant increase in publications, particularly between 2019 and 2023, underscores the field's dependence on factual information and cooperation across many disciplines to enhance understanding and encourage creativity. This trend underscores the critical importance of continuing research and innovation in remote sensing and vegetation mapping to address pressing environmental challenges.

3.4.8 Interconnected Themes in Remote Sensing and Vegetation Mapping Research

3.4.8.1 Examination of VOSviewer Network Visualization

Table 3- 4: Network visualisation map structural information

Label	cluster	weight<Links>	Weight <Total link strength>	Weight <Occurrences>	score<Avg. citations>
Vegetation mapping	1	8	159	59	22
Remote sensing	1	8	157	58	22
Machine learning	1	8	141	50	23
Land use	3	7	38	10	16
land cover	2	7	38	10	18
Evapotranspiration	3	7	19	5	3
climate change	1	8	33	8	11
Accuracy assessment	2	7	49	14	26
Aboveground biomass	1	4	16	5	4

The VOSviewer network visualisation Figure 3-2(a) and Table 3-4 showcase the interconnections between important issues in vegetation mapping research using remote sensing. The primary focal points consist of "vegetation mapping," "remote sensing," and "machine learning," signifying their pivotal positions within this domain, as indicated by their high total link strengths and occurrences. Specifically, "vegetation mapping" has a total link strength of 159 and 59 occurrences, "remote sensing" has a total link strength of 157 and 58 occurrences, and "machine learning" has a total link strength of 141 and 50 occurrences.

The links between these nodes and other terms like "land use," "land cover," "climate change," "evapotranspiration," "aboveground biomass," and "accuracy assessment" suggest that researchers often investigate these subjects together. For instance, "land use" and "land cover" both have a total link strength of 38 and 10 occurrences each, highlighting their connection to the primary focal points. The term "accuracy assessment" is also prominent, with a total link strength of 49 and 14 occurrences, reflecting its importance in validating the research methods used. The interlinking of several disciplines highlights the diverse character of the study, as it combines sophisticated machine-learning methods to tackle different areas of environmental monitoring and vegetation analysis. The significant correlations among these topics indicate a resilient and expanding collection of research that uses remote sensing and machine learning to enhance our understanding of vegetation dynamics and associated environmental processes.

3.4.8.2 Examination of VOSviewer Density Visualisation

The VOSviewer density visualisation Figure 3-2(b) showcases the significance and dominance of major research topics in vegetation mapping via remote sensing. The nodes that stand out the most are "vegetation mapping," "remote sensing," and "machine learning," indicating their significant contributions to the literature. The research area encompasses several interconnected subjects such as "land use," "land cover," "climate change," "evapotranspiration," "aboveground biomass," and "accuracy assessment," highlighting the complex nature of this field of study. The high density at these nodes indicates significant research activity and strong linkages, highlighting the need to use advanced machine learning algorithms to improve the precision and effectiveness of remote sensing methods for vegetation monitoring. Research topics such as vegetation mapping, remote sensing, and machine learning are fundamental while studying land use and land cover change is crucial for comprehending environmental effects. It is important to consider climate change when researching how vegetation changes over time. We use metrics like evapotranspiration, which is the combined process of water evaporation from the land and plant transpiration, and aboveground biomass, which is the total weight of plant material above the ground, as important indicators of the overall health of vegetation. The validation of remote sensing data remains dependent on the accuracy evaluation. The Cradle Nature Reserve in the COHWHS offers a varied karst topography that is ideal for sophisticated approaches to monitoring and assessing vegetation efficiently. This setting emphasises the potential for effective study in vegetation dynamics and environmental monitoring by utilising the interrelated themes found in the visualisation processes.

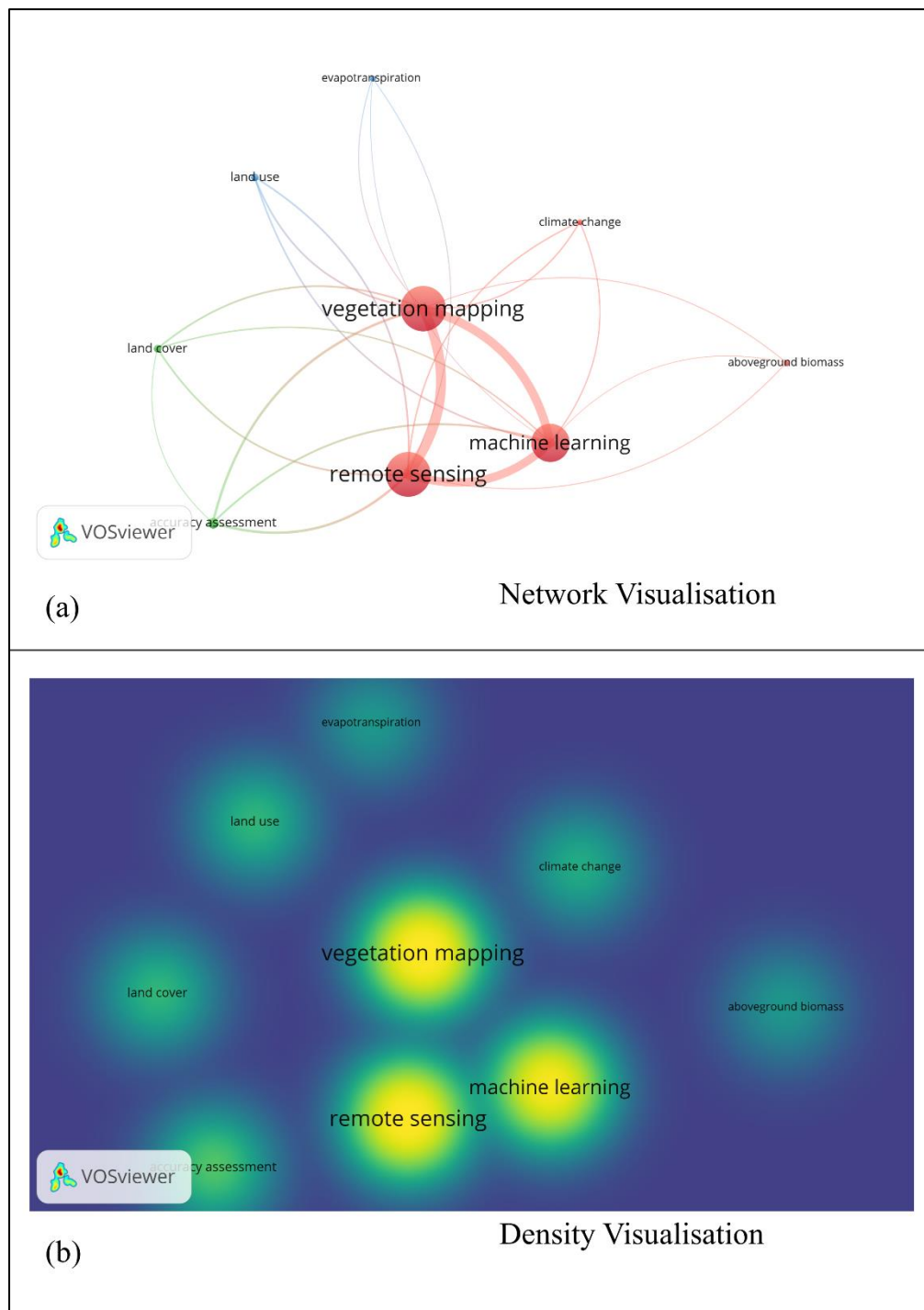


Figure 3- 2: Visualisation of Key Research Themes in Vegetation Mapping Using Remote Sensing, (a) *Network Visualisation*, (b) *Density Visualisation*

3.5 Findings from the Scientometric Review

1. The analysis highlights a substantial increase in publications related to remote sensing and vegetation mapping from 2002 to 2024, with a marked acceleration from 2018 onwards. The number of articles rose significantly from 6 in 2018 and 2019 to 48 in 2023, reaching a total of 162 articles by 2024. This upward trend underscores the

growing recognition of the importance of combining remote sensing technologies with advanced analytical methods for vegetation mapping.

2. There has been a significant rise in publications reflecting advancements in remote sensing technology and the expanding use of machine learning algorithms such as Random Forests, Support Vector Machines, neural networks, and XGBRFCClassifier. These technologies have enhanced the ability to monitor, analyse, and understand vegetation dynamics across various spatial and temporal scales.
3. The study reveals that China leads in the number of research publications, followed closely by the United States. India ranks as the third-largest contributor, highlighting its increasing emphasis on remote sensing technology for environmental monitoring and vegetation analysis. Significant contributions also come from European nations, emphasising the global and cooperative nature of research in this field.
4. Journals like "Remote Sensing," "Remote Sensing of Environment," and the "International Journal of Remote Sensing," along with conferences such as the "International Geoscience and Remote Sensing Symposium (IGARSS)," play crucial roles in disseminating research. "Remote Sensing" showed a notable increase in articles, particularly from 2019 onwards, reflecting its significant role in advancing the field.
5. The VOSviewer network visualisation and Table 3-4 identify "vegetation mapping," "remote sensing," and "machine learning" as the primary focal points, with high total link strengths and occurrences. "Vegetation mapping" has a total link strength of 159 with 59 occurrences, "remote sensing" has 157 with 58 occurrences, and "machine learning" has 141 with 50 occurrences.
6. The analysis reveals significant interconnections between primary themes and other important topics such as "land use," "land cover," "climate change," "evapotranspiration," "aboveground biomass," and "accuracy assessment." For instance, "land use" and "land cover" both have a total link strength of 38 and 10 occurrences each, highlighting their relevance in vegetation mapping research.
7. Research Gaps and Emerging Areas:
 - Despite its importance, "evapotranspiration" has a relatively low occurrence (5) and total link strength (19), as shown in Table 3-4, indicating a gap in comprehensive studies.
 - Aboveground Biomass estimation also has low occurrences (5) and total link strength (16), suggesting the need for more research in biomass estimation using remote sensing technologies.
 - As shown in Table 3-4, climate change is identified as a crucial but less integrated area, presenting opportunities for further investigation. Climate Change has (8) occurrences and a total link strength of 33.
8. Most publications (85.8%) are research articles emphasising original research and experimental discoveries. Conference papers account for 12.3%, highlighting the importance of academic conferences in sharing recent progress. Other categories, such as book chapters, letters, and reviews, account for just 0.6%, indicating that these formats are less commonly used in this field.

9. The subject area distribution reveals an extensive range of fields involved, including Earth and Planetary Sciences (33.3%), Agricultural and Biological Sciences (17.5%), Environmental Science (11.6%), and Computer Science (13.7%). Other fields such as Engineering, Physics and Astronomy, and Social Sciences also contribute, underscoring the multidisciplinary nature of remote sensing and vegetation mapping research.
10. The Chinese Academy of Sciences (CAS) is the leading institution in terms of publications, supported by significant national investments in remote sensing technology. Notable international collaborators include Texas A&M University and the Indian Space Research Organisation (ISRO), demonstrating the global and collaborative nature of the research.

These findings highlight the evolving landscape of remote sensing and vegetation mapping research, emphasising both established areas and potential gaps for future investigation.

3.6 Future Research Directions, Emerging Technologies, and Potential Challenges

The future of remote sensing and vegetation mapping research depends on the integration of rising technology and the resolution of existing issues. There is a distinct necessity to enhance research in domains such as evapotranspiration and aboveground biomass estimation, where substantial gaps persist. Future studies should focus on leveraging multi-source data fusion, combining optical, radar, and LiDAR data to enhance accuracy. Additionally, climate change remains underexplored in this context, and future research should aim to better understand its impact on vegetation dynamics by utilizing long-term satellite data and machine learning models for predictive analysis (Balestra et al., 2024; Jin & Mountrakis, 2022; Li et al., 2023; Zhang, 2010). Deep learning techniques, including convolutional neural networks (CNNs), provide a means to augment the extraction of vegetative characteristics and refine temporal analysis. Integrating UAVs with satellite data to extend their application beyond small-scale investigations could address existing limits concerning flight range and regulatory restrictions (Nex & Remondino, 2014).

Emerging technologies such as hyperspectral imaging, advanced LiDAR, and synthetic aperture radar (SAR) hold great promise for enhancing the accuracy of vegetation mapping. These technologies, in conjunction with edge computing and AI, can enable real-time monitoring and analysis; nevertheless, their integration necessitates addressing data processing and storage difficulties (Khonina et al., 2024; Kuras et al., 2021; Li et al., 2024). Furthermore, the advancement of quantum computing may provide a remedy for managing extensive datasets, facilitating swifter and more efficient analysis. Ensuring global access to these technologies is essential for equitable advancement, as numerous locations, especially in poor nations, lack the resources for efficient implementation of these innovations (Khonina et al., 2024; McKinsey & Company, 2024; World Economic Forum, 2022). Fostering international collaborations will be key to addressing global environmental challenges, ensuring that research benefits both local ecosystems and the global scientific community (Avilés Irahola et al., 2022; Mariani et al., 2022).

3.7 Conclusion

This study highlights significant advancements in combining remote sensing technologies with machine learning algorithms for vegetation mapping. A comprehensive literature review using the Scopus database provided an in-depth understanding of the current research landscape. Employing a systematic search strategy focused on key terminologies related to vegetation mapping and advanced machine learning techniques, we gathered and analysed high-quality studies, ensuring a thorough exploration of the field. Integrating VOSviewer into our methodology enabled effective visualisation and analysis of bibliometric data, revealing key patterns and relationships within the research field. Network and density visualisations highlighted significant clusters and trends, enhancing our understanding of the research progression and focus areas on vegetation mapping through remote sensing.

The systematic review via Scopus revealed a robust and growing body of research emphasising the effectiveness of remote sensing technologies combined with machine learning algorithms. Techniques such as Random Forest, Support Vector Machines, and neural networks have significantly enhanced remote sensing data analysis. VOSviewer proved valuable in visualising complex relationships and trends and identifying influential research areas, key authors, and collaborative networks. Our research underscores the critical importance of advanced remote sensing and machine learning techniques in addressing global environmental challenges. These technologies show significant potential in tackling issues like land cover change, vegetation health assessment, and biomass estimation. However, several research gaps remain. There is a need for more comprehensive studies on evapotranspiration and aboveground biomass, which have relatively low occurrences and link strengths. Additionally, integrating climate change data with remote sensing technologies is underexplored, presenting opportunities for further investigation.

Advances in satellite and UAV technologies, combined with sophisticated data processing algorithms, enable detailed and large-scale environmental monitoring, supporting more accurate and timely decision-making in environmental management. Continuous research and innovation are essential for developing effective strategies for environmental management, conservation, and sustainable development.

Chapter 4 LAND COVER AND LANDSCAPE STRUCTURAL CHANGES USING EXTREME GRADIENT BOOSTING RANDOM FOREST AND FRAGMENTATION ANALYSIS

This Chapter is based on the following manuscript

Matyukira, C., & Mhangara, P. (2023). Land cover and landscape structural changes using extreme gradient boosting random forest and fragmentation analysis. *Remote Sensing (Basel)*, **15**(23), Article 5520. <https://doi.org/10.3390/rs15235520>

Abstract: Land use and land cover change constitute a significant driver of land degradation worldwide, and machine-learning algorithms are providing new opportunities for effectively classifying land use and land cover changes over time. The aims of this study are threefold: Firstly, we aim to compare the accuracies of the parametric classifier Naïve Bayes with the non-parametric classifier Extreme Gradient Boosting Random Forest algorithm on the 2020 LULC dataset. Secondly, we quantify land use and land cover changes in the Cradle of Humankind from 1990 to 2020 using the Extreme Gradient Boosting Random Forest algorithm and post-classification change detection. Thirdly, the study uses landscape metrics to examine landscape structural changes occurring in the same area due to fragmentation. The classification results show that while Naïve Bayes and XGB Random Forest produce classification results of high accuracy, the XGB Random Forest Classifier produced superior results compared to the Naïve Bayes Classifier. From 1990 to 2020, bare ground/rock outcrop significantly increased by 39%, and open bush by 32%. Indigenous forests and natural grasslands lost area (26% and 12%, respectively). The results from this study indicate increasing land cover fragmentation and attest to land degradation, as shown by increases in bare ground and a reduction in indigenous forest and natural grassland. The decline in indigenous forests and natural grassland indicates the degradation of native vegetation, considered as prehistoric plant food sources. The high classification results also attest to the efficacy of the XGBRFC classifier executed in GEE. Land degradation evident in the nature reserve has long-term ecological consequences, such as loss of habitat, biodiversity decline, soil erosion, and alteration of local ecosystems, which together diminish the aesthetic value of the heritage site and negatively impact its tourism value. Consequently, it destroys crucial local economies and threatens sustainable tourism

4.1 Introduction

4.1.1 Land Cover Change Overview

Land cover (LC) changes profoundly harm the environment and cause land degradation worldwide (Ambalam, 2014; Chasek, 1997; Martínez-Valderrama et al., 2023; Pricope et al., 2023). Transformations in LC owing to anthropogenic activities and the dynamics in the humankind-land relationship that cause fragmentation of the natural forest are significant drivers of environmental degradation (Adepoju & Salami, 2017; Kelldorfer, 2019; Martinez del Castillo et al., 2015). Studies have established that land cover degradation can lead to biodiversity and habitat loss in natural forests, negatively impacting plant and animal species (Maitima et al., 2009; Mitchell et al., 2017). Thus, communities that depend on the forest for their resources and livelihoods face potential economic challenges (Zekarias & Gelaw, 2023). The loss of forest cover negatively impacts carbon dioxide sequestering and contributes to climate change (Raihan, 2023). Land cover loss disrupts the essential ecosystem services within a landscape and surrounding communities like water regulation, soil fertility and climate regulation (Shewit et al., 2017). In addition, land cover changes influence the water quality in the landscape, leading to soil erosion and negatively affecting aquatic ecosystems and human water resources (Anh et al., 2023). Therefore, monitoring land cover degradation is a proactive action that helps design effective conservation strategies and restoration plans for natural forests (S. Singh et al., 2023). Satellite-based remote sensing has been proven to be an indispensable tool for monitoring rangeland degradation by assessing temporal changes in land cover due to its ability to provide consistent long-range repetitive measurements at comparable spatial, spectral, and temporal scales (Mitchell et al., 2017). Changes in vegetation cover over time are correlated with the grazing and browsing capacity of rangelands and their ability to sustain game or livestock (Hussein, 2023). Rangeland degradation is threatened by many factors, such as encroachment by alien plant invasive species, overgrazing, deforestation, and extreme climate events such as drought (Abdulahi et al., 2016; Adekiya et al., 2020). Land degradation due to changes in vegetation cover is a complex process strongly influenced by climate variability and is ecologically reversible to an extent (Olsson et al., 2019). The deterioration of vegetation parameters such as vegetation density, structure and species composition reflect forest degradation (L. Zhou et al., 2014). Adjorlolo and Botha, (2015) noted that encroachment of woody vegetation into grasslands or bush thickening is degrading grassland systems into savanna-like landscapes in Southern Africa. Changes in vegetation or forest attributes lead to a lower productive capacity of rangelands (Meshesha et al., 2012).

According to Akter et al., (2021), LULCC research provides baseline information to identify geographic and anthropogenic natural environment modifications. Such information is vital for future investigations and preservation of the archaeological settings in the study area concerned with landscape optimisation and ecological balancing (Braga et al., 2016). According to Fahad, Hussein and Dibs (Fahad et al., 2020), most environmental conservation projects fail because more information on LU and LC variation is needed. Such information is hinged on the correct classification process, enabled by advancements in machine learning methods such as Random Forest (RF) (Camarretta et al., 2018; Davis & Douglass, 2020; Grilli et al., 2019; Guyot et al., 2018;

Mairota et al., 2013; Mitchell, 2006; Tapete & Cigna, 2018; Verschoof-Van der Vaart & Lambers, 2019).

The heterogeneity of vegetation cover in a landscape is generally accepted to be a function of the suitability of the environment to support distinct plant growth and successive responses to various biotic and abiotic factors and processes (Eloff, 2010). According to Fasona and three other authors (Fasona et al., 2018), in assessing the suitability of the environment, it must be noted that landscape change is a continual process that requires temporal and spatial monitoring of the patchy mosaics of the different LC types (Camarretta et al., 2018; C. Fan et al., 2017; Martinez del Castillo et al., 2015; Shahrokhnia & Ahmadi, 2019; Stewart et al., 2018; Tapete & Cigna, 2019). Numerous studies have highlighted edaphic, topographic, climate, and anthropogenic factors, among many other causal factors (Eloff, 2010). These studies have recommended that information associated with factors, such as the habitat extent, landscape configuration, and habitat configuration regarding different plant species, must be collected timeously (Ampofo et al., 2016; Camarretta et al., 2018; Comer et al., 2017; C. Fan et al., 2015; C. Fan & Myint, 2014). This information allows the ongoing generation of LULCC maps and habitat maps essential for continuously monitoring landscape changes of national and international conservation significance (Mairota et al., 2013). These landscape changes tend to happen progressively but are accelerated mainly by human activities (Fahad et al., 2020). According to Gessesse and Melesse (Gessesse & Melesse, 2019), advancements in geospatial and ancillary technologies have driven innovative methodologies and techniques enabling time series analysis, classification, and monitoring of land resources aided by extensive archives of freely available satellite data such as Landsat collections.

4.1.2 Machine Learning Land Cover Classification

According to Shahrokhnia and Ahmad (Shahrokhnia & Ahmadi, 2019), and Viana and three other authors (Viana et al., 2019), accessible Landsat ready-analysis data is available from six satellite series from Landsat 1–8. These provide high spatial resolution images with the longest temporal records of space-based observations for spatiotemporal mapping and environmental monitoring. Studies at various temporal and spatial scales of LC and fragmentation using a broad spectrum of remote sensing techniques gained momentum with the launch of various satellite missions in the mid-20th century (Alam et al., 2020; Ampofo et al., 2016; Britz, 2022; Dang & Trung, 2022; Smiraglia et al., 2015; Southworth et al., 2004). Parallel developments in computer technologies have seen the burgeoning of novel machine learning LULC classification algorithms tailored for temporal analysis of land cover degradation. These have created new vistas and opportunities for improving the accuracy and efficiency of LC classification (Grinand et al., 2020; Kussul et al., 2017; McCarty et al., 2020; Rukhovich et al., 2021; Torabi Haghighi et al., 2021). There are myriad machine learning algorithms on pay-up licenses and the open-source market, all with distinct advantages in modelling landscape structural changes and supplying critical information to decision-makers (Kavzoglu & Teke, 2022). This proliferation of algorithms paralleled with new spatial technologies has leveraged researchers worldwide for the past three decades, affixed with the application of machine learning algorithms in monitoring LULCC (Kavzoglu & Teke, 2022). Unique machine learning techniques such as decision trees, logistic regression, support vector machines (SVM), naïve

Bayes, and artificial neural networks have succeeded in remote sensing, geographic information systems, and many other applications (Chen & Guestrin, 2016; Pafka, 2015).

Machine learning algorithms have been considered more efficient and effective in land cover classification than conventional parametric algorithms and have improved classification accuracies according to (Feizizadeh et al., 2023; Yuh et al., 2023). In contrast, recent research by Kumawat and Khaparde (Kumawat et al., 2024) established that the parametric classifier Naïve Bayes outperforms the non-parametric classifier random forest algorithm in detecting land cover changes. Traditional parametric algorithms need help with extensive dimensional and complex data (Rogan et al., 2003). Ensemble-based classifiers predominately use boosting and bagging techniques. Random Forest classification, for instance, uses bagging or bootstrapping to create an ensemble of CART-like classifiers and selects a random subset of the variables for a split at each CART node (Pande, 2022). This process minimises the correlation between the classifiers and the ensemble. The advantage of Random Forest is that it is not sensitive to noise and overtraining and is computationally efficient (Ao et al., 2019). More recently, Chen and Guestrin, (2016) developed the XGBoost tree-based ensemble machine-learning algorithm that was first implemented in remote sensing for land cover classification (Georganos et al., 2018). They found that it outperformed Random Forest and Support Vector Machines regarding classification accuracies and computational speed (Georganos et al., 2018). The superiority of the XGBoost was also attested by Man et al., (2018), and Hirayama et al., (2019), who compared the performance of XGBoost to non-parametric classifiers. Sun et al., (2019) examined the performance of XGB in imbalanced learning situations and assessed the effect of minority class spectral separability. XGBoost produced better classification accuracy results than Random Forest, showed more excellent stability, and was insensitive to spectral separability issues associated with sample imbalance and uncertainty (Sun et al., 2019). To our knowledge, a comparison of the accuracies of the parametric classifier Naïve Bayes with the non-parametric classifier XGBoost has not yet been performed on LULC classification, forming part of this research aims. Naive Bayes is considered computationally efficient and can handle high-dimensional data, which is common in remote sensing, where each band in the imagery represents a different spectral channel (Kumawat et al., n.d.).

The contribution of machine learning algorithms has culminated in an enhanced understanding of the humankind–land relationship (Chen et al., 2018; Chen & Guestrin, 2016; Kavzoglu & Teke, 2022). However, all machine learning algorithms in remote sensing aim to make predictions based on patterns in some given data. Machine learning algorithms have been proven to have varying degrees of success in achieving their intended goals (Kavzoglu & Teke, 2022) owing to the complexity of the data structures. Regrettably, some of these algorithms lack scalability to all scenarios, limited algorithmic optimisations, and limited out-of-core computation and computing power when dealing with large data sets (Chen & Guestrin, 2016). To achieve better predictive performances, Kavzoglu and Teke, (2022), and Chen and Guestrin, (2016) argued for ensemble learning techniques, which use synergised machine learning techniques to predict more stable models that make an end-to-end system that scales to extensive data with the least amount of cluster resources. The machine learning algorithms for satellite image classification and textual information extraction use a mathematical combination of spectral reflectance from two or more wavelengths (bands) associated with the relative abundance of features of interest

or designated to highlight pixels showing the relative lot or lack of an LC type of interest called spectral indices (Viswambharan & Lenhardt, 2019). In other scientific research initiatives, algorithms such as grey-level co-occurrence matrix, contourlets, lacunarity, local binary patterns, and line support regions have been exploited to extract textual information from satellite images with high accuracy and efficiency (Matarira et al., 2022). However, it has been noted that the practical application of some of these algorithms is compromised owing to the high volume of data and the tedious, time-consuming operations, among other limitations, and that ordinary traditional image processing platforms may not handle (Matarira et al., 2022). In addition to spectral indices, landscape metrics algorithms for landscape composition and configuration have been developed for categorical map patterns or topographic measures that characterise a landscape (Uuemaa et al., 2009). They quantify specific spatial characteristics of the non-linear homogenous or heterogeneous structure in a landscape distinguished from its appearance, called patches, classes of patches, or the entire landscape mosaic (Adepoju & Salami, 2017). Further, these algorithms are used to analyse the qualitative quantitatively in the patches or landscapes, such as the proportion of the landscape in each patch type, patch richness, patch evenness, and patch diversity (Adepoju & Salami, 2017; Camarretta et al., 2018; C. Fan & Myint, 2014; Smiraglia et al., 2015; Sudhira et al., 2012).

The Cradle Nature Reserve rangelands are currently threatened by anthropogenic disturbances emanating from colonisation by invasive alien species (O'Connor & van Wilgen, 2020). This weed is among other invasive species known for playing a detrimental role in land degradation as it helps alter the structure and composition of vegetation, particularly soil erosion (Cammeraat & Imeson, 1999; Valentin et al., 1999; X. Zhang & Huang, 2019). It is also known that these invasive plant species increase in response to disturbances such as the burning regimes (as is done on a five-year cycle in the nature reserve) decreasing grass cover (Le Maitre et al., 2020; O'Connor & van Wilgen, 2020). Pompom weed is resilient to adverse climatic conditions as it is tolerant to wildfires and adverse climatic conditions such as winter frost and droughts, and its perennial root system allows it to store energy and nutrients underground. The overall impact of the invasion on the landscape is a loss in vegetation patchiness and landscape heterogeneity, leading to a dysfunctional ecosystem as it promotes runoff connectivity and inevitable erosion (Rodríguez-Lozano et al., 2023).

The aims of this study are threefold; firstly, we aim to compare the accuracies of the parametric classifier Naïve Bayes with the non-parametric classifier Extreme Gradient Boosting Random Forest algorithm on the 2020 LULC dataset. The primary reason for comparing Naive Bayes with XGBRFClassifier was to evaluate their performance on the classification of the landscape in the cradle nature reserve using the 2020 Landsat imagery. We further quantify land use and land cover changes in the Cradle of Humankind from 1990 to 2020 using the Extreme Gradient Boosting Random Forest algorithm and post-classification change detection. Thirdly, the study examines landscape structural changes occurring in the same study area due to fragmentation using landscape metrics. The Cradle of Humankind is a protected world heritage site with many hominin fossils.

Fossils from 3.5 million years ago have been discovered in the area (Baker et al., 2006). The preservation and sustainability of protected areas in South Africa are threatened by invasion by

alien invasive plants that are known to accelerate environmental degradation (O'Connor & van Wilgen, 2020). The study area is under threat from pompom weed. The degradation of the rangeland reduces vegetation productivity and negatively impacts its grazing capacity and ability to sustain the game, resulting in a loss of income. Environmental degradation eradicates plant foods that are indicators of dietary food sources for the hominins and negatively affects archaeological studies in the nature reserve. This study set out to provide new insights into how alien plant invasion affects a protected World Heritage Site (WHS) through land degradation. The Cradle of Humankind (COH) status as a WHS (hereafter termed the COHWHS) makes these insights significant. It impacts the worldwide interest in studying land degradation in landscapes with paleoanthropological phenomena as features. Findings from the study are also valuable for the preservation and environmental management of cultural and heritage sites globally at risk of land degradation. The literature reviewed indicated limited use of the integrated application of Extreme Gradient Boosting Random Forest and fragmentation analysis to assess archaeological sites for LULCC and degradation. Therefore, results from this study are vital in unfolding new avenues for these applications.

4.2 Materials and Methods

4.2.1 The Study Area

The Cradle Nature Reserve study area in the COHWHS is situated between longitudes 27° 42' 58" and 27°52' 57" and latitudes 25°51' 13" and 25°51' 19" (see Figure 4-1:). The COH was designated a WHS by the United Nations Educational, Scientific and Cultural Organisation (UNESCO) in 1999 to recognise the outstanding paleoanthropological work in Sterkfontein Valley since the 1930s (Rogerson & van der Merwe, 2016). The COH location in the Sterkfontein Valley is 50 kilometres northwest of Johannesburg City and 10 kilometres north of Krugersdorp town; it occupies 47,000 hectares of land in marginal parts of Gauteng and North West provinces, South Africa (Lelliott, 2016; Rogerson & van der Merwe, 2016). The landscape is primarily a product of chemically weathered rocky material that has transformed into a pattern of denudated limestone and dolomitic rocks referred to as karst landforms, named after the German name of Kras, in recognition of the Karst region of Yugoslavia, where the dissolvable landscape was first scientifically researched (Bradley et al., 2010; Eloff, 2010). The dissolving landscape over the years is the cause of the variable topography and environmental heterogeneity found today in the COHWHS. The karst landscape environmental heterogeneity contributes to the high densities of plant species in the COHWHS (Bradley et al., 2010; Eloff, 2010)

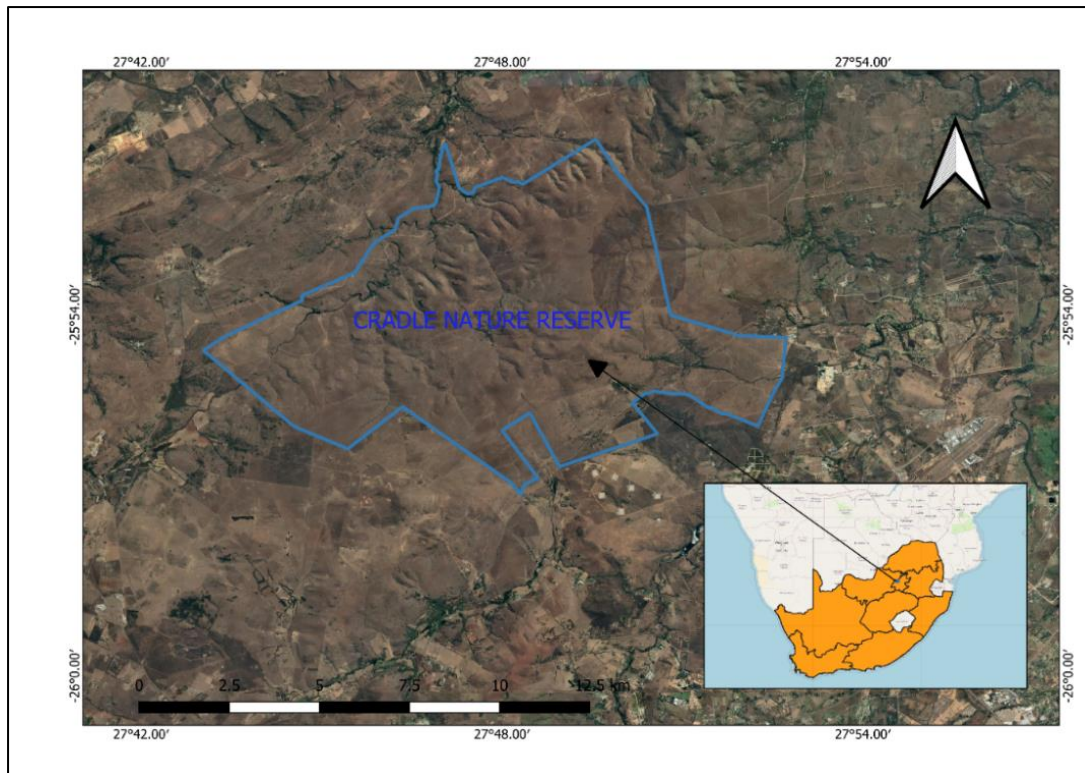


Figure 4- 1: Study Area – Cradle Nature Reserve in South Africa with Overview of the Google Earth Pro Imagery in UTM/WGS84 plane coordinate

The Cradle Nature Reserve extends approximately 8,000 hectares within the COHWHS. It houses a substantial and wide array of plants, dominated by a wide variety of flowering plants and faunal species, including over 200 species of birds (SA-Venues.com, 2022). The nature reserve is woody along ravines and inside the numerous dolomitic sinkholes that shield trees such as white stinkwood and shrubs from natural forest fires (FLOW Communications, 2022). The landscape is associated with Rocky Highveld Grassland, known as fire climax grasslands, based on their adaptation to fire (FLOW Communications, 2022). The landscape has many natural springs, watercourses, and streams that are tributaries to the Magalies and Crocodile Rivers (FLOW Communications, 2022). Most LC is grassland, considered semi-natural because it arises from anthropogenic and natural processes (Mairota et al., 2013). The current landscape has a history of land degradation due to human activities such as subsistent farming by the Bantu people and commercial farming since the 1890s. At the time of the establishment of the Cradle Nature Reserve, the area consisted of consolidated farms (Department of Rural Development and Land Reform, 2022) where there had been a long period of grazing by domesticated livestock and deliberate burning regimes. After conversion to a nature reserve, wild animal species were reintroduced with grazing and herbivorous behaviours differing from the domestic animals. This resulted in shrub invasion of the natural grasslands in the Cradle Nature Reserve (Mairota et al., 2013). rainfall in the nature reserve averages between 650 and 750 mm per year. At the same time, temperatures can rise to 39° C in summer and fall as low as -12° C in winter (SA-Venues.com, 2022). The study area is a significant tourist destination in South Africa due to its rich archaeological history and its association with early human ancestry. Tourism sustains the local economy through income generation for the hospitality

industry and creates employment. Therefore, the area's biodiversity is significant for tourism and archaeological studies, particularly the native vegetation cover, as they are critical indicators of the paleoenvironments and paleo diets. Moreover, the sustainability of rangelands in the nature reserve is important for grazing of game in the nature reserve.

4.2.2 Method

A Google Earth Engine (GEE) code was programmed to handle the downloading, preprocessing, XGBClassification, Naïve Bayes classification and accuracy assessment, as outlined in Figure 4-2 below. In recent years, XGBoost has become a de facto choice of ensemble method (Tomaszewski et al., 2021); it has been proven to provide fast, state-of-the-art results and act as a standard classification yardstick in many classification and regression scenarios (Chen & Guestrin, 2016; Pafka, 2015) more potent than the original Random Forest (Brownlee, 2017). The success of the XGBoost classifier is bolstered by its ability to be scalable in all methods, resulting in systems being ten times faster than existing popular solutions. It has algorithmic optimisation capabilities resulting in parallel and distributed computing power that enables quicker model exploration. It can exploit out-of-core computation that allows a hundred million data to process on a desktop computer. Lastly, the ensemble gives an end-to-end system that scales extensive data with a minimum number of clusters (Chen et al., 2018; Chen & Guestrin, 2016; Kavzoglu & Teke, 2022; Zhang & Chang, 2015). On the other hand, Naive Bayes is a significantly older machine learning algorithm compared to XGBoost which gained prominence in the mid-20th century (Kumawat et al., n.d.). It is a probabilistic model based on Bayes' theorem, assuming conditional independence between features (Wojcik, 2023).

Landscape metrics, LULC change detection maps production, and ground validation of the 2020 classification results were done using open software QGIS (see the workflow schematic in Figure 4-2. We selected landscape metrics in this study due to their ability to compute structural changes in land cover patterns at medium spatial resolution. Shoko and three other authors (Shoko et al., 2016) demonstrated the effectiveness of landscape metrics for studying changes in forested areas using Landsat multispectral imagery with a spatial resolution of 30m. The effectiveness of landscape metrics in assessing land cover change and fragmentation was also attested by (Kamusoko & Aniya, 2007)

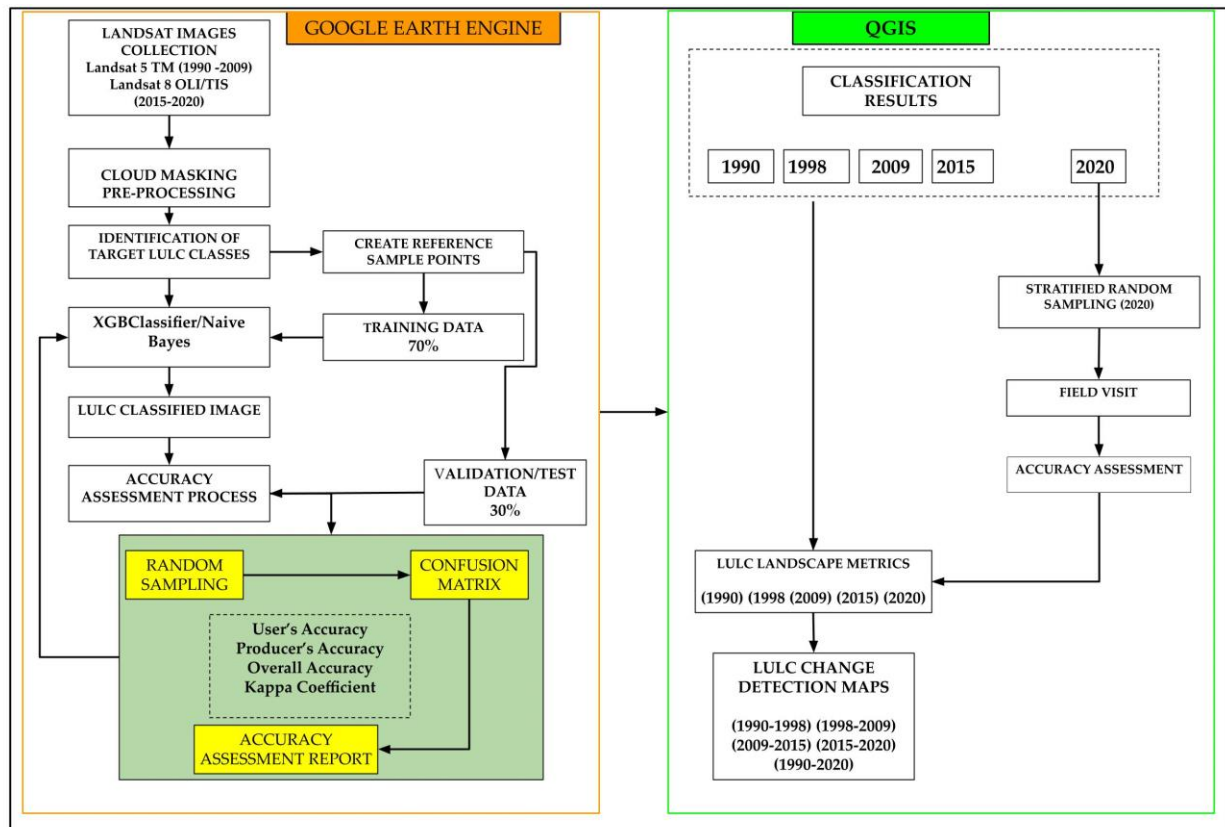


Figure 4- 2: Schematic of Workflow for Satellite data Downloading, Processing, XGBClassification, Accuracy Assessment, and QGIS processing

The workflow 4-2 is summarised as follows.

Google Earth Engine Method

1. Google Earth Engine account must in place and the necessary libraries installed in Python, including the Earth Engine Python API, scikit-learn, and XGBoost.
2. Define the region of interest (ROI) and the date range for Landsat imagery. Filter the Landsat collection to the ROI and date range. Preprocess the imagery by masking clouds and shadows.
3. Identify the target macro and micro LULC classes (Indigenous Forest, Open Bush, Natural Grassland and Bare Rock). Generates uniformly random points within the given classes (Feature Collection). Create training data and validation data. Split data into training (70%) and validation sets (30%). Sample pixels from the Landsat imagery within the (ROI)- (creating training samples).
4. Choose the bands to use. Prepare the training and validation datasets as NumPy arrays. Train the XGBoost classifier (Define the hyperparameters for tuning)/Naive Bayes ($\lambda=0.5$) accuracy assessment using training and validation data sets. If the user's accuracy, producer's accuracy, overall accuracy, and Kappa coefficient are within range, proceed to step 5. Otherwise, repeat steps 3 and 4 (you might need to retune hyperparameters).

5. Use the trained classifier to classify the entire Landsat image. Export the image to Google Drive for use in QGIS.

QGIS stratified random sampling.

1. Open QGIS. Load the images from Google Earth Engine to perform stratified random sampling.
2. Use the macro classes Indigenous Forest, Open Bush, Natural Grassland and Bare Rock for stratification. Calculate the size of the samples within each stratum.
3. Go to the Processing Toolbox (Ctrl+Shift+T). Search for the "Random selection within subsets" tool.
4. Run the tool. This will create a new layer with the stratified random sample.
5. Add the sampled layer to your map to visualise the selected features.
6. Load data to Handheld GPS and field visits
7. Compare the classified image to ground truth for accuracy assessment.

QGIS Landscape Metrics Plugin.

1. Load the images from Google Earth Engine.
2. Go to the "Raster" menu and select "Landscape Metrics." Select the land cover or land use raster layer.
3. Choose the attribute field that represents the land cover or land use classes
4. Choose the metrics you want to calculate from the available options. You can select multiple metrics and specify output options:
5. Choose where to save the output file (e.g., a shapefile).
6. Click the "Run" button to start the calculation.
7. Export the calculated metrics for further analysis or reporting.

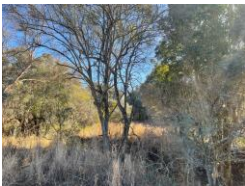
4.2.2.1 Satellite Data Downloading, Processing, and Classification

Satellite imagery from Landsat was collected for the years 1990, 1998, 2009, 2015, and 2020. These images were chosen based on their availability and suitability for interpreting landscape changes. May was selected as the month for image acquisition because it provides optimal conditions for interpreting landscapes based on natural vegetation separation, aligning with a Department of Environmental Affairs (DEA) report (Thompson, 2019). Landsat images were obtained from the United States Geological Survey (USGS) via the Google Earth Engine (GEE) platform. The Landsat data had already undergone atmospheric correction. Pixel values in the band set were converted to reflectance values, a necessary step before image classification. The selection of landscape levels (macro class) for classification was guided by expert knowledge and established classification systems, including Oregon Land Cover Standards, FAO Land

Cover Classification Systems (LCCS) (Hardy & Anderson, 1973), and the South African Land Cover Database Project (Gregorio, 2016). Three landscape levels (macro class) and four class levels (micro class) were chosen for analysis, Table 4-1. Water features in the Cradle Nature Reserve were excluded from the landscape classification levels due to their small size relative to other landscape features and the limitations of the spatial resolution of the imagery.

Aided by field surveys, visual interpretation, and comparison of ETM and temporal Google Earth images from 1990 to 2020, the selection of the reference sample data was accomplished. The visible spectral characteristics of the reference sample data points were identified on the composite image. The coded GEE algorithm calculated the spectral signatures for training the Extreme Gradient Boosting Random Forest Classifier (XGBRFCClassifier) (Southworth et al., 2004). False colour combinations for the identification of the different spectral characteristics of LULC were used guided by Quinn (Quinn, 2001)

Table 4- 1: Descriptions of the LULC types

Macroclasses (landscape level)	Class name (class level)	Adopted from Appendix B: 73 x Class National LC Legend and Class Definition (Department of Environment Forestry and Fisheries, 2021b, 2021a)
Forest	Indigenous forest	Natural tall woody vegetation communities, with canopy cover ranging between 35%–75% and canopy heights exceeding 2.5 m. They are typically represented by dense bush, dense woodland, and scrub communities. 
	Open bush	Natural tall woody vegetation communities, with canopy cover ranging between 10%–35% and canopy heights exceeding 2.5 m. They are typically represented by open bush and woodland communities. 
Grassland	Natural grassland	Natural and semi-natural indigenous grasslands typically lack significant tree or bush cover, and the grassland component is dominant over adjacent exposed bare ground. Generally representative of low, grass-dominated vegetation communities in the Grassland and Savanna Biomes. 
Bare	Bare ground/rock outcrop	Semi-natural or man-created non-vegetated areas. It is typically associated with permanent or near permanent bare ground sites that have insufficient spatial or temporal characteristics to be otherwise classified. 

4.2.2.2 XGBRFFClassifier

Random Forest is an ensemble technique constructed by combining many decision trees. One such ensemble technique that underpins this study is the Extreme Gradient Boosting (XGBoost) technique, which implements gradient tree boosting decision tree algorithms where a predictive solution is achieved by simplifying the problem objectively and reducing the number of iterations to get an optimised solution (Kavzoglu & Teke, 2022). XGBoost, also known as gradient boosting, multiple additive regression trees, stochastic gradient boosting, or gradient boosting machines, consists of an ensemble technique called Boost, in which errors made by existing models are corrected by sequential addition of new models until there is no further improvement (Brownlee, 2018), according to (Brownlee, 2017) boosting aims to determine whether a weak learner could be modified to improve. The first known accomplishment of boosting was through the application of adaptive boosting, where the vulnerable learners in the algorithm were the decision trees with a single split, also known as decision stumps. In recent years, adaptive boosting and related algorithms have been remodelled in statistical frameworks and are now known as gradient-boosting machines (Brownlee, 2017). These new models cast boosting as a numerical optimisation problem where the objective is to add weak learners to a model and use a gradient descent procedure to minimise loss by the model (Brownlee, 2017). Predictions of the residuals of prior models are summed up to make the final prediction in an approach that involves three elements: loss function optimisation, weak learner prediction, and additive model to vulnerable learners to minimise the loss function called Gradient Boost (Brownlee, 2017, 2018).

In recent years, XGBoost has become a de facto choice of ensemble method (Tomaszewski et al., 2021) has been proven to provide fast, state-of-the-art results and act as a standard classification yardstick in many classification and regression scenarios (Chen & Guestrin, 2016; Pafka, 2015) more potent than the original Random Forest (Brownlee, 2017). The success of the XGBoost classifier is bolstered by its ability to be scalable in all methods, resulting in systems being ten times faster than existing popular solutions (Abedi et al., 2022; Chen & Guestrin, 2016; Hendrawan et al., 2022). It has algorithmic optimisation capabilities resulting in parallel and distributed computing power that enables quicker model exploration (Chen & Guestrin, 2016). It can exploit out-of-core computation that allows a hundred million data to process on a desktop computer (Chen & Guestrin, 2016; Hendrawan et al., 2022). Lastly, the ensemble gives an end-to-end system that scales extensive data with a minimum number of clusters (Chen & Guestrin, 2016). The XGBRFFClassifier was selected for LC classification because of its computation efficiency and classification effectiveness compared to the conventional LC per pixel parametric and non-parametric classifiers, and it is a relatively new machine learning algorithm (Chen & Guestrin, 2016). Its difference from other machine learning algorithms is attributed to its computational proficiency, which is bolstered by the algorithmic optimisation that enables it to simultaneously synchronise the objective function, loss function, and regularisation of the model complexity, enabling parallel computing and computational speed (Brownlee, 2017, 2018; Chen & Guestrin, 2016; McCarty et al., 2020; Pafka, 2015; Sagar, 2019). So far, new opportunities for studying temporal LC changes that affect land degradation have been created by integrating XGBoost, Random Forest, and fragmentation analysis (Al-Hameedi et al., 2022; Chen & Guestrin, 2016; Kussul et al., 2017; McCarty et al., 2020).

Implementing the XGBoost classifier involved coding the algorithm in GEE and tuning hyperparameters. Model training and validation parameters were 70/30, training and testing. These parameters were adopted from a successful study, 'Evaluation of light gradient boosted machine learning technique in large scale land use and land cover classification' (McCarty et al., 2020). In the GEE algorithm, Bands SRB1 (Blue), RSB2 (Green), and SRB3 (Red) for 1990–2009 and SRB2 (Blue), SRB3 (Green), and SRB4 (Red) for 2015 to 2020 were used for image classification. In XGBRFClassifier, it is paramount to explore various hyperparameter configurations to find the best configuration that yields the best performance, and it is not easy to get the optimal one (Maladkar, 2018; Sagar, 2019). Hyperparameter tuning is essential for shaping the model architecture to achieve high precision and accuracy. This study employed the built-in code in the GEE environment 'ee.Classifier.smileGradientTreeBoost' to search for the best hyperparameter configurations (see Table 4-2). Changing this hyperparameter did improve the overall accuracy of the classifications.

4.2.2.3 Naïve Bayes

The concept of Bayes' theorem, based on Naive Bayes, was developed by the Reverend Thomas Bayes in the 18th century (precisely, in the 1700s) (Kumawat et al., 2024; Wojcik, 2023). The "naive" variant of Bayes' theorem, which assumes conditional independence among features, was later introduced and popularised in machine learning and statistics (Dewi et al., 2023). The parametric classification algorithm gained prominence in the mid-20th century, particularly in natural language processing and text classification (Sunil Ray, 2023). Naive Bayes is simple to implement, computationally efficient, and particularly fast when dealing with high-dimensional data (Sunil Ray, 2023; Wojcik, 2023). Its disadvantage is that it assumes feature independence, which can be a limitation in cases where features are dependent. It can be sensitive to noisy or irrelevant features and may not perform as well on more complex datasets (Sunil Ray, 2023). Its advantages are that it can perform well when the naive independence assumption is reasonably valid, such as in text classification tasks, is computationally efficient, and scales well to large datasets. Typically, it has fewer hyperparameters to tune, making it easier to use "out of the box." (Dewi et al., 2023; Sunil Ray, 2023; Wojcik, 2023). Implementing the Naïve Bayes classifier involved coding the algorithm in GEE and tuning hyperparameters. Model training and validation parameters were 70/30, training and testing. These parameters were the same as for the XGBRFClassifier; SRB2 (Blue), SRB3 (Green), and SRB4 (Red) for 2020 were used for image classification. The only hyperparameter to be tuned was lambda, which was set to 0.5.

Table 4- 2: Hyperparameters configurations.

Hyperparameter	Value
Number of decision trees	20
Shrinkage (the shrinkage parameter controls the learning rate of the procedure)	0.05
Sampling rate (the sampling rate for stochastic boosting)	0.70
Maximum node (the maximum number of leaf nodes in each tree)	20
Loss (loss function for regression)	Least Absolute Deviation
Seed (the randomisation seed)	0

4.2.2.4 Assessment of Classification Accuracy

It is prudent that before using the classification maps as decision-making tools, an essential step to assess how effectively the pixels using the classification algorithm are sampled into the correct LC classes (Rwanga & Ndambuki, 2017). The accuracy assessment is a fundamental concept necessary to address reliability issues on the mapped changes corresponding to the actual change areas. It quantitatively evaluates the suitability of maps for the intended application (Olofsson et al., 2013). Generally, by comparing the three accuracies, UA, PA, overall accuracies and F1-score, researchers can select the most suitable algorithm for a given classification problem. We used the comparison of Naïve Bayes and XGBRFCClassifier to set a baseline performance for our task. We used the 2020 data set for the comparison as it was the more recent data set which compares well with ambient landscape configuration, and which could also be validated by ground truthing. Naive Bayes is a simple and often fast algorithm that can serve as a benchmark. If XGBoost doesn't significantly outperform Naive Bayes, it might not be worth the additional complexity, which requires more resources. This study used classified image data from 1990 as the benchmark for analysis of the preceding years. The Confusion Matrix generated by the GEE codes for the training data and the test was used for the LULC accuracy assessment. The three accuracies, the UA, the PA, the overall accuracy, and the kappa index, were automatically computed using the codes. These two accuracies were, in turn, used to determine the F-score, a pixel-based accuracy assessment of the classifying algorithm; it shows the goodness of the classifier in the context of the PAs and UAs (Matarira et al., 2022).

$$F - score = 2 * (UA*PA)/(UA+ PA)) \quad (1)$$

The F-score percentage deviation was calculated for the corresponding classes in the study years to assess the classifier's accuracy over the study years.

4.2.2.5 Ground Truthing Sampling Techniques and Field Surveys

Stratified random sampling within the Cradle Nature Reserve was applied to collect field data using a Garmin eTrex 20 handheld GPS. This probability sampling technique, which divides

the population into smaller groups with shared characteristics, was ideal for the already defined subgroups (strata) or areas of uniform thematic composition (Nusser & Klaas, 2003). The number of random samples in each LULC was proportional to the total area covered by each stratum according to the Random Forest classification of 2020. The Random Forest classification raster data (tif map) had to be polygonised (raster to vector conversion) and the geometry fixed (fixed geometries) in the QGIS plugin. The fixed geometries belonging to the same class were then combined (that is, dissolved) into Random Forest classes for 2020. Using the analysis tool, the sampling points inside the polygons (classes) were generated (random points inside polygons) (Congedo, 2021; Grinberg, 2022; Henrico et al., 2021). These points were then converted to WGS 84 coordinates for use in the field for surveying ground-truthing and accuracy assessment data.

The targeted points were located using the cardinal direction (N-S or E-W). Point attribute data were collected according to the predefined classification criteria for each surveyed or stacked point. In areas where this survey method fails due to the rugged terrain, natural topography, and drainages, Google Earth images from May 2020 were used to assist in populating the ground truthing data.

4.2.2.6 The Landscape Metrics

Landscape metrics underpin the study of natural forest fragmentation; they provide numerical information and temporal analysis of the landscape composition, configuration, and dimensions (Martinez del Castillo et al., 2015). Fragmentation metrics at the patch, class, and landscape levels for the different LULC classes were performed using Landscape Ecology Statistics (LecoS), the QGIS python plugin (Congedo, 2021; Fasona et al., 2018; Southworth et al., 2004). LecoS has the function for calculating metrics on raster and vector data layers based on metrics derived from FRAGSTATS software and is embedded with functions to manipulate classified raster images (Congedo, 2021). FRAGSTATS software is well known for its detailed spatial and summary statistics that quantitatively describe patterns at patch, class, and landscape levels (Southworth et al., 2004). According to Matsushita and two other authors (Matsushita et al., 2006), although FRAGSTATS can calculate more than 100 landscape metrics, most metrics are highly correlated. The following metrics adapted from (Martinez del Castillo et al 2015; are effective in evaluating forest cover changes using remote sensing data and were used in this study:

- a) Total landscape area (ha) (TA): useful for landscape fragmentation analysis. It is the sum of the area of all patches in the landscape. TA increases without limit as the size of the landscape increases.
- b) Percentage of Landscape (PLAND): useful for class-level fragmentation analysis. PLAND approaches zero as the proportional class area decreases, and if one patch is present, then PLAND will equal 100.
- c) Largest patch index (LPI): determines the area of the most extensive patch in each class, expressed as a percentage of total landscape area, useful for landscape and class-level fragmentation analysis. LPI is a measure of dominance; as the value approaches zero, the largest patch gets smaller; an LPI of 100 indicates that one patch is present.

- d) The number of patches (NP): indicates the total number of patches. It is helpful for landscape and class-level fragmentation analysis. For a single patch, NP equals one, and the NPs increase as NP increases unlimitedly, the more fragmented the landscape.
- e) Patch density (PD): indicates the number of patches per unit area. It is useful for landscape and class-level fragmentation analysis. Higher PD tells a highly fragmented landscape.
- f) Mean patch size (MPS): provides the average patch size for the class in hectares. It is useful for landscape and class-level fragmentation analysis. A small MPS implies a highly fragmented landscape.
- g) Patch cohesion index (COHESION): provides valuable information for class-level connectivity analysis. COHESION approaches zero as the patches become more isolated, and higher values indicate more aggregated patches.
- h) Shannon's diversity index (SHDI) provides valuable information for landscape-level heterogeneity analysis. Its value ranges from 0 to 1; it approaches 0 as the landscape is dominated by one LC type or less diversity. It approaches one as the LC types become roughly equal, implying a more diversified landscape.

From the listed metrics, the study derived the hypothesis testing of the landscape metrics Table 4-3. Hypothesis testing of landscape metrics is essential to landscape ecology and spatial analysis (Abedini et al., 2020; Mcalpine & Eyre, 2003). Landscape metrics provide quantitative measures of landscape patterns and spatial characteristics, and hypothesis testing allows researchers to draw meaningful conclusions about the ecological processes and phenomena driving these patterns (Abedini et al., 2020; Mcalpine & Eyre, 2003). It enables researchers to explore ecological questions, compare landscapes, detect changes over time, and make informed decisions about land management and conservation strategies based on objective and statistically sound evidence (Mcalpine & Eyre, 2003).

Table 4- 3: Hypotheses for landscape metrics

Landscape metric	Hypothesis
Total Landscape area (TA)	The total landscape area for each class in the cradle nature reserve has been altered by land cover degradation during the study period (1990 to 2020)
Landscape Proportion	Land cover degradation has altered the proportion of landscape area for each class during the study period (1990 to 2020).
Patch Density	There was an increase in landscape fragmentation in the study period (1990 to 2020) due to the rise in the number of patches per unit area.

Number of Patches	There is an increase in landscape fragmentation in the study period (1990 to 2020) due to the rise in the total number of patches.
Largest Patch index	One class of land cover dominates during the period (1990 to 2020) in the study area.
Mean Patch Area	There is a decrease in the average size of patches in each class due to land cover degradation during the study period (1990to 2020)
Patch cohesion index	There are no isolated classes (landscape class-connectivity) in the cradle nature reserve landscape during the study period (1990 to 2020)
Shannon Index	The cradle nature reserve landscape is dominated by one land cover class during the study period (1990 to 2020)

4.2.2.7 Land Use/Land Cover Changes

The LULCC detection was done using the QGIS plugin SCP postprocessing LC change tool for 1990–1998, 1998–2009, 2009–2015, 2015–2020, and 1990–2020. The input data for this process was the landscape classification maps/tagged image file (tif) produced using the XGBRFCClassifier. The classification nomenclature was identical (number and sequence of LULC Macroclasses and classes) for all the years to generate harmonised geometric and thematic content (Smiraglia et al., 2015). Maps showing the transition of landscape patches within the time frames were developed to depict the changes.

4.3 Results

4.3.1 Comparison of Accuracy Assessment of Classification Algorithms using 2020 data set

Table 4-4 show the comparison of the three accuracies, UA, PA, overall accuracies and F1-score for the 2020 data. As already stated in section 2.2.4, if XGBoost accuracies and F1-score doesn't significantly outperform Naive Bayes, as demonstrated in our study see Tables 3, it might not be worth the additional complexity, which requires more resources. However, in this study, we were not resource-constrained. We elected to use XGBRFCClassifier after assessing the comparison results in Table 4-4 instead of Naive Bayes, which is generally less resource-intensive and saves computational resources and time (Kumawat et al., 2024). The following reasons motivated our selection:

- **Future-Proofing:** Even if XGBRFCClassifier does not significantly outperform Naive Bayes on our current dataset, it may be more adaptable to future changes in data distribution or feature set(Andriy Burkov, 2019). Naive Bayes is relatively simple and may not handle data shifts or feature additions as gracefully as XGBRFCClassifier (Hendrawan et al., 2022).
- **Continuous Model Improvement:** In machine learning competitions and real-world applications, practitioners often use a variety of algorithms, including

XGBRFClassifier, to continually improve model performance. XGBRFClassifier can be an essential tool in this iterative process (Andriy Burkov, 2019).

- **Advanced Techniques:** XGBRFClassifier supports advanced techniques like gradient boosting, early stopping, and custom loss functions, which can be leveraged to improve performance in specific scenarios(Andriy Burkov, 2019; Irwanto & Goeirmanto, 2023).
- **Scalability:** XGBRFClassifier is designed to scale efficiently to large datasets, making it suitable for situations where you have a massive amount of data that Naive Bayes may struggle to handle effectively(Andriy Burkov, 2019; Hendrawan et al., 2022; Irwanto & Goeirmanto, 2023).
- **Transferability:** in future if we plan to apply our model to different datasets or similar classification tasks, XGBRFClassifier might offer better transferability (Andriy Burkov, 2019). It can adapt to varying data distributions and capture different patterns effectively(Hendrawan et al., 2022).
- **Hyperparameter Tuning:** XGBRFClassifier offers more hyperparameter tuning options and flexibility compared to Naive Bayes (Hendrawan et al., 2022). If we have the resources and time to perform thorough hyperparameter tuning, we may be able to fine-tune XGBRFClassifier to achieve better performance than the current results (Andriy Burkov, 2019; Hendrawan et al., 2022).

Table 4- 4: Accuracy Assessment for NaiveBayes and XGBRFClassifier for 2020 Confusion Matrix Derivatives

Naive Bayes (lambda=0.5)				XGBRFClassifier		
70%	Producer's accuracy	User's accuracy	F1	Producer's accuracy	User's accuracy	F1
Indigenous forest	0.87	0.78	0.82	0.88	0.85	0.86
Open bush	0.71	0.85	0.77	0.83	0.87	0.85
Natural grass	0.91	0.82	0.86	0.92	0.93	0.92
Bare ground/rock-outcrop	0.82	0.86	0.84	0.95	0.92	0.93
Overall accuracy		0.83			0.90	
Kappa index		0.76			0.86	
30%						
Indigenous forest	0.88	0.78	0.83	0.78	0.78	0.78
Open bush	0.7	0.81	0.75	0.72	0.77	0.74
Natural grass	0.93	0.77	0.84	0.96	0.83	0.89

Bare ground/rock-outcrop	0.83	0.97	0.89	0.93	0.98	0.95
Overall accuracy		0.83			0.85	
Kappa index		0.78			0.8	

4.3.2 Ground Truthing Accuracy Assessment

Data collected by the field visit could not sufficiently cover the study area owing to inaccessibility challenges outlined in the previous section (2.2.3.1). Despite the challenges 120 data points were surveyed, distributed as 30, 35, 28, 27 for Indigenous Forest, Open bush, Natural grass and Bare ground/rock-out-crop respectively. The confusion matrix derivatives (see Table 4-5) and benchmark accuracy assessment from the Naïve Bayes algorithm are high enough to confirm the usability of the classified maps for future LULC assessments of the Cradle Nature Reserve.

Table 4- 5: Accuracy Assessment for Ground Truthing Confusion Matrix Derivatives

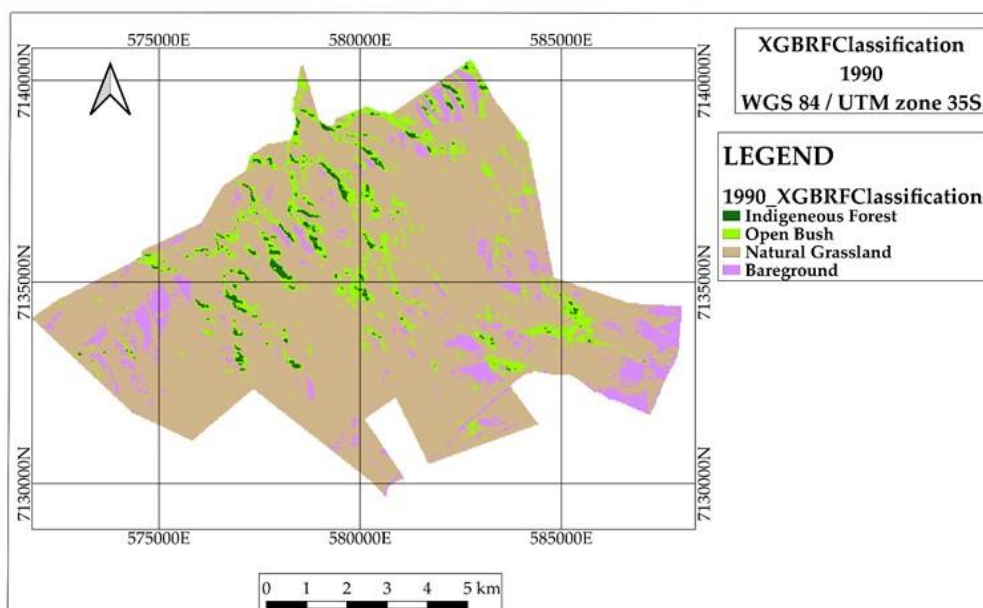
Ground truthing	2020		
	Producer's accuracy	User's accuracy	F1
Indigenous forest	0.93	0.93	0.93
Open bush	0.77	0.90	0.83
Natural grass	0.93	0.87	0.90
Bare ground/rock-outcrop	0.96	0.87	0.91
Overall accuracy		0.89	
Kappa index		0.86	

4.3.3 Accuracy Assessment and Land Cover Digital Classification of Study Area (1990-2020)

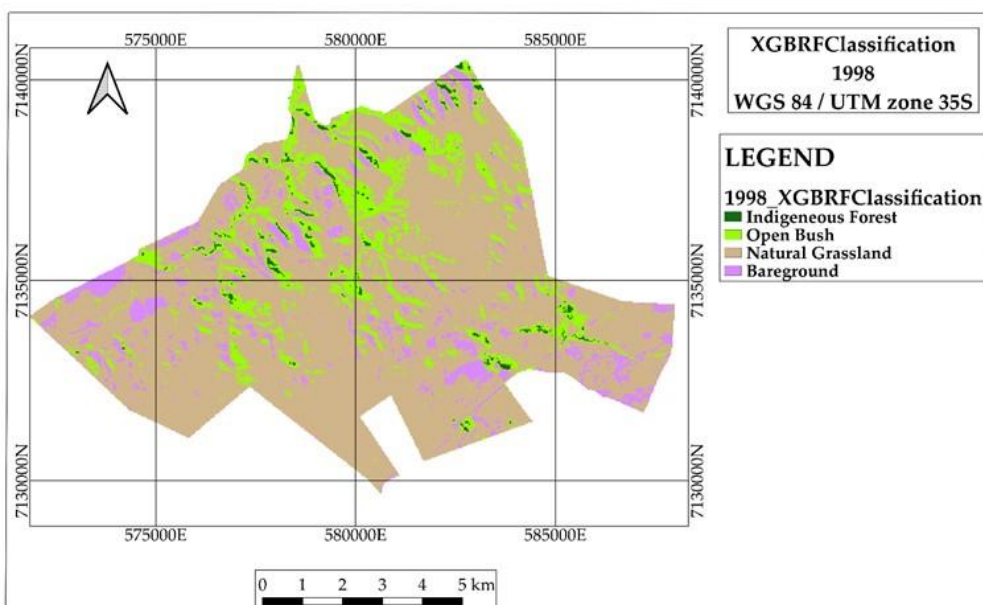
Figure 4-3(a–e) show the XGBRFClassifier classified images. The UA, PA, overall accuracy, kappa index, and F1 score are shown in Table 4-5 and Table 4-6 using a 70/30 training/testing evaluation model. An inspection of Table 4-5 and Table 4-6 shows that the overall accuracy, kappa coefficient, and F-score are sufficiently high for the onward use of the classified maps. Indigenous forest and open bush overall accuracies are generally lower than the rest because of the difficulty distinguishing them during the training data preparation.

Table 4- 6: Accuracy Assessment for XGBRFClassifier Confusion Matrix Derivatives

XGBRFClassifier	1990			1998			2009			2015		
70%	Producer's accuracy	User's accuracy	F1	Producer's accuracy	User's accuracy	F1	Producer's accuracy	User's accuracy	F1	Producer's accuracy	User's accuracy	F1
Indigenous forest	0.93	0.97	0.95	0.92	0.90	0.91	0.91	0.89	0.90	0.86	0.96	0.91
Open bush	0.95	0.92	0.93	0.82	0.89	0.85	0.84	0.91	0.87	0.90	0.84	0.87
Natural grass	0.99	0.96	0.97	0.97	0.92	0.94	1.00	0.92	0.96	0.97	0.89	0.93
Bare ground/rock-outcrop	0.97	0.98	0.97	0.99	0.99	0.99	0.96	1.00	0.98	0.94	0.98	0.96
Overall accuracy	0.96			0.92			0.93			0.92		
Kappa index	0.95			0.89			0.90			0.89		
30%												
Indigenous forest	0.93	0.80	0.86	0.92	0.76	0.83	0.88	0.77	0.82	0.72	0.88	0.79
Open bush	0.79	0.94	0.86	0.78	0.85	0.81	0.67	0.89	0.76	0.86	0.84	0.85
Natural grass	0.92	0.92	0.92	0.90	0.90	0.90	1.00	0.81	0.90	0.97	0.84	0.90
Bare ground/rock-outcrop	1.00	0.95	0.97	0.90	1.00	0.95	0.94	1.00	0.97	0.91	0.91	0.91
Overall accuracy	0.91			0.87			0.87			0.88		
Kappa index	0.88			0.83			0.82			0.84		

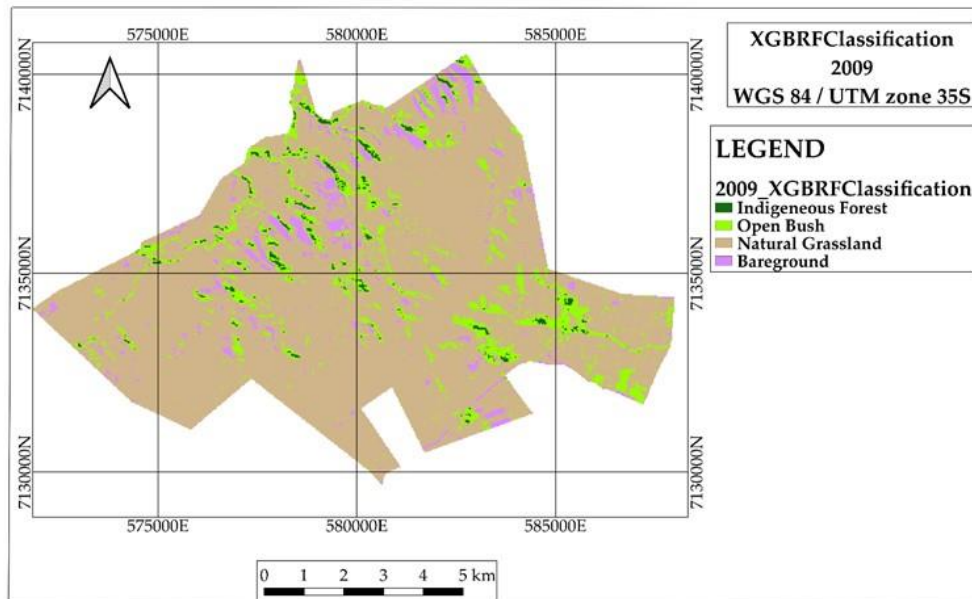


(a)

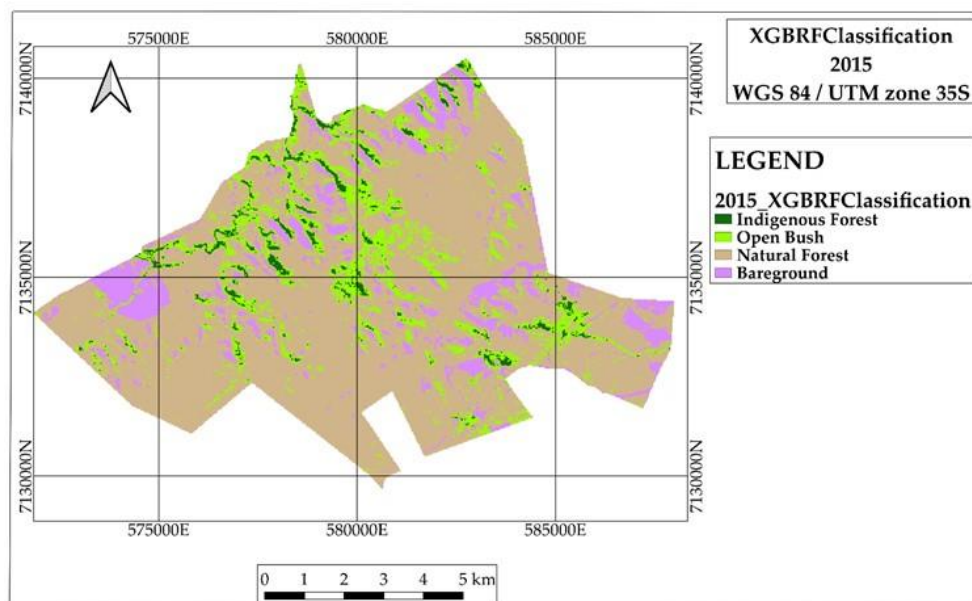


(b)

Figure 4-3. *cont.*

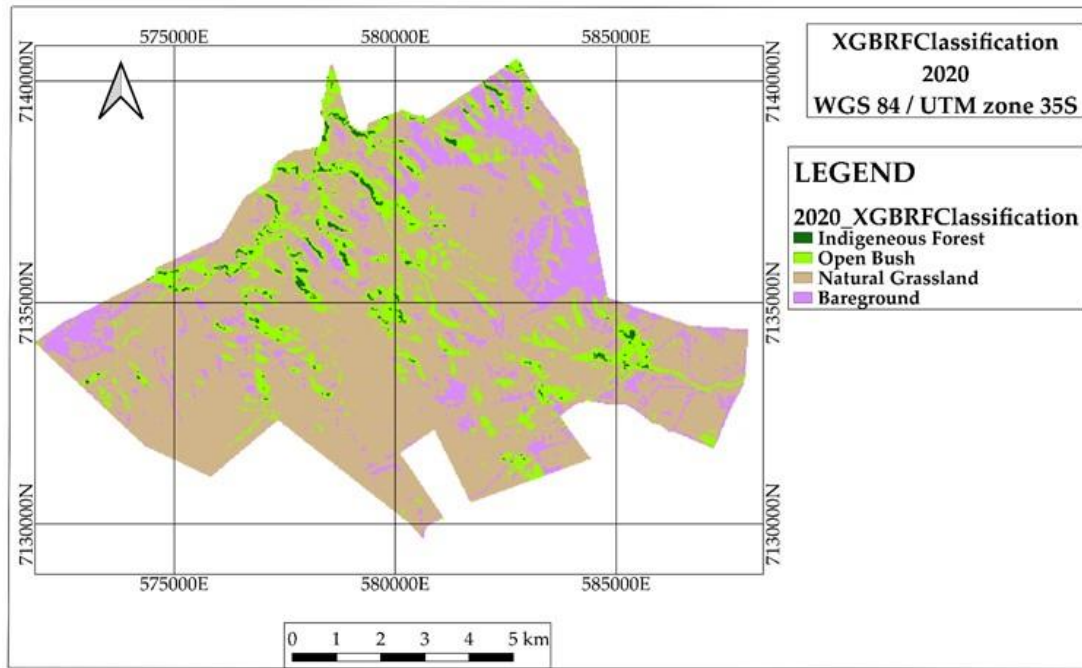


(c)



(d)

Figure 4-3. *Cont.*



(e)

Figure 4- 3: (a) XGBRFClassification image 1990; (b) XGBRFClassification mape 1998; (c) XGBRFClassification image 2009; (d) XGBRFClassification image 2015; (e) XGBRFClassification image 2020

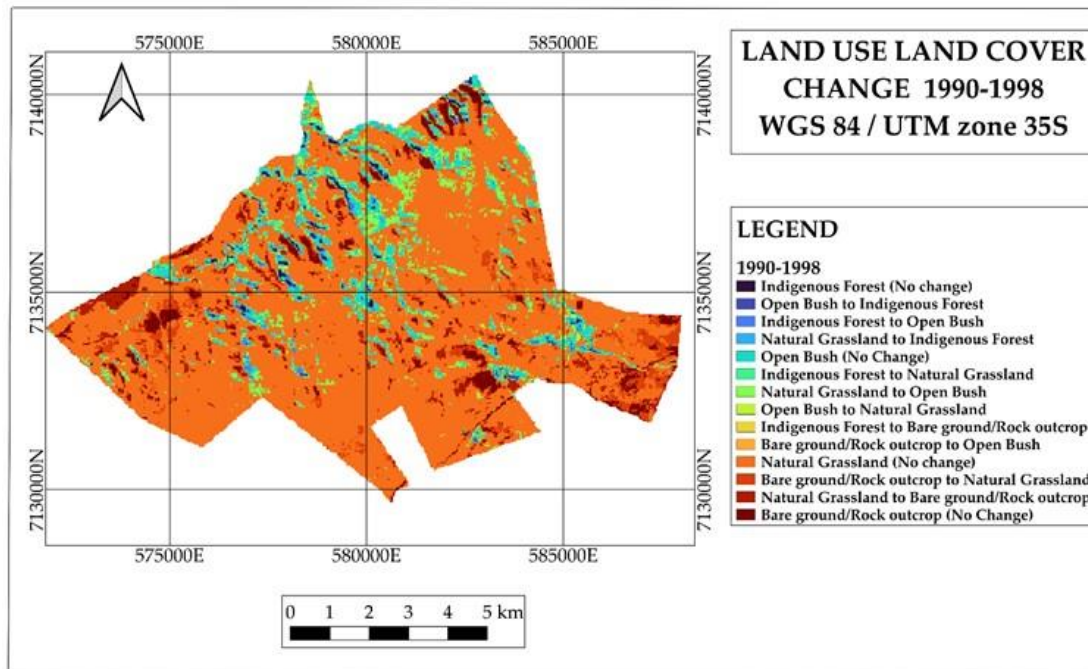
4.3.4 Land Use/Land Cover Spatial Temporal Change Detection

The LULC variations in the study area, 8624.77 hectares throughout the study period (1990–2020), are presented in Figure 4-4(a–j). It can be deduced from Table 4-7 that over the three decades, the area covered by bare ground/rock outcrop increased significantly. In 1990–1998, the landscape dominated by indigenous forest lost 45.41 hectares, open bush gained 431.76 hectares, natural grassland lost 436.93 hectares, and bare ground/rock outcrop gained 50.58 hectares. From 1998 to 2009, the landscape dominated by indigenous forest gained 15.27 hectares, open bush lost 312.83 hectares, natural grassland gained 647.16 hectares, and bare ground/rock outcrop lost 349.60 hectares. From 2009 to 2015, the landscape dominated by indigenous forest lost 120.30 hectares, open bush gained 233.66 hectares, natural grassland lost 896.09 hectares, and bare ground/rock outcrop gained 542.13 hectares. Between 2015 and 2020, a landscape dominated by indigenous forest lost 118.93 hectares, open bush lost 6.87 hectares, natural grassland lost 93.80 hectares, and bare ground/rock outcrop gained 205.86 hectares. Over the 1990–2020 period, landscape dominated by indigenous forest lost 28.76 hectares, open bush acquired 359.45 hectares, natural grassland lost 779.66 hectares, and bare ground/rock outcrop acquired 448.97 hectares.

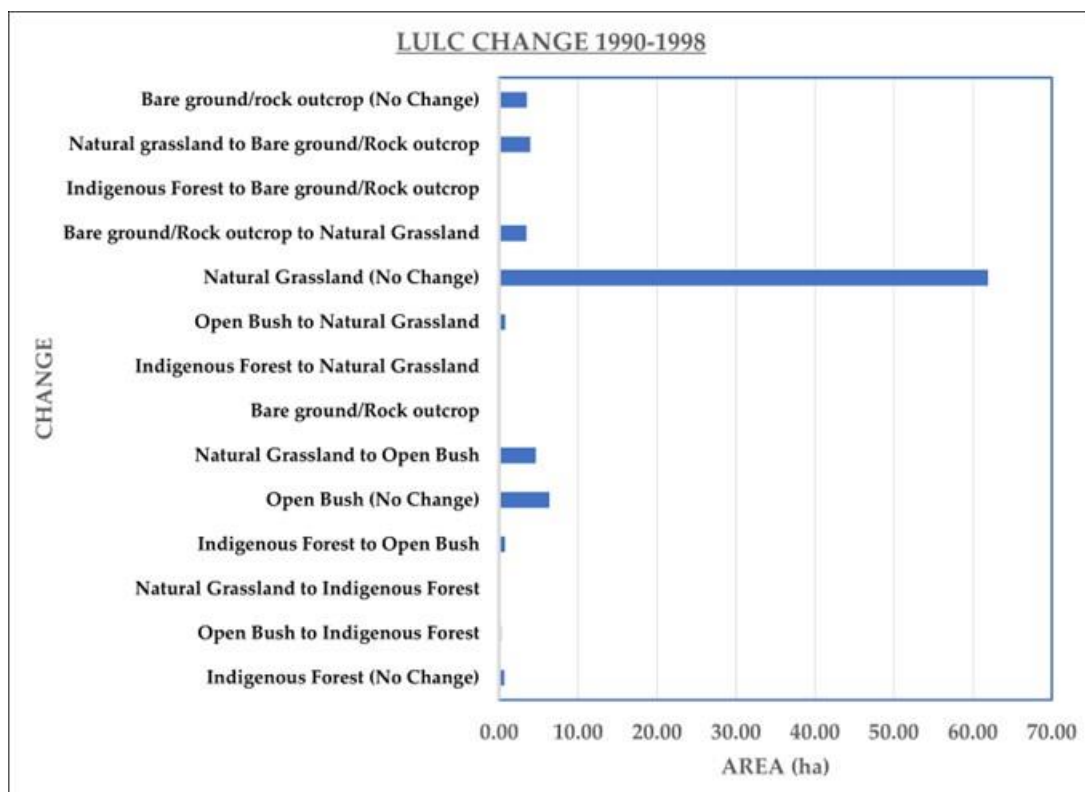
Table 4- 7: Land Use-Land Cover Spatial-Temporal Change Detection Matrices

1.	2.	1990-1998 land cover change matrix [ha]					3.	1998-2009 land cover change matrix [ha]				
4.	5. New class					6. New class						
7. Refer ence class	8.	9.	10.	11.	12. total	13.	14.	15.	16.	17. total		
18. 1	19. 5.85	20. 1.83	21. .32	22. .08	23. 38.08	24. 0.76	25. 1.75	26. .16	27. .00	28. 2.67	29.	
29. 2	30. 5.77	31. 34.64	32. 8.94	33. .00	34. 39.35	35. 5.08	36. 93.43	37. 32.51	38. .08	39. 171.11	40.	
40. 3	41. .05	42. 64.40	43. 190.69	44. 96.54	45. 052.68	46. .89	47. 16.77	48. 262.83	49. 35.25	50. 615.74	51.	
51. 4	52. .00	53. .24	54. 45.80	55. 48.63	56. 94.67	57. .21	58. 6.32	59. 67.39	60. 60.32	61. 45.24	62.	
62. Total	63. 2.67	64. 171.11	65. 615.74	66. 45.24	67. 624.77	68. 07.94	69. 58.28	70. 262.90	71. 95.65	72. 624.77	73.	
73.	74.	2009-2015 land cover change matrix [ha]					75.	2015-2020 land cover change matrix [ha]				
76.	77. New class					78. New class						
79. Refer ence class	80.	81.	82.	83.	84. total	85.	86.	87.	88.	89. total		
90. 1	91. 2.99	92. 4.95	93. .00	94. .00	95. 07.94	96. 7.44	97. 29.84	98. .97	99. .00	100. 28.24	101.	
101. 2	102. 29.43	103. 35.02	104. 84.94	105. .89	106. 58.28	107. 1.88	108. 48.88	109. 28.19	110. .99	111. 091.93	112.	
112. 3	113. .82	114. 38.82	115. 100.92	116. 17.35	117. 262.90	118. .00	119. 17.66	120. 421.77	121. 27.39	122. 366.82	123.	
123. 4	124. .00	125. .15	126. 0.96	127. 11.54	128. 95.65	129. .00	130. .42	131. 22.09	132. 13.26	133. 37.78	134.	
134. Total	135. 28.24	136. 091.93	137. 366.82	138. 37.78	139. 624.77	140. 09.31	141. 098.80	142. 273.01	143. 143.64	144. 624.77	145.	
145.	146.	1990-2020 land cover change matrix [ha]					147.					
148.	149. New class					150. key						
151. Refer ence class	152.	153.	154.	155.	156. total	157.	158. Class	159. alue	160.			
161. 1	162. 1.99	163. 6.09	164. .00	165. .00	166. 38.08	167.	168. Indigenou s Forest	169.	170.			
171. 2	172. 6.03	173. 98.76	174. 04.14	175. .40	176. 39.35	177.	178. Open Bush	179.	180.			
181. 3	182. .29	183. 27.00	184. 758.60	185. 65.79	186. 052.68	187.	188. Natural Grassland	189.	190.			

191.	4	192.	193.	194.	195.	196.	197.	198.	199.	200.
		.00	.95	10.27	77.45	94.67		Bare ground/Rock outcrop		
201.	Total	09.31	098.80	273.01	143.64	624.77	207.	208.	209.	210.

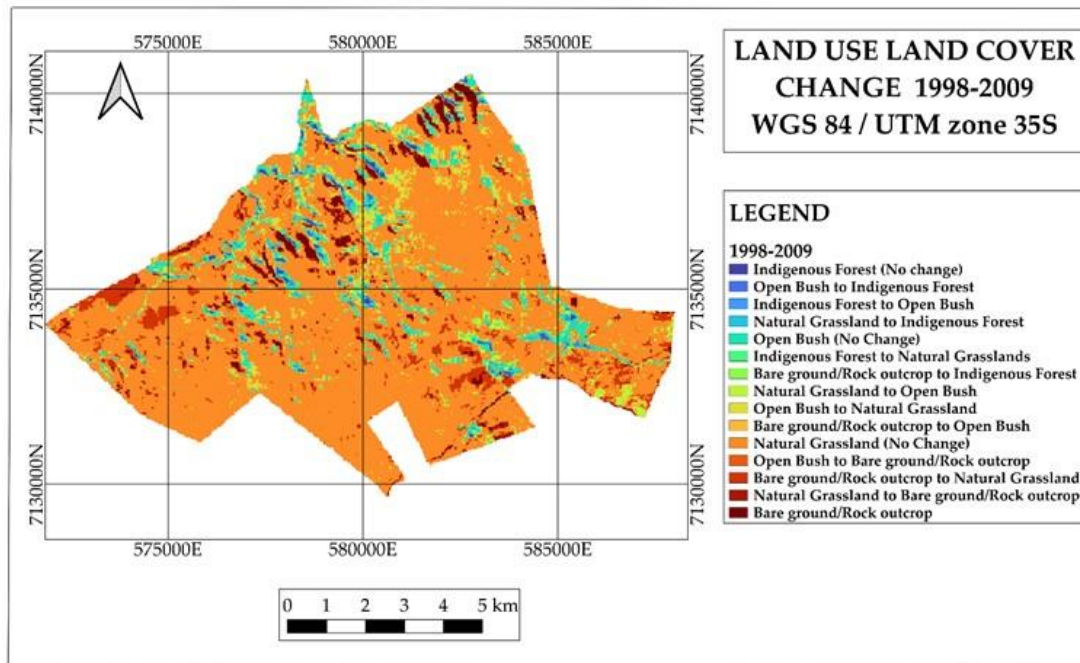


(a)

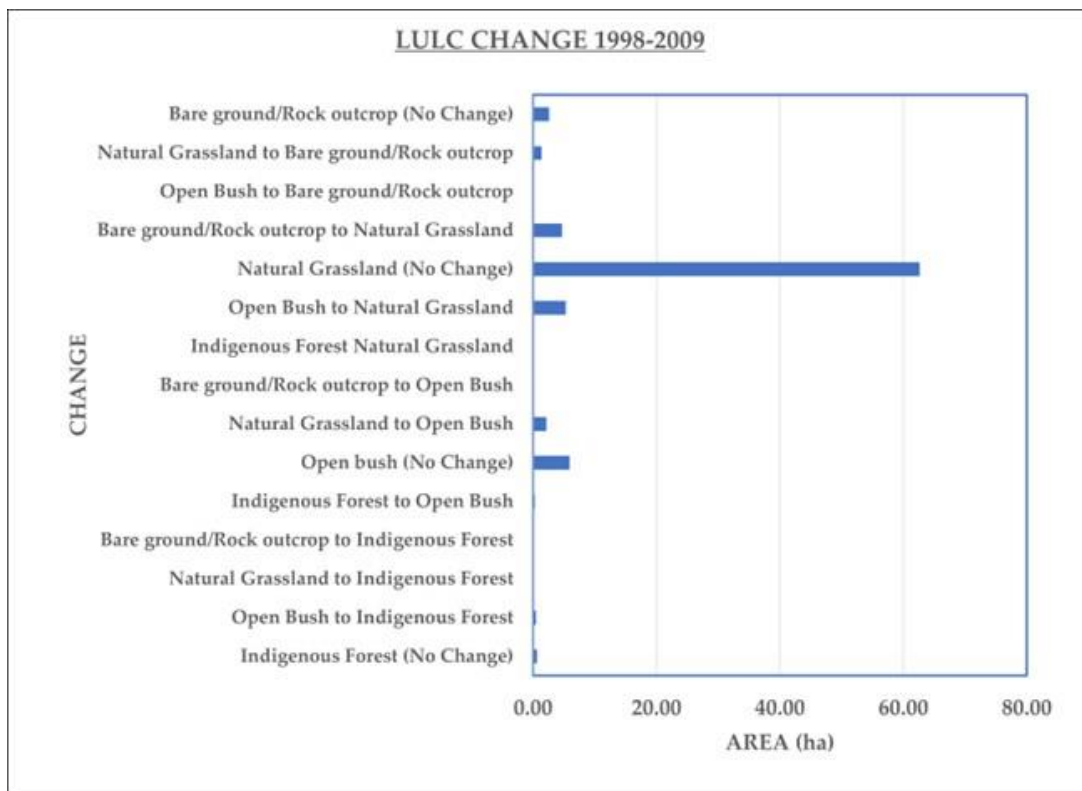


(b)

Figure 4-4. *Cont.*

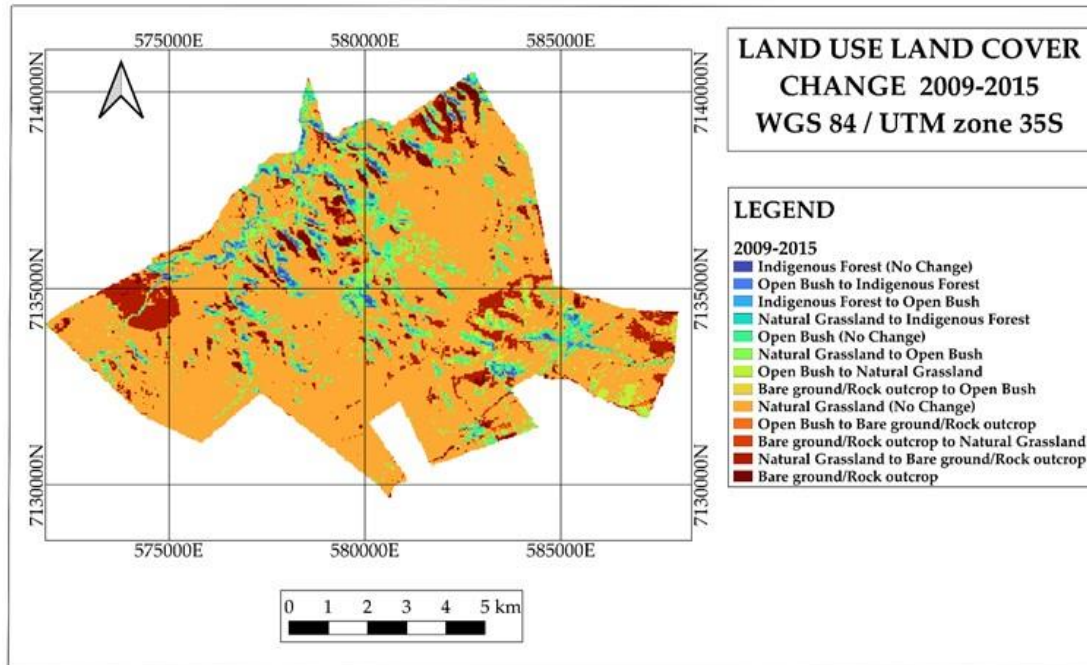


(c)

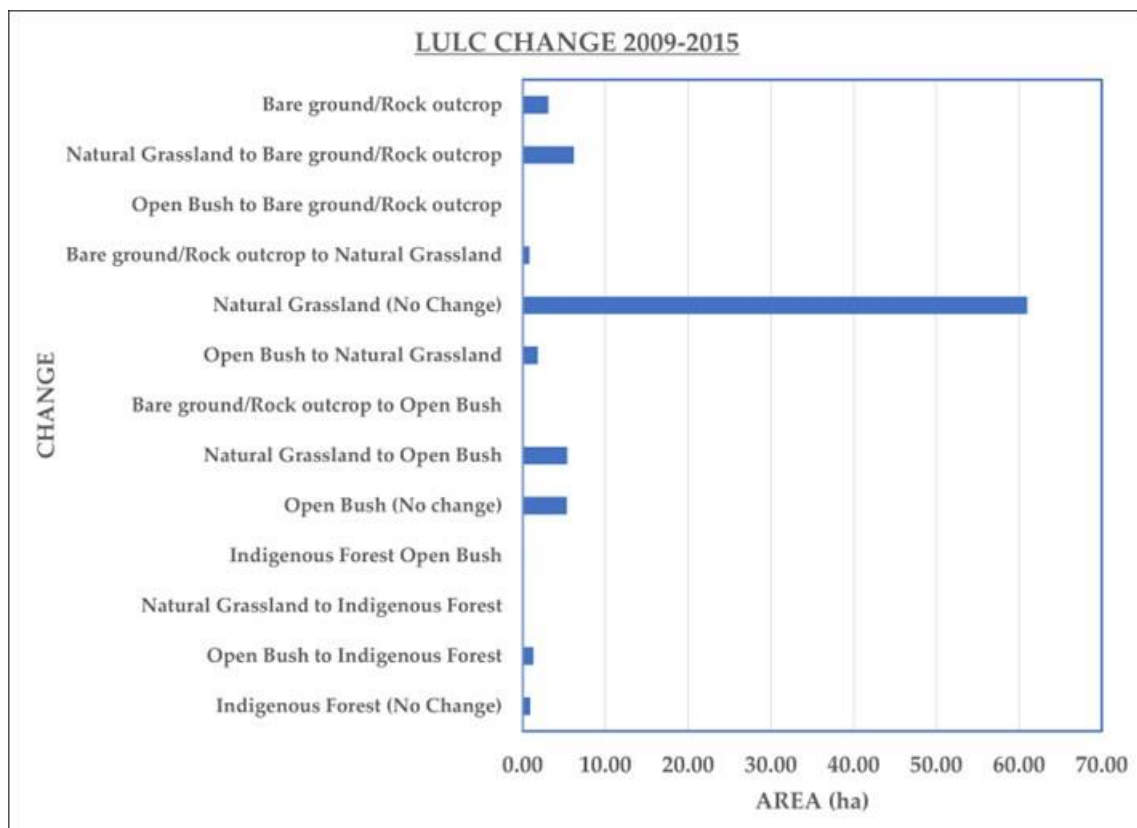


(d)

Figure 4-4. *Cont.*

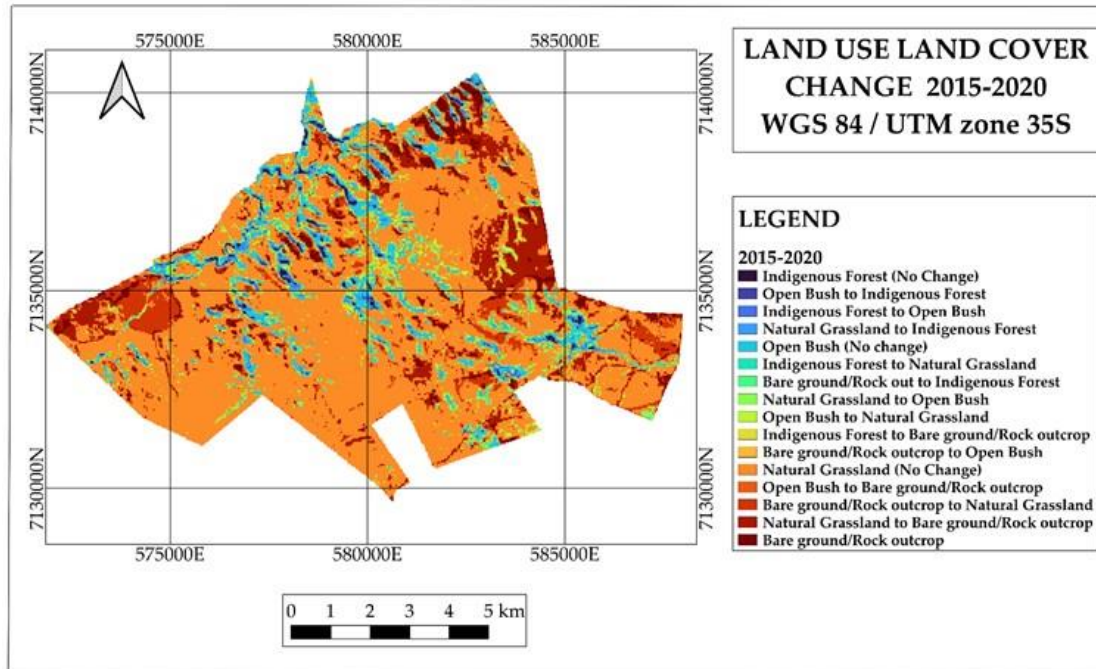


(e)

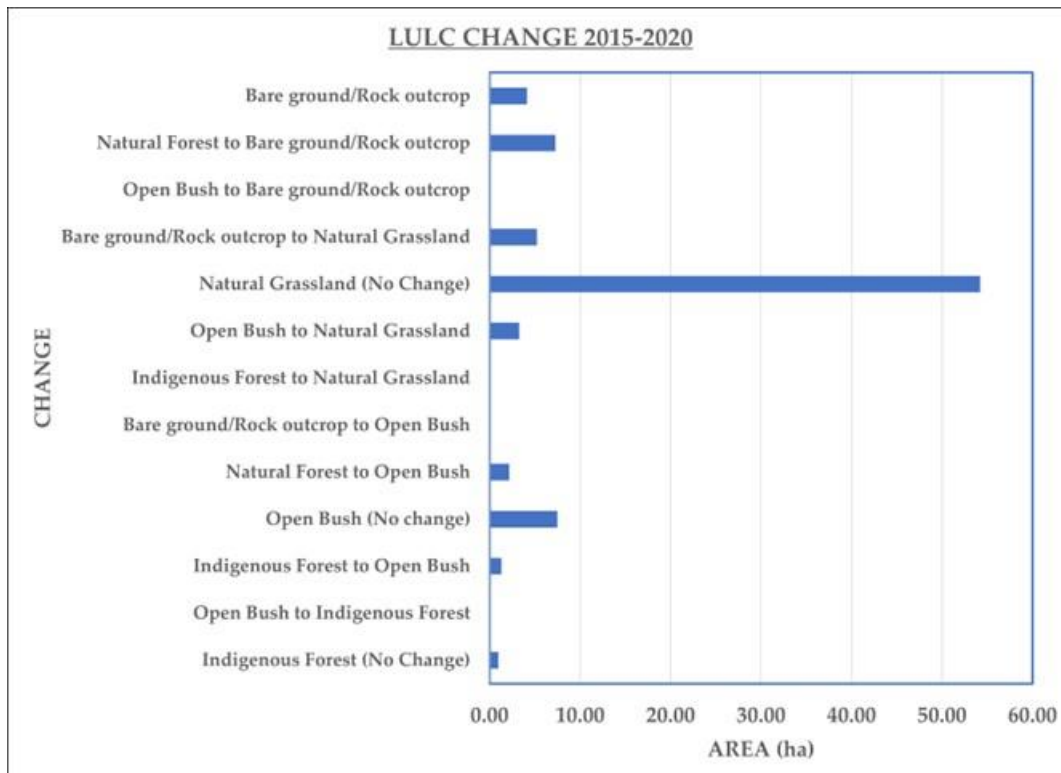


(f)

Figure 4-4. *Cont.*

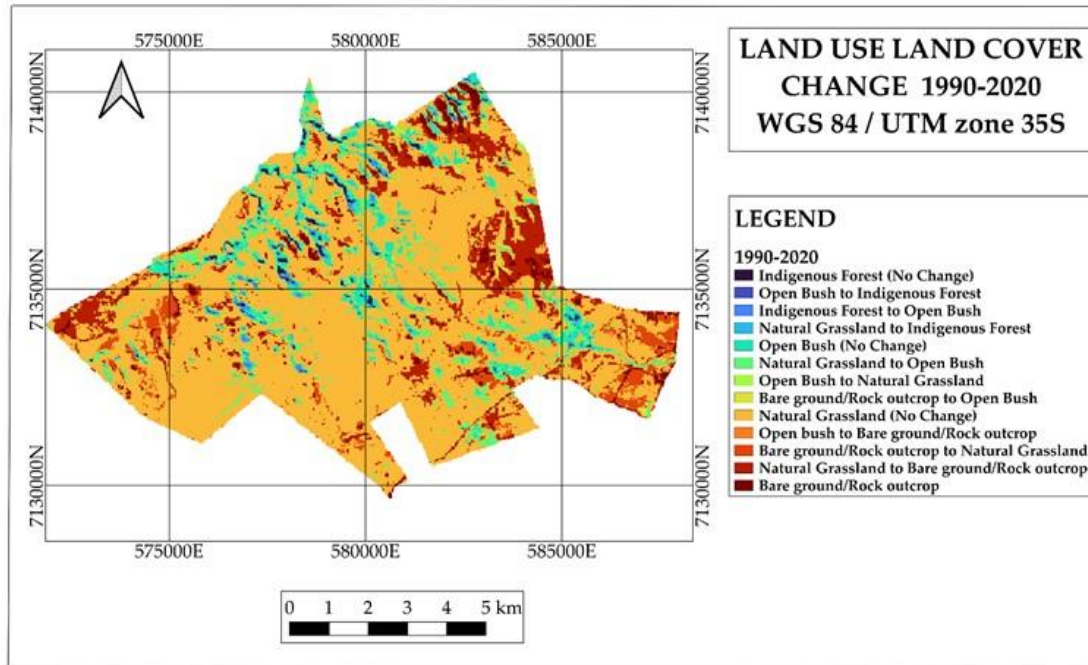


(g)

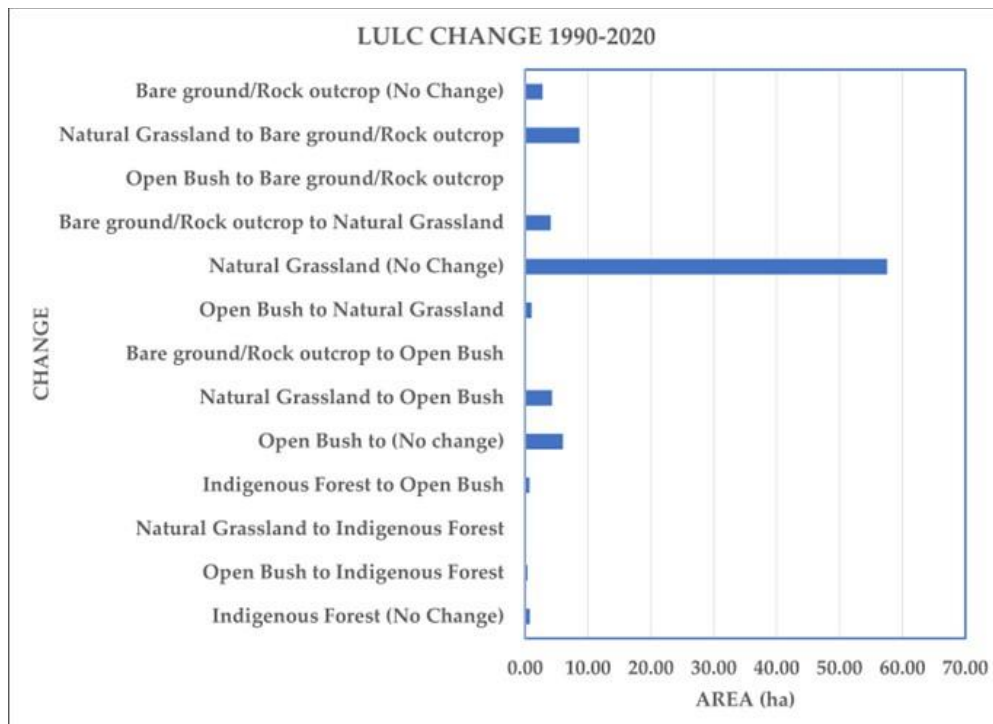


(h)

Figure 4-4. *Cont.*



(i)



(j)

Figure 4- 4: (a) LULC change 1990–1998; (b) LULC change area 1990–1998; (c) LULC change 1998–2009; (d) LULC change area 1998–2009; (e) LULC changes 2009–2015; (f) LULC change area 2009–2015; (g) LULC change 2015–2020; (h) LULC change area 2015–2020; (i) LULC change 1990–2020; (j) LULC change area 1990–2020.

4.3.5 The Landscape Metrics and Dynamics: Class Level

The total landscape areas (TA) (see Table 4-8) do not depict a straightforward pattern from one study year to another. However, over the three decades 1990–2020, from the LULC temporal change detection matrices (see Table 4-7), it can be deduced that the landscape dominated by indigenous forest lost 28.76 hectares (0.34%), open bush gained 359.45 hectares (4.23%), natural grassland lost 779.66 hectares (9.18%), and bare ground/rock outcrop gained 448.97 hectares (5.29%). The LPI for natural grassland (see Table 4-8) is significantly more than other landscape classes in the study area, indicating the dominance of grassland in the Cradle Nature Reserve. This agrees with the landscape description of the study area given by (FLOW Communications, 2022). In addition, it can be deduced from Table 4-8 that the MPS decreased by 44% from 77.19 hectares in 1990 to 43.14 hectares in 2020 for the natural grassland, indicating an increased fragmentation in the class.

The NP increased by 11% during the 1990–2020 period, indicating a more fragmented landscape in 2020 than in 1990 (see Table 4-8). There was a gradual increase in the number of patches from 1990 to 1998 (5%), 1998 to 2009 (23%), 2009 to 2015 (22%), and a significant drop in number of patches from 2015 to 2020 (29%), however the overall increase in the number of patches indicate a more fragmented landscape in 2020. A substantial change in the open bush density in the patches from 1990 to 2020 (4.72 to 9.49) indicates that the class was significantly fragmented over the three decades. The PD for natural grassland and indigenous forest shows a marginal increment of 1.06 to 2.44 and 1.94 to 3.56, respectively, indicating increased landscape fragmentation in these classes (see Table 4-8). Bare ground/rock outcrop PD dropped from 5.39 to 5.15 over the three decades, implying consolidation of the patches and a decrease in class fragmentation.

The COHESION did not change significantly over the study period (see Table 4-8). None of the index values approaches zero, indicating that the patches are not isolated and that the landscape patches did not become aggregated over the study period. The SHDI from 1990 to 2020 increased from 0.65 to 0.82, although it dipped to 0.57 in 2009 (see Table 4-8). Generally, the trend indicates a loss of dominance by one LC class. This trend confirms the dominance of natural grassland in the landscape as depicted in XGBRFC classification for 1990 to 2020 (see Figures 4–4(a-j)). However, the increase in SHDI confirms the loss of dominance of natural grassland owing to a noticeable gain in the LC by the open bush and bare ground/rock outcrop LCs (Cucco et al., 2023; Mensah et al., 2023; Mousazadeh et al., 2023; Osipova et al., 2020).

Table 4- 8: Landscape Metrics from 1990 to 2020

211. <u>Landscape Matrices May 2020</u>														
Total Landscape Area (ha)	214. Landscape Proportion	215. Patch density	216. Number of Patches	217. Largest Patch Index	218. Mean patch area	219. Patch cohesion index	220. Metric	221.						
123.57	225. 1.28	226. 2.06	227. 198	228. 0.07	229. 0.62	230. 8.03	DIV_SH	232.						
1229.22	236. 12.76	237. 4.06	238. 391	239. 2.48	240. 3.14	241. 9.59		243.						
6989.40	247. 72.55	248. 1.68	249. 162	250. 69.21	251. 43.14	252. 9.94		254.						
1292.13	258. 13.41	259. 6.76	260. 651	261. 3.13	262. 1.98	263. 9.63		264.						
	267.	268.	269. 1402	270.	271.	272.		273.						
274. <u>Landscape Matrices May 2015</u>														
Total Landscape Area (ha)	277. Landscape Proportion	278. Patch density	279. Number of Patches	280. Largest Patch Index	281. Mean patch area	282. Patch cohesion index	283. Metric	284.						
254.07	288. 2.64	289. 3.56	290. 343	291. 0.15	292. 0.74	293. 8.52	DIV_SH	295.						
1236.15	299. 12.83	300. 9.49	301. 914	302. 2.48	303. 1.35	304. 9.52		306.						
7091.01	310. 73.60	311. 2.44	312. 235	313. 70.34	314. 30.17	315. 9.94		317.						
1053.09	321. 10.93	322. 5.15	323. 496	324. 1.02	325. 2.12	326. 9.43		327.						
	330.	331.	332. 1988	333.	334.	335.		336.						
337. <u>Landscape Matrices May 2009</u>														
Total Landscape Area (ha)	340. Landscape Proportion	341. Patch density	342. Number of Patches	343. Largest Patch Index	344. Mean patch area	345. Patch cohesion index	346. Metric	347.						
121.50	351. 1.26	352. 2.23	353. 215	354. 0.07	355. 0.57	356. 7.91	DIV_SH	358.						
961.92	362. 9.98	363. 8.87	364. 855	365. 1.01	366. 1.13	367. 9.23		369.						
8103.96	373. 84.12	374. 1.19	375. 115	376. 83.49	377. 70.47	378. 9.95		380.						
446.94	384. 4.64	385. 4.57	386. 440	387. 0.26	388. 1.02	389. 8.87		391.						

	395.		396.		397.	1625		398.		399.		400.		401.		402.
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Table 4-8. Cont.

404. <u>Landscape Matrices May 1998</u>															
Total pe Area (ha)	407.	Landscape Proportion	408.	Patch density	409.	Number of Patches	410.	Largest Patch Index	411.	Mean patch area	412.	Patch cohesion index	413.	Metric	414.
106.29	418.	1.10	419.	1.79	420.	172	421.	0.06	422.	0.62	423.	7.80	424.	DIV_SH	425.
1309.05	429.	13.59	430.	4.69	431.	452	432.	5.22	433.	2.90	434.	9.73	435.		436.
7374.33	440.	76.54	441.	1.60	442.	154	443.	75.34	444.	47.89	445.	9.94	446.		447.
844.65	451.	8.77	452.	5.64	453.	543	454.	0.66	455.	1.56	456.	9.16	457.		458.
	462.		463.		464.	1321	465.		466.		467.		468.		469.
471. <u>Landscape Matrices May 1990</u>															
Total pe Area (ha)	474.	Landscape Proportion	475.	Patch density	476.	Number of Patches	477.	Largest Patch Index	478.	Mean patch area	479.	Patch cohesion index	480.	Metric	481.
156.06	485.	1.62	486.	1.94	487.	187	488.	0.12	489.	0.83	490.	8.40	491.	DIV_SH	492.
822.06	496.	8.53	497.	4.72	498.	455	499.	0.78	500.	1.81	501.	9.34	502.		503.
7873.83	507.	81.73	508.	1.06	509.	102	510.	81.05	511.	77.19	512.	9.94	513.		514.
782.37	518.	8.12	519.	5.39	520.	519	521.	0.81	522.	1.51	523.	9.34	524.		525.
	529.		530.		531.	1263	532.		533.		534.		535.		536.

4.4 Discussion

4.4.1 Comparison of Naïve Bayes and Gradient Boosting Random Forest Classifiers

XGBRFClassifier successfully classified land cover and land use in the Cradle Nature Reserve from 1990 to 2020. The ensemble classifier performed well for PA, UA, overall accuracies, kappa index, and F-score when compared with Naive Bayes and previous studies by Alam et

al. (2020), Rwanga and Ndambuki (2017), Kavzoglu and Teke (2022), and Britz (2022) (Alam et al., 2020; Britz, 2022; Kavzoglu & Teke, 2022; Rwanga & Ndambuki, 2017). The classification results are shown in Figure 4-3(a-e), and periodic changes in 1990–1998, 1998–2009, 2009–2015, and 2015–2020, Figures 4-4(a–j). From 1990–2020, Figure 4-4(i–j), 29 hectares of indigenous forest were converted to other landscape classes, mostly into open bush. Three hundred fifty-nine hectares changed from indigenous forest and natural grassland to open bush. A significant hectareage of the natural grassland (780 hectares) was lost to other landscape classes, mainly to bare ground/rock outcrop and, to a lesser extent, open bush. Bare ground/rock outcrop grew significantly by 449 hectares over the years, mainly due to the natural grassland's disappearance. Over the 30 years, some areas may have reverted to tree/bush cover in the natural grassland landscape, or inter-annual seasonal differences could account for the changes.

In recent years, XGBoost has acted as a standard classification yardstick in many classification and regression scenarios (Chen & Guestrin, 2016; Pafka, 2015) more potent than the original Random Forest (Brownlee, 2017). In recent studies, the ensemble of XGBoost and Random Forest (XGBRFClassifier) has been considered as having superior capabilities in dealing with real-world problems, such as in mapping landslide-susceptible areas in Macka County situated in Trabzon Province, Turkey (Kavzoglu & Teke, 2022), and in Dazhou town located in Wanzhou District, China (Zeng et al., 2023), mapping areas of susceptible to flooding in Spercheios river Greece (Plataridis & Mallios, 2023), and Bâsca Chiojdului River Basin in Romania (Abedi et al., 2022). In all scenarios, the ensemble demonstrated its capabilities in capturing intricate patterns in fragmented landscapes, which exhibit complex and nonlinear relationships between various landscape features and their classes, resonating well with the karst terrain in the cradle nature reserve. The ensemble found its space in predicting susceptible landslide and flood areas; in this study, areas susceptible to alien species invasion were informed by the increasing presence of bare ground. As established in these noted examples, the choice of the ensemble is buttressed to the robustness of the ensemble in the presence of irrelevant features, as it assigns low importance to them during the feature selection process, avoidance of overfitting with limited landscape data as is the case in the cradle nature reserve and flexibility to hyperparameter tuning which was also employed in this study to optimise the performance in classifying the cradle nature reserve landscape.

This study used the family of Kappa indices to accurately assess the land cover classification. While the Kappa indices remain the most widely used accuracy assessment indices in remote sensing land cover classification, researchers have highlighted the shortcomings of the Kappa indices. Pontius and Millones (Pontius & Millones, 2011) emphasise that the Kappa indices have flaws and recommend the use of quantity disagreement and allocation disagreement parameters. Olofsson and five other authors (Olofsson et al., 2013) provide good practice recommendations for accuracy assessment and area estimation by focusing the procedure for accuracy assessment on sampling design, response design and analysis. In contrast to Pontius and Millones (Pontius & Millones, 2011) who announced the demise of the Kappa indices, Olofsson and five other authors (Olofsson et al., 2013) provided a more balanced approach that embraced acceptable practices that yielded scientifically credible results, such as the Kappa indices. Notwithstanding its shortcomings, the Kappa indices remain the most widely used accuracy assessment indices despite the emergence of more novel indices.

The sampling technique used in this study was stratified random sampling. Although it is considered effective in reducing bias, it has issues even if adequately implemented. The vegetation in the cradle nature reserve is seasonal and subjected to burning regimes; depending on the time of the year, some strata must be better defined, and the sampling technique suffers from selection biases. Some areas that could have been covered by natural grass might appear bare ground for the natural grasslands' classification, even though the grass will grow later in the rainy season. In addition, even with the implementation of correct sampling procedures, measurement biases still occur. The karst terrain of the nature reserve resulted in some random samples being placed in geographically inaccessible areas, such as in the middle of flowing streams and on top of mountains with rugged terrain to climb. For this reason, ground truthing these areas relied on Google Earth images, and the result could have been different if these places were physically visited.

4.4.2 Land use and land cover changes from 1990 to 2020

It was noted that the Cradle Nature Reserve was previously farmland (Department of Rural Development and Land Reform, 2022) used for pastures and crop farming; the change in LU following the conversion of the land to a nature reserve may have contributed to the significant transformation of the landscape from natural grassland to other landscape classes. The depletion of the indigenous forest versus gain by open bush could be attributed to the introduction of herbivores, including buffalo, giraffe, and wildebeest, which survive by eating the branches of the indigenous forest. The decrease in grassland could also be attributed to the worldwide phenomenon of climate change; studies have established that climate change results in high rates of land degradation from enhanced desertification and nutrient-deficient soils (Arora, 2019). Overgrazing could have also opened the natural grassland to invasive species growth and conversion of the landscape to bare ground/rock outcrop class.

The opportunities for recycling nutrients and the movement of resources around landscapes are hampered by the scarcity or disappearance of long-lived plants (Holm et al., 2002). Soil surface conditions, water redistribution on the soil surface and landscape functionality are exhibited by patchy vegetation patterns owing to reduced plant cover (Van De Koppel et al., 2002). Consequently, the degradation of the original plant cover is primarily attributed by many scholars to anthropogenic disturbances and climatic fluctuations (X. Zhang & Huang, 2019). Similarly, the land degradation and ecological succession witnessed in this Cradle Nature Reserve landscape study can be attributed to temporal LC changes driven by anthropogenic and climate conditions (Nkonya et al., 2016). Abiotic stress factors such as natural phenomena like drought, floods, and global warming contribute to landscape fragmentation that negatively impacts LC and geomorphological processes (Adekiya et al., 2020; Matsushita et al., 2006; Nkonya et al., 2016; Roncero-Ramos et al., 2019). The landscape variability can be attributed to consolidating different farms with different land use and ecosystem functionality (Department of Rural Development and Land Reform, 2022). Biotic factors such as animal grazing patterns impact the LC dynamics in the nature reserve (Adekiya et al., 2020; Nkonya et al., 2016; Roncero-Ramos et al., 2019). The introduction of wild game species during the establishment of the Cradle Nature Reserve and the conversion of previous farmlands to game reserves is likely to have been a significant source of anthropogenic-driven changes in the landscape (SA-Venues.com, 2022). It implies an induced redistribution, dispersion, and changes in the area's diversity of flora and fauna (Ampofo et al., 2016; Maladkar, 2018; Matsushita et al., 2006; Sudhira et al., 2012). Grazing patterns, for instance, affect the

vegetation cover's structure and composition, critical in protecting the landscape from soil erosion, a driving force in land degradation (Pickup & Chewings, 1994; Wei et al., 2023). As already discussed, the invasion of grasslands by shrubs and alien invasive plants such as the pompom weed often results in a semiarid environment characterised by a vegetation pattern that combines vegetated and bare patches with various spatial characteristics (Goodall et al., 2011; Henderson et al., 2006; Trethowan et al., 2011; Turnbull et al., 2008). Land fragmentation can be viewed as a cause and a consequence of LU change (Adepoju & Salami, 2017; Ampofo et al., 2016; Martinez del Castillo et al., 2015; Smiraglia et al., 2015; Southworth et al., 2004). In the Cradle Nature Reserve context, it is fair to say that the introduction of wild game species, the shift from agricultural lands to natural grasslands, and the spread of invasive alien species have contributed to the current land fragmentation.

This study has established that the Cradle Nature Reserve landscape becomes more fragmented as the natural grasslands are converted to bare ground/rock outcrop. The pervasive nature of invasive alien plant species on the rangelands is detrimental to the growth of native vegetation. It has been established that invasive plants reduce grass cover and increase in response to disturbances such as the burning regimes in the grasslands, as in the Cradle Nature Reserve case (Le Maitre et al., 2020; O'Connor & van Wilgen, 2020). Bare ground/rock outcrop increases exposure to soil erosion. Guided by these findings from the study, it is recommended that speedy eradication of invasive alien plants (especially pompom weed) needs to be carried out; this should be done to preserve the grasslands that provide food for the thriving nature reserve and maintain the source of information for documenting hominin dietary ecologies. Keeping the Cradle Nature Reserve is also critical in maintaining the rangelands supporting game farming and COH tourism. It is also suggested that the Cradle Nature Reserve environmental managers should revisit their burning regimes to align with initiatives for eradicating invasive species, including the pompom weed.

4.4.3 Landscape structural changes due to fragmentation

Global trends of habitat fragmentation versus spatial patterns in the Cradle Nature Reserve can be determined by analysing the landscape fragmentation in the nature reserve over the last three decades (FAO, 2000). From 1990 to 2015, the total number of patches in the nature reserve generally increased, as shown in Table 4-8, although by 2020, there was a significant drop in patch numbers. Landscape fragmentation also slowed down from 2015 to 2020 for the other landscape classes. Importantly (as noted in other studies of LC change at the national level and Gauteng province in which the Cradle Nature Reserve is situated), this mirrored the trend for the rest of the country from 1990 to 2020. These studies noted a general increase in land fragmentation due to increased human population and residential development, pressure from industrial expansion, and alien species invading natural grassland (Department of Environment Forestry and Fisheries, 2021a; Nath et al., 2021; O'Connor & van Wilgen, 2020; Rwanga & Ndambuki, 2017; Schoeman et al., 2013; Southworth et al., 2004; Viana et al., 2019; Zengeya et al., 2020).

In the study area, the conversion of the farms to the nature reserve could have accelerated the fragmentation of the landscape from 1990 to 2015 and may have slowed down from 2015 to 2020 owing to management interventions; the latter may have allowed the vegetation of the nature reserve to recover naturally. Limiting the numbers and types of game species based on vegetation monitoring and adherence to controlled veld burning regimes was implemented by the nature reserve management (L. Berger & Maduwa, 2023). Shannon's diversity and COHESION values did not indicate significant changes in LC except for 2009 when the value

was significantly low (0.57). However, the overall trend from 1990 to 2020 reflects the dominance of natural grassland, which resonates well with the game species present in the nature reserve.

As noted by (Nagendra et al., 2004), the shift from analysing spatial heterogeneity of ecological systems using static frames to dynamic frameworks has been made possible by the advent of fragmentation analysis techniques. These techniques have greatly expanded the influential capabilities of remote sensing-based research (Nagendra et al., 2004). Fragmentation metrics in managing nature reserves and agricultural ecosystems share some similarities. Fragmentation metrics in both circumstances help management understand how changes in the arrangement and connectivity of landscapes impact ecosystem services and subsequently influence land use decisions (Nagendra et al., 2004; Southworth et al., 2004). In both cases, fragmentation often results in smaller isolated fields or patches that result in the loss of natural habitat and increased edge effects, ultimately declining the biodiversity and the landscape capacity to support ecosystem services (Dadashpoor et al., 2019; Nagendra et al., 2004; Wei et al., 2020; Zhao et al., 2019). Studies with similar themes have established that anthropogenic factors are significant players in the increase of landscape fragmentation. Some of these studies themes include land use changes due to urbanisation and change in landscape pattern (Dadashpoor et al., 2019), landscape fragmentation and analysis of LULC (Nagendra et al., 2004), essential fragmentation metrics for agricultural policies (Wei et al., 2020), and landscape pattern analysis and ecological network planning (S. ming Zhao et al., 2019) whose findings resonate well with the revelations from this study. Anthropogenic factors such as tourism development (road networks and infrastructure development), land tenure and ownership issues (consolidation of farms and change of land use), and fire management practices (grass burning regimes) all contributed to the study area landscape fragmentation. These activities exposed the cradle nature reserve to colonisation of parts of the landscape by invasive alien species such as the pompom weed. As established by other studies (F. L. Gao et al., 2021; Pyšek et al., 2020; Zengeya et al., 2020) the impact of the colonisation of the landscape by invasive alien species contributes to habitat alteration (transforming of original habitat structure), altered fire regimes (change of natural fire alters the composition and structure of vegetation), edge effects (reduce the quality of interior habitat), biological invasions (lead to shifts in vegetation patterns and ecosystem dynamics), corridor disruption (limit effectiveness of conduits for native species movement), predation and competition (disruption of food webs), spread mechanisms (introduction of new species to uninvaded areas) and hybridisation.

It is also possible that invasive trees/bushes have intruded into the natural grassland. Ecological studies are pursuing the impact of invasive species on the South African landscape (Zengeya et al., 2020); studies have shown that this phenomenon seriously impacts biodiversity. While this study did not directly quantify the impact of invasive alien species on the Cradle Nature Reserve, the transformation of natural grasslands to bare ground/rock outcrop is a testament to the effect of invasive alien plants. Ground truthing surveys established that some invasive plants drastically reduce grass cover. Pompom weed has been sighted in the nature reserve (L. Berger & Maduwa, 2023; Goodall et al., 2010; O'Connor & van Wilgen, 2020; Zengeya et al., 2020) and could contribute to the natural grassland's degradation, which is discussed further below.

Invasive alien plants are of concern in South Africa as it is known to invade disturbed areas and natural grasslands in South Africa (L. Berger & Maduwa, 2023). Our ground truthing surveys confirmed the widespread distribution of the pompom weed. This mirrors the pattern of the

pompom weed currently invading the Grassland and Savanna Biomes in the rest of South Africa; researchers further predict that this will continue spreading in the southern African sub-region (Goodall et al., 2011; O'Connor & van Wilgen, 2020; Villalobos Perna et al., 2023; Zengeya et al., 2020). The gradual landscape degradation owing to the invasion of grasslands and agricultural land by exotic plant species has been well studied and documented (Goodall et al., 2011; Henderson et al., 2006; Hulme, 2012; O'Connor & van Wilgen, 2020; Pyšek et al., 2020; Qu et al., 2021). Among the studies, Valentin and two other authors (Valentin et al., 1999) suggests two main hypotheses to elucidate the origins and development of vegetation and bare soil surface mosaics (also known as banded vegetation patterns) in arid areas. Specifically, this involves the gradual degradation of an initially uniform plant cover owing to climatic or human disturbances and the colonisation of previously degraded bare areas under improving climatic or land use conditions. Dunkerley and Brown, (1995), Bryan and Brun, (1999), and Lepron, (1999) have supported these hypotheses and have converged on the point that rangeland deterioration resulted from the disruption of a formerly more continuous vegetation cover by overgrazing, trampling and precipitation decline. For instance, abandoned fields in semiarid southeast Spain are reported by Cammeraat and Imeson, (1999) as having been colonised by *Stipa tenacissima* under drought and grazing pressure conditions.

The application of Extreme Gradient Boosting Random Forest and landscape metrics in studying land cover change within a protected archaeological area is relatively novel, and this study recommends that future studies should pay greater attention to land degradation induced by invasive plants within protected areas, particularly archaeological world heritage sites. In addition, studying land cover degradation in a heritage site, as in the cradle nature reserve, has significant implications for preserving and managing the site's cultural and natural values. Some of the implications are as follows:

- The increasing fragmentation and decline in vegetation will ultimately reduce the grazing and browsing capacity of the nature reserve and the area's game-carrying capacity. Loss of native vegetation species associated with paleo-diets also impacts archaeological studies in the world heritage site.
- An unchecked land cover degradation has long-term ecological consequences because it disrupts the delicate balance of the natural environment within and around the nature reserve, including loss of habitat, biodiversity decline, soil erosion and alteration of local ecosystems, which together diminish the aesthetic value of the heritage site and negatively impact the tourism value of the heritage site. Consequently, it destroys the crucial local economies and threatens sustainable tourism.
- The results from the study are informative to the development and implementation of effective legal and policy frameworks for the cradle nature reserve site management and conservation. It is hoped that findings from the study highlight the need for more stringent regulations and enforcement measures to protect the reserve from invasive alien species like the pomp pom weed.

4.5 Conclusions

Using satellite imagery, the XGBRFCclassifier successfully classified the Cradle Nature Reserve landscape into four classes: indigenous forest, open bush, natural grassland, and bare

ground/rock outcrop. This classification revealed LULCC trends in the landscape from 1990 to 2020, showing environmental degradation over this period. In addition, the landscape metrics derived from the classified images confirmed the ground-truthing findings, namely the dominance of the natural grassland class and the presence of the invasive pompom weed. The degradation of the dominant grassland class is evidenced by increased landscape fragmentation, as demonstrated by the increased number of landscape patches in 2020 (compared to 1990) in the natural grassland.

Over the 1990–2020 study period, the area covered by bare ground/rock outcrop increased significantly (448.97 hectares), representing 39% of the landscape cover change in bare ground/rock outcrop since 1990. The second-most significant change was the gain in open bush landscape cover (359.45 hectares), representing 32% of the landscape. Indigenous forest and natural grassland lost their share of the landscape cover in the Cradle Nature Reserve over the same period by 28.76 hectares (26%) and 779.66 hectares (12%), respectively. The loss was primarily to bare ground/rock outcrop. While these changes in the landscape cover are anticipated to occur naturally (because of the dynamic nature of the landscape), they are accelerated by anthropogenic factors. Such factors include the introduction of various species of game and invasive plants such as the pompom weed. The latter species is known to accelerate the degradation of environments and indigenous plant food sources associated with hominin diets. Therefore, it is prudent for Cradle Nature Reserve environment management to speed up processes or programmes to eradicate invasive alien plants.

**Chapter 5 MONITORING VEGETATION GROWTH DYNAMICS USING
ENHANCED VEGETATION INDEX AND PRINCIPAL COMPONENT ANALYSIS
IN THE KRAST ENVIRONMENT: A CASE OF THE CRADLE NATURE RESERVE,
GAUTENG PROVINCE, SOUTH AFRICA.**

This Chapter is based on the following manuscript

Matyukira, C., Mhangara, P., Gidey, E., & Hussein, J. (2024). Monitoring vegetation growth dynamics using enhanced vegetation index and principal component analysis in the Krast Environment: A case of the Cradle Nature Reserve, Gauteng Province, South Africa. *Annals of GIS* (In review).

Abstract: The Cradle Nature Reserve, a grassland ecosystem focusing on game range management, has been studied using pairwise correlation analysis and principal component analysis (PCA) to understand complex ecological processes. The Enhanced Vegetative Index (EVI) shows strong positive and statistically significant ($p=0.00$) associations with rainfall ($r=0.71$), soil moisture ($r=0.62$), and temperature ($r=0.76$), indicating the significant influence of these climatic conditions on vegetation health. The correlation between EVI and environmental parameters highlights the susceptibility of grassland ecosystems to changes in hydrological and thermal conditions. The PCA's primary components (F1 and F2) account for 90.080% of the variability in the data. F1 examines the impact of environmental factors on overall plant well-being, while F2 investigates the individual effects of temperature and moisture on plant health. Eigenvector analysis provides more clarity on the intricate connections between environmental factors and vegetation health. The positive correlations of F1 indicate a combined impact on plant growth, crucial for the survival of the game population. F2's emphasis on temperature and moisture demonstrates how grassland plants have evolved to cope with seasonal variations, affecting the amount of food available for game animals. This analysis provides strong evidence for the use of PCA as a beneficial technique for making ecological decisions and managing grassland landscapes. Policymakers should employ environmental data analysis for sustainable land management, creating policies based on data, devising climate adaptation methods, and advocating for activities that enhance soil moisture.

Keywords: vegetation, enhanced vegetation index, environmental factors, cradle nature reserve, South Africa

Highlights

- The Enhanced Vegetative Index (EVI) significantly correlates with rainfall, soil moisture, and temperature, indicating its impact on vegetation health.
- PCA's primary components (F1 and F2) account for 90.080% of data variability.
- F1 examines the impact of environmental factors on overall plant well-being, while F2 investigates individual effects of temperature and moisture on plant health.
- Eigenvector analysis clarifies the intricate connections between environmental factors and vegetation health.

5.1 Introduction

The use of remote sensing and advanced statistical approaches has improved the environmental monitoring of sensitive ecological heritage sites (Rapiya et al., 2023; Sebald et al., 2023). The Enhanced Vegetation Index (EVI) is a crucial instrument for evaluating the condition of grassland ecosystems like the Cradle Nature Reserve by quantifying the level of vegetation greenness, productivity, and density (Ogungbuyi et al., 2023b). Rainfall, temperature, and soil moisture are important environmental factors that contribute significantly to the growth and well-being of different grass species (Santiago et al., 2022). These grass species comprise 26% of the Earth's land surface and over 70% of the total agricultural land worldwide. They play a vital role in capturing carbon and cycling nutrients within these ecosystems (Encabo et al., 2023; Q. Xie et al., 2022). The capacity of grasslands to provide essential ecosystem products and services is strongly affected by seasonal climate fluctuations (Crabbe et al., 2019; Encabo et al., 2023). These grasslands function as agroecosystems, playing a vital role in supplying livestock with feed and sustaining the livelihoods of millions of people throughout Africa (Shoko et al., 2019). The interaction between climate and grassland production in agroecosystems, like the Cradle Nature Reserve, highlights the significance of these ecosystems in ecological and socio-economic aspects (Encabo et al., 2023; Matyukira & Mhangara, 2023b).

By utilising their unique seasonal photosynthetic patterns, remote sensing technology, specifically the Sentinel 2A Multispectral Instrument (MSI), has significantly changed the classification and mapping of grass species (Fernández-Habas et al., 2021; Schwieder et al., 2020; Q. Xie et al., 2022). The incorporation of Sentinel-2's Enhanced Vegetation Indices (EVIs) enhances this advancement by precisely estimating vegetation health and productivity. EVIs are highly sensitive to chlorophyll content and canopy structure, allowing for a nuanced assessment. The spectral arrangement of the satellite, encompassing red-edge and near-infrared bands, perfectly suits the evaluation of grassland conditions by detecting significant changes in plant biochemistry (Matsushita et al. 2007a; Ogungbuyi et al. 2023; Zhen et al. 2023). Sentinel-2's ability to make frequent trips and capture a wide range of spectral data enables continuous grassland monitoring. This makes it easier to analyse the quality of forage and support sustainable farming practices (Fernández-Habas et al., 2021; Schwieder et al., 2020). The use of Sentinel-2-produced EVIs has become critical in making immediate decisions for livestock management, emphasising the importance of remote sensing in preserving the ecological integrity of various grassland ecosystems (Fernández-Habas et al., 2021; M. M. Rahman et al., 2022; Schwieder et al., 2020).

The strategic use of NASA/POWER CERES/MERRA-2 Native Resolution data has become crucial in grassland monitoring endeavours (Shen et al., 2022). This dataset contains essential meteorological variables, specifically T2M_MAX_MERRA-2 and T2M_MIN_MERRA-2, which reflect the highest and lowest air temperatures recorded daily at a height of two meters above the ground (NASA Global Modeling and Assimilation Office (GMAO), 2020; Shen et al., 2022). In addition, it includes PRECTOTCORR MERRA-2 for accurately measured total rainfall and GWETROOT MERRA-2 for soil moisture in the root zone (NASA Global

Modeling and Assimilation Office (GMAO), 2020; Shen et al., 2022). These parameters are crucial for comprehending and predicting the ecological consequences of climate fluctuations. The goal of incorporating this high-resolution data into monitoring techniques is to improve ecological models' precision (Shen et al., 2022). Consequently, this contributes to reinforcing more strategic conservation methods, enhancing the ability of crucial ecosystems, such as those found in the Cradle Nature Reserve, to withstand and maintain their sustainability. The primary goal is to use these extensive databases to provide information and improve grassland management, ensuring future generations' well-being and vigour (Shen et al., 2022).

Historical research emphasises the crucial significance of temperature, rainfall, and soil moisture in monitoring agroecosystems. These components are crucial in influencing the health and productivity of agricultural land. Research on the effects of climate change on China's agroecosystems shows that changes in surface temperature, rainfall, and extreme weather events have a significant impact on soil moisture levels, net primary productivity (NPP), the amount of carbon stored in the soil, and the distribution of crop pests (Bao et al., 2023). In addition, remote sensing technology has played a crucial role in accurately mapping and providing real-time data on the quality of soil and water. This data is essential for effectively managing these resources (de Paul Obade et al., 2013). In arid ecosystems like those found in western North America, the soil temperature and moisture levels act as indicators of the ability to withstand disturbances and resist the growth of invasive plants (Bradford et al., 2019). Developing and analysing a comprehensive soil moisture dataset is crucial to comprehend the energy exchange between the Earth and the atmosphere, which in turn influences climate regulation (Myeni et al., 2021). Historically, researchers have used multilinear regression to understand the crucial role of climatic elements in managing and conserving agroecosystems.

Multilinear regression is a statistical method used to analyse the connection between a dependent variable and two or more independent variables (Jobson, 1991; Rebecca, 2023). When considering environmental factors such as EVI (Enhanced Vegetation Index), rainfall, temperature, and soil moisture, all of which vary with the seasons, a multilinear regression model can be used to analyse the individual contributions of these independent variables to changes in the dependent variable, while accounting for the influence of the other variables (Jobson, 1991; Rebecca, 2023; Zaiontz, 2024). To address the seasonal variations in the independent variables, one can use seasonal dummy factors or employ a time series regression model if the data is collected over a period (Zaiontz, 2024). Researchers can utilise known data on rainfall, temperature, and soil moisture to make predictions about EVI. Additionally, this data can help researchers determine the nature (positive or negative) and intensity of these interactions. This approach is highly effective in unravelling intricate environmental relationships (Jobson, 1991; Rebecca, 2023; Zaiontz, 2024). Nevertheless, multilinear regression models may not effectively represent the link between variables if they do not consider seasonality, particularly when the variables exhibit a cyclical pattern. Excluding dummy variables or other techniques to address seasonality in the model could lead to erroneous attribution of effects to the independent variables based on the time of year (Helali et al., 2022; Zaiontz, 2024). For instance, if there is a tendency for rainfall to increase when the Enhanced plant Index (EVI) declines, but the EVI increases with rainfall because of plant

growth, omitting the consideration of seasonality can result in a model that is misleading (Rebecca, 2023; Zaiontz, 2024). The model fails to acknowledge that the correlation between EVI and rainfall is not direct, but rather influenced by seasonal variables such as temperature and daylight hours, which impact both EVI and rainfall. To address this issue, one can use dummy variables representing different seasons or employ a time series model with seasonal decomposition. These approaches effectively separate the seasonal effects from the actual influence of the independent factors on the dependent variable (Jobson, 1991; Rebecca, 2023; Zaiontz, 2024). By adopting this approach, the model can achieve a higher level of precision in representing the actual connections between the variables.

The regression study examines the relationship between the Enhanced Vegetative Index (EVI) and the independent variables of rainfall, temperature, and soil moisture. The Pearson correlation coefficient is used to assess the linear association between EVI and each predictor. A value close to +1 or -1 indicates a strong positive or negative link, respectively (EZSPSS, 2024; Ruben, 2024). The significance of these correlations will be evaluated using the one-tailed sig. value, where lower p-values indicate a significant impact of the independent variables on EVI (EZSPSS, 2024; Ruben, 2024). The Durbin-Watson statistic assesses the presence of autocorrelation in the residuals. A value close to 2 indicates that the residuals are independent, which is an important assumption for the validity of the model (EZSPSS, 2024; Ruben, 2024). These statistical methods will improve the accuracy of the model in capturing the actual relationship between EVI and major climatic parameters, ensuring that management plans produced from this model are based on accurate and meaningful relationships. The Enhanced Vegetation Index (EVI) is a crucial dependent variable used in environmental data analysis to measure the vitality and productivity of vegetation (Zhang et al., 2018). This score is highly responsive to many structural characteristics of the canopy, including the Leaf Area Score (LAI), type of canopy, plant phenology, and concentration of chlorophyll in the leaves (Zhang et al., 2018). EVIs are successfully predicted using multilinear regression models, which consider important independent variables such as rainfall, temperature, and soil moisture. Each of these variables plays a critical role in the growth and health of plants (Helali et al., 2022; Zaiontz, 2024).

Nevertheless, the inherent seasonality of certain environmental elements can impede the straightforward implementation of multilinear regression (Jamali et al., 2011). For example, although rainfall is an essential supply of water for plants, it may not directly result in an elevation of the EVI (Enhanced Vegetation Index) due to factors such as the soil's ability to retain water and the current temperatures. Temperature fluctuations can have either a positive or negative effect on the process of photosynthesis, which in turn affects the Enhanced Vegetation Index (EVI). The level of moisture in the soil, which indicates the amount of water that plants can absorb, has a direct impact on the process of photosynthesis and the level of stress in plants. This, in turn, affects the readings of the Enhanced Vegetation Index (EVI). If regression models may misrepresent the impact of variables on EVI if they do not consider the seasonal interplay between them. This has been demonstrated by research that has examined the temporal correlations between these variables and vegetative indices (Jamali et al., 2011; H. Zhang et al., 2018; S. Zhang et al., 2022). Principal component analysis (PCA) is often used

by researchers instead of adding dummy variables to multilinear regression models (Marukatat, 2023; Zach, 2021) to better understand how environmental variables change over time and how they affect the health of plants. Principal Component Analysis (PCA) is a powerful method for effectively handling the intricacies of datasets with many dimensions, as well as the common problem of multicollinearity among independent variables (Fatima et al., 2022; Marukatat, 2023). This technique efficiently transforms a dataset consisting of linked variables into a new framework of principal components. These principal components are linearly uncorrelated variables that capture the fundamental characteristics of the original data. The process of transformation not only improves the interpretability and efficiency of the model but also greatly decreases the likelihood of overfitting (Fatima et al., 2022; Marukatat, 2023).

The first principal component explains the highest amount of variation in the dataset, whereas each successive component explains less variation. This allows for a reduction in dimensionality while still retaining the important structure of the data (Fatima et al., 2022; Marukatat, 2023; Y. Zhao et al., 2024). Eigenvalues and eigenvectors are crucial in measuring the amount of variance that each component represents and determining the direction of the highest variance in the feature space, respectively (Y. Li et al., 2020; Marukatat, 2023; Moura et al., 2016). Factor loadings clarify the degree to which the variability of the original variables is represented in each component. They can be seen as a metric like their correlation (Marukatat, 2023; Y. Zhao et al., 2024). The initial correlations across variables highlight the effectiveness of PCA in reducing dimensionality. Visualisation tools like biplots offer a graphical depiction of the sample scores and variable loadings on the components, providing insights into the contribution of each variable to the model, which may be quantified by squared loadings. The squared cosines provide a measure of how well the variables are represented on the components (Mair, 2018; Moura et al., 2016). By including Principal Component Analysis (PCA) into the analytical procedure, scientists may guarantee a more precise and comprehensive understanding of the genuine connections between environmental variables, such as rainfall, temperature, and soil moisture, and the Enhanced Vegetation Index (EVI) (Y. Li et al., 2020; Mair, 2018; Moura et al., 2016). This unsupervised technique enables the reduction of dimensionality prior to applying a regression model to the modified data. As a result, it preserves the fundamental patterns required for exploratory analysis and pattern identification (Abonyi et al., 2022; Marukatat, 2023; Y. Zhao et al., 2024). Therefore, Principal Component Analysis (PCA) allows researchers to simplify intricate datasets into more easily understandable forms, which in turn facilitates a more thorough investigation of the factors that influence the health of plants (Y. Li et al., 2020; Moura et al., 2016).

Although remote sensing technologies have made significant progress, there has been reluctance to embrace them for pasture monitoring. The aim of this study was to: **i)** analyse the spatio-temporal trends of EVI and other environmental factors; **ii)** determine the statistical associations between vegetation index and climatic factors to connect technological capabilities with practical application by introducing a comprehensive methodology that utilises remote sensing data, multilinear correlation statistics, and principal component analysis (PCA) to monitor the health of grasslands and provide information for sustainable management practices. The multilinear regression analysis will investigate the correlations between the EVI

and environmental variables (Jamali et al., 2011; L. Yuan et al., 2021). Simultaneously, principal component analysis (PCA) will be employed to decrease the number of dimensions in the data, improving its comprehensibility while maintaining the variability inherent in the dataset. Statistical methods play a vital role in controlling human-induced activities like grazing, which have an impact on the distribution of plant species and the overall health of the reserve's flora.

5.2 Materials and Method

5.2.1 Study area

The Cradle Nature Reserve, referred to as Figure 5-1, covers an area of almost 8000 hectares within the COHWHS. It is renowned for its diverse plant life, with a particular emphasis on blooming plants. The reserve also boasts a broad range of animal species, including over 200 different types of birds (Matyukira & Mhangara, 2023b; SA-Venues.com, 2022). Meteorological variables such as temperature and rainfall, essential for plant growth and development, impact the vegetation in the reserve. The region receives an annual rainfall of 650 to 750 mm, with summer temperatures reaching a maximum of 39°C and winter temperatures dropping as low as -12°C. This climatic variability creates a dynamic environment conducive to the growth of plants (SA-Venues.com, 2022). The reserve is located in a climatic region characterized by Rocky Highveld Grassland, which is well-suited to fire and has a major influence on the vegetation structure (FLOW Communications, 2022). Natural springs, watercourses, streams, and tributaries to the Magalies and Crocodile Rivers provide vital moisture that sustains the diverse plant life (FLOW Communications, 2022). Furthermore, the reserve's historical utilization of land, which includes both subsistence and commercial farming, has resulted in alterations to the distribution of flora. The reintroduction of wild animal species, which have distinct grazing tendencies compared to domesticated cattle, has further impacted these changes (Matyukira & Mhangara, 2023b). The unusual vegetation dynamics observed in the area are a result of the climatic circumstances and the reserve's geological features, including dolomitic sinkholes that protect tree species from natural forest fires (FLOW Communications, 2022). These circumstances, combined with the importance of the reserve as a tourist attraction and its value for biodiversity in protected heritage areas, highlight the necessity of comprehending and conserving the original plant cover. This flora serves as an indicator of historical habitats and diets (Matyukira & Mhangara, 2023b). The preservation of rangelands is critical for wildlife grazing within the nature reserve, highlighting the intricate relationship between climate and vegetation. (Du et al., 2024) conducted a comprehensive study that examines the impact of rainfall, temperature, and solar radiation on various vegetation biomes. It provides a deep understanding of the cumulative impacts and mechanisms of climatic elements on vegetation growth. Xu et al., (2023) examine the impact of climate and human influences on vegetation changes in East Africa. Their findings may be relevant to the Cradle Nature Reserve.

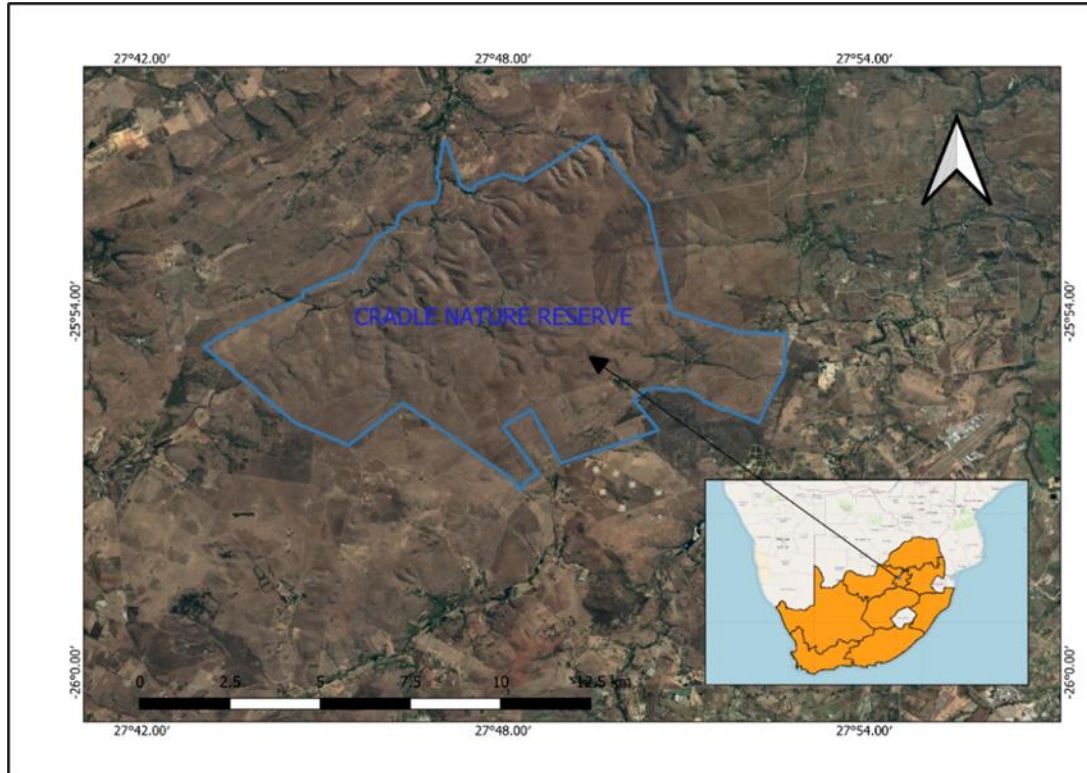


Figure 5- 1: Study Area – Cradle Nature Reserve in South Africa with Overview of the Google Earth Pro Imagery in UTM/WGS84 plane coordinate

5.2.2 Methods of data acquisition, processing, and analysis

The study obtained Sentinel-2 multispectral imagery spanning from January 2019 to December 2024. We obtained the images via the Copernicus Open Access Hub, a platform that provides unrestricted and complimentary access to Sentinel data. Sentinel's Application Platform (SNAP) toolkit (European Space Agency (ESA), 2022) automated the download process, facilitating the batch retrieval of the necessary images based on predetermined parameters like the percentage of cloud cover, the area of interest indicated by a shapefile, and the specified time range. We analysed the images using QGIS, a freely available geographic information system, after obtaining them. The QGIS version 3.36.0 (Maidenheadn) Raster Calculator (Eq.5- 1) provided the formula for computing the Enhanced Vegetation Index (*EVI*) for each image:

$$EVI=2.5\times NIR+6\times RED-7.5\times BLUE+INIR-RED \quad (5-1)$$

where *NIR*, *RED*, and *BLUE* are the reflectance values for the near-infrared, red, and blue bands, respectively (MapScaping, 2023; QGIS Development Team, 2020). This index is designed to optimise the vegetation signal with improved sensitivity in high biomass regions while minimising soil and atmosphere influences (QGIS Development Team, 2020).

Afterwards, we combined the individual *EVI* images monthly to provide average *EVI* values. The process involved arranging the *EVI* images on top of each other for each month and calculating the average value for each pixel. This produced a composite image that depicts the typical *EVI* for that month (MapScaping, 2023; QGIS Documentation., 2024). We then saved the monthly composites as TIFF files to ease further analysis. This strategy guaranteed a

uniform approach to monitoring changes in plant life over a period, resulting in a significant collection of data for ecological and environmental research. The use of open-source software like QGIS ensured the approach's accessibility and replication for future research. Afterwards, the individual EVI images were combined monthly to provide average EVI values. The process involved aggregating the EVI images for each month by stacking them together and calculating the average value for each pixel. This resulted in a composite image that depicts the mean EVI for that month (MapScaping, 2023; QGIS Documentation., 2024). Subsequently, the monthly composites were saved as TIFF files to facilitate subsequent analysis. This strategy guaranteed a uniform approach to monitoring changes in plant life over a period, resulting in a significant collection of data for ecological and environmental research. The utilisation of open-source software such as QGIS guaranteed that the approach was easily obtainable and capable of being replicated for further investigations. Furthermore, surface maps were meticulously generated using ArcGIS version 10.8.2 software, leveraging datasets from 14 strategically selected stations to ensure comprehensive spatial coverage of the study area. To ensure the replicability of the study, a detailed methodological approach was adopted for generating surface maps using ArcGIS version 10.8.2 software, which involved a series of carefully structured steps (Figure 2). In this study, we generated 180 surface maps, with 60 maps for each variable over the 60 months from January 2019 to December 2023. These maps were utilised to generate monthly data for further analysis, including cause-effect relationship and association among each environmental factor using multilinear regression model and Pearson correlation coefficient as follows (Eq. 5-2):

$$EVI = \beta_0 + \beta_1(Rainfall) + \beta_2(Temperature) + \beta_3(Soil Moisture) + \epsilon \quad (5-2)$$

Here, β_0 is the intercept, β_1 , β_2 , and β_3 are the coefficients that represent the change in *EVI* for a one-unit change in rainfall, temperature, and soil moisture, respectively, and ϵ is the error term (Jobson, 1991; Rebecca, 2023).

The formula for calculating the Pearson correlation coefficient (Eq. 5-3) (Turney, 2024) was as follows:

$$r = \Sigma (X_i - \bar{X})(Y_i - \bar{Y}) / \sqrt{(\Sigma(X_i - \bar{X})^2 * \Sigma(Y_i - \bar{Y})^2)} \quad (5-3)$$

where X_i and Y_i are the individual data points, $\bar{X}$ and $\bar{Y}$ are the means of X and Y respectively.

We classified a Pearson correlation coefficient value greater than $r = 0.5$ as a strong positive correlation. A value between 0.3 and 0.5 was considered a moderate positive correlation, while a value between 0 and 0.3 indicated a weak positive correlation. A correlation coefficient of 0 indicated no correlation. A value between -0.3 and -0.5 represented a moderate negative correlation, and a value less than -0.5 indicated a strong negative correlation (Turney, 2024). In addition, the study utilized principal component analysis (PCA) to offer a comprehensive perspective on the meteorological conditions that influence the growth of vegetation in the studied area. This rigorous methodology ensured precise extraction and thorough investigation of climatic variables, providing useful insights, and allowing for study replication for future research.

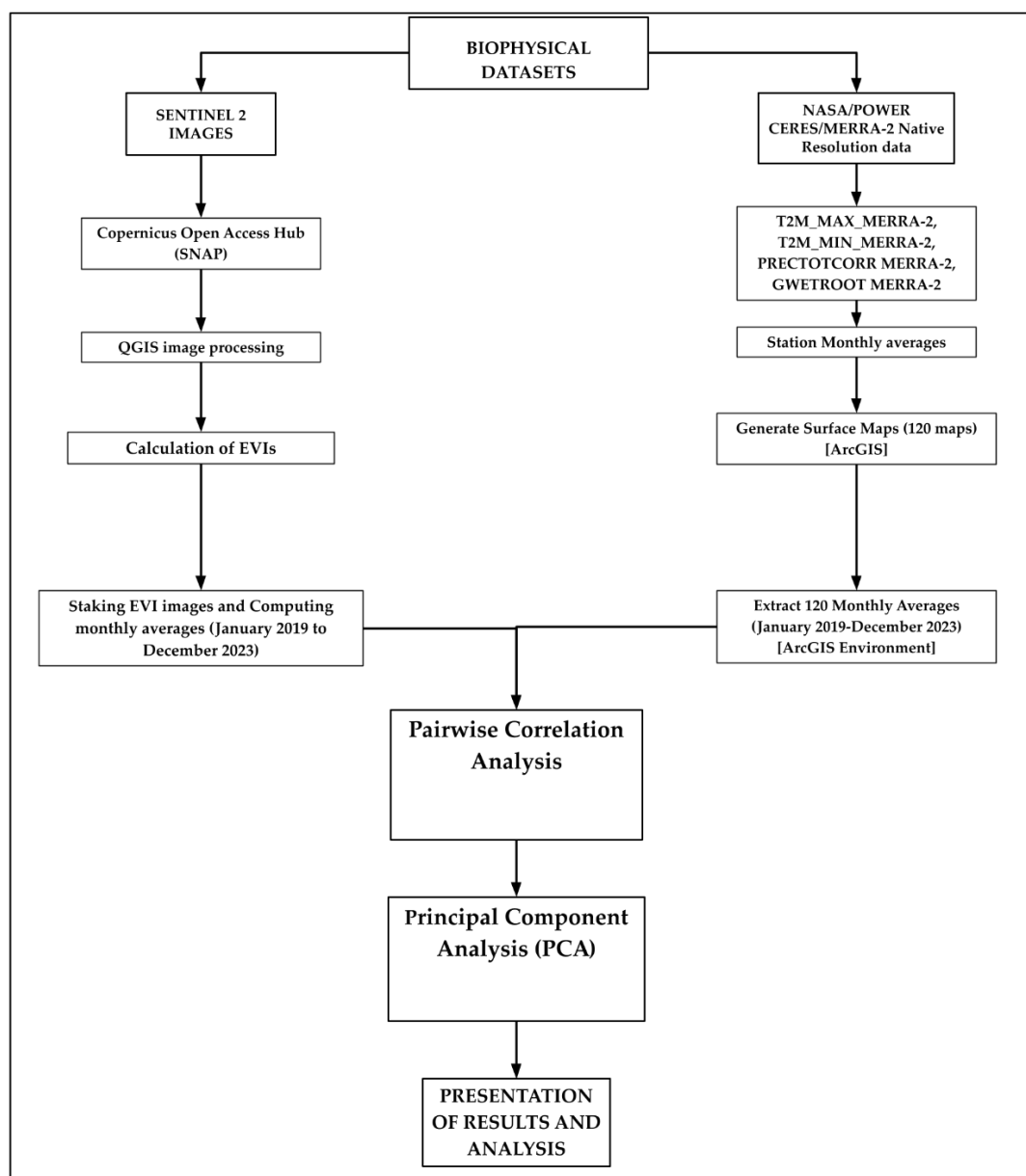


Figure 5- 2: Schematic of workflow for data collection, processing, EVI computation, surface map generation, extraction of data statistics, pairwise correlation analysis, PCA, and results analysis

5.3 Results

5.3.1 A spatio-temporal analysis of EVI and other environmental factors

This finds out that the seasonal changes in vegetation (EVI) closely match the monthly pattern of rainfall (Figures 5-(3-4)). During periods of heavy rainfall, the EVI demonstrates elevated levels, suggesting strong photosynthetic activity and the accumulation of biomass. During the period of 2019 to 2023, the Cradle Nature Reserve underwent a spatial-temporal analysis that brought to light significant seasonal fluctuations. The summer, the peak growing season, records the highest EVIs of 0.8, indicating robust vegetation development, while the winter, particularly in 2021, records the lowest EVIs of -0.02. Patterns of rainfall demonstrate that the maximum amounts occur during the summer, particularly in 2020 with 391.79 ml (Figures 5-(3-4)). The lowest rainfall of 60.4 ml during the winter of 2020 typifies dry winters.

Temperatures throughout the summer reach their highest point, with 2023 having the highest temperature of 22.06 degrees Celsius. On the other hand, temperatures during the winter season plummet, with 2022 recording the lowest temperature of 9.84 degrees Celsius. Rainfall throughout the summer months causes soils to have increased amounts of moisture in the root zone, providing a contrast to the dry conditions that prevail during the winter months (Figure 5-(3-4)). On the other hand, the fact that the levels of soil moisture remained stable throughout the period indicates that there is a requirement for additional research into the relationship between soil moisture and EVI dynamics. These findings are significant because they highlight the importance of understanding seasonal fluctuations in order to develop conservation and management methods that are effective within the Cradle Nature Reserve. The association between the Enhanced Vegetation Index (EVI) and rainfall strengthens the understanding of how vegetation changes throughout the seasons. Notably, the second graph displays a wide range of annual maximum EVI values. The peak EVI in tropical evergreen forests occurs during the transition from the late dry season to the early wet season, which goes against what was expected. This suggests that leaf phenology in these forests is not primarily determined by the seasonality of rainfall. To summarize, although rainfall is an important factor influencing plant behaviour, there is a need for more research to fully understand the complex variations in leaf phenology in different habitats. This will contribute to our overall understanding of the interaction between climate, vegetation, and ecosystems.

The total amount of rainfall that occurred in the study area indicates a decrease as the time or months grow ($y = -0.0606x + 56.581$), which is demonstrated by the negative coefficient (-0.0606), which indicates that there is a decrease in rainfall (Figure 5-(3-4)). The y-intercept, which is 56.581, is a representation of the baseline rainfall value. This number should be considered. When the pattern is viewed in its entirety, it suggests that the amount of rainfall will steadily diminish over the course of time. Taking into consideration EVI ($y = -0.0005x + 0.2124$) is yet another factor. Because the coefficient is negative (-0.0005), it is possible to draw the conclusion that the EVI decreases as time goes on (x grows). This is because the coefficient is negative. According to the y-intercept, the value of the first EVI is 0.2124. This value is represented by the coefficient. Based on this pattern, it appears that the plants' overall health or the amount of photosynthetic activity is gradually declining. The value is a temperature denoted by the equation $y = -0.0048x + 17.3$. It is corroborated by the coefficient that the temperature decreases as time goes on (x increases), as indicated by the fact that the coefficient is negative (-0.0048), which shows that the temperature decreases. For example, the y-intercept (17.3) represents the temperature that was present at the beginning of the cycle. The pattern of the trend reveals, in general, a pattern of cooling over the course of time. The moisture content of the soil is also taken into consideration ($y = -0.0001x + 0.441$). Because the coefficient is negative (-0.0001), it is possible to draw the conclusion that the amount of moisture present in the soil continues to decrease as time goes on (x rises). 0.441 is the value of the y-intercept, which is a representation of the initial moisture content of the soil being measured. This graph clearly demonstrates that there has been a gradual reduction in the amount of moisture that is present in the soil.

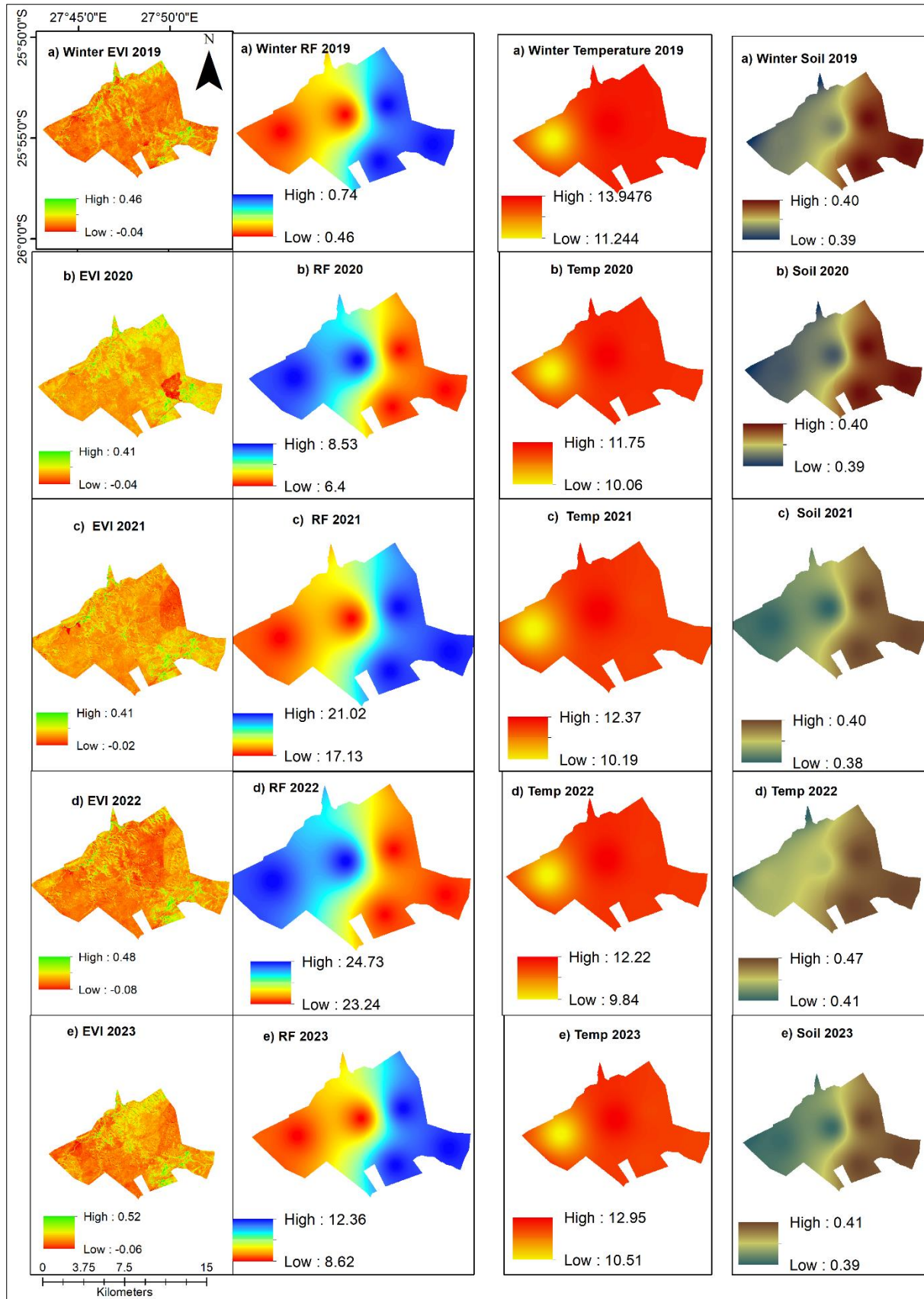


Figure 5- 3: A spatio-temporal analysis of EVI and other environmental factors during winter season from 2019-2023.

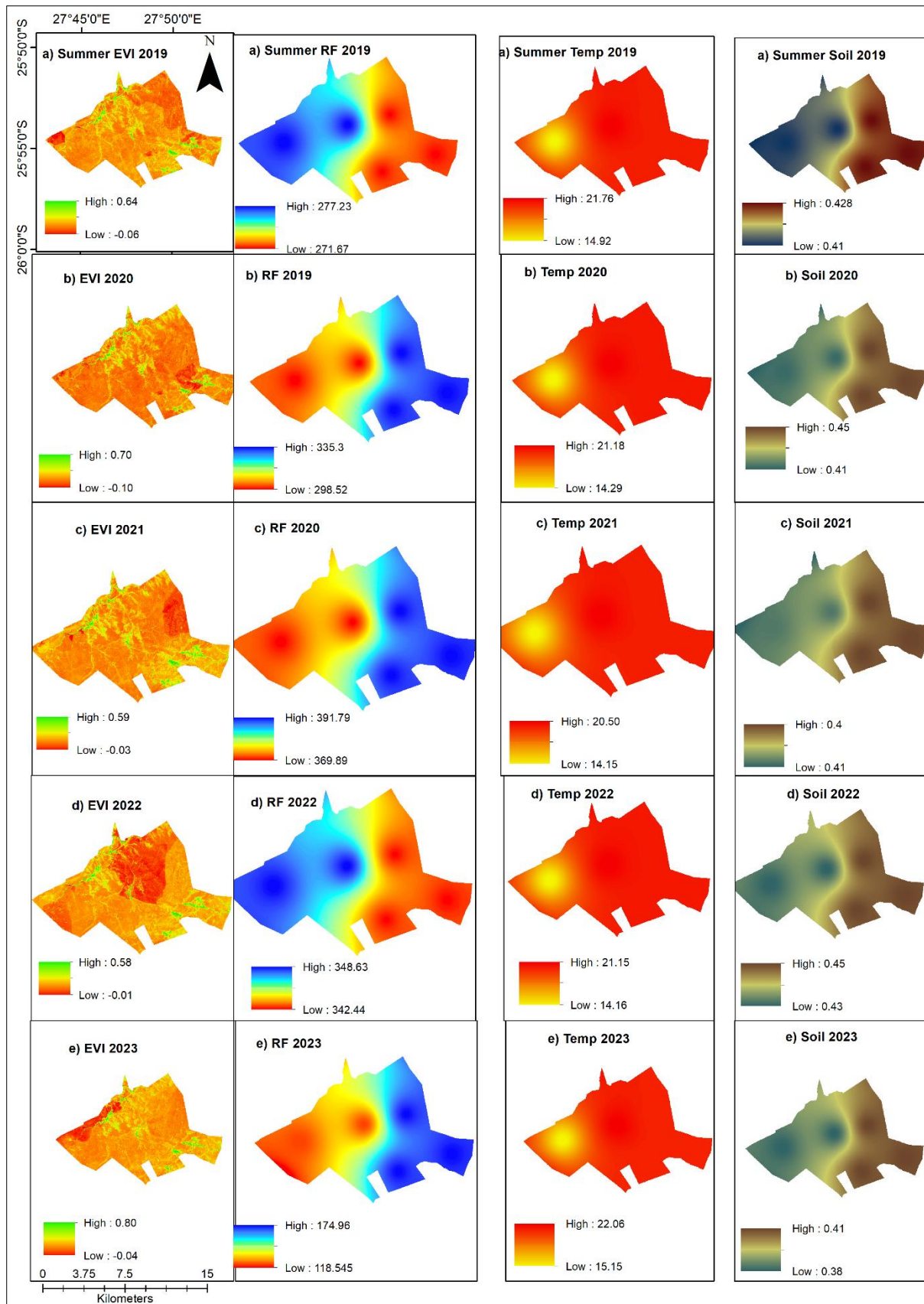


Figure 5- 4: A spatio-temporal analysis of EVI and other environmental factors during summer winter season from 2019-2023.

5.3.2 Statistical analysis of vegetation and climatic factors

Table 5-(1a) presents Pearson Correlation coefficients and their significance levels, indicating the strength and direction of the linear relationships among EVI, Rainfall, Temperature, and Soil Moisture. The EVI exhibits significant positive relationships with rainfall ($r = 0.70$), temperature ($r = 0.62$), and soil moisture ($r = 0.76$). This indicates that the EVI also tends to increase as these independent variables increase. The correlation coefficient between rainfall and soil moisture is 0.767, suggesting a strong positive relationship. Similarly, the correlation coefficient between rainfall and temperature is 0.576, showing a moderately positive relationship. This implies a connection between higher rainfall, higher soil moisture, and slightly higher temperatures. The correlation coefficient of 0.296 indicates a modest link between temperature and soil moisture. The significance levels (Sig. 1-tailed) show that all correlations are statistically significant ($p < 0.001$), except for the link between temperature and soil moisture, which is significant at the $p < 0.011$ level. This indicates that the correlations are highly unlikely to be the result of random chance. There is a probability of less than 1% (or 1.1%, specifically for temperature and soil moisture) that such significant correlations would happen without an actual relationship.

Table 5- 1(a-b): Correlation and Regression Analysis of EVI with Climatic and Soil Variables ($n=60$)

			EVI	Rainfall	Temperature	Soil Moisture
		Mean	0.20	54.73	17.15	0.44
		Std. Deviation	0.07	56.19	3.72	0.04
(a)	Pearson Correlation	EVI	1.00	0.71	0.62	0.76
		Rainfall	0.71	1.00	0.58	0.77
		Temperature	0.62	0.58	1.00	0.30
		Soil Moisture	0.76	0.77	0.30	1.00
	Sig. (1-tailed)	EVI	.	<0.001*	<0.001*	<0.001*
		Rainfall	0.00	.	0.00	0.00
		Temperature	0.00	0.00	.	0.01
		Soil Moisture	0.00	0.00	0.01	.
(b)	R	R ²	Std. Error of the Estimate	Change Statistics		
				R ² Change	F Change	df1
	0.87	0.75	0.04	0.75	55.98	3.00
					Sig. F Change	df2
					<0.001*	56
					PRESS	Durbin-Watson
					0.084	0.76

* Statistically significant at 1%

PRESS is a measure of a model's predictive accuracy, *df* denotes the number of values free to vary, *F* is a statistic for comparing model fits, and *Sig.* indicates the probability of the result occurring by chance.

Table 5-(1b) presents a concise overview of a regression model where EVI is the dependent variable. The R (0.866) indicates a significant and positive correlation between the independent variables (rainfall, temperature, and soil moisture) and the dependent variable (EVI). The coefficient of determination (R^2) value of 0.75 indicates that the independent variables used in the model can account for 75% of the variability seen in EVI. The adjusted coefficient of determination (R^2) (0.737) is a measure that considers the number of predictors in the model. It indicates significant explanatory power. The estimate's standard error (0.0356) is the average deviation of the observed values from the regression line. A lower score implies a more optimal fit of the model to the data. The F change (55.976) and Sig. F change (<0.001) values indicate that the regression model as a whole is statistically significant, with the independent variables demonstrating a good ability to predict EVI. PRESS (Predictive Residual Sum of Squares) quantifies the model's ability to make accurate predictions. A lower score (0.084) indicates a higher level of forecasting accuracy. The Durbin-Watson statistic of 0.76 suggests the presence of positive autocorrelation in the residuals. This is a concern because it can impact the dependability of the regression results. Overall, the model shows a strong and significant relationship between the independent variables and EVI, but the Durbin-Watson value suggests that the residuals are not independent, which could be a concern for the model's assumptions.

Table 5- 2(a-d): Statistical Analysis of Environmental Factors Influencing EVI

(a) ANOVA					
	Sum of Squares	df	Mean Square	F	Sig.
Regression	0.21	3.00	0.07	55.98	<0.001
Residual	0.07	56.00	0.00		
Total	0.28	59.00			
(b) Coefficients					
	Unstandardised Coefficients		Standardised Coefficients	t	Sig.
	B	Std. Error	Beta		
(Constant)	-0.49	0.09		-5.51	<0.001
RAINFALL	0.00	0.00	-0.10	-0.77	0.44
TEMPERATURE	0.01	0.00	0.47	5.50	<0.001
SOIL MOISTURE	1.23	0.19	0.70	6.42	<0.001
(c) 95.0% Confidence Interval for B Collinearity Statistics					
	LB	UB	T	VIF	
(Constant)	-0.66	-0.31			
RAINFALL	0.00	0.00	0.28	3.60	
TEMPERATURE	0.01	0.01	0.62	1.62	
SOIL MOISTURE	0.85	1.61	0.38	2.64	
(d) Residuals Statistics					
	Min	Max	Mean	Stddev.	
Predicted Value	0.08	0.29	0.20	0.06	
Residual	-0.07	0.06	0.00	0.03	
Std. Predicted Value	-1.93	1.51	0.00	1.00	
Std. Residual	-1.89	1.75	0.00	0.97	

Note: The dependent variable of this study was EVI.

The ANOVA Table 5-2(a) indicates that the regression model is statistically significant in its whole, with an F-value of 55.976 and a p-value of less than 0.001. This shows that the model offers a significant explanation for the differences in the dependent variable. Upon scrutinising the coefficients in Table 5-2(b), we notice a mixture of favourable and unfavourable results:

The coefficient for RAINFALL is 0.0, indicating that rainfall has no significant effect on the model. This is supported by a p-value of 0.444. The variable TEMPERATURE has a coefficient of 0.009 and a p-value of less than 0.001, suggesting a significant and positive impact on the dependent variable. The soil moisture coefficient is 1.2300, and its p-value is less than 0.001, indicating a significant and positive correlation with the dependent variable. The results may not be very useful in explaining the relationship between the variables because the minuscule amount of rainfall can have a pivotal impact in real-life scenarios. The Durbin-Watson statistic of 0.76, as shown in the table, suggests the existence of positive autocorrelation. This means that the residuals, or errors, are not independent. This statement challenges a basic assumption of regression analysis and could lead to inaccurate estimations. Although statistically significant, the temperature coefficient may not have a major practical impact. In conclusion, while the model demonstrates statistical significance, the practical significance and reliability of the findings are unknown due to the lack of significance in rainfall and potential issues with autocorrelation. It is critical to address these challenges before relying on the model for further interpretation or decision-making. These findings highlight the interconnectedness of climatic conditions and their collective influence on plants, underscoring the importance of comprehensive environmental research for ecological comprehension. Moreover, the existence of robust relationships necessitates further investigation of the environmental components by principal component analysis (PCA). The results of the multilinear regression analysis for Tables 5-2 (c) and 5-2 (d) show that the constant term hurts the dependent variable EVI, as shown by the negative confidence interval. The rainfall coefficients are zero within the confidence range, indicating that they do not significantly predict EVI. Additionally, rainfall has a high variance inflation factor (VIF) of 3.6, suggesting multicollinearity issues.

The relationship between temperature and EVI is positive and statistically significant. A decent VIF value suggests that there is less concern about multicollinearity. The soil moisture variable is a strong EVI predictor. However, its variance inflation factor (VIF) of 2.6370 indicates the possibility of multicollinearity. The residual statistics show that the model's predictions are consistent, with a mean of zero and standard deviations within an acceptable range. However, Principal Component Analysis (PCA) might be better in this case because it reduces the number of dimensions, making the model simpler by turning correlated predictors into a smaller group of uncorrelated components. PCA components reduce multicollinearity by being orthogonal, preventing the new predictors in the regression model from being affected by multicollinearity. Principal Component Analysis (PCA) enhances model interpretation by identifying the most significant variance components, thereby facilitating comprehension of the fundamental structure of the data. In summary, PCA could provide a more robust and interpretable model, especially when multicollinearity is a concern, as indicated by the VIF values in the regression analysis. The use of PCA in analysing the Enhanced Vegetative Index (EVI) and its environmental factors is important due to the strong correlations and multicollinearity identified in the multilinear regression analysis. PCA's capacity to condense intricate and interconnected variables into major components simplifies the data, improving comprehensibility and uncovering the main elements that impact vegetation health. This approach not only simplifies the interrelationships between several variables but also helps to visually represent the data, promoting a more profound comprehension of how climatic factors such as rainfall, temperature, and soil wetness collectively influence vegetation. Therefore,

principal component analysis (PCA) is essential for obtaining a deeper ecological understanding and guiding strategic decision-making in environmental research conducted at the Cradle Nature Reserve.

5.3.3 Principal Component Analysis (PCA)

Table 5-3 comprises Enhanced Vegetative Index (EVI) measurements, rainfall, temperature, and soil moisture. The data set is comprehensive and does not include any missing values, which makes it reliable for analysis. The range of values for each variable indicates the variety in environmental conditions, with the EVI displaying a moderate mean and low standard deviation. This means that vegetation health is less volatile. Rainfall has a broad spectrum and a large standard deviation, suggesting significant rainfall fluctuations. The temperature and soil wetness exhibit minor fluctuations.

Table 5- 3: Descriptive Statistics and Principal Component Analysis of Environmental Variables Affecting EVI ($n= 60$)

Variable	Min	Max	Mean	Std. deviation
EVI	0.10	0.32	0.20	0.07
Rainfall	0.02	181.45	54.73	56.19
Temperature	9.75	21.66	17.15	3.72
Soil Moisture	0.38	0.53	0.44	0.04
Eigenvalues	F1	F2	F3	F4
Eigenvalue	2.88	0.72	0.29	0.10
Variability (%)	72.12	17.96	7.30	2.62
Cumulative %	72.12	90.08	97.38	100.00

Adding these factors to the PCA analysis (Table 5-3) shows that the first main component (F1) explains a substantial 72.121% of the variation. This represents the effect of the four environmental variables on the health of the plants. The second component (F2) contributes an additional 17.959%, representing an additional aspect of the environmental impact. For instance, it can measure and distinguish the specific effects of temperature and moisture on EVI, which are distinct from the overall pattern that F1 represents. F1 and F2 together account for 90 % of the total variance, indicating their effective capture of most of the dataset's information. The first two components account for a substantial proportion of the variance, which is a valid reason to proceed with PCA. This analysis would facilitate a concise yet complete comprehension of the connections between EVI and environmental parameters, thereby assisting in ecological decision-making and policy formulation. The F3 and F4 components account for a lesser proportion of the variation and may reflect more specific or subtle correlations within the data. They can capture the subtle or less noticeable impacts of the variables on vegetation health that are less evident than those obtained by F1 and F2.

The eigenvector analysis in Table 5-4 provides a concise representation of the complex relationship between environmental variables and their influence on the health of vegetation. Factor 1 (F1) is a composite indicator representing overall environmental vitality. It positively correlates with vegetation health (EVI), rainfall, temperature, and soil moisture. This suggests that these factors work together to promote vegetative development patterns. On the other hand, Factor 2 (F2) separates the contrasting effects of temperature (thermal conditions) and soil

moisture, which may indicate changes that occur over the seasons. Regardless of other factors, factor 3 (F3) highlights the direct and contrasted impacts of rainfall on vegetation. It can serve as an indicator of unfavourable conditions for vegetation, such as drought. Factor 4 (F4) exhibits an intricate combination, where soil moisture shows a positive correlation while EVI and rainfall show a negative correlation. This suggests the presence of localised environmental elements or anomalies, such as riparian vegetation, in the water channels of the research area. These elements reveal the complex environmental patterns that control vegetation changes, providing essential knowledge for ecological research and policy development.

Table 5- 4: Factor Loadings and Variable Correlations in Environmental Data Analysis

Eigenvectors				
Factors	F1	F2	F3	F4
EVI	0.54	-0.01	-0.69	-0.49
Rainfall	0.53	-0.10	0.72	-0.43
Temperature	0.42	0.82	0.04	0.40
Soil Moisture	0.50	-0.57	-0.06	0.65
Correlations between variables				
EVI	0.92	-0.01	-0.37	-0.16
Rainfall	0.91	-0.08	0.39	-0.14
Temperature	0.71	0.69	0.02	0.13
Soil Moisture	0.85	-0.48	-0.03	0.21

Table 5-4 shows the factor loadings and correlations for a factor analysis that encompasses four variables: EVI, rainfall, temperature, and soil moisture. The study is performed on four factors, specifically F1, F2, F3, and F4. The EVI demonstrates a strong positive correlation with F1, showing a significant level of connection with this component. It has a negligible negative effect on the other metrics. Rainfall has a notable and favourable impact on F1 and a moderately favourable impact on F3, indicating that it is mostly associated with these components. The temperature has a substantial positive impact on both F1 and F2, indicating a dual link. Soil moisture has a notable positive effect on F1 and a slight negative effect on F2. The relationships between EVI, rainfall, and F1 show significant positive linkages, which are similar to the factor loadings. Temperature has a clear correlation with both F1 and F2. There is a strong positive correlation between the moisture level in the soil and F1 and a negative correlation between the moisture level and F2. Analysis of factor loadings and correlations reveals a multifaceted relationship between the Enhanced Vegetative Index (EVI) and key environmental variables. EVI exhibits a robust positive association with Factor 1, alongside Rainfall and Soil Moisture, suggesting a shared underlying environmental influence captured by this factor. Temperature, uniquely, shows a dual association with both Factor 1 and Factor 2, indicating its complex role in the ecological model. These findings underscore the intricate interplay between climatic elements and vegetation health, with Factor 1 reflecting overarching environmental conditions. In contrast, Factor 2 captures an additional dimension of variability, particularly related to Temperature. This nuanced understanding is crucial for developing targeted environmental policies and sustainable land management practices responsive to ecological systems' dynamic nature. Figure 5-5's biplot is intended to visually represent multivariate data. The biplot displays the two primary components, F1 and F2, which account for a substantial amount of

the variance in the data. The plot displays temperature, EVI, rainfall, and soil moisture contributions to these primary components. The variable with the strongest positive association to axis F1 is temperature, while soil moisture shows a negative link to both axes, with a stronger negative correlation to axis F1. The variables EVI and RF have positive correlations with both axes, but their correlation is stronger towards F2. This representation facilitates comprehension of the interconnections between the variables and the major components within the dataset.

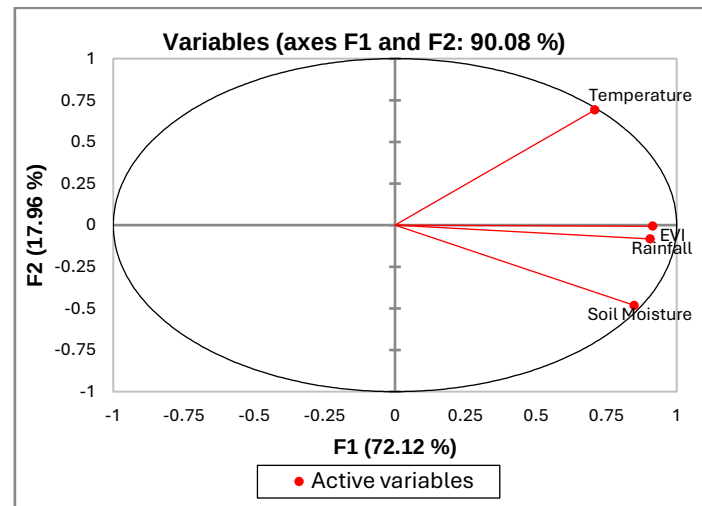


Figure 5- 5: Biplot of Variables and the most influential factors F1 and F2

Table 5-5 presents environmental data for four fields, illustrating the relationship between vegetation health (EVI), rainfall, temperature, and soil moisture. Field F3 displays the highest EVI (Enhanced Vegetation Index) and rainfall values due to abundant rainfall, indicating the presence of vigorous vegetation. In contrast, the low Enhanced Vegetation Index (EVI) and high F2 temperature suggest that the vegetation is stressed due to extreme heat. The high soil moisture levels observed in F4 indicate favourable conditions for plant growth, but F3's vegetation demonstrates resilience by thriving despite lower moisture levels. This data is essential for comprehending and overseeing agricultural ecosystems, as it accurately represents each field's distinct circumstances and activities. Table 5-5 presents the squared cosines of the variables, illustrating the extent to which the factors accurately represent the variables. When values approach 1, the factor accurately represents the variable. Values that are close to 0 indicate that the factor does not accurately represent the variable. The relationship between EVI and Factor 1 (F1) is high, as indicated by a squared cosine value of 0.838. F1's representation of rainfall is also quite accurate, as evidenced by a squared cosine value of 0.821. The temperature has a moderate influence on F1 and F2, as indicated by the squared cosine values of 0.504 and 0.479, respectively. For F1, the representation of soil moisture is strong, as indicated by a squared cosine value of 0.722. F2 also provides a moderate representation of soil moisture, with a squared cosine value of 0.233.

Table 5- 5: Variable Contributions and Squared Cosines in Principal Component Analysis

Contributions of the variables (%)				
Factors	F1	F2	F3	F4
EVI	29.03	0.01	46.99	23.97
Rainfall	28.45	0.96	52.48	18.11
Temperature	17.48	66.65	0.13	15.74
Soil Moisture	25.03	32.38	0.41	42.18
Squared cosines of the variables				
EVI	0.84	0.00	0.14	0.03
Rainfall	0.82	0.01	0.15	0.02
Temperature	0.50	0.48	0.00	0.02
Soil Moisture	0.72	0.23	0.00	0.04

A multifactorial examination of environmental variables reveals that Factor 1 strongly influences both the Enhanced Vegetative Index (EVI) and rainfall, as indicated by high squared cosine values. Temperature has a moderate correlation with Factor 1 and a significant association with Factor 2, indicating an intricate interplay with other ecological parameters. Factor 1 provides a strong representation of soil moisture, while Factor 2 has a secondary relationship, highlighting soil moisture's important function in vegetation dynamics. These findings emphasise the complex relationships between climatic conditions and the health of vegetation, underscoring the importance of conducting comprehensive environmental evaluations in ecological research and land management methods.

5.4 Discussion

Within the Cradle Nature Reserve, a grassland ecosystem focused on managing game ranges, the use of multilinear regression analysis and principal component analysis (PCA) allows for a thorough understanding of the ecological dynamics. The Enhanced Vegetative Index (EVI) exhibits substantial positive associations with rainfall and soil moisture, along with a moderate correlation with temperature, suggesting that these climatic factors play a crucial role in maintaining the health of vegetation. The strong correlation between EVI and important climatic parameters highlights the susceptibility of grassland ecosystems to hydrological and thermal conditions. (M. Xu et al., 2023; Zhong et al., 2010b). The insights obtained are extremely important for managing the habitat in the Cradle Nature Reserve, where game species protection is of utmost importance. The PCA analysis shows that the first two main components (F1 and F2) explain 90.08% of the variation in the data, which is a significant finding. (C. Chen et al., 2022; Greenacre et al., 2022). The F1 metric is highly likely to encompass the combined impacts of environmental factors on plants' overall well-being. Simultaneously, F2 seems to distinguish the distinct effects of temperature and moisture, which are crucial variables in grassland environments that are prone to extreme climatic conditions (Y. Wang et al., 2022; Zhong et al., 2010a).

The eigenvector analysis provides a more detailed understanding of the complex relationships between environmental factors and vegetation's well-being. The substantial positive connections between F1 and EVI, rainfall, temperature, and soil moisture indicate that F1 has

a combined impact on vegetative growth. This is important for sustaining the food resources needed for the resident game population (Arshad et al., 2023; Zhang et al., 2022). On the other hand, F2's focus on the specific impacts of temperature and soil moisture can indicate how grassland plants have evolved to cope with seasonal changes, affecting the amount of food available for game animals (Finger-Higgins et al., 2022). The biplot visualisation and factor analysis provide further insight, as F1 and F2 explain a substantial percentage of the environmental variance. The inverse relationship between soil moisture and both axes is particularly significant since it may suggest the difficulties that water scarcity presents for plant life. This situation could potentially have far-reaching consequences for the entire trophic hierarchy of the reserve (Abonyi et al., 2022). The analysis of variances (%) and squared cosines of the variables uncovered an intricate association between vegetation health, quantified by the Enhanced Vegetative Index (EVI), and the remaining meteorological conditions. Field F3 exhibited the most elevated EVI (Enhanced Vegetative Index) and rainfall levels, indicating that abundant rainfall plays a significant role in promoting strong vegetative health (Hopke, 1992). On the other hand, Field F2's low EVI, combined with high temperatures, indicates vegetation is experiencing stress, caused by extreme heat (Q. Yang et al., 2023). Field F4, characterized by its elevated soil moisture, demonstrates conducive circumstances for plant growth, whereas the ability of vegetation in Field F3 to persist despite lower moisture levels underscores the resilience of these ecosystems (Y. Li et al., 2020; Teague & Kreuter, 2020; Zaiontz, 2024). Factor analysis provides additional clarity on these correlations, as seen by the high squared cosine values, which confirm that EVI and rainfall are highly associated with Factor 1, highlighting their substantial impact on the environment (Milazzo et al., 2023; Zaiontz, 2024). The moderate representation of temperature in Factors 1 and 2 indicates its subtle influence on the health of vegetation (Hopke, 1992; Young & Young, 1992). The substantial correlation between soil moisture and Factor 1 and, to a lesser extent, Factor 2, highlights the significance of soil moisture in vegetation dynamics (Young & Young, 1992). These observations highlight the importance of using comprehensive environmental assessments to guide ecological research and land management. These assessments should consider the specific circumstances and practices of each agricultural area.

5.5 Conclusion

In conclusion, the thorough analysis reported in this study not only supports the use of PCA as a tool for making ecological decisions in the Cradle Nature Reserve but also gives a strong argument for its ongoing application in monitoring and managing grassland landscapes. The comprehensive comprehension of environmental factors provided by principal component analysis (PCA) and correlation analysis is essential for developing policies aimed at maintaining the intricate equilibrium of grassland ecosystems, thus guaranteeing the well-being of both the vegetation and the game species that rely on it. To promote sustainable land management, policymakers should utilise environmental data analysis to develop evidence-based policies that promote the growth of healthy vegetation, create seasonal plans based on the impact of temperature and moisture, and allocate resources to places where vegetation is under stress. In addition, they can formulate climate adaptation methods to cultivate robust vegetation, initiate educational campaigns regarding the environmental effects on vegetation well-being, and advocate for activities that improve soil moisture. Additionally, continuous research and monitoring are crucial for assessing the success of policies and adjusting tactics to achieve sustainable land management. This is important for maintaining a balance between

ecological well-being and meeting human needs, leading to a more resilient future. This research can provide valuable guidance for implementing good grassland management strategies in various ways: By conducting multilinear regression analysis, one can determine notable positive connections between the Enhanced Vegetative Index (EVI) and variables such as rainfall and soil moisture. Furthermore, there are moderate associations with temperature. Managers can prioritise these climatic aspects in their conservation efforts by comprehending these relationships. For instance, they can adjust the grazing intensity according to the expected rainfall or irrigation plans to optimise grass productivity. Principal Component Analysis (PCA) is a method that helps streamline extensive data sets by finding the crucial environmental variables, enabling managers to focus on those that have the greatest influence. The first two factors in this study accounted for over 90% of the variability in the data, indicating that a few important criteria may provide a comprehensive understanding of grassland health. This simplification can serve as a structure for targeted interventions. Eigenvector analysis: This analysis assists managers in understanding the magnitude and direction of the impact of different environmental factors on the health of plants. Positive correlations with the first principal component suggest that implementing strategies that enhance vegetative growth, such as utilising soil additives or employing controlled burns to manage invasive species, is advisable. Biplot visualisation and factor analysis offer a visual representation of the relationships between variables, helping to achieve educational goals and making it easier to communicate complex data to stakeholders. Moreover, they assist in identifying outliers or anomalies in grassland conditions that may require specific attention. Policy formulation: The insights gained from this research can assist policymakers in formulating evidence-based policies that encourage sustainable land management methods. An effective strategy is implementing policies that enhance the soil's capacity to retain moisture. This significantly influences vegetation's health and ability to endure water stress. Strategies for adapting to climate change: Examining the vulnerability of grasslands to alterations in water flow and temperature could yield significant knowledge for formulating climate adaptation measures. Continuous Monitoring: The study emphasises the importance of regularly examining environmental data. Continuous monitoring allows for assessing policy effectiveness and adapting management strategies based on new information or changing conditions. This research has the practical benefit of simplifying intricate ecological data into useful insights. We can then use these insights to guide various strategies for managing grasslands, aiming to maintain ecological health and promote sustainable utilisation of these critical ecosystems.

Chapter 6 UTILISING RGB DRONE IMAGERY AND VEGETATION INDICES FOR ACCURATE ABOVE-GROUND BIOMASS ESTIMATION: A CASE STUDY OF THE CRADLE NATURE RESERVE, GAUTENG PROVINCE, SOUTH AFRICA

This Chapter is based on the following manuscript.

Matyukira, C., & Mhangara, P. (2024). Utilising RGB drone imagery and vegetation indices for accurate above-ground biomass estimation: A case study of the Cradle Nature Reserve, Gauteng Province, South Africa. *Geocarto International*, **39**(1).
<https://doi.org/10.1080/10106049.2024.2390512>

Abstract: Accurate estimation of above-ground biomass (AGB) is a crucial aspect of ecosystem management, particularly in game reserves like the Cradle Nature Reserve. This study utilises 2018 AGB at a 50 m resolution to estimate AGB by integrating RGB drone imagery vegetation indices, normalised digital surface model (nDSM), and field-measured chlorophyll concentrations. Principal Component Analysis (PCA) and stepwise regression were employed to identify significant predictors of AGB. The final model for non-riparian forest area explained 66% ($R^2 = 0.66$), with nDSM and red-blue vegetation index (RBVI) as key predictors. In contrast, the riparian model explained 42% ($R^2 = 0.42$), with chlorophyll content and blue-green vegetation index (BGVI) as significant predictors. Our findings highlight the significant influence of nDSM and chlorophyll content on AGB. Vegetation indices such as the green-blue vegetation index (GBVI), green-red vegetation index (GRBI), and RBVI showed diverse correlations with chlorophyll levels, capturing plant greenness and vitality and directly influencing biomass. Comparative analyses of riparian and non-riparian vegetation models revealed that chlorophyll content and BGVI were significant predictors in riparian zones, reflecting interactions between water availability, nutrient flow, and vegetation health. In non-riparian areas dominated by tall trees, nDSM and RBVI were key predictors, underscoring the importance of plant height and stress indicators. This study underscores the effectiveness of drones in remote sensing applications for forest management. These findings contribute to the growing body of knowledge on drone-based biomass estimation, offering valuable insights for managing and conserving ecosystems such as the Cradle Nature Reserve, thereby providing practical implications for ecosystem management and conservation.

Keywords: Cradle nature reserve, above-ground biomass, chlorophyll concentrations, vegetation indices, normalised digital surface model

6.1 Introduction

Precisely assessing the amount of biomass present above the ground (AGB) is crucial for efficient management of ecosystems (Flores et al., 2019; E. Song et al., 2024), especially in protected areas like game reserves and nature reserves such as the Cradle Nature Reserve. AGB provides critical data on plant health, carbon storage, and habitat quality, all of which are necessary for biodiversity conservation and sustainable management techniques (Bazzo et al., 2023; Y. Gao et al., 2018; Numata et al., 2010; E. Song et al., 2024). Conventional techniques for estimating biomass, such as conducting field surveys and observations, are often characterised by their need for extensive manual effort, significant time investment, and potential negative impact on the environment (Bazzo et al., 2023; Nyamukuru et al., 2023; E. Song et al., 2024). As a result, remote sensing technologies have become a cost-effective and dependable option for monitoring plant biomass across large areas (Khumalo et al., 2024; Rapiya et al., 2023; G. Wang et al., 2023). Recent advancements in drone technology have transformed the discipline of remote sensing, providing high-resolution pictures and intricate 3D models of plant structures (Bazzo et al., 2023; E. Song et al., 2024; G. Wang et al., 2023). Researchers have demonstrated the usefulness of drone imaging using the RGB (Red, Green, and Blue) colour model in evaluating plant features (Agapiou, 2020; E. Song et al., 2024; G. Wang et al., 2023; Yue et al., 2017). Methods such as photogrammetric imaging and structure from motion (SfM) can generate digital surface models (DSMs) and digital terrain models (DTMs) (Holata et al., 2018; D. Turner et al., 2012). These models can then be used to construct normalised digital surface models (nDSM), which are obtained by subtracting the DTM from the DSM Equation (1) (Rose, 2021). The nDSM provide precise measurements of plant height, a critical component for determining aboveground biomass (AGB) (Rose, 2021; Viljanen et al., 2018).

$$nDSM = (DSM - DTM) \quad (1)$$

Multiple studies have shown that using drone-based RGB images and vegetation indices is useful for estimating biomass (Bazzo et al., 2023; G. Wang et al., 2023). For example, Bareth et al. (2015) used drone-based canopy height models (CHMs) to quantify grass height and biomass. They discovered that photogrammetric CHMs provided precise estimates of height throughout the advanced phases of plant growth. Nevertheless, these models exhibited lower precision in the first phases of development when the canopy was less dense. Possoch et al. (2016) also used, a low-cost RGB drone system to calculate canopy height models (CHMs) and RGB vegetation indices (RGBVIs) to estimate grassland biomass. The study emphasises the promise of using drones for remote sensing to measure aboveground biomass (AGB) (Possoch et al., 2016). However, they also emphasise the need for more studies to enhance accuracy across various development phases and kinds of vegetation (Possoch et al. 2016). Vegetation indices obtained from RGB drone footage are crucial for assessing vegetation characteristics and states. Indices such as BGVI, excess green index (ExG), GBVI, GRBI, normalised green-red difference index (NGRDI), and RBVI provide useful insights into the distribution and health of vegetation (Kazemi & Parmehr, 2023; Lóránt et al., 2024). These indices use the spectral characteristics of vegetation to increase the difference between different vegetation types and emphasise vegetation's presence (Bareth et al., 2015; Kazemi & Parmehr, 2023; Possoch et al., 2016). This makes them valuable for applications such as remote sensing and environmental monitoring. However, RGB imagery lacks the spectral richness of

hyperspectral data, which can capture a broader range of wavelengths and provide more detailed spectral information for AGB estimation. Hyperspectral data can mitigate issues like spectral saturation and provide more accurate AGB estimates across different growth stages due to its ability to capture subtle variations in reflectance (Y. Liu, Fan, et al., 2024; Y. Liu, Feng, Fan, et al., 2024; Y. Liu, Feng, Yue, et al., 2024)). Nonetheless, hyperspectral sensors are often more expensive, require more complex data processing, and have higher computational demands, which can hinder their widespread adoption. The hyperspectral approach also faces challenges in achieving robustness across various growth stages and environmental conditions due to the dynamic nature of spectral features (Y. Liu, Feng, Yue, et al., 2024).

While texture feature extraction from RGB images presents an alternative method that can capture detailed spatial patterns and structures of vegetation, research often emphasises height and spectral features due to their significant effectiveness in biomass estimation (Y. Liu, Feng, Yue, Li, et al., 2022). Texture features, such as those derived from the Gray Level Co-occurrence Matrix (GLCM) and Gabor filters, can provide detailed information about vegetation characteristics, but they add complexity to the data processing pipeline and require additional computational resources and time (Azeez et al., 2018; Y. Liu et al., 2023; Y. Liu, Feng, Yue, Jin, et al., 2022; Y. Liu, Feng, Yue, Li, et al., 2022; Mirzapour & Ghassemian, 2015). Previous research has shown that crop height directly correlates with the vertical structure of vegetation, making it a crucial indicator of above-ground biomass (AGB), while spectral indices derived from UAV images effectively capture vegetation health and vigor (Cui et al., 2023; Y. Liu et al., 2023; Y. Liu, Feng, Yue, Jin, et al., 2022). Studies have demonstrated that combining crop height with texture features such as GLCM-based and Gabor-based textures significantly improves the accuracy of biomass estimation models (Y. Liu et al., 2023; Y. Liu, Feng, Yue, Jin, et al., 2022). However, focusing on height and spectral features simplifies data processing and analysis, making it more efficient while maintaining high accuracy (Poley & McDermid, 2020). Thus, while texture features offer some advantages, the increased complexity and resource demands often lead researchers to leverage the effectiveness and efficiency of height and spectral features in biomass estimation (Poley & McDermid, 2020).

Principal component analysis (PCA) is a robust statistical method that reduces the number of variables in complex datasets while maintaining essential information, making it valuable for investigating correlations between above-ground biomass (AGB) and various vegetation indices, calculated nDSM, and chlorophyll content (Abonyi et al., 2022; Marukatat, 2023). By identifying the primary components that explain the highest variation, PCA simplifies analysis and highlights the most relevant factors impacting AGB, which can be further refined through stepwise regression to pinpoint the most influential predictors for accurate biomass estimation (Ruengvirayudh & Brooks, 2016). Stepwise regression, a process of adding and removing variables based on their statistical significance, has been shown in various studies to select the most predictive subset for the final model, balancing complexity and forecasting accuracy (Wagner & Shimshak, 2007; Yamashita et al., 2007; L. Yuan et al., 2021). Research has demonstrated that stepwise regression produces a clear, comprehensible model suitable for biomass estimation and can achieve similar accuracy to other regression techniques like support vector machines (SVM) and partial least squares regression (PLSR) (Kiala et al., 2016; Marabel & Alvarez-Taboada, 2013; Ruengvirayudh & Brooks, 2016; Shi et al., 2013). By

combining PCA with stepwise regression, researchers can leverage the strengths of both methods: PCA's ability to condense and summarise complex data and stepwise regression's capability to fine-tune the model by selecting the most pertinent predictors. This hybrid approach results in a more robust, parsimonious, and accurate model for estimating above-ground biomass, as it integrates comprehensive data representation with statistical rigour in variable selection (Y. Li et al., 2008; Y. Liu, Feng, Yue, Jin, et al., 2022; Shukla et al., 2004).

The precise assessment of aboveground biomass (AGB) in the Cradle Nature Reserve is a scientific endeavour crucial for efficient ecosystem administration. Understanding the distribution of AGB is critical to effectively monitoring plant health, controlling the grazing patterns of wild animals, and preserving ecological equilibrium. This research aims to provide essential data to the reserve's management, enabling well-informed decisions about conservation policies, sustainable tourism, and habitat restoration initiatives. Additionally, precise AGB assessments will significantly evaluate carbon stocks, contributing to broader environmental and climate change mitigation objectives. To achieve this, we will utilise data from southern Africa's 2018 AGB at 50 m resolution, RGB drone-derived vegetation indices, vegetation heights obtained from nDSM, and field-measured chlorophyll concentration. We will employ PCA to condense and summarise complex data and stepwise regression to fine-tune the model by selecting the most pertinent predictors, providing a robust, parsimonious, and accurate model for estimating AGB. Given the complexity and resource demands associated with texture-based methods, we have chosen to focus on height and spectral features, which have proven to be highly effective and efficient in previous research.

6.2 Materials and Method

6.2.1 Study Area

The Cradle Nature Reserve is located in the Sterkfontein Valley, about 50 kilometres northwest of Johannesburg, South Africa, and about 10 kilometres north of Krugersdorp (Lelliott, 2016; Rogerson & van der Merwe, 2016). The site occupies an estimated 8,000 hectares within the Cradle of Humankind World Heritage Site (COHWHS) (Lelliott, 2016). The reserve is located within the geographical coordinates of 27°42'58" and 27°52'57" longitude and 25°51'13" and 25°51'19" latitude (see Figure 6-1). In 1999, UNESCO designated this location as a world heritage site because of its profound significance in the study of paleoanthropology (Rogerson & van der Merwe, 2016). The COHWHS covers a total area of 47,000 hectares in South Africa's Gauteng and North-West regions. The average annual rainfall in the nature reserve ranges from 650 to 750 mm, while temperatures may reach a maximum of 39° C during summer and drop as low as -12° C in winter (SA-Venues.com, 2022).

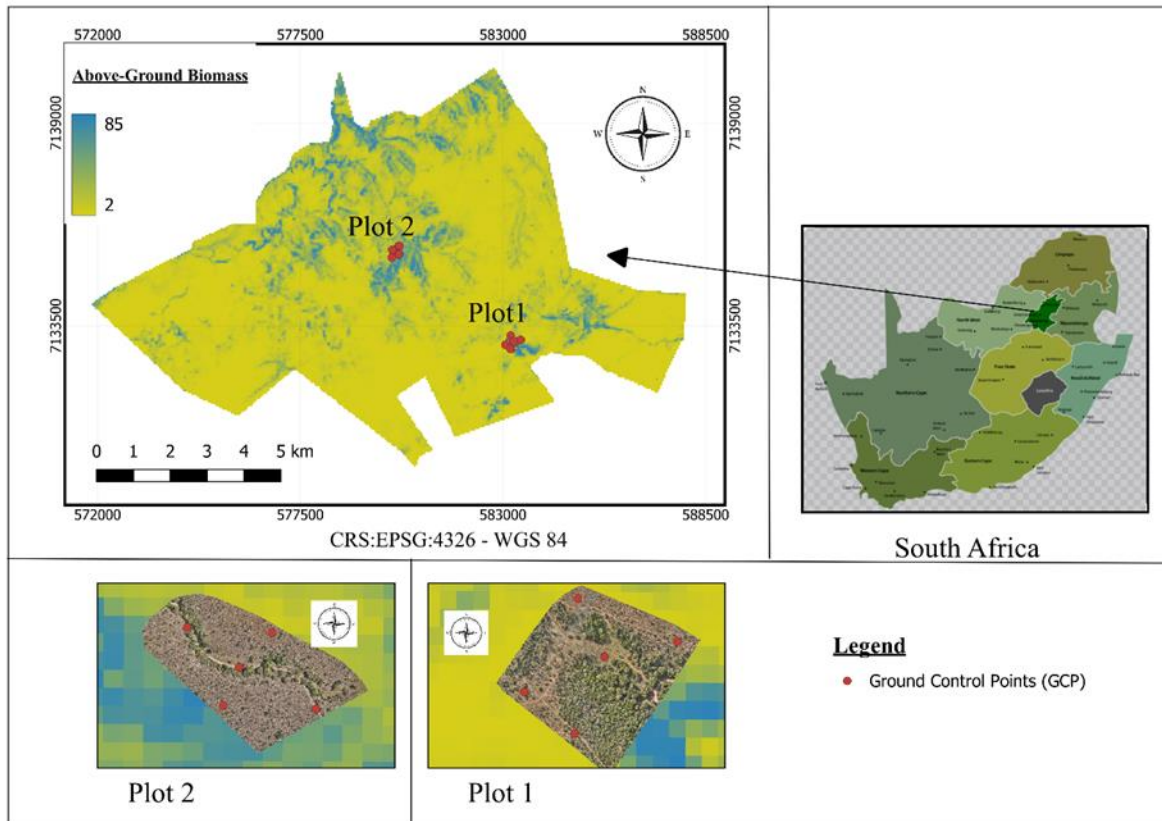


Figure 6- 1: Study Area-Cradle Nature Reserve in South Africa, Gauteng Province

In the Cradle Nature Reserve, the chemical weathering of limestone and dolomitic rocks forms karst landforms, resulting in a denudated pattern of rocky elements (Bradley et al., 2010). The distinctive landscape, shaped by a gradual process of disintegration, enhances the environmental diversity and promotes a high concentration of plant species in the area (Eloff, 2010). The karst environment supports various plant life, such as grasslands and wooded regions along ravines and dolomitic sinkholes (FLOW Communications, 2022). These places provide natural fire protection for trees, like white stinkwood and other plants ((FLOW Communications, 2022). We chose two plots for this study: a non-riparian forest region and a riparian forest area.

Plots 1 and 2, Figure 1, located within the rolling plains of the study area and part of the Magaliesberg Biosphere (designated an international Biosphere Reserve by UNESCO on June 9, 2015), showcase the diverse landscape of the savanna biome known as Moot Plains Bushveld (Magaliesberg Biosphere, 2024) . Characterised by stony clay-loam soils, Plot 1 gently slopes to the northeast and features a mix of open to closed low-growing thorn savannas dominated by Acacia species, particularly in the bottomlands and plains. Open areas intersperse dense clusters of green vegetation, with higher tree concentrations in the central and lower parts of the plot transitioning to more open spaces towards the edges. Plot 2, with a northwest slope, includes a stream tributary of the Crocodile River, lined with tall trees reflecting riparian vegetation. The rest of Plot 2 features a varied vegetation density typical of savanna ecosystems. Both locations boast dense stands of native tall trees, making them ideal for accurately measuring aboveground biomass (AGB) and comparing various developed models.

These plots provide a wide range of climatic variables for evaluating and confirming techniques for estimating AGB, highlighting the distinct bands of vegetation adapted to local soil and topographic conditions and emphasising the environmental gradients created by slope and water availability.

6.2.2 Procedure for doing random field measurements of chlorophyll using the Apogee MC-100 Chlorophyll Concentration Meter and N3 IMU GNSS Receiver

The aim of this approach was to quantify and document the chlorophyll levels in different species of plants at randomly selected field sites using the Apogee MC-100 Chlorophyll Concentration Meter and to establish the XY coordinates using the N3 IMU GNSS Receiver. This procedure's necessary equipment and supplies consisted of an Apogee MC-100 Chlorophyll Concentration Meter, an N3 IMU GNSS Receiver, a pole pruner, a moist towel, and a field notebook. Before conducting any tests, the Apogee MC-100 Chlorophyll Concentration Meter underwent calibration in accordance with the manufacturer's instructions to guarantee precise results (Apogee Instruments, 2024). The data collection was conducted randomly in several field areas consisting of grass, bushes, and trees. This approach ensured an impartial sampling process. A pole pruner was used to reach the uppermost foliage of the towering trees. Before measuring the chlorophyll content, the gathered leaves were delicately wiped with a moist cloth to eliminate soil or debris. The chlorophyll concentration in the field was determined by putting the Apogee MC-100 sensor on a representative leaf, establishing proper contact, and waiting for the reading to reach a stable state. Each plot was considered as one field, with several measurements of chlorophyll concentration collected from various leaves to ensure accurate and representative outcomes. Plot 1 included 34 trees, 13 shrubs, and 15 grass samples, while Plot 2 included 45 trees, 12 shrubs, and 13 grass samples. The XY coordinates of the location were recorded using the N3 IMU GNSS Receiver, which was positioned to have an unobstructed view of the sky (ComNav Technology Ltd 2024). The vegetation types, tree (TR), shrub (SH), and grass (GR), were recorded as "Code" on the GPS controller, while the chlorophyll content was recorded as 'Tag'. To assure accuracy, all data inputs on the GPS controller were cross-verified with the field notebook.

6.2.3 Construction of 3D models using the techniques of photogrammetry and UAV imaging.

The process of creating a very precise 3D model using photogrammetry entails a series of crucial phases, beginning with the development of Ground Control Points (GCPs). Georeferenced Control Points (GCPs) are very accurate geographical markers that improve the spatial precision of the model. In this research, strategically positioned Ground Control Points (GCPs) were set inside the surveyed area covered by the DJI Mavic 3T drone. The DJI Mavic 3 T drone features a 48 MP wide-angle camera with a 1/2-inch CMOS sensor, a tele camera, and a thermal imaging camera to provide high-resolution RGB and thermal images. The camera has an equivalent focal length of 24 mm, ensuring a wide field of view for capturing large areas. The drone offers a maximum flight time of up to 46 min and a transmission range of up to 15 km, allowing extensive area coverage. Its omnidirectional obstacle sensing and avoidance systems ensure safe operation, while the foldable design provides portability and quick deployment. In this study, the flying height was set to 60 meters, resulting in a spatial resolution

of approximately 3.5 cm per pixel. Each image had a resolution of 4000×3000 pixels, which confirms high-resolution data capture suitable for detailed analysis. These advanced characteristics make the DJI Mavic 3 T an ideal tool for detailed and precise data collection in environmental monitoring (MapperX.com, 2023).

To get precise coordinates, the GCPs were surveyed using high-precision GPS (N3 IMU RTK GNSS Receiver (ComNav Technology Ltd, 2024)) technology. During the aerial survey, the drone flew in altitude mode at 60metres above ground level and took pictures of the regions that overlapped with each other. This ensured that Ground Control Points (GCPs) were visible in numerous pictures. This would help align the photos accurately during the processing step in Agisoft Metashape Professional version 2.1.1 (Agisoft LLC., 2024; Stöcker et al., 2017). After aligning the photos, Agisoft Metashape's Build Dense Cloud function produced a dense point cloud. The function was set to the maximum quality and was compatible with the hardware being used. This process greatly enhances the amount of 3D information compared to the original point cloud, effectively capturing the surface characteristics with high precision (Westoby et al., 2012). The compact point cloud was thereafter carefully refined to eliminate anomalies and incorrect points that do not adequately depict the surface. To maintain the accuracy of the dataset, any points that were found to be above the vegetation or below the real topography were detected and removed.

This is an important step, especially in places with diverse surface characteristics, such as forests and urban contexts (James & Robson, 2012). After refining the point cloud, Digital Surface Models (DSM) and Digital Terrain Models (DTM) were generated. The DSM, including all visible structures such as buildings and plants, was immediately produced from the high-density point cloud (Oliveira et al., 2024; Remondino et al., 2014) and vehicles captured were manually removed from the DSM. Superfluous features were eliminated so the DTM could reflect the naked ground surface. Ultimately, an orthomosaic was produced by merging the georeferenced aerial photos into a smooth and accurate map that considers differences in topography and distortions caused by perspective (Dandois & Ellis, 2010, 2013). The orthomosaic underwent raster modification to extract distinct red, green, and blue bands, which accurately depict the colour information of the scene. The DTM, DSM, and RGB bands were exported as final outputs for viewing, analysis, and integration using Quantum GIS version 3.28.3-Firenze. This export ensured precise texture rendering and interoperability with 3D viewers (Verhoeven, 2011).

6.2.4 Use of AGB 50m resolution for Southern Africa (Bouvet et al., 2018)

The 2018 AGB dataset from the Theia African Biomass Map was chosen for this study mainly because of the Cradle Nature Reserve's consistent land use and plant cover. In recent years, the Cradle Nature Reserve has consistently maintained land use patterns that mostly revolve around animal grazing and browsing, with no notable changes in agricultural or urban growth. Research has shown that regions characterised by consistent land use often have limited fluctuations in biomass over a period of time (Baldocchi & Penuelas, 2019; Bessou, 2018; Erb et al., 2018; Numata et al., 2010). In addition, the plant cover, which includes forests and riparian landscapes, has remained mostly unaltered, save for isolated- occurrences of invasive weed incursions, which have had no substantial influence on the main study region. Historical AGB data, consistent with plant cover, is a reliable reference point for estimating current

biomass levels (Zianis et al., 2005). We obtained the 50-meter-resolution map from Theia and cropped it using the research area shapefile in QGIS (QGIS Documentation., 2024).

In 2012, nine French government institutes specialising in earth observation and environmental sciences founded Theia, which focuses on the study of continental surfaces (Bouvet et al., 2018). Theia offers the scientific community and public policy a diverse array of pictures, goods, methodologies, and training pertaining to monitoring land surfaces from space (Bouvet et al., 2018). Theia also provides a dataset that estimates woody AGB at a resolution of 50 m $\times$ 50 m for savannahs and woods in continental Africa and Madagascar (Bouvet et al., 2018). These estimates are made by using 144 reference plots and are obtained through a Bayesian inversion of an L-band synthetic aperture radar (SAR) mosaic from ALOS PALSAR (horizontal transmit, horizontal receive (HH), and horizontal transmit vertical receive (HV) polarisations) (Bouvet et al., 2018). The mosaic has a resolution of 50 m x 50 m. In utilising the 2018 above-ground biomass map, this study recognises the constraints associated with using the information from 2018. The time difference between the data collection and the current research period creates uncertainty because environmental variables such as changes in climate might have influenced biomass quantities (Bhan et al., 2021; J. Xiao et al., 2019). Furthermore, the dataset's 50 m resolution may not be sufficient to capture small-scale changes that drone data with a higher resolution could detect. Although there are limits, historical AGB data may provide useful insights and act as a benchmark for identifying patterns and changes compared to more current, higher-resolution data (Goetz et al., 2009; Zianis et al., 2005). By recognising and considering these limitations, the research guarantees a fair and scientifically rigorous examination of the amount of biomass above the ground in the two Plots studied in the Cradle Nature Reserve.

6.2.5 Analysis of vegetation using QGIS and UAV imaging

The essential datasets for each plot, consisting of Red, Green, and Blue (RGB) photos, a Digital Surface Model (DSM), and a Digital Terrain Model (DTM), were imported into QGIS, an open-source Geographic Information System. As stated, these datasets were processed from drone photographs using Agisoft Metashape Professional. In addition, chlorophyll data obtained from field surveys utilising an N3 IMU GNSS Receiver were prepared for integration. The data layers were imported into QGIS as raster layers for raster data analysis (QGIS Documentation., 2024). The RGB pictures generated several vegetation indices, while the DSM and DTM were utilised to produce the nDSM.

The QGIS raster calculator tool was used to calculate several vegetation indices that are crucial for vegetation study (Lóránt et al., 2024; QGIS Documentation., 2024). The indices included the BGVI, ExG, BVI, GRBI, NGRDI, and RBVI. Table 1 provides the precise calculations applied to the RGB bands to derivate each index (Kazemi & Parmehr, 2023; Lóránt et al., 2024).

Table 6- 1: Vegetation index equations using an RGB drone image.

Equation	Formula
1	$BGVI = (Blue - Green) / (Blue + Green)$ (X. Yu et al., 2018)
2	$ExG = 2 \times Green - Red - Blue$ (Meyer & Neto, 2008)

3	$GBVI = (Green - Blue) / (Green + Blue)$ (Mehrotra & Srinivasan, 2019)
4	$GRBI = (Green - Red) / (Green + Blue)$
5	$NGRDI = (Green - Red) / (Green + Red)$ (Tucker, 1979b)
6	$RBVI = (Red - Blue) / (Red + Blue)$ (Kawashima & Nakatani, 1998)

The vegetation indices in Table 6-1 were selected due to their effectiveness in various vegetation monitoring and biomass estimation applications. BGVI and BVI are sensitive to chlorophyll content, indicating plant health, while ExG differentiates green vegetation from other land cover types. GRBI and NGRDI assess vegetation vigour and are less affected by soil background effects, and RBVI enhances the contrast between vegetation and non-vegetation areas. These indices collectively provide a comprehensive assessment of vegetation condition, enhancing the accuracy of aboveground biomass estimation (Xue & Su, 2017).

Next, we determined the nDSM by subtracting the DTM from the DSM (Holman et al., 2016). This stage was crucial in comprehending the structure and height of vegetation. The calculated indices and nDSM provided comprehensive information on vegetation attributes, which is crucial for further spatial analysis. To combine the chlorophyll data collected during field surveys with the calculated vegetation indices and nDSM, we imported the field data, consisting of XY coordinates, into QGIS as a point layer. Subsequently, the ‘Sample Raster Values’ tool (QGIS Documentation., 2024) was used to get the associated raster values (vegetation indices and nDSM) for every field data point. This integration facilitated the creation of a complete dataset by merging data collected in the field with data obtained via remote sensing. The obtained data was exported in CSV format, including chlorophyll readings, vegetation indices, and nDSM values. The CSV data were then used in Minitab version 18 for the Principal Component examination (PCA) and regression modelling. This allowed for a comprehensive statistical examination of the correlation between chlorophyll content, several vegetative factors, and vegetation heights (nDSM) (Ruengvirayudh & Brooks, 2016; Wagner & Shimshak, 2007).

6.2.6 Performing Principal Component Analysis (PCA) and Stepwise Regression Analysis using Minitab Version 18

This approach utilised Minitab Version 18 to conduct PCA and Stepwise Regression Analysis on a dataset comprising variables such as AGB, normalised digital surface model (nDSM), chlorophyll concentration (Chloro), and vegetation indices derived from the RGB DJI Mavic 3 T for Plot 1 and Plot 2. First, the datasets are imported into Minitab, and PCA is performed to minimise the dimensionality of the data by finding the principal components that account for the bulk of the variation. This stage included selecting relevant factors, adjusting the number of principal components based on cumulative explained variance, and interpreting the outcomes to comprehend the contributions of each variable. Afterwards, a stepwise regression analysis was conducted to determine the most accurate prediction model for AGB using nDSM, chloro, and vegetation indicators as predictors. This procedure involves putting up sequential configurations, executing the regression, and assessing the model’s performance using R-squared values and Variance Inflation Factor (VIF) to tackle multicollinearity. Variables exhibiting high VIF values were eliminated, and the model was then rerun to check its trustworthiness. The completed model is verified by identifying relevant predictors and

ensuring low VIF values. The validation process includes detailed recording and reporting of the results, which includes regression equations and insights into the dependability of the model.

6.3 Results and Analysis

6.3.1. Comparison of variable statistics between non-riparian and riparian areas

The results in Table 6-2, non-riparian area, and Table 6-3, riparian area, show that, in general, the mean values for variables in Plot 2 (riparian area) with 70 observations are slightly lower than those in Plot 1 (non-riparian area) with 80 observations. For instance, the mean AGB decreases from 44.33 in Plot 1 to 23.63 in Plot 2, and the mean nDSM decreases from 7.21 in Plot 1 to 5.41 in Plot 2. Additionally, the standard deviations are generally lower in Plot 2, indicating less variability in the riparian area dataset. Notably, the mean chlorophyll (Chloro), field-observed, decreases from 314.52 in Plot 1 to 287.22 in Plot 2. The standard deviation of chlorophyll is also lower in Plot 2 (165.14) compared to Plot 1 (205.97), suggesting less variability in chlorophyll levels within the riparian area compared to the non-riparian area (Table 6-3).

Table 6- 2: Summary statistics plot 1 (non-riparian).

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
nDSM	80	0	80	0.00	19.00	7.21	5.91
Chloro	80	0	80	24.30	877.80	314.52	205.97
AGB	80	0	80	2.00	85.00	44.33	32.16
BGVI	80	0	80	-0.35	-0.01	-0.16	0.08
ExG	80	0	80	-17.00	71.00	20.06	17.25
GBVI	80	0	80	0.01	0.37	0.17	0.08
GRBI	80	0	80	0.45	0.75	0.56	0.06
NGRDI	80	0	80	-0.15	0.09	-0.03	0.05
RBVI	80	0	80	0.05	0.35	0.19	0.07

Table 6- 3: Summary statistics plot 2 (riparian).

Variable	Observations	Obs. with missing data	Obs. without missing data	Minimum	Maximum	Mean	Std. deviation
nDSM	70	0	70	0.00	16.00	5.41	4.38
Chloro	70	0	70	19.10	693.60	287.22	165.14
AGB	70	0	70	6.00	44.00	23.63	9.35
BGVI	70	0	70	-0.56	-0.03	-0.18	0.12
ExG	70	0	70	-10.00	54.00	17.49	15.70
GBVI	70	0	70	0.03	0.39	0.15	0.09
GRBI	70	0	70	-0.21	0.06	-0.05	0.05
NGRDI	70	0	70	-0.12	0.04	-0.03	0.04
RBVI	70	0	70	0.00	0.47	0.20	0.09

6.3.2. Comparison of principal components analysis (PCA) results

Tables A1 (a) and A2 (a), Appendix A both present the eigenvalues, variability percentages, and cumulative percentages obtained from principal components analysis (PCA), highlighting their importance in explaining the variability of the data. In Table A1 (a), a non-riparian area, F1 explains 68.07% of the overall variance, with F1 alone accounting for the highest proportion, followed by F2 and F3. The combination of F1 and F3 contributes to 96.35% of the variability. Similarly, Table A2(a), riparian area, shows that F1 has the greatest eigenvalue, explaining 39.27% of the total variance. The cumulative percentages indicate that F1 alone contributes 39.27%, with the combined impact of F1, F2, and F3 accounting for 70.62%. In both cases, most of the variability stems from the F1 factor, and we should disregard eigenvalues with smaller significance.

Furthermore, the eigenvectors in Tables A1 (b) and A2 (b), Appendix A, both reveal the individual impacts of several variables on Factor 1 (F1). In the non-riparian area, Table A1 (b), the significant contributors to F1 include nDSM (0.34), Chloro (0.34), AGB (0.30), ExG (0.38), GBVI (0.36), GRBI (0.38), and RBVI (0.23), with ExG, Chloro, and GRBI making notably significant contributions. Similarly, in the riparian area, Table A2 (b) shows that nDSM (0.39), AGB (0.38), ExG (0.38), GBVI (0.38), and Chloro (0.37) are significant contributors, indicating that F1 is a combination of these variables.

Finally, Tables A1(d) and A2(d), Appendix A, both show the variable percentage contributions to Factor 1 (F1). In the non-riparian area, plot 1, the significant contributors to F1 are nDSM (11.81%), Chloro (11.84%), AGB (9.10%), BGVI (13.42%), ExG (14.40%), GBVI (13.02%), GRBI (14.24%), NGRDI (7.08%), and RBVI (5.12%), with GRBI, ExG, BGVI, GBVI, and Chloro having notable impacts. AGB and NGRDI have less significant impacts, and RBVI has a limited influence. Similarly, Table A2 (b), riparian area, plot 2, indicates that the significant contributors to F1 are nDSM (15.29%), Chloro (13.42%), AGB (14.50%), BGVI (12.42%), ExG (14.46%), GBVI (14.58%), NGRDI (7.47%), and RBVI (7.40%), with GBVI, ExG, AGB, Chloro, and BGVI making significant contributions. While RBVI and NGRDI also play roles, their contributions are comparatively smaller, and GRBI makes very little contribution to F1.

6.3.3. Pairwise comparison of regression models for non-riparian and riparian plots in the Cradle Nature Reserve

The regression analysis for non-riparian (Plot 1) and riparian (Plot 2) areas in the Cradle Nature Reserve reveals distinct differences in model performance and predictor significance (Tables 6-4 and 6-5). The non-riparian model exhibits a strong correlation ($R = 0.81$) and explains 66% of the variance in Above Ground Biomass (AGB) ($R^2 = 0.66$), compared to the riparian model's moderate correlation ($R = 0.57$) and 33% variance explanation ($R^2 = 0.33$). The standard error of the estimate is higher for the non-riparian model (19.38) versus the riparian model (7.77), indicating greater variability in predictions in the non-riparian area. Additionally, both models show some positive autocorrelation in residuals, with the non-riparian model having a slightly higher Durbin-Watson value (1.22) than the riparian model (1.15). The critical predictor, nDSM, significantly influences AGB in both models, showing a more substantial impact in the non-riparian area ($\text{Beta} = 0.76$, $p < 0.001$) compared to the riparian area ($\text{Beta} = 0.35$, $p = 0.02$). In contrast, GBVI, GRBI, and RBVI are not significant predictors in either model, with GBVI showing high multicollinearity in the non-riparian model ($\text{VIF} = 9.28$).

Table 6- 4: Stepwise regression modelling Plot 1(non-riparian).

Model Summary								
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson			
1	0.81	0.66	0.64	19.38	1.22			
a. Predictors: (Constant), RBVI, nDSM, GRBI, GBVI								
b. Dependent Variable: AGB								
Coefficients								
Model		Unstandardised Coefficients B	Std. Error	Standardised Coefficients Beta	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
1	(Constant)	17.66	46.38		0.38	0.71		
	nDSM	4.20	0.61	0.76	6.88	<.001	0.49	2.06
	GBVI	69.78	97.90	0.17	0.71	0.48	0.11	9.28
	GRBI	24.02	91.90	0.04	0.26	0.80	0.23	4.40
	RBVI	-141.32	69.38	-0.31	-2.04	0.05	0.26	3.79
Collinearity Diagnostics								
Model	Dimension	Eigenvalue	Condition Index	(Constant)	nDSM	GB VI	GRBI	RBVI
1	1	4.58	1.00	0.00	0.01	0.00	0.00	0.00
	2	0.30	3.91	0.00	0.48	0.00	0.00	0.00
	3	0.09	6.99	0.01	0.19	0.06	0.00	0.09
	4	0.03	13.48	0.00	0.29	0.34	0.01	0.54
	5	0.00	61.79	0.99	0.04	0.60	0.99	0.36
Residuals Statistics								
	Minimum	Maximum	Mean	Std. Deviation	N			
Predicted Value	1.06	97.73	43.68	26.12	62.00			
Residual	-43.19	35.98	0.00	18.73	62.00			
Std.	-1.63	2.07	0.00	1.00	62.00			
Predicted Value								
Std.	-2.23	1.86	0.00	0.97	62.00			
Residual								
Descriptive Statistics								
	N	Minimum	Maximum	Mean	Std. Deviation			
AGB	18	2	84	46.56	33.06			
Predicted _AGB	18	6.70	90.20	52.55	27.04			
Valid N (listwise)	18							

Table 6- 5: Stepwise regression modelling Plot 2 (riparian).

Model Summary								
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Durbin-Watson			
1	0.57	0.33	0.27	7.77	1.15			
a. Predictors: (Constant), nDSM, RBVI, GRBI, GBVI								
b. Dependent Variable: AGB								
Coefficients								
Model		Unstandardised Coefficients		Standardised Coefficients	t	Sig.	Collinearity Statistics Tolerance	Collinearity Statistics VIF
		B	Std. Error	Beta				
1	(Constant)	15.51	3.30		4.70	<.001		
	GBVI	20.02	17.48	0.20	1.15	0.26	0.50	1.99
	GRBI	37.13	24.82	0.19	1.50	0.14	0.95	1.05
	RBVI	13.16	17.30	0.12	0.76	0.45	0.61	1.65
	nDSM	0.74	0.31	0.35	2.42	0.02	0.76	1.32

Collinearity Diagnostics								
Model	Dimension	Eigenvalue	Condition Index	Variance Proportions				Variance Proportions
				(Constant)	GBVI	GRBI	RBVI	nDSM
1	1	4.06	1.00	0.01	0.01	0.02	0.01	0.01
	2	0.51	2.82	0.00	0.01	0.42	0.00	0.27
	3	0.24	4.11	0.01	0.06	0.42	0.10	0.51
	4	0.13	5.59	0.45	0.46	0.12	0.01	0.00
	5	0.06	8.55	0.53	0.46	0.03	0.89	0.20
Residuals Statistics								
	Minimum	Maximum	Mean	Std. Deviation	N			
Predicted Value	13.50	33.37	22.64	5.20	47			
Residual	-12.37	17.01	0.00	7.43	47			
Std. Predicted Value	-1.76	2.07	0.00	1.00	47			
Std. Residual	-1.59	2.19	0.00	0.96	47			
Descriptive Statistics								
	N	Range	Minimum	Maximum	Mean	Std. Deviation	Variance	
AGB	23	31	13	44	25.65	9.80	95.96	
Predicted_ AGB	23	15.27	15.75	31.02	24.44	4.70	22.12	
Valid N (listwise)	23							

The residual statistics further emphasise the differences between the two models. The non-riparian model displays a broader range of predicted values (1.06–97.73) and residuals (–43.19 to 35.98), reflecting more significant prediction variability. In comparison, the riparian model shows a narrower range of predicted values (13.50–33.37) and residuals (–12.37 to 17.01). The descriptive statistics indicate that AGB in the non-riparian area has a higher mean (46.56) and greater variability (Std. Deviation = 33.06) compared to the riparian area, which has a lower mean AGB (25.65) and less variability (Std. Deviation = 9.80). The predicted AGB values are close to the actual values in both areas but show a slight overestimation in the non-riparian area. The non-riparian model demonstrates a stronger fit but faces significant multicollinearity and greater prediction variability. In contrast, despite explaining less variability in AGB, the riparian model benefits from lower multicollinearity and more consistent predictions. These findings highlight the different dynamics in AGB prediction for non-riparian and riparian plots, underscoring the importance of considering local environmental characteristics in predictive modelling.

6.3.4. Comparative performance of regression models for non-riparian and riparian plots in the Cradle Nature Reserve

The regression models for non-riparian and riparian plots in the Cradle Nature Reserve reveal distinct differences in their predictive performance and residual behaviour. The non-riparian model demonstrates a stronger correlation between predicted and observed AGB values ($R=0.81$) and explains a higher proportion of variance ($R\text{ Square} = 0.66$) compared to the riparian model ($R=0.57$, $R\text{ Square} = 0.33$). However, the non-riparian model exhibits more pronounced systematic bias, with residuals showing a discernible pattern where AGB is overestimated for predicted values around 60–80 and underestimated for values below 40 and above 80. This model also shows significant outliers, with residuals ranging from –60 to 40,

indicating substantial prediction errors. Additionally, heteroscedasticity is more severe in the non-riparian model, with the spread of residuals increasing with higher predicted AGB values, suggesting that the model's reliability decreases for higher biomass estimates (Figures 6-2 and 6-3).

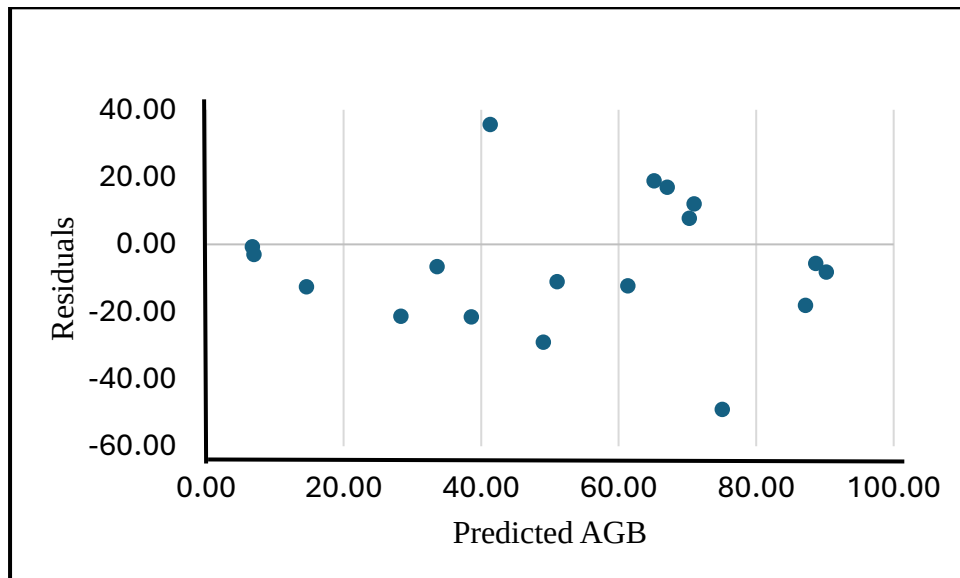


Figure 6- 2: Scatter plot of residuals versus predicted AGB for Plot1 (non-riparian).

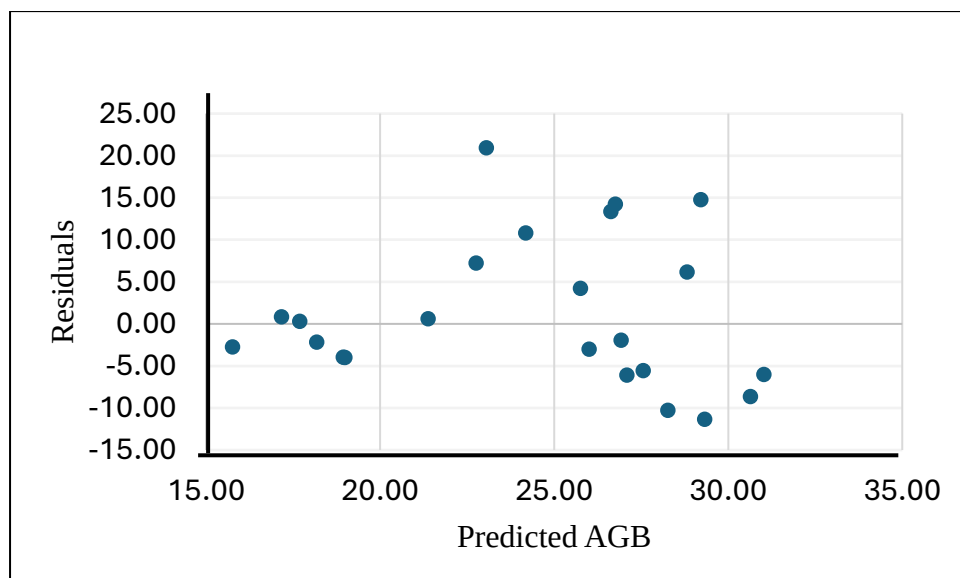


Figure 6- 3: Scatter plot of residuals versus predicted AGB for Plot 2 (riparian).

In contrast, while explaining less variance, the riparian model displays a more random distribution of residuals with fewer pronounced biases. The residual range is narrower (–10 to 20), indicating smaller deviations between observed and predicted values. This model exhibits slight heteroscedasticity, with residuals clustering around predicted AGB values of 25–30, but the effect is less pronounced than in the non-riparian model. Despite the lower R Square value, the riparian model's consistency and fewer significant outliers suggest better overall

performance in terms of prediction accuracy. The significant predictors, such as nDSM, show a moderate impact on AGB in both models but with a stronger influence in the non-riparian area (Beta = 0.76) compared to the riparian area (Beta = 0.35). These differences highlight the need for tailored model refinements, such as addressing systematic biases and heteroscedasticity, to improve the robustness and reliability of AGB predictions in both non-riparian and riparian plots.

6.4 Discussion

6.4.1. Effectiveness of RGB drone imagery in estimating above-ground biomass

The study demonstrates mixed results regarding the effectiveness of RGB drone imagery in estimating above-ground biomass (AGB) for non-riparian and riparian forest areas. In the non-riparian area, Factor 1 (F1) explains 68.07% of the variance, with significant contributors including nDSM (0.34), Chloro (0.34), ExG (0.38), GBVI (0.36), and GRBI (0.38). In the riparian area, F1 explains 39.27% of the total variance, with significant contributors being nDSM (0.39), AGB (0.38), ExG (0.38), GBVI (0.38), and Chloro (0.37). Regression analysis reveals that the non-riparian model explains 66% of the variance in AGB ($R^2 = 0.66$) with a strong correlation ($R = 0.81$), while the riparian model explains only 33% of the variance ($R^2 = 0.33$) with a moderate correlation ($R = 0.57$). The critical predictor, nDSM, significantly influences AGB in both models, with a more substantial impact in the non-riparian area (Beta = 0.76, $p < 0.001$) compared to the riparian area (Beta = 0.35, $p = 0.02$). Despite the overall usefulness of RGB drone imagery, the lower R^2 values in the riparian model indicate that the indices derived from RGB images were less effective in explaining AGB variance in these areas. The non-riparian model shows greater prediction variability, with a standard error of the estimate at 19.38, compared to 7.77 in the riparian model. Additionally, the non-riparian model has a higher Durbin-Watson value (1.22) compared to the riparian model (1.15), suggesting more positive autocorrelation. Variance Inflation Factor (VIF) values for the non-riparian model are higher, especially for GBVI (9.28), indicating more severe multicollinearity. In contrast, the riparian model benefits from lower multicollinearity and more consistent predictions, as evidenced by the tighter clustering of residuals and lower VIF values (all below 5). These findings highlight that while RGB drone imagery can be effective, its indices may not always sufficiently capture the complexity of biomass in riparian zones, particularly where vegetation heights vary significantly from grass to tall trees (Dormann et al., 2013; Nagler et al., 2018; Richardson et al., 2001).

Similar studies have shown varying degrees of effectiveness when using RGB drone imagery for AGB estimation. (Bareth et al., 2015) demonstrated the utility of drone-based canopy height models (CHMs) in accurately estimating biomass, particularly in advanced stages of plant growth. Possoch et al., (2016) found that low-cost RGB drones effectively estimate grassland biomass using CHMs and RGB vegetation indices. Further research by Bendig et al., (2014) confirmed the reliability of UAV-based RGB imaging for assessing crop biomass in uniform vegetation such as potatoes and rice, showing high accuracy where vegetation height is relatively consistent. A study by Lisein et al., (2013) also established the effectiveness of UAVs in forest biomass estimation, highlighting their ability to provide high-resolution data over large areas with uniform canopy. However, our study had varying vegetation heights from grass

to tall trees, which might have contributed to the lower R² values in riparian areas. Moreover, research by Wallace et al., (2012) underscored the potential of UAVs in mapping and monitoring forest structure, supporting the current study's findings.

6.4.2 Differentiating predictive performance in riparian and non-riparian vegetation models

The riparian vegetation model has an R² value of 0.33, explaining 33% of the AGB variation. The standard error of the estimate is 7.77, indicating moderate prediction variability. Key predictors in this model include nDSM (Beta = 0.35, p = 0.02), which has a moderate positive impact on AGB. The Durbin-Watson value is 1.15, showing slight positive autocorrelation in residuals. The model indicates that significant predictors like nDSM, Chloro, and ExG contribute notably to AGB, while variables such as GBVI, GRBI, and RBVI do not show significant predictive power. The lower VIF values suggest minimal multicollinearity issues. The residuals exhibit a relatively narrow range (−12.37 to 17.01), indicating smaller prediction deviations. This model emphasises the importance of vegetation indices and height in biomass estimation in riparian zones, influenced by water availability and nutrient flow. Previous studies have similarly highlighted the role of vegetation indices such as NDVI, ExG, and chlorophyll concentration in assessing biomass in riparian areas (Richardson et al. 2001; Nagler et al. 2018). Furthermore, the integration of nDSM in biomass estimation has been validated by research demonstrating its effectiveness in capturing vegetation structure and height, crucial factors in riparian ecosystems (Y. Gao et al., 2018; Richardson et al., 2001).

Conversely, the vegetation model for non-riparian areas, which primarily consists of tall trees and does not grow near a river, demonstrates a stronger ability to explain the data, achieving an R-value of 0.81 and an R² value of 0.66. This model finds nDSM and certain vegetation indices to be important predictors. The nDSM has a significant and favourable impact on AGB, with a beta coefficient of 0.76 and a p-value less than 0.001. High VIF values, particularly for GBVI (9.28), indicate significant multicollinearity in the model, necessitating careful interpretation of the coefficients. The Durbin–Watson statistic's closeness to 1.22 suggests that there is a slight concern about positive autocorrelation compared to the riparian model. The findings emphasise the critical role of vegetation height and specific stress indicators in clarifying biomass in non-riparian, wooded regions. Previous studies have validated the use of nDSM in biomass estimation, highlighting its ability to capture vegetation structure and height, which are crucial factors in non-riparian ecosystems (Y. Gao et al., 2018; X. Tian et al., 2024). Additionally, research has shown that vegetation indices like GBVI, despite potential multicollinearity issues, can significantly contribute to biomass estimation in forested areas (D. Lu et al., 2016).

The contextual disparities between the two models illustrate the many environmental conditions and biological processes that affect biomass in riparian and non-riparian zones. Previous research has shown that Chloro has a beneficial effect and BGVI has a detrimental effect in riparian environments (Nagler et al., 2018). These findings support the idea that chlorophyll concentration and stress indices are important factors in these dynamic ecosystems (Kancheva et al., 2014; Nagler et al., 2018; Raddi et al., 2022). On the other hand, nDSM is a

good predictor of above-ground biomass in places without water, where tall trees are the main type of vegetation (Y. Gao et al., 2018; Wilkes et al., 2018; J. Zhang et al., 2024). This aligns with previous research in forest ecology that stresses how important plant height is (Andersen et al., 2006). Distinct stressors, separate from those in riparian zones, may exacerbate the adverse effects of RBVI in non-riparian regions, underscoring the intricate interaction of environmental elements in diverse biological settings (Nagler et al., 2018). These observations emphasise the need for customised remote sensing methods to precisely evaluate and control biomass and vegetation well-being in various settings (Abbas et al., 2020; Fagua et al., 2019; X. Yuan et al., 2016).

6.4.3 Limitations of RGB drone imagery, nDSM, and chlorophyll measurements in estimating above-ground biomass in riparian and non-riparian areas

Although there are important discoveries, there are various constraints that impact the effectiveness of RGB drone photography, nDSM, and chlorophyll measurements in predicting above-ground biomass (AGB) in riparian and non-riparian environments. RGB cameras only record the wavelengths of light that are visible to the human eye, which range from around 0.4 to 0.7 μm . However, they do not catch the crucial near-infrared (NIR) and middle-infrared wavelengths that are required for the precise study of vegetation and biomass determination (Alevizos et al., 2022; H. G. Jones & Vaughan, 2010; Sweet et al., 2022). This constraint reduces the dependability of vegetation health assessments and the ability to identify the first indications of vegetation strain (Feng et al., 2022; Sweet et al., 2022). The presence of high reflectance saturation in places with thick vegetation might complicate the analysis and perhaps result in incorrect estimations of biomass (Gamon et al., 1995). The lack of NIR data makes it harder to accurately calculate commonly used vegetation indices like the Normalized Difference Vegetation Index (NDVI), which limits the study's ability to fully assess the health of the vegetation. In addition, the restricted range of spectral data limits the capacity to distinguish between various species of vegetation and precisely measure moisture content. These factors are crucial for effectively estimating biomass (Feng et al., 2022; Gamon et al., 1995; Sweet et al., 2022). The analysis reveals that the nDSM has high VIF values, which suggests the presence of significant multicollinearity. This makes it challenging to acquire precise coefficient estimates, especially in riparian regions with intricate plant structures (Bazzo et al., 2023; Chave et al., 2014). Plant height, which fluctuates considerably due to environmental variables like water availability and soil conditions, greatly influences the estimation of biomass in nDSM. This variability may lead to less reliable biomass estimations. Precise computation of normalized Digital Surface Model (nDSM) necessitates accurate Digital Surface Model (DSM) and Digital Terrain Model (DTM) data. Any inaccuracies in these models may have a direct impact on the precision of the nDSM and, subsequently, biomass estimations (Abdullah et al., 2021; Bazzo et al., 2023; Feng et al., 2022; Lefsky et al., 2002). The chlorophyll content is an important factor in predicting aboveground biomass (AGB), but its correlation with biomass may vary depending on the plant species, health, and climatic circumstances. This variability introduces uncertainty in biomass predictions (Gitelson et al., 2003). The precision of chlorophyll measurements derived from Apogee MC-100 sensor may be lower compared to measurements acquired from multispectral or hyperspectral sensors. This difference in precision could have an impact on the accuracy of chlorophyll-related

vegetation indices and their association with biomass. Plant and water levels are closely connected in riparian zones, which makes it harder to figure out which predictor variables have the most effect on biomass (Gitelson et al., 2003; Naiman & Decamps, 1997; Zarco-Tejada et al., 2001). Significant multicollinearity complicates the regression analysis and reduces the interpretability of the model, especially for variables like nDSM and chlorophyll (Bazzo et al., 2023; Dormann et al., 2013; Li et al., 2008). In locations that are not next to a river, the predictors GBVI and GRBI have high VIF values, which suggest the presence of strong multicollinearity. As a result, it is important to interpret the coefficients with caution. The negative impacts of RBVI in areas not near rivers, where tall trees are the dominant plant species, underscore the intricate interplay of environmental factors that the existing model may not adequately represent (Bazzo et al., 2023; Dormann et al., 2013; Li et al., 2008). It is critical to deal with multicollinearity and ensure the stability of the regression model in order to get trustworthy estimates of biomass. Combining RGB data with extra spectral data from multispectral or hyperspectral sensors can improve the accuracy of biomass estimates and get around the problems that come with using only RGB imaging (Asner et al., 2012; Bazzo et al., 2023; Dormann et al., 2013; Li et al., 2008). To get around these problems, future research might focus on improving data collection methods, such as using different kinds of sensors, and analytical models to make above-ground biomass estimates more accurate and reliable in a range of ecological settings (Poley and McDermid 2020).

6.5 Conclusion

The comparative analysis of riparian and non-riparian vegetation models underscores the distinct ecological processes and environmental factors influencing above-ground biomass (AGB) in these different contexts. The study's key findings can be summarised with quantitative indicators to highlight the main conclusions. In riparian zones, the model explained 33% of the variance in AGB ($R^2 = 0.33$) with a standard error of 7.77. Significant predictors included normalised Digital Surface Model (nDSM, Beta = 0.35, $p = 0.02$) and chlorophyll content, reflecting the dynamic interactions between water availability, nutrient flow, and vegetation health. The lower multicollinearity issues in the riparian model, with all Variance Inflation Factor (VIF) values below 5, indicate the robustness of these predictors. These findings align with existing research emphasising the importance of chlorophyll and vegetation indices in assessing riparian vegetation health and productivity.

Conversely, the non-riparian vegetation model demonstrated a stronger explanatory power, explaining 66% of the variance in AGB ($R^2 = 0.66$) with a standard error of 19.38. Key predictors included nDSM (Beta = 0.76, $p < 0.001$) and the red-blue vegetation index (RBVI). The model exhibited higher multicollinearity, particularly for GBVI (VIF = 9.28), necessitating careful interpretation of the coefficients. The Durbin-Watson statistic for the non-riparian model was 1.22, suggesting slight positive autocorrelation. Despite these challenges, the significant predictors provided valuable insights into the factors driving biomass in non-riparian environments, consistent with studies on forest ecology that highlight the critical role of structural metrics like vegetation height.

Overall, these findings illustrate the necessity for tailored remote sensing approaches and specific ecological considerations when assessing and managing biomass and vegetation health across varied landscapes. The study highlights that while RGB drone imagery can be effective, its indices may not always sufficiently capture the complexity of biomass in riparian zones,

particularly where vegetation heights vary significantly. Future research should focus on improving data collection methods and incorporating additional spectral data to enhance the accuracy and reliability of biomass estimates in diverse ecological settings.

Chapter 7 MODELLING TOPOGRAPHIC INFLUENCES ON VEGETATION VIGOUR IN THE CRADLE NATURE RESERVE, GAUTENG PROVINCE, SOUTH AFRICA

This Chapter is based on the following manuscript

Matyukira, C., Mhangara, P., & Gidey, E. (2024). Modelling topographic influences on vegetation vigour in the Cradle Nature Reserve, Gauteng Province, South Africa. *Geocarto International*, **39**(1). <https://doi.org/10.1080/10106049.2024.2395313>

Abstract: The study explores topography and vegetation changes in the Cradle Nature Reserve's landscape, which is characterised by interconnected water infiltration and drainage patterns with geological features such as sinkholes, using indices such as the Enhanced Vegetation Index (EVI), the Topographic Position Index (TPI), the Topographic Ruggedness Index (TRI), and the Topographic Wetness Index (TWI). The high-resolution satellite images, including Sentinel-2A, the Shuttle Radar Topography Mission Digital Elevation Model, and NASSA Power Rainfall, Temperature, and Ground Wetness in the Root Zone-Modern Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2), were analysed using advanced statistical models. The software tools Stata/SE v.13.1, QGIS v.3.36, and ArcGIS desktop v. 10.8.2 were utilised for this analysis. The results emphasise the significance of incorporating topography into ecological research and highlight the necessity of focused conservation initiatives to address habitat suitability and erosion risk in challenging landscapes. Specifically, the results show that the Enhanced Vegetation Index (EVI) has a strong negative correlation with the Topographic Position Index (TPI) ($R^2 = 0.95$), indicating that TPI usually decreases as EVI increases. This relationship is influenced by landscape features such as sinkholes and depressions, which impact plant health. Additionally, the strong positive relationship between EVI and percentage slope gradient ($R^2 = 0.85$) offers valuable insights for environmental studies and land management practices. Additionally, TRI shows a negative correlation with EVI ($R^2 = 0.94$), emphasising the impact of terrain ruggedness on vegetation density. TWI analysis strongly correlates with slope gradients ($R^2 = 0.96$), highlighting topography's role in hydrological dynamics. Despite these insights, we acknowledge limitations such as scale dependency and the inability to capture fine terrain details. Integrating topographic information into ecological assessments and land management strategies is crucial for promoting conservation, sustainable practices, landscape ecology understanding, and biodiversity preservation decision-making.

HIGHLIGHTS

- EVI strongly correlates negatively with TPI, suggesting how plant health is impacted by topographic positioning.
- The negative correlation between TRI and EVI emphasises how terrain ruggedness impacts vegetation density.
- The TWI analysis highlights how slope gradients influence moisture distribution and hydrological dynamics.
- Efficient topographic information is necessary for understanding ecosystem conservation and sustainable management.

7.1 Introduction

The effects of topographic influences on vegetation health are one of the most significant environmental issues that have accelerated the phenomenon of land degradation in Africa (Gidey et al., 2023). For instance, the management and research endeavours in the Cradle Nature Reserve, situated in South Africa, encounter the urgent matter of comprehending and resolving the complex interrelationships among vegetation dynamics, hydrology, and topography within the reserve's distinctive karst environment. The ecological system in question is distinguished by its intricate topography, in which variables including the distribution of moisture, the condition of the vegetation, and the ruggedness of the terrain have significant impacts on ecological processes (Berhanu & Bisrat, 2018; Kopecký et al., 2021). The Topographic Wetness Index (TWI) and Enhanced Vegetation Index (EVI) are pivotal metrics that provide essential information regarding the distribution of vegetation and the availability of moisture throughout the terrain (Cantón et al., 2004; Kopecký et al., 2021). Nevertheless, habitat suitability, water runoff, and soil erosion are all impacted by slope gradients, which further complicates the management and conservation of this ecosystem (Talebi Khiavi & Mostafazadeh, 2022; M. Wu et al., 2018). Additionally, the Topographic Position Index (TPI) and the Terrain Ruggedness Index (TRI) provide crucial information regarding the relative elevation and ruggedness of the terrain, thereby facilitating comprehension of hydrological processes and the characteristics of various landscapes (Al-Sababnah, 2023; Dilts et al., 2022; K. B. Jones et al., 2000; Rózycka et al., 2017). To safeguard the distinctive ecosystem services and biodiversity of the Cradle Nature Reserve, it is critical for management strategies to comprehend the synergies and trade-offs that exist among these indicators. Monitoring, evaluation, and management strategies must incorporate these elements to educate conservation efforts and guarantee this fragile karst ecosystem's long-term viability and resilience.

The interaction between wetness and vegetation, as expressed as TWI and the EVI, provides valuable information about the influence of topography on ecosystem dynamics (Berhanu & Bisrat, 2018; Kopecký et al., 2021). TWI is a metric that quantifies the impact of landform characteristics on the movement and storage of water (Berhanu & Bisrat, 2018; Kopecký et al., 2021). Within the Cradle Nature Reserve, TWI plays a vital role in indicating the availability and distribution of moisture across the karst landscape. Interconnected water infiltration and drainage patterns characterise this landscape, which is closely tied to geological features like sinkholes and underground caves (W. Zhou & Beck, 2008). In addition to TWI, EVI offers a quantitative evaluation of vegetation health and density, providing a way to analyse the spatial arrangement of plant communities in relation to topographic characteristics (Berhanu & Bisrat, 2018). A thorough assessment of TWI and EVI indices leads to an understanding of how topographic factors influence vegetation dynamics in the karst environment. This includes the impact of wetness and vegetation on species composition, habitat suitability, and ecosystem resilience (Cantón et al., 2004; Kopecký et al., 2021). Within the Cradle Nature Reserve, the integration of TWI and EVI assessments elucidates the complex interactions between topography, hydrology, and vegetation within the karst landscape (Allende-Prieto et al., 2024; Berhanu & Bisrat, 2018; A. Sharma, 2010; W. Zhou & Beck, 2008). (Geremew et al., 2023; J.

Yang et al., 2020). Conversely, low TWI values indicate drier upland areas with sparse or patchy vegetation (Berhanu & Birsat, 2018; Cantón et al., 2004; Chipatiso, 2023; Kopecký et al., 2021; Minh et al., 2024; A. Sharma, 2010; W. Zhou & Beck, 2008). By harnessing the complementary information provided by TWI and EVI, conservation efforts in the Cradle Nature Reserve can prioritise areas of ecological significance, identify vulnerable ecosystems, and implement targeted management strategies to safeguard the unique biodiversity and ecosystem services supported by the karst landscape (HEŠTERA et al., 2024; Monz et al., 2021; Thannoun & Ismaeel, 2024).

The relationship between the TWI and the percentage slope gradients tells us a lot about how the landscape changes over time and how water moves through it (Talebi Khiavi & Mostafazadeh, 2022; M. Wu et al., 2018). We observe a distinct pattern in landscape dynamics, where flat and level areas exhibit higher TWI values than sloping and steep terrain. This suggests that regions with minimal slope gradients can retain moisture more. As the steepness of slopes increases, the values of the TWI progressively decrease, indicating a decrease in water accumulation and an increase in the potential for runoff (Talebi & Mostafazadeh, 2022). Topography significantly influences the distribution of moisture and the occurrence of hydrological processes in karst landscapes (A. Sharma, 2010; D. Xiao et al., 2023; W. Zhou & Beck, 2008). Similar patterns in previous studies conducted in similar karst environments suggest that we can universally apply the TWI as a tool to understand landscape heterogeneity and guide land management and conservation strategies in karst regions (C. Liu et al., 2021; Talebi Khiavi & Mostafazadeh, 2022). In addition, slope gradients have a significant impact on ecological processes in natural landscapes, including water runoff, soil erosion, nutrient cycling, microclimate dynamics, and landslide risks (Matsushita et al., 2007; J. Yang et al., 2020).

Increased inclines frequently enhance water runoff, leading to elevated soil erosion and sediment transportation. These processes have a significant impact on nutrient cycling, soil structure, and the overall health of the ecosystem (Dani et al., 2023; Wubie & Assen, 2020). The movement of water across the terrain, influenced by the steepness of slopes, impacts the flow of streams, the replenishment of groundwater, and the creation of wetlands. Steeper slopes lead to faster runoff, while gentler slopes promote better water retention and infiltration (Dani et al., 2023; B. Wang et al., 2015; J. Yang et al., 2020). In addition, slopes impact local microclimates by affecting the amount of sunlight and moisture, affecting the distribution of vegetation, the composition of species, and the suitability of habitats. In addition, slopes have an impact on local microclimates by affecting the amount of sunlight and moisture, which in turn affects the distribution of vegetation, the composition of species, and the suitability of habitats (Cantón et al., 2004; Wagari & Tamiru, 2021; Wubie & Assen, 2020; J. Yang et al., 2020). Specific slope angles support diverse plant communities, which in turn contribute to the formation of vegetation zones, increased biodiversity, and varied habitats along gradients (Dani et al., 2023). The availability of nutrients is also impacted by the steepness of slopes, which in turn affects the growth patterns of plants and the dynamics of nutrient cycling (B. Wang et al., 2015). Furthermore, the inclination of a slope directly affects the likelihood of landslides, as steeper slopes are more susceptible to such occurrences. These landslides can have detrimental

effects on the stability of vegetation and the structure of the soil (Dani et al., 2023; Toni Jo Smith et al., 2010; B. Wang et al., 2015; Wubie & Assen, 2020; J. Yang et al., 2020). In addition, a slope's inclination directly affects the likelihood of landslides, as steeper slopes are more susceptible to such occurrences. Landslides, in turn, can disrupt the stability of vegetation and the structure of the soil (J. Yang et al., 2020).

Nevertheless, vegetation can alleviate this danger by securing the soil and diminishing erosion. Finally, the distribution of plant roots adjusts to the slope's incline, with species with shallow roots flourishing on steep slopes and trees with deep roots providing stability on more gradual slopes. This adaptation affects both the stability of the soil and the absorption of nutrients. References (Wagari & Tamiru, 2021; Wubie & Assen, 2020; J. Yang et al., 2020) support this information. The interconnected processes highlight the importance of incorporating topography into ecological studies, as they collectively shape ecosystems and enhance their ability to withstand and maintain stability over time. The interconnections between these processes highlight the importance of incorporating topography into ecological studies, as they collectively mold ecosystems and enhance their ability to withstand and maintain their long-term viability. The comprehensive understanding of erosion control and soil stability guides the efficient administration of these issues, which include a range of strategies that incorporate vegetation cover, water management, ecological restoration, land use planning, conservation priorities, and educational outreach (Raihan, 2023; W. Zhang et al., 2023). An essential aspect of these efforts is acknowledging vegetation cover as a crucial factor in soil stabilisation, utilising its ability to improve water retention, decrease surface runoff, mitigate flood hazards, and establish riparian buffer zones (B. Wang et al., 2015; Wubie & Assen, 2020). Techniques such as slope revegetation and terracing effectively tackle erosion challenges, while knowledge of EVI-slope relationships guides decision-making in land use planning and conservation priorities (Fasona et al., 2018). Educational outreach initiatives also raise community awareness about the critical importance of vegetation cover and promote the adoption of sustainable land use practices, ultimately supporting ecosystem resilience and sustainability (Stephenson, 2019).

The Topographic Position Index (TPI) is a crucial tool in landscape analysis that determines the relative elevation of points in relation to their surrounding terrain using elevation data (Al-Sababhah, 2023; K. B. Jones et al., 2000). TPI is a method that compares the elevation of each cell in a Digital Elevation Model (DEM) with the average elevation of the surrounding area. Positive values in TPI indicate higher positions, such as ridges. Conversely, negative values signify depressions, such as valleys, as indicated by references (Al-Sababhah, 2023; K. B. Jones et al., 2000; W. Zhang et al., 2023). TPI is crucial in understanding the complex karst landscapes found in the Cradle Nature Reserve. It helps to unravel the hydrological complexities, including the balance of water, the movement of cold air, the effects of wind, soil erosion and deposition, and the suitability of habitats. Also, the fact that TPI is related to other topographic factors like the EVI, hillshade, aspect, TWI, and slope gradients makes it easier to describe larger areas. It shows how complexly landforms and ecosystem dynamics interact (Al-Sababhah, 2023; K. B. Jones et al., 2000; Talebi Khiavi & Mostafazadeh, 2022; B. Wang et al., 2015). Many studies, including those by Robinson et al., (2019), show that EVI and TPI

are positively related. These studies show how changes in the height of the land affect the health and distribution of plants in a complex way.

However, using TPI has inherent limitations, notably its scale dependency, which introduces nuances in result interpretation (Al-Sababhah, 2023; K. B. Jones et al., 2000). TPI computations depend on the size of the neighbourhood used to determine mean elevation, and variations in this parameter result in disparate TPI values and potentially skew the identification of specific landforms such as depressions or ridges (Al-Sababhah, 2023; K. B. Jones et al., 2000). Additionally, while TPI provides a window into the relative positioning of points within their terrain context, it may fall short of capturing the intricacies of landform size and shape (K. B. Jones et al., 2000). TPI might not be able to tell the difference between different types of landforms, which could make it less useful for getting more detailed information about where plants are found (Al-Sababhah, 2023; K. B. Jones et al., 2000), especially in karst environments with sinkholes, caves, and other complicated features. TPI is a key tool for determining how topography affects plant life in karst ecosystems. It works best when combined with other terrain analysis methods and used correctly at the right scales.

As quantified by the Terrain Ruggedness Index (TRI), topographic ruggedness is pivotal in understanding ecological dynamics and landscape characterisation (Rózycka et al., 2017). TRI, defined as the mean of the absolute differences in elevation between a focal cell and its surrounding cells, provides valuable insights into the total elevation change across neighbouring cells (Amatulli et al., 2018; Dilts et al., 2022) highlight the multifaceted relationship between TRI and ecological variables such as EVI, emphasising the need for researchers to consider various aspects of ruggedness, including elevation variability and aspect diversity in ecological applications. Moreover, (Matsushita et al., 2007) demonstrated the feasibility of using TRI alongside vegetation indices like NDVI for mapping rugged terrain suitable for agricultural purposes, showcasing the practical relevance of TRI in land management studies.

Nevertheless, TRI has certain constraints. However, quantifying elevation changes may not accurately represent the intricate features of terrain morphology and microtopography (Dilts et al., 2022; Rózycka et al., 2017). In addition, TRI may be susceptible to variations in cell size and resolution, which could impact the accuracy of its measurements, especially in regions with diverse terrain (Amatulli et al., 2018; Dilts et al., 2022). Although TRI has limitations, it is a valuable tool for assessing terrain roughness and understanding its impact on ecological processes and landscape management. (Rózycka et al., 2017) illustrate the range of TRI values observed in various terrains and landforms, highlighting its usefulness in comprehending changes in the landscape. (Bradley et al., 2010) have shown that incorporating TRI into groundwater resource mapping highlights its significance in environmental studies and land management practices.

This study aims to find out how using the TWI, EVI, TRI, TPI, and percentage slope gradient assessments can help us learn more about how the karst landscape of the Cradle Nature Reserve's topography affects how ecosystems work. By analysing these important topographic factors, we aim to clarify how they collectively affect vegetation growth and changes, moisture

distribution, terrain roughness, and habitat suitability in the distinct karst environment. Through this thorough analysis, we will gain a valuable understanding of the interaction between topography and ecosystem processes, which will guide the development of land management strategies, conservation efforts, and ecological restoration initiatives tailored to karst landscapes' unique challenges and opportunities.

7.2 Method and Materials

We utilised QGIS version 3.36.0 (Maidenhead) to execute the following approach:

1. Digital Elevation Model (DEM) Acquisition:
 - The DEM was obtained using the STRM Downloader plugin (Daniel Odonohue, 2023) and a shapefile of the designated study area, 'STUDY_AREA'.
2. DEM Preprocessing:
 - To ensure an accurate representation of the terrain, the Fill Sinks tool (L. Wang & Liu, 2006) was used on the DEM to address any depressions or sinks.
 - This tool was accessed via the Processing menu: Processing → Toolbox → SAGA → Terrain Analysis → Hydrology → Fill Sinks.
 - The input DEM was specified, and the tool was executed to fill the sinks in the elevation model.
3. Slope Calculation:
 - The slope values were calculated using the 'Slope' tool to understand the terrain's degree of steepness (QGIS Documentation., 2024).
 - The tool was accessed via the Processing menu: Processing → Toolbox → Raster Terrain Analysis → Slope.
 - The input DEM was specified, and the tool was executed to generate a new layer containing slope values measured in degrees.
4. Slope Classification:
 - Slope gradients were categorised into groups based on FAO guidelines (Food and Agriculture Organization of the United Nations., 2006), referring to [Table 1](#).
 - The reclassify tool in the QGIS GRASS plugin was utilised for this purpose.
 - This tool was accessed via the Processing menu: Processing → Toolbox → SAGA → Terrain Analysis—Morphometry → Reclassify.
 - Slope ranges and their corresponding classes were defined accordingly.
5. Satellite Image Analysis:
 - The study employed Sentinel-2 multispectral images for December 2023.
 - These images were obtained from the Copernicus Open Access Hub, which provides unrestricted access to Sentinel data (European Union, 2024).
 - The Sentinel Application Platform (SNAP) toolkit facilitated the download process, enabling batch retrieval based on parameters such as cloud cover percentage, area of interest (defined by a shapefile), and specified time range (European Union, 2024).
6. Vegetation Index Calculation:
 - Once the images were acquired, they were analysed using QGIS.
 - The Enhanced Vegetation Index (EVI) for each image was calculated using the raster calculator in QGIS, following the equation ([Eq. 1](#)).

- The EVI formula integrates reflectance measurements from the near-infrared (NIR), red (RED), and blue (BLUE) spectral bands. The EVI improves vegetation detection while minimising the influence of soil and atmospheric conditions (MapScaping 2023).

$$EVI = 2.5 \times \frac{(NIR - RED)}{(NIR + 6 \times RED - 7.5 \times BLUE + 1)} \quad (\text{Eq. 1})$$

7. EVI Aggregation and Classification:

- Individual EVI images were aggregated by overlaying them and calculating the average value for each pixel. This process produced a composite image showing the mean EVI for December 2023.
- The composite was saved as a tiff file for further analysis.
- Using NDI threshold values adopted from (Gidey et al., 2018), [Table 2](#), the EVI values were categorised into groups
- The classification process was performed using the reclassify tool in the QGIS GRASS plugin.
- Utilising NDVI values as a threshold for EVI ensures accurate evaluation of vegetation, effectively capturing vegetation responses with greater precision under different conditions. This approach was believed to ensure uniformity when transitioning to EVI while enhancing sensitivity, making it optimal for research on plant health and ecosystem dynamics within the designated study area (Matsushita et al., 2007).

8. Slope to Vector Conversion:

- The ‘Raster to Vector (Polygon)’ tool was employed to transform the raster slope layers into a vector format, specifically a polygon shapefile, to facilitate subsequent analysis and visualisation (QGIS Server Guide/Manual (QGIS 3.36.0), 2023a).
- This plugin was accessed via the Processing menu: Processing → Toolbox → GDAL → Raster conversion → Rasterize (vector to raster).

9. Data Streamlining:

- The ‘Dissolve’ tool (QGIS Server Guide/Manual (QGIS 3.36.0), 2023a) combined neighbouring polygons with identical slope classifications into larger polygons, effectively streamlining the dataset.
- This tool was accessed via the Vector menu: Vector → Geoprocessing Tools → Dissolve, specifying the field containing slope class information.

10. Topographic Indices Calculation:

- The Topographic Wetness Index (TWI), Topographic Position Index (TPI), and Terrain Ruggedness Index (TRI) were calculated from a filled DEM in QGIS.
- TWI was computed using the plugin SAGA tools integrated within QGIS, employing the equation ([Eq. 2](#)), where ‘a’ represented the upslope contributing area and ‘B’ denoted the slope gradient in radians (OpenCourseWare for GIS, 2024; QGIS Server Guide/Manual (QGIS 3.36.0), 2023a).
-

$$TWI = \ln \left(\frac{a}{\tan(B)} \right) \quad (\text{Eq. 2})$$

- PI was computed by comparing the elevation of each cell in the DEM to the mean elevation of its surrounding neighbourhood, characterising the terrain as ridges, flat areas, or valleys (QGIS Server Guide/Manual (QGIS 3.36.0), 2023a).
- TRI was derived using the equation (Eq. 3) to calculate the elevation differences between adjacent cells, where ‘ z_i ’ represented the elevation of each cell, ‘ z_{mean} ’ denoted the mean elevation of the surrounding cells, and ‘ n ’ represented the number of cells within the analysis window (QGIS Server Guide/Manual (QGIS 3.36.0), 2023a).

$$TRI = \frac{\sqrt{\sum_{i=1}^n (z_i - z_{mean})^2}}{n} \quad (\text{Eq. 3})$$

11. Random Points Generation and Raster Value Extraction:

- Random points were created in QGIS using the Vector → Research Tools → Random Points Inside Polygons function, with the study area shapefile as the input layer and 500 points selected.
- A minimum distance of 100 meters between points was set, and the points were generated within the region of interest (ROI).
- Raster values were extracted by accessing the Processing → Toolbox menu, locating the Sample Raster Values tool, choosing the randomly generated point layer as the input, and selecting the raster TIFF as the layer to sample from.
- The tool was used to retrieve the raster values at the precise locations of each randomly selected point, and a new point layer containing attributes with the extracted raster values was created for further analysis or visualisation.

12. Correlation Matrix Calculation:

- Raster values were used to calculate the correlation matrix in Stata/SE 13.1 Windows version.
- A strong positive correlation was deemed to have a Pearson correlation coefficient greater than $r = 0.5$.
- Correlation coefficients (r) were categorised as follows: 0.3-0.5 (moderate positive correlation), 0–0.3 (weak positive correlation), 0 (no correlation), –0.3 to –0.5 (moderate negative correlation), and less than –0.5 (strong negative correlation) (Turney, 2024).

13. Environmental Data Acquisition:

- Environmental data was obtained using NASA/POWER CERES/MERRA-2 Native Resolution data, focusing on four variables: T2M_MAX_MERRA-2, T2M_MIN_MERRA-2, PRECTOTCORR MERRA-2, and GWETROOT MERRA-2 (NASA Global Modeling and Assimilation Office (GMAO), 2020; National Aeronautics and Space Administration, 2023).

- Data was collected from 14 strategically positioned meteorological stations, ensuring comprehensive spatial coverage within and around the study area as defined by our study area shapefile.
- T2M_MAX_MERRA-2 provided insights into the highest temperatures recorded at 2 meters above the Earth's surface, while T2M_MIN_MERRA-2 provided data on the lowest temperatures.
- Monthly station temperature for December 2023 was determined by averaging these two temperature variables.
- PRECTOTCORR MERRA-2 indicated water input, while GWETROOT MERRA-2 determined soil wetness (NASA Global Modeling and Assimilation Office (GMAO), 2020; National Aeronautics and Space Administration, 2023; Shen et al., 2022).
- Monthly averages of PRECTOTCORR MERRA-2 and GWETROOT MERRA-2 were calculated to generate surface maps.
- The NASA POWER Data Access Viewer was used to choose the 'CERES/MERRA-2 Native Resolution' dataset, customise data retrieval parameters, and obtain the dataset in NetCDF format, which was then converted to CSV format for ArcGIS integration (National Aeronautics and Space Administration, 2023; Shen et al., 2022).
- Rigorous quality control measures were implemented to ensure data reliability, including outlier detection, spatial and temporal consistency checks, and validation against historical records from ground stations (Shen et al., 2022).

14. Further Analysis and Visualisation:

- Statistical measures for each dissolved classified EVI zone within TWI, TPI, and TRI TIFF maps were calculated to analyse plant health on different slopes.
- Dissolved and classified percentage gradient zones within the EVI and TWI TIFF maps were analysed to measure vegetation health across different slope gradients.
- Patterns and trends in vegetation changes in response to slope gradients and soil factors were identified.
- These insights provided valuable information for understanding ecology, managing land, and planning conservation strategies.

Table 7- 1: Slope gradient classes (Food and Agriculture Organization of the United Nations., 2006)

Class	Description	%
1	Flat	0-0.2
2	Level	0.2-0.5
3	Nearly Level	0.5-1.0
4	Very Gentle Sloping	1-2
5	Gently Sloping	2-5
6	Sloping	5-10
7	Strong Sloping	10-15

8	Moderate Sloping	15-30
9	Steep	30-60
10	Very Steep	> 60

Table 7- 2: Vegetation health and density value interpretation.

Vegetation health and density status	EVI Value
Very poor	– 0.10 to 0.12
Poor	0.12 to 0.22
Normal	0.22 to 0.42
Good	0.42 to 0.72
Very good	0.72 to 1.00

By systematically following this approach, we ensured a comprehensive and coherent terrain and vegetation analysis method in the designated study area.

7.3 Results and Discussion

7.3.1 Evaluation of environmental factors and vegetation vigour

A nuanced ecological landscape unfolds after careful examination of Figure 7-1 and Table 7-3 in tandem with Table 7-1. The weak positive correlations between the Enhanced Vegetation Index (Figure 1a), precipitation (Figure 1g), and air temperature (Figure 7-1e), while statistically significant only for temperature, underscore the role of these climatic factors in influencing vegetation health, albeit not as robustly as initially anticipated (Rózycka et al., 2017). The weak positive correlation between EVI and the Topographic Ruggedness Index (Figure 1d) piques our interest, suggesting that plants thrive slightly better in rougher terrain. This intriguing finding could be attributed to a more diverse range of habitats in such landscapes, sparking further curiosity and the desire for deeper exploration (Nainggolan et al., 2024; Pinto-Correia et al., 2018). However, the lack of statistical significance in the weak positive correlation between EVI and the Topographic Wetness Index (Figure 7-2b) suggests that other factors may influence the relationship between vegetation health and soil moisture. We expect a strong positive correlation between RF and temperature, as warmer temperatures often increase evaporation and, consequently, precipitation. There aren't many strong or statistically significant links between RF and other topographic indices (TPI and TRI) or between Temp and other topographic indices (TPI, TRI, and TWI). This means that temperature and rainfall do not have a lot of direct effects on the landforms (Gidey et al., 2018; J. Zhu et al., 2018). The moderately negative correlations between TPI and TWI, as well as between TRI and TWI, are highly significant, indicating that the wetness decreases as the topography becomes more rugged or the position more extreme. This could have implications for water runoff, erosion, and the distribution of vegetation types (Rózycka et al., 2017). These correlations present a rich and multi-faceted understanding of how various environmental factors interact with each other and the landscape. They underscore the crucial role of

considering a multitude of variables, a key aspect of our work, when studying ecological patterns and processes, reinforcing the significance of our research.

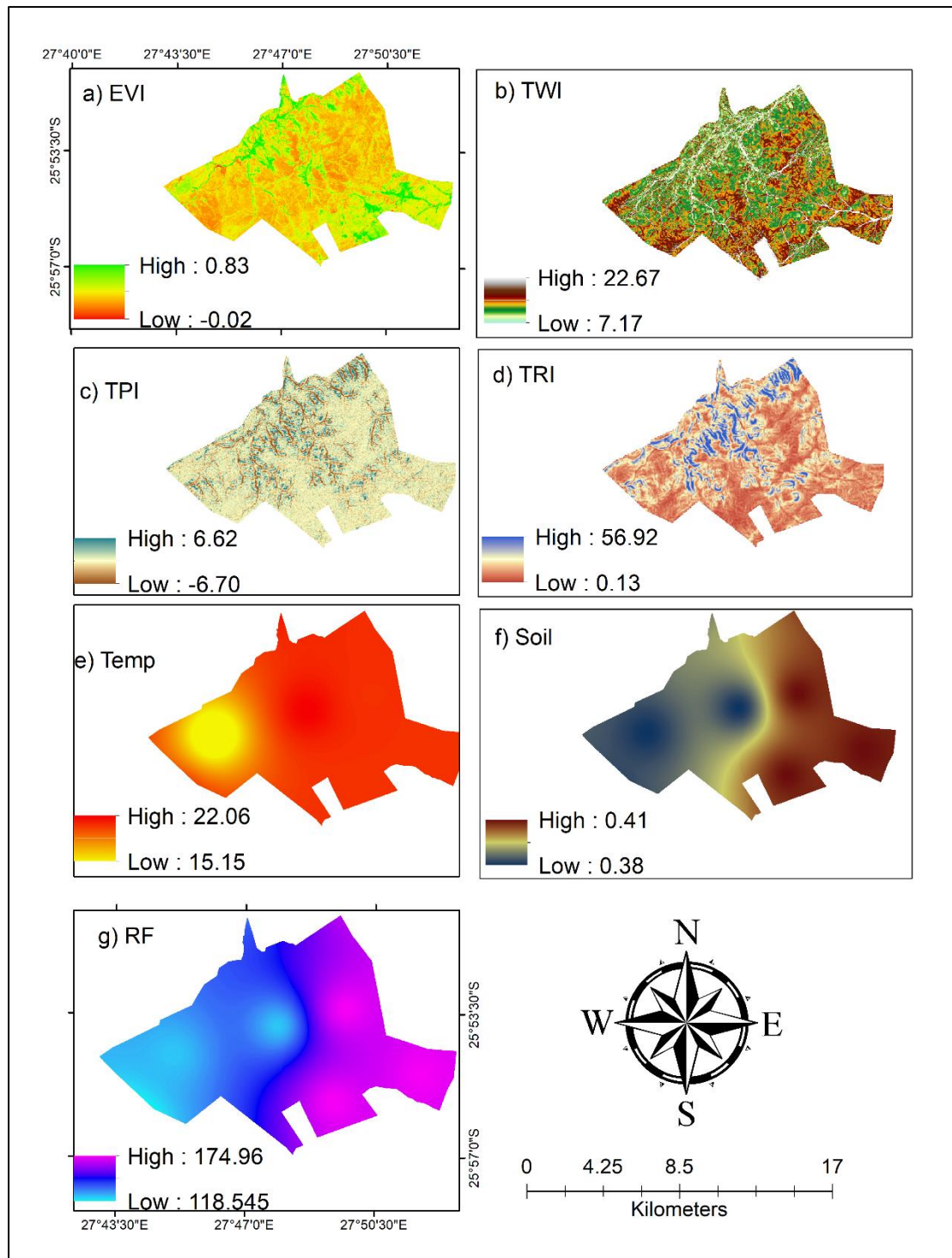


Figure 7- 1: The spatial distribution of a) enhanced vegetation index (EVI), b) topographic wetness index (TWI), c) topographic position index (TPI), d) topographic ruggedness index (TRI), e) air temperature (Temp), f) root zone soil moisture (Soil), g) total precipitation (RF)

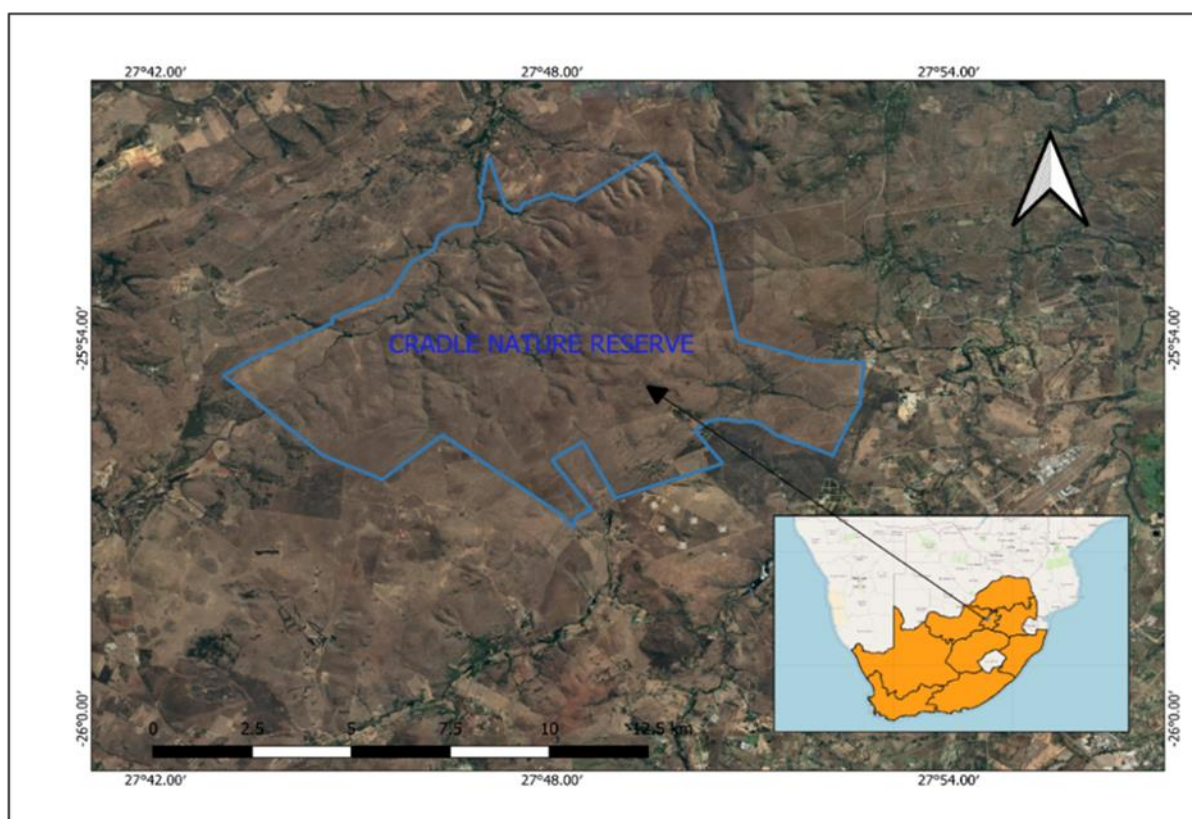


Figure 7- 2: Location of the study (Matyukira & Mhangara, 2023b)

Table 7- 3: Summary of topographic, vegetation, meteorological, and hydrological variables.

Topographic and Vegetation Indices		
Variable	Low	High
EVI	-0.02	0.83
TWI	7.17	22.67
TPI	-6.7	6.62
TRI	0.13	56.92
Meteorological and Hydrological variables.		
Air temperature (Temp)	15.15	22.06
Root zone soil moisture (Soil)	0.38	0.41
Total precipitation (RF)	118.55	174.96

7.3.2. Determination of vegetation health status along slope gradients

Table 7-4 reveals that flat areas, which make up only 0.27% of the land, have an average EVI of 0.31, suggesting moderate vegetation health. Flat regions, which make up 0.25% of the land, have an average EVI of 0.27, suggesting slightly lower vegetation health. Nearly level slopes, which make up 0.60% of the land, have an average EVI of 0.26, suggesting they are more prevalent and have comparable vegetation health to level areas. Gently sloping areas, which make up 13.87% of the land, have an average EVI of 0.26, suggesting they are common and can sustain moderate vegetation health. The reserve is predominantly characterized by sloping areas, accounting for 31.08% of the land. Steep slopes, which account for 20.39% of the land,

have the lowest average EVI value of 0.25, suggesting less dense or less healthy vegetation. Moderate slopes, which account for 24.70% of the total area, contribute to moderate vegetation health. Steep slopes, which make up 6.55% of the total area, have a higher average EVI value of 0.30, indicating improved vegetation health on more inclined gradients. Very steep slopes, which occupy only 0.09% of the land, have the highest average EVI value of 0.38, indicating resilient vegetation.

Table 7- 4: Relationship between the Enhanced vegetation Index (EVI) and slope gradient

Slope Gradient Description	Percentage Slope			EVI			
	Range-% slope	Area in km2	Area%	Min	Max	Mean	STD
Flat	0-0.2	0.23	0.27	0.0	0.68	0.31	0.11
Level	0.2-0.5	0.22	0.25	0.0	0.70	0.27	0.08
Nearly Level	0.5-1.0	0.52	0.60	0.0	0.61	0.26	0.06
Very Gentle Sloping	1-2	1.92	2.21	0.0	0.68	0.26	0.07
Gently Sloping	2-5	12.08	13.87	0.0	0.75	0.26	0.07
Sloping	5-10	27.07	31.08	0.0	0.83	0.26	0.07
Strong Sloping	10-15	17.76	20.39	0.0	0.73	0.25	0.06
Moderate Sloping	15-30	21.52	24.70	0.0	0.74	0.26	0.06
Steep	30-60	5.71	6.55	0.2	0.68	0.30	0.07
Very Steep	> 60	0.08	0.09	0.2	0.77	0.38	0.10

The study on vegetation health and slope gradients in Cradle Nature Reserve reveals a complex relationship between these variables. The R2 value of 0.8447 indicates a close relationship between EVI and percentage slope gradients, providing valuable insights for environmental studies and land management (Figure 7-3). Steep slopes, although rare, exhibit robust vegetation health, while more common, strong-sloping areas show lower vegetation health. Factors such as soil stability, moisture availability, and microclimate conditions could be responsible for these variations. These findings align with previous research on soil compaction and porosity, which shows significant variations influenced by land cover change and slope gradient. Cultivated land and steeper slopes tend to have a higher bulk density and lower total porosity, whereas forested land and gentler slopes exhibit a lower bulk density and higher porosity. Changes in land cover and slope gradient can negatively affect soil quality, such as soil fertility, stability, and overall ecosystem health. Furthermore, changes in land use, land cover, and slope gradient can affect soil organic carbon (SOC) content, potentially reducing carbon footprints in agri-food systems. Overall, these results emphasize the importance of considering topography when assessing plant health and understanding slope gradients' impact on ecological processes, soil dynamics, and ecosystem functioning in semi-arid areas.

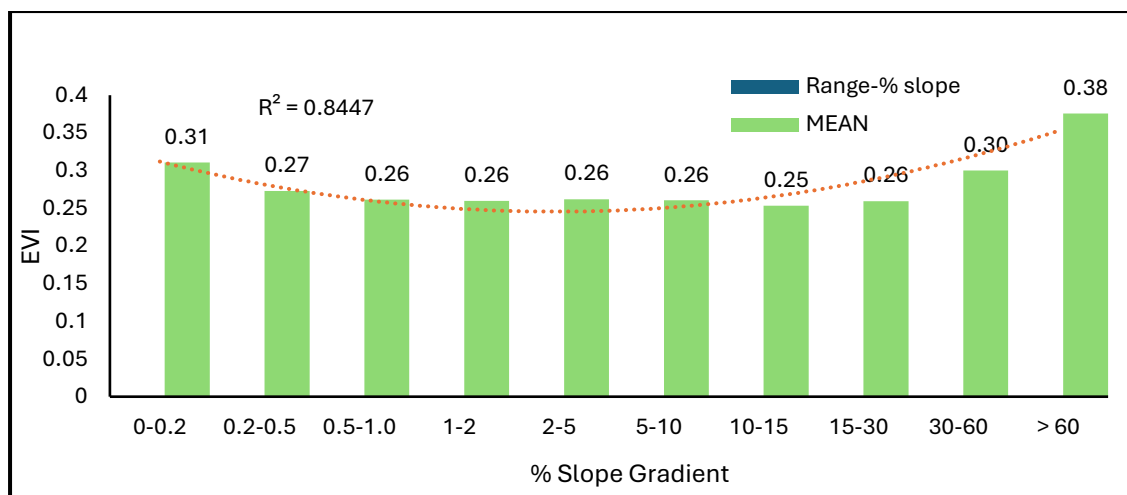


Figure 7- 3: Relationship Between the Enhanced Vegetation Index (EVI) and Slope Gradient

7.3.3. Statistical relationships among the environmental factors and vegetation vigour

Table 7-5 displays the correlations between different environmental variables. There is a weak positive correlation between the Enhanced Vegetation Index (EVI) and precipitation (RF), but this correlation is not statistically significant ($r = 0.1115$, $p = 0.0128$). On the other hand, there is a weak positive correlation between EVI and air temperature (TEMP), which is statistically significant ($r = 0.1432$, $p = 0.0014$). Additionally, there is a moderately negative correlation between EVI and the topographic position index (TPI), which is highly significant ($r = -0.2238$, $p = 0$). Furthermore, there is a weak positive correlation between EVI and the topographic ruggedness index (TRI), which is statistically significant ($r = 0.1378$, $p = 0.0021$). Lastly, there is a weak positive correlation between EVI and the topographic wetness index (TWI), but this correlation is not statistically significant ($r = 0.101$, $p = 0.0238$). Furthermore, there is a strong and highly significant positive relationship between precipitation (RF) and air temperature (TEMP), with a correlation coefficient (r) of 0.5755 and a p -value of 0. On the other hand, there is a weak positive correlation between RF and TPI with a correlation coefficient of 0.0734, but this correlation is not statistically significant ($p = 0.1017$). Additionally, there is a moderately negative and highly significant correlation between RF and TRI, with a correlation coefficient of -0.1578 and a p -value of 0.0004. Finally, there is a weak positive correlation between RF and TWI with a correlation coefficient of 0.0871, but this correlation is also not statistically significant ($p = 0.052$). Additionally, there are low positive correlations between TEMP and TPI ($r = 0.0386$, $p = 0.3897$), TEMP and TRI ($r = 0.0928$, $p = 0.0385$), and TEMP and TWI ($r = 0.0441$, $p = 0.3261$), all of which are not statistically significant. The Total Performance Index (TPI) and the Total Wellness Index (TWI) display a moderate negative correlation, which is highly significant ($r = -0.2828$, $p = 0$). Similarly, TRI and TWI also demonstrate a moderate negative correlation, which is highly significant ($r = -0.4154$, $p = 0$). These findings emphasise the intricate connections between environmental factors, revealing both meaningful and meaningless correlations. This calls for additional research to gain a deeper understanding of the underlying dynamics.

Table 7- 5: Correlation of EVI with climatic and topographic variables (n = 500).

	EVI	RF	TEMP	TPI	TRI	TWI
EVI	1.000					
RF	0.112	1.000				
TEMP	0.143	0.576	1.000			
TPI	-0.224	0.073	0.039	1.000		
TRI	0.138	-0.158	0.093	0.022	1.000	
TWI	0.101	0.087	0.044	-0.283	-0.415	1.000

Statistically significant at 5%.

Note: EVI: Enhanced vegetation index; TWI: Topographic wetness index; TPI: Topographic position index; TRI: Topographic ruggedness index; TEMP: Mean air temperature; RF: Total precipitation.

The correlation analysis results provide valuable insights into ecological dynamics and landscape characterisation, consistent with previous studies that have examined the connections between topography, vegetation, and climate variables. The weakly positive relationship between the EVI and the TRI suggests that areas with rough terrain may have less vegetation cover. This aligns with research indicating that regions characterised by more pronounced inclines and poorer soil conditions typically exhibit lower levels of vegetation coverage (Dilts et al., 2022). The inverse correlation between the EVI and the TPI indicates that areas with depressions or sinkholes tend to have more robust vegetation. This finding aligns with previous studies that have demonstrated the impact of topographic characteristics on the spatial arrangement of plant life (Branton & Robinson, 2020; Robinson et al., 2019; Yates et al., 2019). The results emphasise the significance of incorporating topography into ecological research and the necessity of focused conservation initiatives to tackle habitat suitability and erosion risk in challenging landscapes. Furthermore, the correlations discovered in the study can provide valuable insights for developing field experiments and sampling strategies. Researchers may choose to concentrate their efforts on regions characterised by high TWI values in order to investigate water-related ecological processes or vegetation dynamics. This approach is based on the understanding that the availability of moisture has a significant impact on the health of vegetation (Nainggolan et al., 2024). Similarly, recognising the inverse correlation between TRI and EVI can aid in sampling across various levels of terrain roughness to investigate its impact on vegetation. This knowledge can then improve data comprehension and facilitate ecological process modelling. Ultimately, these discoveries can contribute to conservation and land management strategies by integrating data on the correlation between various factors and vegetation indices, such as EVI (Rózycka et al., 2017). This will facilitate habitat restoration, biodiversity conservation, and the implementation of sustainable land use practices.

Additionally, the multiple linear regression analysis of the dependent variable EVI, based on a large sample size of 101,360, provides reliable estimates (Table 6). The model, while statistically significant with a high F-statistic of approximately 1467.918, demonstrates low explanatory power with an R-squared value of around 8%. This indicates that the predictors explain only a small portion of the variance in EVI. The prediction errors are moderate, with

an RMSE of approximately 55.201 and an MAE of about 44.597. The large negative intercept value (-1239.137) and the information criteria (AIC and BIC) suggest that the model is reasonably well-fitted, with AIC being slightly better due to less penalization.

Table 7- 6: Multi-linear regression analysis using all the pixels of the remote sensing data.

Model Summary		Total sample units (population) (n=101360)					
R-squared	Adjusted R-squared	Root Mean Squared Error	Mean Absolute Error	F-statistic	Intercept		
Rsq	Rsqadj	RMSE	MAE	F	b0	AIC	BIC
0.08	0.08	55.2	44.6	1467.92	-1239.14	813121.11	813187.8

Variables	Coefficients		AIC	BIC
	Coefficient	F-statistic		
RF	-4.4	829.84	813945.63	813991.26
Soil	8408.68	728.16	813844.72	813890.35
Temp	4.71	959.8	814074.46	814120.09
TPI	10.12	2459.67	815549.58	815595.22
TRI	-1.76	3528.09	816587.42	816633.06
TWI	-3.03	955.43	814070.13	814115.76

EVI = Dependent Variable; AIC=Akaike Information Criterion; BIC=Bayesian Information Criterion

Among the predictors, Root Zone Moisture (Soil) stands out as the most influential, boasting the highest positive coefficient and the lowest AIC and BIC values, indicating an excellent model fit. Total Precipitation (RF) and Topographic Wetness Index (TWI) also exhibit good model fits with relatively low AIC and BIC values and significant F-statistics. While TRI and TPI are strong predictors with high F-statistics, they add more complexity to the model, as reflected in their higher AIC and BIC values. Air Temperature (Temp) and TWI maintain a good balance between influence and model fit. The direction of the relationships is such that positive coefficients (Root Zone Moisture, Air Temperature, TPI) indicate direct relationships with EVI, whereas negative coefficients (Total Precipitation, TRI, TWI) indicate inverse relationships. In summary, Root Zone Moisture (Soil) is the most impactful predictor with the best model fit, while other predictors like TRI, TPI, Total Precipitation, TWI, and Air Temperature also significantly influence EVI, each with varying degrees of model fit and complexity.

7.3.3.1. Determining the statistical relationship between the EVI and TWI

The analysis of vegetation health and density status in relation to the EVI range Table 7-7, the percentage of the study area (Cradle Nature Reserve), and the mean TWI reveal distinct patterns. The study area is predominantly characterised by the 'Normal' EVI range, which covers the largest portion of the land area (60.55 km², or 70.49% of the study area). In comparison, a substantial proportion falls within the 'Very Poor to Poor' category (22.46 km², 26.15% of the study area), indicating lower vegetation health. Conversely, areas classified as 'Good' and 'Very Good' are limited, with 'Good' covering 2.88 km² (3.35% of the study area) and 'Very Good' encompassing a negligible 0.01 km² (0.01% of the study area), suggesting that higher vegetation health and density are less prevalent. Mean TWI values generally correspond with vegetation health, with higher values indicating better water content and health, except for the 'Very Good' category, which exhibits a mean TWI (10.93) similar to the

‘Very Poor to Poor’ class, possibly due to its small area representation. Changes in TWI can explain approximately 67.72% of the variability in EVI, according to the R-squared value of 0.6772 (Figure 4). The analysis results indicate a strong relationship between vegetation health, as indicated by the EVI range, and the mean TWI within the study area of Cradle Nature Reserve. As TWI increases (indicating higher moisture availability), there tends to be an associated increase in EVI (reflecting healthier vegetation). Regions with higher TWI values indicate enhanced moisture retention and will likely foster more vigorous vegetation growth. Drier upland areas with lower TWI values may exhibit sparser vegetation cover. The predominance of the ‘Normal’ EVI range, covering the largest portion of the study area, suggests that most of the landscape exhibits average to moderate vegetation health. This aligns with previous studies that have found a positive correlation between moderate EVI values and healthy vegetation cover (Almalki et al., 2022; Z. Li et al., 2010; Martin et al., 2021; Mpanyaro et al., 2024). These studies emphasised remote sensing, particularly the Enhanced Vegetation Index (EVI), for monitoring vegetation health and mapping changes in arid environments like the Cradle Nature Reserve. Further, they highlighted the moderate positive correlation between precipitation, streamflow, and vegetation health, suggesting the utility of EVI and TWI in assessing ecosystem dynamics and human impacts within the reserve. Conversely, the substantial proportion of the study area classified as ‘Very Poor to Poor’ indicates areas with lower vegetation health. This situation is attributed to factors such as land degradation, habitat fragmentation, or human activities, as concluded in our previous study of the same study area (Matyukira & Mhangara, 2023b).

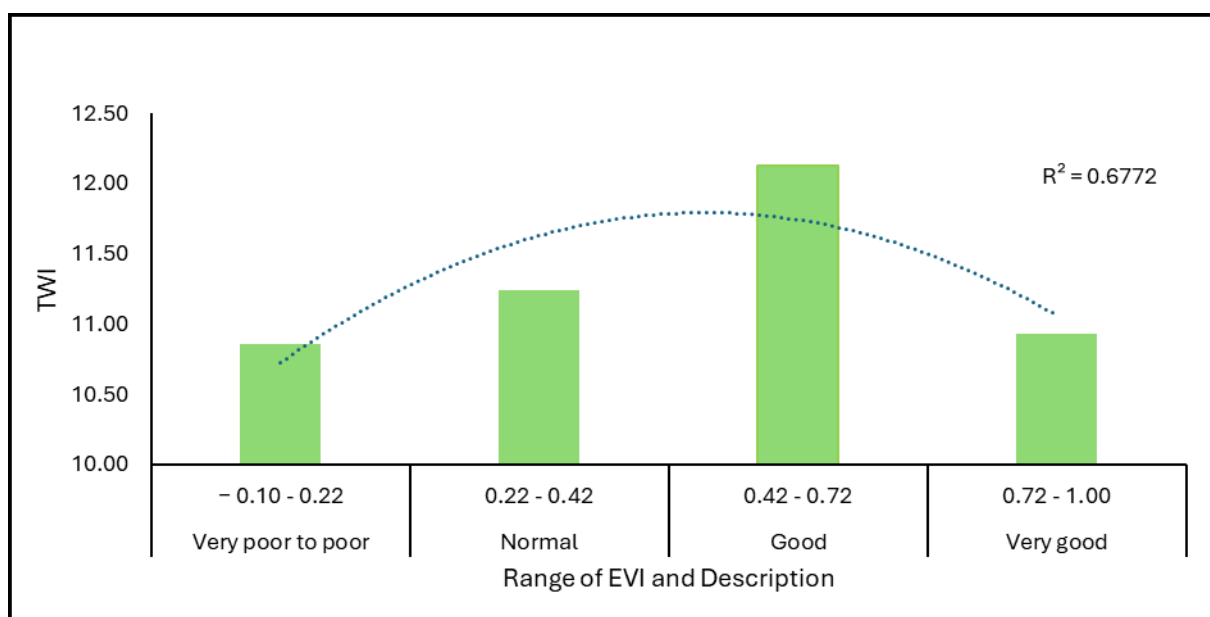


Figure 7- 4: Relationship between the Enhanced vegetation Index (EVI) and topographic wetness Index (TWI).

Table 7- 7: Relationship between Enhanced vegetation Index (EVI) and topographic wetness Index (TWI).

Vegetation health and density status	EVI			TWI			
	Value	Area in km2	%	Min	Max	Mean	STD
Very poor to poor	- 0.10 to 0.22	22.46	26.15	7.9	21.78	10.85	1.55

Normal	0.22 to 0.42	60.55	70.49	7.2	22.67	11.24	2.05
Good	0.42 to 0.72	2.88	3.35	7.2	22.6	12.13	3.21
Very good	0.72 to 1.00	0.01	0.01	8.5	13.66	10.93	1.9
	Total:	85.89	100	-	-	-	-

The low number of areas classified as ‘Good’ and ‘Very Good’ suggests that the Cradle Nature Reserve has a lower prevalence of high vegetation health and density. This discovery aligns with research emphasising the difficulties of preserving excellent vegetation cover in protected areas, frequently caused by invasive species, habitat degradation, or insufficient management techniques (Ekka et al., 2022; Pulido-Chadid et al., 2023). Remarkably, average TWI values typically align with vegetation’s health, as higher TWI values indicate superior water content and overall health (Mpanyaro et al., 2024). This discovery aligns with prior studies that have shown the significant role of topographic wetness in shaping vegetation dynamics. Researchers have observed that regions with greater moisture levels sustain more robust vegetation (Almalki et al., 2022). Nevertheless, it is worth mentioning that the ‘Very Good’ category displays a mean TWI that is comparable to the ‘Very Poor to Poor’ class despite its relatively small area representation. Local variations in topography, soil composition, or microclimate conditions within the Cadle Nature Reserve may account for the discrepancy. Topography influences climate variations over small distances, resulting in a range of microclimates distinguished by variations in temperature, moisture levels, and exposure to wind and sunlight. Microclimates are important indicators of the distribution of various natural ecosystems (A joint project of NatureServe and The National Park Service National Capital Region, 2024). Additional examination of these anomalies could yield valuable insights into the intricate relationships among topography, hydrology, and vegetation health (Ekka et al., 2022). In summary, the findings emphasise the significance of considering the EVI and the TWI when evaluating changes in vegetation and the overall landscape condition. This information is valuable for guiding conservation and management initiatives in the Cradle Nature Reserve and other similar ecosystems.

7.3.3.2. Analysis of the relationship between TWI and slope gradient

Table 7-8 shows that a small fraction (0.27%) of the landscape consists of flat areas with a slope ranging from 0.2% to 0.2%. These flat areas have an average TWI of 18.35. Similarly, level areas with a slope between 0.2% and 0.5% comprise another small portion (0.25%) of the landscape, with an average TWI of 15.00. Approximately 0.60% of the land consists of nearly level areas with a slope ranging from 0.5% to 1.0%. These areas have an average TWI of 13.89. On the other hand, gentle slopes with a slope ranging from 1% to 2% cover about 2.21% of the land and have an average TWI of 12.91. Most of the land is sloping, with a slope ranging from 2% to 5%, accounting for 13.87% of the total area. These areas have an average TWI of 12.25. The largest category of slopes is the strong slopes, with a slope ranging from 5% to 10%, covering 31.08% of the total area. These slopes have an average TWI of 11.61. The slopes with a moderate gradient (10–15% slope) have a substantial coverage of 20.39% and an average TWI of 10.94. On the other hand, the steeper slopes (30–60% slope) are smaller but still significant, covering 6.55% of the area and having a mean TWI of 9.78. Steep slopes with a gradient greater than 60% are uncommon, accounting for only 0.09% of the total. These slopes

have an average TWI value of 8.96. These findings shed light on the distribution of wetness across various slope gradients, providing crucial insights into the landscape's diversity and the hydrological processes in the study area. Changes in the slope gradient account for around 96.33% of the variation in TWI, as indicated by the high R-squared value (approaching 1) in Figure 7-5. The TWI decreases as the slope gradients get steeper, indicating reduced moisture availability. Simply put, the TWI decreases when the slope gradient becomes steeper

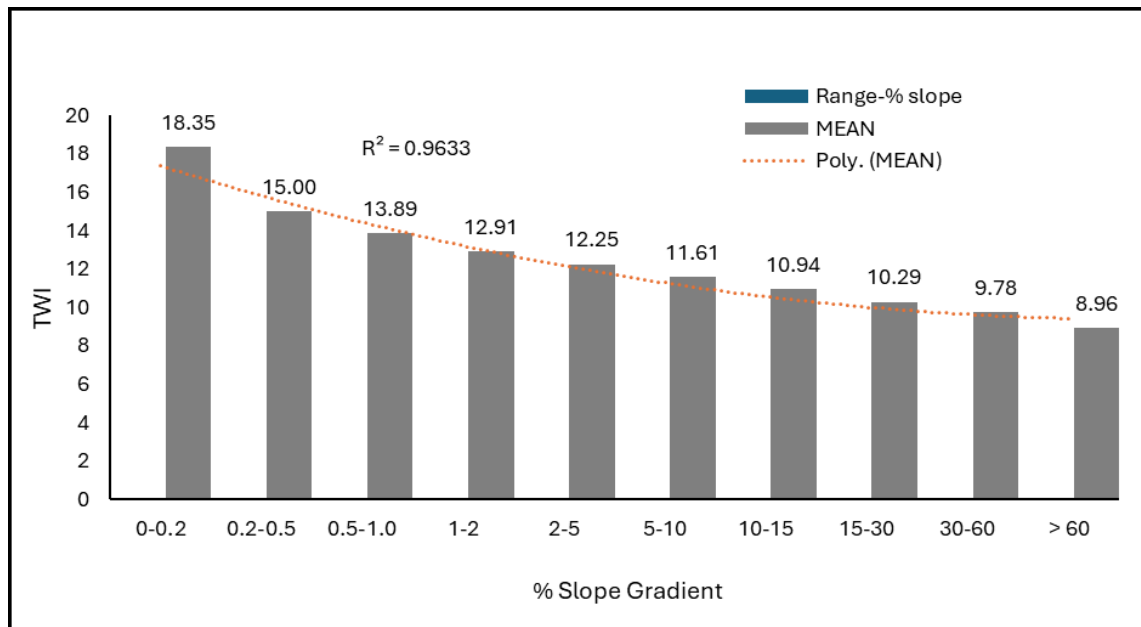


Figure 7- 5: Relationship between topographic Wetness Index and slope gradient.

Table 7- 8: Relationship between the TWI and slope gradient

Slope Gradient Description	Percentage Slope			TWI			
	Range-% slope	Area in km2	%	Min	Max	Mean	STD
Flat	0-0.2	0.23	0.27	12.98	22.67	18.35	3.02
Level	0.2-0.5	0.22	0.25	12.08	22.64	15	2.64
Nearly Level	0.5-1.0	0.52	0.6	11.35	21.33	13.89	2.44
Very Gentle Sloping	45293	1.92	2.21	10.66	21.13	12.91	2.27
Gentle Sloping	45327	12.08	13.87	9.74	21.52	12.25	2.01
Sloping	45422	27.07	31.08	9.05	20.68	11.61	1.73
Strong Sloping	45580	17.76	20.39	8.64	20.15	10.94	1.62
Moderate Sloping	15-30	21.52	24.7	7.95	19.8	10.29	1.71
Steep	30-60	5.71	6.55	7.28	19.1	9.78	1.82
Very Steep	> 60	0.08	0.09	7.17	12.59	8.96	1.09
Total: 87.12			100				

The results of this study demonstrate a distinct correlation between the TWI and the steepness of slopes in the Cradle Nature Reserve. These results provide a valuable understanding of the area's landscape diversity and water movement. Steep slopes have reduced moisture retention while increasing water flow and drainage patterns, as low TWI values indicate. This, in turn,

affects the distribution of vegetation (Geremew et al. 2023; Yang et al. 2020). Flat and nearly level areas with minimal slope gradients have higher average TWI values than sloping and steep terrain. For example, flat areas with slopes between 0 and 0.2% show the highest average TWI of 18.35, which suggests that these regions have a greater ability to retain moisture. As the steepness of slopes increases, the average TWI values gradually decrease, indicating a decrease in water accumulation and an increase in the potential for runoff. This pattern is especially noticeable in regions with steep inclines (>5% slope), where the average TWI decreases to 11.61, suggesting reduced moisture retention and increased runoff rates. These findings align with prior research investigating the correlation between TWI and slope gradients in different landscapes, offering valuable insights into landscape dynamics and hydrological processes (Winzeler et al., 2022). Previous research in similar settings has found similar patterns, showing that flat or slightly sloped areas tend to have higher TWI values than steep areas (Winzeler et al., 2022; M. Wu et al., 2018). The study showed a clear pattern: areas that are flat or almost flat have higher TWI values than those that are sloped or steep, meaning that areas with less slope gradients are better at keeping water. Research in various ecosystems, including mountainous areas and coastal plains, has also documented similar trends of declining TWI as slope gradients increase (Winzeler et al., 2022). As slopes' steepness increases, the TWI values decrease gradually, indicating a decrease in water accumulation and an increase in the potential for runoff. This relationship highlights the importance of topography in shaping the distribution of moisture and hydrological processes within Karst landscapes (Bradley et al., 2010; Buchanan, 2010; D. Xiao et al., 2023). Comparable Researchers have found similar patterns in similar Karst environments, showing that TWI is a useful tool for understanding landscape diversity and planning land management and conservation strategies in Karst regions (Bradley et al., 2010; Cantón et al., 2004; Winzeler et al., 2022; M. Wu et al., 2018). This study enhances our comprehension of landscape heterogeneity by examining moisture distribution across various slope gradients. It provides information for land management and conservation strategies to maintain the Cradle Nature Reserve's hydrological integrity.

7.3.3.3. Exploration of the statistical relationship between TPI and EVI

Table 7-9 demonstrates clear correlations between the Enhanced Vegetation Index (EVI) and Topographic Position Index (TPI) for various vegetation categories in the study area. Approximately 26.15% of the area has Very Poor to Poor Vegetation. These areas have a mean TPI of 0.23, which suggests that the terrain is slightly elevated. Most of the landscape, accounting for 70.49%, comprises normal vegetation areas. These areas have a mean TPI value of approximately zero (-0.06), indicating relatively flat terrain. On the other hand, the Good and Very Good Vegetation categories, which comprise 3.35% and 0.01% of the total area, respectively, exhibit negative mean TPI values (-0.52 and -0.49), indicating the presence of lower-lying regions or depressions. These findings emphasise the impact of topographic position on the distribution of vegetation. The high R-squared value of 0.9456 (Figure 7-6) indicates a robust correlation between TPI and EVI, providing strong evidence for the association between topography and vegetation patterns. This highlights the significance of considering both aspects in landscape analysis. The findings from the analysis provide valuable insights into the relationship between TPI and EVI within a karst environment, such as the study area under consideration. Understanding the interplay between topography and vegetation is crucial in karst landscapes, where terrain features such as sinkholes and ridges

are prevalent. The results indicate that areas categorised as Very Poor to Poor Vegetation, which may correspond to depressions or sinkholes, exhibit slightly elevated mean TPI values (0.23), suggesting these regions are not as depressed as expected. Conversely, Normal Vegetation areas, typically associated with flat terrain, show a mean TPI close to zero (-0.06), aligning with the expectation of relatively flat landforms. However, the Good and Very Good Vegetation categories, representing lower-lying regions or depressions, display negative mean TPI values (-0.52 and -0.49, respectively), indicating the presence of sinkholes or depressions where vegetation might thrive due to increased moisture availability. These findings are consistent with similar studies conducted in karst environments. For example, Robinson et al., (2019) observed comparable relationships between TPI and vegetation health in semiarid south-western Australia regions, highlighting the importance of considering topographic influences on vegetation dynamics. Similarly, W. Zhang et al., (2023) and Wang et al., (2015) found correlations between TPI and EVI in arid basins and river basins, respectively, emphasising the universal applicability of TPI-EVI relationships across diverse landscapes. Overall, the results underscore the significance of topographic position in shaping vegetation distribution and health in karst environments, providing valuable insights for ecological modelling and conservation efforts.

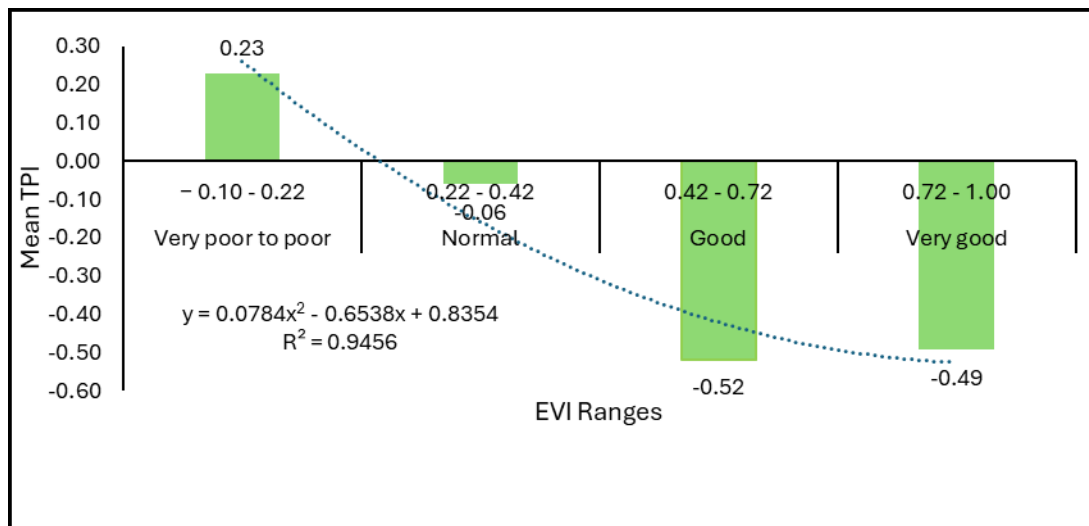


Figure 7- 6: Relationship between the topographic position Index (TPI) and EVI.

Table 7- 9: Relationship between the TPI and EVI.

Vegetation health and density status	EVI			TPI			
	Range-EVI	Area in km2	%	Min	Max	Mean	STD
Very poor to poor	- 0.10 - 0.22	22.46	26.15	-3.78	4.48	0.23	0.7
Normal	0.22 - 0.42	60.55	70.49	-6.7	6.62	-0.06	0.9
Good	0.42 - 0.72	2.88	3.35	-6.46	4.73	-0.52	1.2
Very good	0.72 - 1.00	0.01	0.01	-2.48	0.87	-0.49	0.8
Total: 85.89 100				-	-	-	-

While the findings provide valuable insights into the relationship between the TPI and the EVI, it's essential to acknowledge certain limitations inherent in the use of TPI (Al-Sababhah, 2023;

K. B. Jones et al., 2000; Robinson et al., 2019). One significant limitation is its scale dependency, which can influence the interpretation of results. The neighbourhood size, which determines the mean elevation around each cell in the DEM (Al-Sababhah, 2023), influences TPI calculations. As a result, variations in neighbourhood size can lead to different TPI values and may affect the identification of specific landforms, such as depressions or ridges (Al-Sababhah, 2023; K. B. Jones et al., 2000). Additionally, while TPI provides valuable information about the relative position of a point within its surroundings, it does not account for the size or shape of landforms (Al-Sababhah, 2023). Therefore, TPI alone may not fully capture the complexity of terrain features in karst environments, where sinkholes, caves, and other intricate landforms are common (Al-Sababhah, 2023; W. Zhang et al., 2023). Furthermore, TPI may not differentiate between different depressions or ridges, limiting its ability to provide detailed insights into vegetation distribution patterns. Despite these problems, TPI is still useful for studying how topography affects plant life in karst environments (Al-Sababhah, 2023; K. B. Jones et al., 2000; W. Zhang et al., 2023) when used with other terrain analysis methods and at the right scales.

7.3.3.4. TRI and EVI relationship

Table 7-10 demonstrates the range of the EVI across various land quality categories, spanning from -0.10 to 1.00 . The TRI notably impacts this variation. The area categorised as Very Poor to Poor covers 22.46 km^2 , which accounts for 26.15% of the total area. The TRI values in this category range from 0.13 to 50.52 , with an average of 8.53 and a standard deviation of 4.73 . In the normal category, which accounts for 60.55 km^2 (70.49% of the total area), the TRI ranges from 0.13 to 56.92 . The average TRI value is 10.08 , with a standard deviation of 7.10 . The Good category covers 2.88 km^2 , which accounts for 3.35% of the total area. The TRI values in this category range from 0.13 to 52.33 , with an average of 10.57 and a standard deviation of 8.67 . Finally, the Very Good category encompasses an area of 0.01 km^2 , which accounts for 0.01% of the total area. The TRI values in this category range from 4.14 to 49.90 , with an average of 16.44 and a standard deviation of 17.92 . The correlation between TRI and EVI suggests that as TRI values increase, EVI values decrease, indicating a reduction in vegetation in rough terrain. Lower TRI values are typically associated with higher EVI values, indicating a higher vegetation density in smoother terrain. Furthermore, the strong correlation between TRI and EVI, as evidenced by the high R-squared value of 0.942 (Figure 7-7), provides additional support for the connection between topography and vegetation patterns. This highlights the importance of considering both factors in landscape analysis. The inverse relationship between topography and vegetation distribution emphasises the impact of landforms on plant life's spatial arrangement, providing valuable knowledge for land management and ecological research.

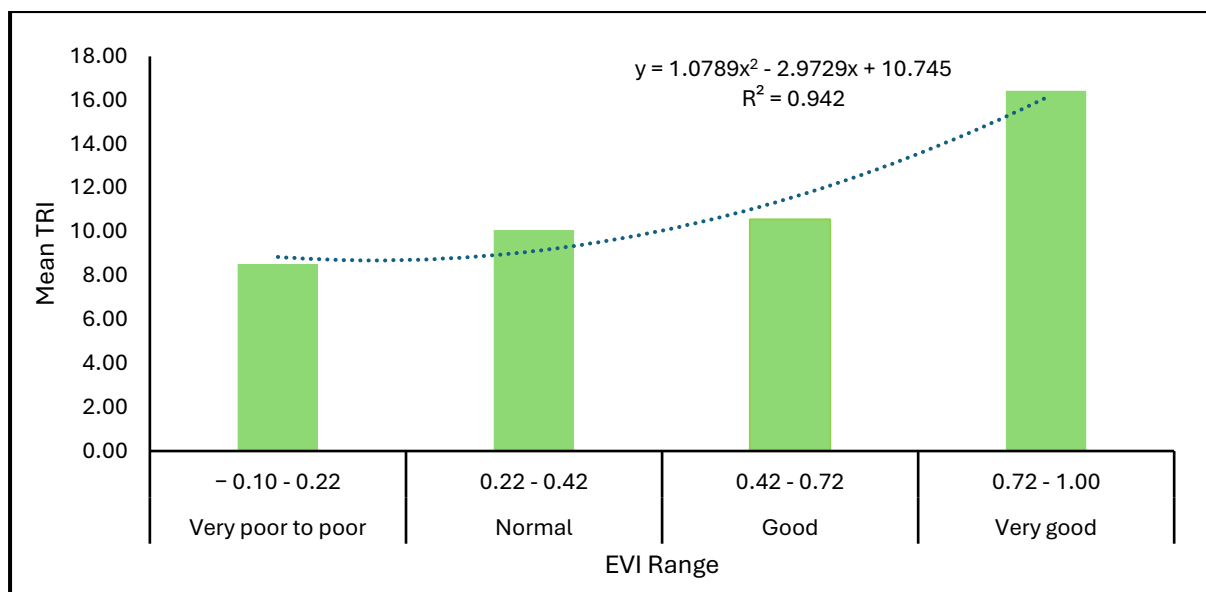


Figure 7- 7: Relationship between the topographic ruggedness Index (TRI) and EVI.

Table 7- 10: TRI and EVI relationship.

Vegetation health and density status	EVI			TRI			
	Range-EVI	Area in km2	%	Min	Max	Mean-TRI	STD
Very poor to poor	- 0.10 - 0.22	22.46	26.15	0.13	50.52	8.53	4.73
Normal	0.22 - 0.42	60.55	70.49	0.13	56.92	10.08	7.1
Good	0.42 - 0.72	2.88	3.35	0.13	52.33	10.57	8.67
Very good	0.72 - 1.00	0.01	0.01	4.14	49.9	16.44	17.92
	Total:	85.89	100	-	-	-	-

The summary's results strongly link the TRI and the EVI in the Cradle Nature Reserves. These results are typical of larger patterns seen in similar settings. The relationship between TRI and EVI is important for understanding how vegetation changes over time in karst areas like the Cradle Nature Reserves, where topography changes a lot (Rózycka et al., 2017). Research elsewhere confirms a negative correlation between TRI and EVI, highlighting the impact of rugged terrain on vegetation density. These results align with more general ecological ideas and affect how land is managed in karst landscapes. They show how important it is to use targeted conservation efforts and sustainable development methods to protect ecosystem functionality and biodiversity (J. Zhu et al., 2018). The study by Dilts et al., (2022) says that the connection between the EVI and the TRI is complicated and is affected by different aspects of topographic ruggedness (Dilts et al., 2022). In ecological settings, variations in elevation and diversity in aspect may be important. This means that the relationship between EVI and TRI may be different depending on these factors (Dilts et al., 2022; K. B. Jones et al., 2000; Riley & Degloria, 1999). This nuanced understanding highlights the intricate relationship between topographic ruggedness and vegetation dynamics, indicating the influence of multiple factors and ecological processes like habitat concealment and escape terrain (Pinto-Correia et al., 2018; Riley & Degloria, 1999; Stojilković, 2022).

7.4. Conclusion

Our study examines the complex connection between the physical features of the land and the changes in plant life in karst environments, specifically in the Cradle Nature Reserve. We can gain an extensive understanding of landscape diversity, water flow, and ecosystem health by examining the EVI in conjunction with the TPI, the TRI, and the TWI. The results highlight the importance of topographic characteristics such as sinkholes, depressions, and slope gradients in influencing the distribution and condition of vegetation. A strong correlation between TPI and EVI is evident, with variations among various vegetation categories indicating the impact of moisture availability on vegetation patterns. Also, the fact that TRI goes down as EVI increases shows how rough terrain affects vegetation cover since smoother terrains tend to have more vegetation. Our study of TWI also demonstrates the impact of slope gradients on moisture dispersion, emphasising the significant influence of topography on water movement in karst terrains. These observations enhance our comprehension of how ecosystems function and provide valuable information for managing and conserving the Cradle Nature Reserve and similar habitats. Nevertheless, it is crucial to recognise the inherent limitations of topographic indices like TPI and TRI, including their dependence on scale and inability to represent intricate terrain features accurately. Hence, we advise exercising prudence and performing supplementary analyses when interpreting the findings. In summary, our research emphasises the significance of incorporating topographic data into ecological evaluations and land management plans to advance conservation efforts and promote sustainable ecosystem management practices in karst environments. Our research findings help to enhance our understanding of landscape ecology by explaining the intricate relationships between topography and vegetation dynamics. Additionally, these findings provide valuable insights for decision-making processes aimed at preserving biodiversity and ensuring the functionality of ecosystems.

**Chapter 8 IMPACTS OF LAND USE CHANGE ON ANNUAL
EVAPOTRANSPIRATION IN THE CRADLE NATURE RESERVE (2000-2023)
USING MODIS DATA AND XGBOOST CLASSIFICATION: A CASE OF THE
CRADLE NATURE RESERVE, GAUTENG PROVINCE, SOUTH AFRICA**

This Chapter is based on the following manuscript

Matyukira, C., Mhangara, P., & Gidey, E. (2024). Impacts of land use change on annual evapotranspiration in the Cradle Nature Reserve (2000–2023) using MODIS data and XGBoost classification: A case of the Cradle Nature Reserve, Gauteng Province, South Africa. *Annals of GIS* (In review).

Abstract: This study uses MODIS and Landsat data to examine evapotranspiration (ET) trends and land cover changes in the Cradle Nature Reserve from 2000 to 2023. Annual ET statistics reveal significant fluctuations, with notable peaks in 2020 (mean ET = 78.13 mm) and 2023 (mean ET = 68.49 mm), suggesting a positive response to improved climatic conditions and effective water management. ET values dropped significantly in 2005 (mean ET = 68.38 mm) and remained low through 2015 (mean ET = 53.61 mm), indicating periods of water stress. A marked recovery in 2020 reflects better water availability and vegetation health. Linear regression analysis shows an inverse relationship between ET and elevation, with higher elevations generally experiencing lower ET rates. The correlation coefficient (R) values ranged from -0.472 in 2020 to 0.0872 in 2005, indicating variability influenced by biophysical and climatic factors. October ET values across land cover types reveal distinct trends. In 2000, ET values were high across all types, with indigenous forest at 45.59 mm, open bush at 44.79 mm, natural grass at 47.75 mm, and bare ground/rock outcrop at 48.44 mm. A decline in 2005 saw ET values drop to 29.78 mm for indigenous forests and 31.21 mm for natural grass. By 2020, ET values increased to 59.89 mm for indigenous forest and 56.86 mm for natural grass. Landsat sensor improvements enhanced land cover classification accuracy. Indigenous forest areas declined from 13.1 hectares in 2000 to 0.7 hectares in 2010, partially recovering to 3.7 hectares in 2023. Natural grass areas peaked at 74.1 hectares in 2010 before decreasing to 54.5 hectares in 2023. These findings emphasise that conservation efforts are crucial for sustaining the ecological health of the reserve amid climate changes.

Keywords: evapotranspiration, land cover classification, MODIS Data, XGBoost Random Forest Classifier, Cradle Nature Reserve, South Africa

Highlights

- Evapotranspiration fluctuated significantly in annual evapotranspiration (ET) in the Cradle Nature Reserve from 2000 to 2023, peaking at 78.13 mm in 2020 and dropping to 53.61 mm in 2015.
- Land Cover Classification Accuracy and reliability of land cover classification improved significantly, overall accuracy for training data increased from 87% in 2000 to 93% in 2010, with Kappa index values rising from 0.83 to 0.91.
- There is a negative correlation between ET and elevation

8.1 Introduction

Evapotranspiration (ET) is an essential component of the hydrological cycle, connecting atmospheric and terrestrial water activities. It includes both the process of water turning into vapour from soil and water surfaces, as well as the process of water vapour being released by plants (U.S. Geological Survey, 2023a). Recent studies have highlighted the significance of ET in understanding hydrological dynamics and surface energy balance. For instance, Dimitriadou and Nikolakopoulos (2023) discuss the dependence of ET on key environmental variables and its role in groundwater levels, particularly in semi-arid regions and tropical forests, where it significantly impacts water availability and ecosystem health (Dimitriadou & Nikolakopoulos, 2021). Comprehending ET trends is crucial for the management of water resources, the study of climate change, and the evaluation of ecosystem health (Konapala et al., 2020). ET may be determined by using traditional techniques like hydrological, meteorological, and micro-meteorological approaches (Tan et al., 2021). Hydrological procedures, such as water balance approaches, include quantifying the input and output of water within a defined geographical region (Shoko et al., 2015). Meteorological techniques, such as the Penman-Monteith equation, use meteorological data (such as temperature, humidity, and wind speed) to approximate evapotranspiration (Shoko et al., 2015). Micro-meteorological techniques, such as eddy covariance and Bowen ratio systems, provide direct measurements of the water vapour exchange between the Earth's surface and the atmosphere (Food and Agriculture Organization of the United Nations, 2024). Although these approaches are precise, their effectiveness is sometimes restricted by the extent of their geographical and temporal coverage (Derardja et al., 2024; Tan et al., 2021).

The use of remote sensing technology has greatly transformed the estimate of ET by offering extensive, uninterrupted, and replicable readings on a broad scale (Derardja et al., 2024). The incorporation of remote sensing data such as MODIS/061/MOD16A2GF provides extensive and uninterrupted ET observations, enabling the tracking of temporal variations from 2000 to 2023 and beyond (LP DAAC 2024). Remote sensing has many benefits, such as comprehensive coverage of large areas and frequent observations, which are crucial for capturing the fluctuations in ET during different seasons and years (Derardja et al. 2024). Additionally, advancements in remote sensing technologies have facilitated more accurate and extensive monitoring of ET, essential for managing water resources and studying climate change effects (Derardja et al., 2024; L. Jin et al., 2024).

Machine learning methods have greatly transformed land cover categorisation by allowing the examination of extensive and intricate datasets with enhanced precision and speed (Talukdar et al., 2020; S. Zhao et al., 2023). Supervised machine learning techniques need labelled training data to acquire patterns and generate predictions, while unsupervised algorithms discern intrinsic patterns in data without the presence of labelled instances (Talukdar et al., 2020b; S. Zhao et al., 2023). The XGBoost Random Forest Classifier (XGBRFClassifier), which falls under the category of supervised learning techniques, has shown outstanding performance in challenges related to land cover categorisation (Matyukira & Mhangara, 2023b). The XGBRFClassifier algorithm combines the advantages of gradient boosting and random

forest methods, providing excellent performance in dealing with extensive datasets, addressing missing values, and avoiding overfitting (T. Chen & Guestrin, 2016a). This approach has been shown to be effective in a range of classification tasks, including the difficult karst terrain. It is particularly adept at dealing with intricate, non-linear connections within the data (Matyukira & Mhangara, 2023b). Additional notable machine-learning algorithms in the same category include Support Vector Machines (SVM), Convolutional Neural Networks (CNN), and Random Forests (Zagajewski et al., 2021).

Recent developments in Landsat sensor technology have greatly improved the accuracy and reliability of land cover classifications (USGS Earth Explorer, 2024). Using Landsat 8 and 9 has increased radiometric resolution, greater signal-to-noise ratios, and enhanced calibration (USGS Earth Explorer, 2024). These advancements in Landsat imagery, particularly with the introduction of Landsat 8 and 9, have significantly improved the accuracy of ecological monitoring (Phiri & Morgenroth, 2017). These enhancements are crucial for precisely representing intricate terrain and various land cover categories in areas like the Cradle Nature Reserve. (Phiri & Morgenroth, 2017) emphasised these developments, pointing out that the newer satellites' higher spatial, spectral, and temporal resolutions enable more detailed and accurate land cover classification, a crucial aspect of effective environmental management and conservation efforts. Using the latest satellite data guarantees the utmost data quality, accurate ecological monitoring, and efficient environmental management (Chaves et al., 2020; USGS Earth Explorer, 2024)

This research used Google Earth Engine (GEE) to implement a classification method because it provides access to large datasets and computing resources. GEE is a cloud-based tool designed to streamline the study of extensive environmental data. It facilitates diverse machine learning methods and streamlines the application of these approaches to remote sensing data, allowing for the effective and scalable study of alterations in land cover (Google Earth Engine Team, 2024a). Integrating the latest Landsat data with GEE's capabilities ensures high-quality, precise monitoring and management of ecologically sensitive areas, thereby supporting comprehensive environmental conservation strategies.

This study aims to evaluate the yearly patterns of evapotranspiration (ET), assess how ET is distributed throughout different areas, and explore the correlation between ET and Digital Elevation Model (DEM) data. Furthermore, it investigates the relationship between ET and changes in land cover, offering a valuable understanding of the ecological consequences of both climate change and land management strategies. Comprehending these connections is crucial for formulating adaptive management methods to uphold the ecosystems of the reserve in the face of shifting climate trends (Arnell et al., 2019; Gilman & Wu, 2023).

This work adds to the expanding body of knowledge on the dynamics of evapotranspiration (ET) and the relationships between land cover, providing vital data for conservation initiatives and ecological monitoring. This research employs advanced remote sensing technology, GEE, and robust classification methods to conduct a thorough evaluation of ET trends and their causes in the Cradle Nature Reserve. The study emphasises the significance of ongoing monitoring and adaptive management in preserving ecological well-being.

8.2 Materials and Method

8.2.1 Study area

Figure 8-1 illustrates the expansive Cradle Nature Reserve, which covers an area of about 8,000 hectares inside the Cradle of Humanity World Heritage Site (COHWHS). The reserve is well-known for its wide range of plant species, especially those that bloom. Additionally, it is home to more than 200 bird species and several other types of animals (Braga et al., 2016; Rogerson & van der Merwe, 2016). Important climatic factors such as temperature and precipitation, which are critical for plant growth and development, have an impact on the vegetation in the area. The reserve experiences annual rainfall ranging from 650 to 750 mm, with summer temperatures reaching a maximum of 39 °C and winter temperatures dropping as low as -12 °C. The fluctuation in climate creates a dynamic environment that promotes the development of plants (FLOW Communications, 2022; Matyukira & Mhangara, 2023b). Fire significantly impacts the reserve's plant structure, given its location in the Rocky Highveld Grassland climatic area. The presence of natural springs, watercourses, streams, and tributaries to the Magalies and Crocodile Rivers is crucial for providing enough moisture, which in turn sustains the wide range of plant species in the area (Caruana & Stratford, 2019; Lelliott, 2016).

Both subsistence and commercial farming have used the reserve's land throughout history, changing the distribution of plant life (Matyukira & Mhangara, 2023b). The re-establishment of wild animal species with different grazing patterns compared to domesticated cattle has further influenced these alterations (Makokotlele, 2009). The prevailing climate and the geological characteristics of the reserve, such as the presence of dolomitic sinkholes that protect tree species from forest fires, influence the region's distinct patterns of plant growth (Matyukira & Mhangara, 2023b). These criteria emphasize the importance of understanding and preserving the original plant cover in the reserve, its value for biodiversity in protected historic areas, and its role as a tourist attraction. The nature reserve uses the presence of this plant species as a reliable indicator of past environments and food sources, crucial for animal feeding (Matyukira & Mhangara, 2023b). The complex correlation between temperature and vegetation highlights the need to conserve rangelands to sustain the diverse ecosystems within the reserve.

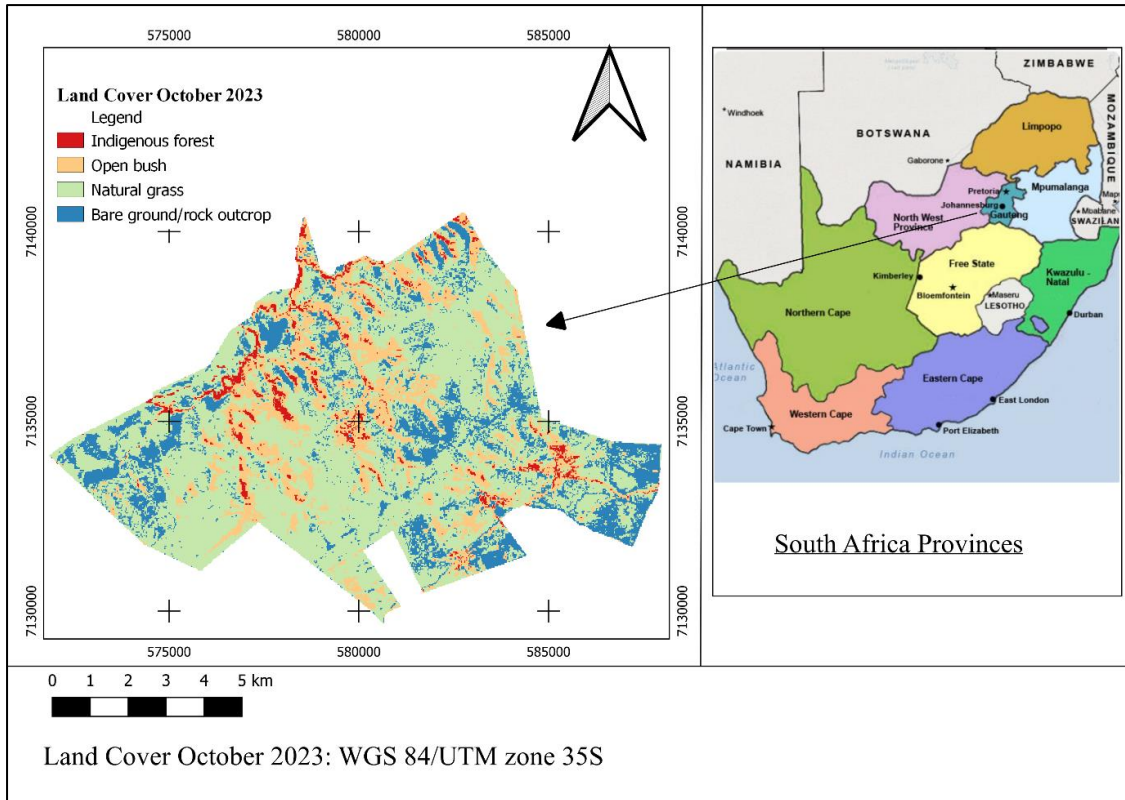


Figure 8- 1: Study Area-Cradle Nature Reserve in South Africa, Gauteng Province

8.2.2 Methods of data acquisition, processing, and analysis

8.2.2.1 Retrieving and Analysing MODIS/061/MOD16A2GF Data

The dataset MODIS/061/MOD16A2GF offers worldwide terrestrial evapotranspiration (ET) estimates, calculated using the Penman-Monteith equation (LP DAAC, 2024). The dataset, obtained from the MODIS sensor on NASA's Terra satellite, provided 8-day composite data with a spatial resolution of 500 meters (LP DAAC, 2024). Thanks to its frequent updates and worldwide coverage, it is especially useful for research on water cycles, the effects of climate change, and agricultural productivity (LP DAAC, 2024). The gap-filled version (MOD16A2GF) rectified data gaps resulting from cloud cover, hence offering more dependable data compared to previous ET datasets (Mu et al., 2007a, 2011). This research employed MODIS/061/MOD16A2GF data to compute yearly evapotranspiration (ET) statistics and construct time series charts for the Cradle Nature Reserve. The analysis focused on the period from 2000 to 2023, specifically October, to capture the transition from the dry to the wet season (Shoko et al., 2015).

To do this, we used Google Earth Engine (GEE), a cloud-based platform designed for extensive analysis of environmental data (Google Earth Engine Team, 2024b). The research region was delineated, and the dataset was refined to include the relevant geographical and temporal features. We created a code that computes yearly ET statistics, including the mean, minimum, maximum, median, and standard deviation values. The function was implemented for each year

throughout the research period, resulting in a full collection of yearly ET data. The findings were exported as a CSV file and shown as a time series chart using GEE's `ui.Chart` module (Google Earth Engine Team, 2024a). This methodology facilitated the effective management of extensive datasets and yielded resilient observations on the patterns of evapotranspiration (ET) and their correlation with changes in climate and land cover.

8.2.2.2. Investigating the Relationship between October 2023 Evapotranspiration Data and Digital Terrain Model

This research examined the correlation between evapotranspiration (ET) data from the MODIS/061/MOD16A2GF dataset in October 2023 and the digital terrain model (DTM) from the Shuttle Radar Topography Mission (SRTM). DEM is crucial for comprehending terrain characteristics such as elevation, slope, and aspect, which substantially impact evapotranspiration (ET) patterns via their effect on local climatic conditions and the distribution of plants (Sánchez-Emeterio et al., 2024). The internationally accessible SRTM DEM, with a high level of resolution at 30 meters, offers precise topographical data essential for conducting terrain research (NASA Earthdata, 2024). The Digital Elevation Model (DEM) was acquired from the United States Geological Survey (USGS) Earth Explorer or NASA Earthdata platform and then cropped to the specific area of interest (ROI) using the Cradle Nature Reserve shapefile. The procedure included importing the Digital Elevation Model (DEM) into QGIS and using the 'Clip Raster by Mask Layer' tool to isolate the elevation data relevant to the designated research region (QGIS Server Guide/Manual (QGIS 3.36.0), 2023b).

To verify that both raster datasets (ET and DEM) had the same resolution, extent, and alignment, they needed to be on the same coordinate reference system (CRS) and aligned using the 'Align Rasters' tool in QGIS (QGIS Server Guide/Manual (QGIS 3.36.0), 2023b). This step is essential to prevent any spatial inconsistencies that may impact the regression analysis.

Many procedures were executed to do the regression analysis between the ET data and the DEM using QGIS. The October 2023 MODIS/061/MOD16A2GF ET raster data and the SRTM DEM raster data were first imported and then trimmed to fit the boundaries of the Cradle Nature Reserve shapefile. The regression study used the `r.regression.line` tool from the GRASS GIS plugin, using the ET raster as the dependent variable and the DEM raster as the independent variable. Executing this tool resulted in the generation of the regression equation and statistical outputs, which included the correlation coefficient and significance values. By interpreting these data, we were able to get insight into the correlation between elevation and ET. The slope and intercept of the regression line provided valuable information about the magnitude and direction of this association. The study's conclusions considered constraints such as the disparity in spatial resolution between the DEM (30m) and ET data (500m), the possible impact of cloud cover, and the accuracy of the shapefile bounds.

8.2.2.3 Estimating Evapotranspiration Over Different Land Covers

This study aimed to estimate evapotranspiration (ET) over different land covers in the Cradle Nature Reserve for the years 2000, 2005, 2010, 2015, 2020, and 2023 using data from the MODIS/061/MOD16A2GF dataset. To achieve this, the land cover of the Cradle Nature Reserve was classified into four categories: Indigenous Forest, Open Grass, Natural Grass, and Bare Ground/Rock Outcrop using the XGBRFCClassifier in Google Earth Engine (GEE). The classification process involved downloading Landsat datasets for October of the study years:

LANDSAT/LT05/C02/T1_L2 for 2000, 2005, and 2010; LANDSAT/LC08/C02/T1_L2 for 2015 and 2020; and LANDSAT/LC09/C02/T1_TOA for 2023.

The selection of different Landsat datasets for various years was based on the availability and advancements in satellite technology over time. Landsat 5 (LANDSAT/LT05/C02/T1_L2) provides historical surface reflectance data, crucial for continuity and consistency in long-term environmental monitoring (USGS Earth Explorer, 2024). Landsat 8 (LANDSAT/LC08/C02/T1_L2) offers improved radiometric resolution, higher signal-to-noise ratio, and more accurate reflectance data, making it suitable for recent years where higher data quality is required (USGS Earth Explorer, 2024). Landsat 9 (LANDSAT/LC09/C02/T1_TOA), the latest in the series, provides further enhancements in calibration and radiometric performance, ensuring the most accurate and reliable data for the most recent year in the study, 2023 (USGS Earth Explorer, 2024).

The study began by downloading the appropriate Landsat datasets for each year from GEE. These datasets were used to generate training data by collecting sample points for each land cover class and labelling them using satellite imagery and field data (Matyukira & Mhangara, 2023b). The labelled points were split into training (70%) and test (30%) sets (Matyukira & Mhangara, 2023b). In GEE, the training data were used to train the XGBRFClassifier, leveraging its efficiency in handling large datasets, managing missing values, and preventing overfitting (Matyukira & Mhangara, 2023b). The classifier's performance was evaluated using a confusion matrix to provide metrics such as overall accuracy, producer's accuracy, user's accuracy, and the Kappa index (Matyukira & Mhangara, 2023b). The resulting land cover classification map was used to analyse ET values. In QGIS, the 'Zonal Statistics' tool was utilised to calculate the mean ET values for each land cover class (QGIS Server Guide/Manual (QGIS 3.36.0), 2023b). This involved importing the classified raster and the Cradle Nature Reserve shapefile into QGIS and summarising the ET values by land cover type (QGIS Server Guide/Manual (QGIS 3.36.0), 2023b), providing insights into the spatial distribution of ET across different land covers in the Cradle Nature Reserve.

8.3 Results and Analysis

8.3.1 Annual Evapotranspiration Statistics in the Cradle Nature Reserve (2000-2024)

Table 8- 1: Annual Evapotranspiration Statistics mm (2000-2024)

Year	Min	Max	Median	Mean	StdDev
2000	60.78	119.15	76.17	77.43	9.95
2005	54.17	99.48	67.85	68.38	6.62
2010	60.24	121.17	73.39	74.52	7.54
2015	42.80	102.00	52.09	53.61	6.95
2020	65.30	126.35	76.09	78.13	9.12

2023

51.73

109.68

68.13

68.49

8.13

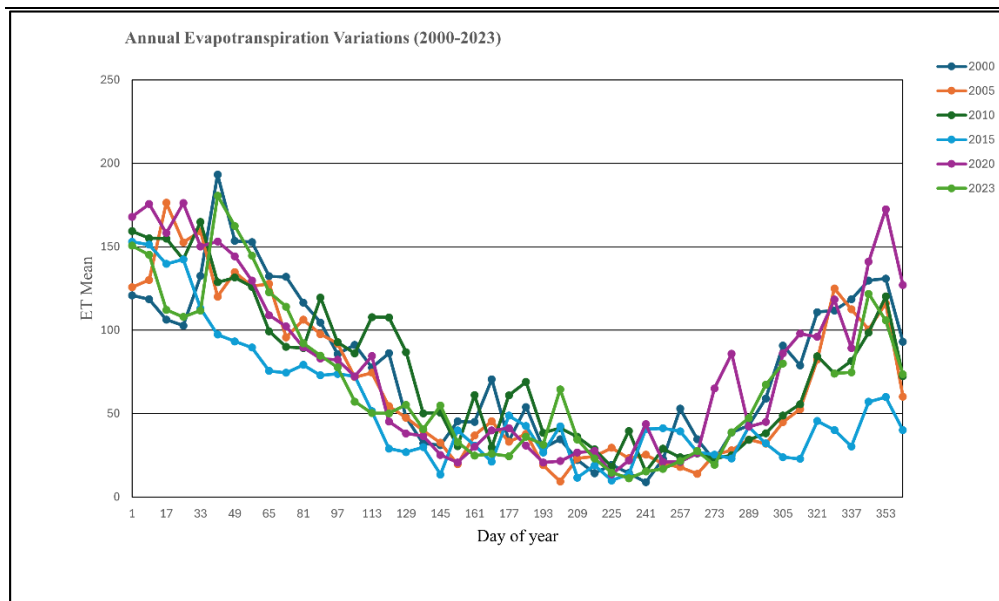


Figure 8- 2: Annual Evapotranspiration Variation (2000-2023)

Using MODIS/061/MOD16A2GF data to look at evapotranspiration (ET) patterns in the Cradle Nature Reserve shows that they change a lot from season to season and year to year. The study identifies clear ET patterns observed between 2000 and 2023, Figure 8-2, characterised by peaks and troughs corresponding to plant and soil moisture reactions to seasonal climate changes. The summary figures reveal increased average evapotranspiration (ET) in recent years. For instance, in 2020, the mean ET was 78.13 mm, with a standard deviation of 9.12 mm, Table 8-1. Understanding these changes is crucial for comprehending the reserve's energy balance since higher evapotranspiration (ET) rates indicate increased water consumption by plants, affecting the hydrological cycle.

The observed fluctuations in evapotranspiration (ET) are consistent with larger trends linked to global warming, such as rising temperatures and changes in precipitation patterns, suggesting a connection between these results and climate change. The average evapotranspiration (ET) values showed an increase from 68.38 mm in 2005 to 78.13 mm in 2020, Table 8-1, indicating a noticeable reaction to changes in climate. Elevated temperatures amplify evapotranspiration (ET), leading to a greater amount of water vapour in the atmosphere. Meanwhile, alterations in rainfall may either intensify or alleviate this phenomenon. The recent rise in evapotranspiration (ET) may mean that the reserve is responding to changes in the climate. This shows how important it is to keep an eye on things to fully understand and control the health of the ecosystem and the balance of water in the lake.

The ET trends provide a valuable understanding of the connections between land use, land cover, and climate within the land use and land categorisation framework. Various land cover types, such as woods, grasslands, and urban areas, display unique evapotranspiration (ET) properties. Forests often exhibit greater evapotranspiration (ET) rates than grasslands or urban settings, mostly because of their vast root systems and larger leaf areas. Changes in land cover,

such as deforestation or less vegetation coverage, may have contributed to the decrease in evapotranspiration (ET) in 2015 (with an average of 53.61 mm), Table 8-1, compared to previous years. The MODIS sensor is critical for this study because it provides useful data for monitoring changes in land cover and their impact on evapotranspiration (ET). Although MODIS has several limitations, such as its geographical resolution and the possibility of data gaps caused by cloud cover, it continues to be crucial for long-term environmental monitoring and educated land management techniques (Mu et al., 2007a, 2011).

8.3.2 Analysis of October Evapotranspiration Fluctuations in the Cradle Nature Reserve from 2000 to 2023 Using MODIS Data

The analysis of ET maps from October 2000 to October 2023 for the Cradle Nature Reserve, based on MODIS sensor data, reveals significant fluctuations in water availability and vegetation health during the transition from the dry to the wet season. In 2000, Figure 8-3 (a) October ET values ranged from 28 to 82, indicating healthy vegetation and good water availability. However, by 2005, Figure 8-3 (b), ET values dropped to a range of 23 to 41, suggesting a reduction in vegetation health or water availability. This trend continued in October 2010, Figure 8-3 (c), with ET values between 27 and 44, and in October 2015, Figure 8-3 (d), with values from 27 to 43, indicating stable but suboptimal vegetation health. A marked improvement occurred in October 2020, Figure 8-3 (e), with ET values increasing to a range of 52 to 67, suggesting better water availability and vegetation health. This positive trend continued in October 2023, Figure 8-3 (f), with ET values between 38 and 69. Spatial patterns also show that high ET areas were more localised in the early years but became more widespread in October 2020 and 2023, indicating overall improvement. These fluctuations point to periods of water stress and recovery, with recent years showing significant gains likely due to better water management, conservation efforts, or favourable climatic conditions.

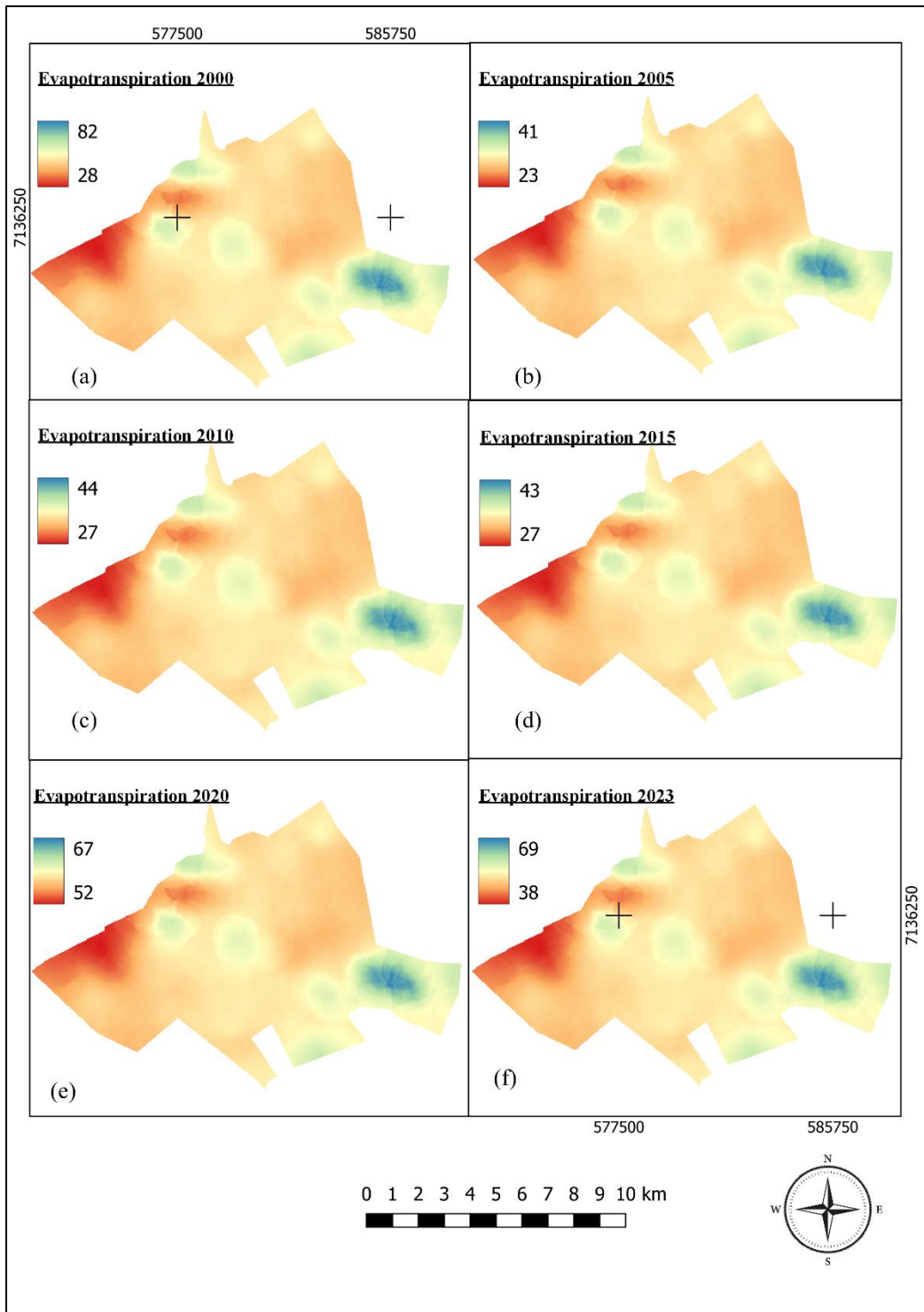


Figure 8- 3: Spatial Annual Evapotranspiration Variation in the Cradle Nature Reserve (2000-2024)

8.3.3 Relationship Between Evapotranspiration (ET) and Digital Elevation Model (DEM)

Regression model ET versus DEM

Table 8- 2: Regression coefficients

Year	a(offset)	b(Gain)	R	N	F	Mean X	sdX	MeanY	sdY
2000	57.169	-0.007	-0.039	95807	147.948	1476.697	57.369	47.115	9.947
2005	24.995	0.004	0.087	95807	734.518	1476.697	57.369	31.074	2.707
2010	45.898	-0.009	-0.202	95807	4090.807	1476.697	57.369	31.946	2.678
2015	41.213	-0.006	-0.134	95807	1761.342	1476.697	57.369	32.018	2.658
2020	93.600	-0.245	-0.472	95807	27445.550	1476.697	57.369	57.316	2.987
2023	71.491	-0.014	-0.195	95807	3794.315	1476.697	57.369	50.666	4.145

$$\text{Evapotranspiration} = a + b \cdot \text{DEM} \quad (\text{Eq. 1})$$

The linear regression results for the relationship between evapotranspiration (ET, denoted as Y) and the Digital Elevation Model (DEM, denoted as X) for the Cradle Nature Reserve from 2000 to 2023 reveal significant insights. The intercept (a) and slope (b) values fluctuate over the years, with the intercept ranging from 24.995 in 2005 to 93.6 in 2020 and the slope generally remaining negative, except in 2005 ($b = 0.0041$), indicating an inverse relationship between DEM and ET. The correlation coefficient (R) values range from -0.472 in 2020 to 0.0872 in 2005, suggesting a generally weak inverse relationship, except in 2005, where a weak positive correlation is observed. The number of observations (N) is consistent at 95,807 across all years, and the F-statistic (F), which measures the overall significance of the regression model, peaks in 2020 at 27,445.55, indicating a particularly strong significance that year. The mean ET values (MeanY) increase from 47.115 in 2000 to 57.316 in 2020, reflecting an overall increase in ET over time, while the standard deviation of ET values (sdY) shows notable variability, with significant increases in 2020 and 2023. These results highlight the dynamic relationship between elevation and ET in the Cradle Nature Reserve, with elevation generally inversely affecting ET, influenced by both biophysical and climatic factors, particularly evident in the strong inverse relationship observed in 2020.

8.3.4 Land cover classification using XGBRFCClassifier in Cradle Nature Reserve

The land cover classification outcomes for the Cradle Nature Reserve, obtained via utilising the XGBRFCClassifier, demonstrate substantial ecological alterations in October. This month is a crucial transitional time, signifying the dry season's conclusion and the rainy season's commencement. In 2000 and 2005, Figures 8-4 (a-b), the region was mostly covered by Natural Grass, with significant areas of Indigenous Forest and Bare Ground/Rock Outcrop. Nevertheless, in 2010, Figure 8-4 (c), there was a significant rise in the area of Indigenous Forest, namely in the northern areas. This indicates either deliberate replanting initiatives or spontaneous ecological rebound, which may be influenced by the alteration in seasonal precipitation patterns. In 2015, Figure 8-4 (d) shows the pattern of expanding Indigenous

Forests and increasing Open Bush remained. These shifts suggest alterations in land management methods or natural succession processes, which may be influenced by the move to wetter conditions over the season. Between 2020 and 2023, Figures 8-4 (e-f) showed a noticeable rise in the importance of Indigenous Forest and Open Bush. This may be attributed to ongoing or expanded efforts in reforestation and the natural development of vegetation. These positive changes were a response to the greater water availability at the beginning of the rainy season.

Overall, these classifications emphasise the ever-changing characteristics of the ecosystem in the Cradle Nature Reserve and the beneficial influence of conservation initiatives during the duration of the research. The rise in forest and shrub coverage and the decrease in regions of bare ground and rock outcrops indicate a successful establishment of vegetation and enhanced ecological well-being. This is primarily driven by the crucial shift from dry to rainy circumstances in October. These results highlight the significance of continuous conservation efforts to oversee and protect the various reserves' ecosystems, guaranteeing their sustainability and capacity to adapt to seasonal climate changes and conservation policies in the long run.

8.3.5 Land cover classification using XGBoost Random Forest Classifier (2000-2023)

8.3.5.1 70% Training Data Analysis

The XGBRFCClassifier Table 8-3 consistently demonstrates great accuracy and reliability when trained on 70% of the data from the years 2000, 2005, 2010, 2015, 2020, and 2023. In the Indigenous Forest class, the Producer's Accuracy varied from 0.83 in 2023 to 0.94 in 2000, while the User's Accuracy fluctuated between 0.84 and 0.94 during the years. The Open Bush class exhibited constant and steady accuracies, with the Producer's Accuracy consistently ranging from 0.81 to 0.89 and the User's Accuracy between 0.81 and 0.91. The Natural Grass class demonstrated a notable Producer's Accuracy, reaching a top of 0.97 in 2010, and a commendable User's Accuracy, with a maximum of 0.93 in the same year. The Bare-ground/Rock Outcrop class performed excellently, especially in 2010, with a Producer's Accuracy of 1.00 and a User's Accuracy of 0.97. The overall accuracy of the predictions varied between 0.85 and 0.93. The highest Kappa index, which measures the agreement between projected and actual classifications, was seen in 2010 and had a value of 0.91, suggesting a significant level of agreement.

8.3.5.2 30% Testing Data Analysis

When the classifier was tested on 30% of the data, Table 8-3, its performance showed a greater degree of variation, suggesting possible overfitting problems. In 2000, the Indigenous Forest class had poorer accuracy metrics, with a Producer's Accuracy of 0.88 and a User's Accuracy of 0.55. However, by 2023, there was an improvement, with a Producer's Accuracy of 0.76 and a User's Accuracy of 0.79. The Open Bush class had significant swings, with a Producer's Accuracy ranging from a low of 0.55 in 2000 to a high of 0.81 in 2023. The Natural Grass class had robust performance in 2010 and 2015, with Producer's Accuracy values of 0.97 and 0.92, respectively. The Bare-ground/Rock Outcrop class continuously achieved high performance, especially in 2010 and 2015, with a Producer's Accuracy of 0.96 and 0.97 and a User's Accuracy of 1.00 and 0.97. The overall accuracy of the testing data varied from 0.65 in 2000

to 0.87 in 2010. The associated Kappa index values ranged from 0.53 to 0.83, demonstrating differences in the dependability of categorisation.

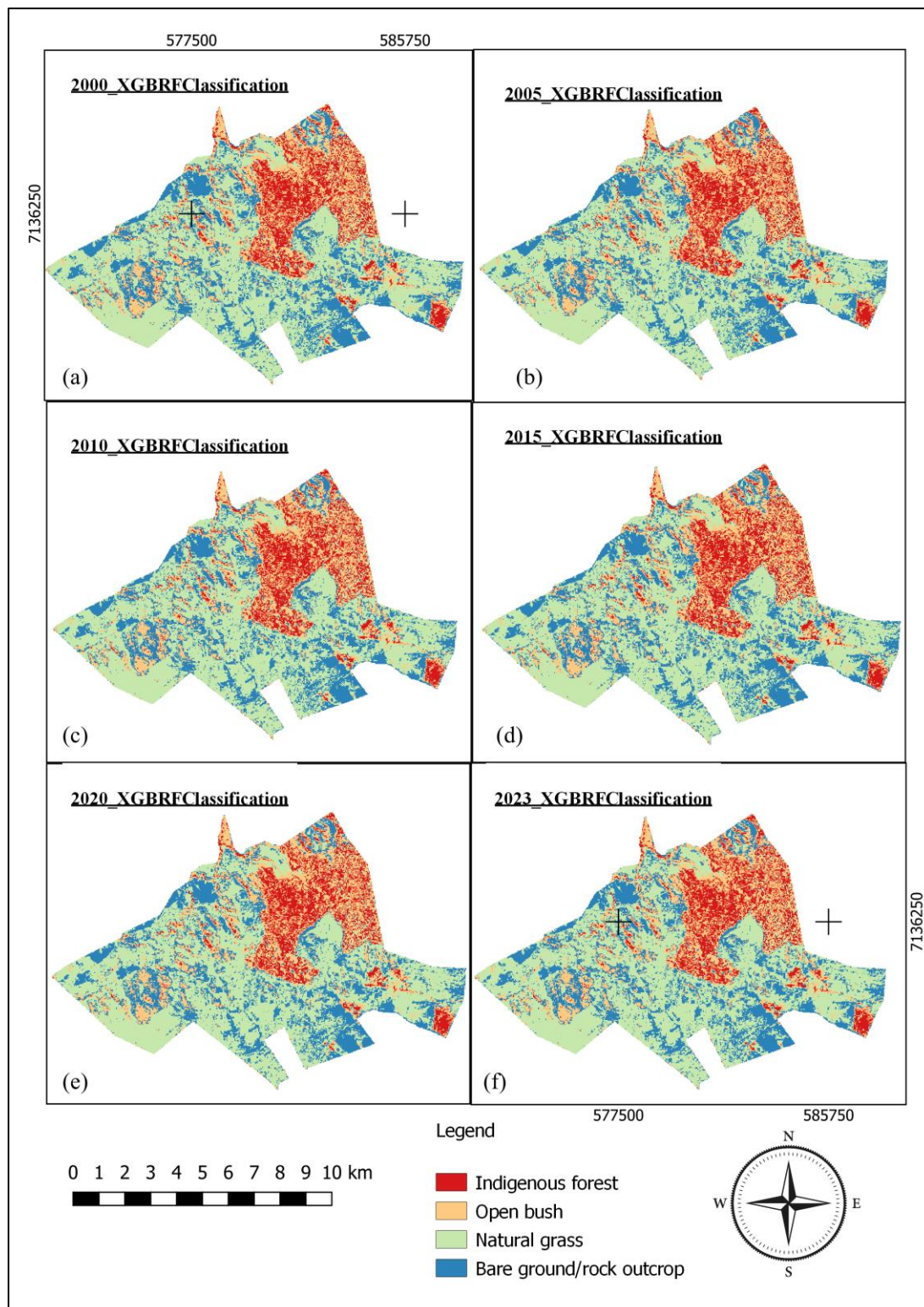


Figure 8- 4: Temporal land cover classification using XGBoost Random Forest Classifier (2000-2023)

Table 8- 3: Performance Metrics of XGBRFCClassifier for Land Cover Classification in the Cradle Nature Reserve (2000-2023)

XGBRFCClassifier	2000			2005			2010		
70%	P	U	F1	P	U	F1	P	U	F1
Indigenous forest	0.94	0.87	0.90	0.84	0.84	0.84	0.88	0.94	0.91
Open Bush	0.86	0.88	0.87	0.81	0.81	0.81	0.88	0.89	0.89
Natural grass	0.86	0.84	0.85	0.88	0.84	0.86	0.97	0.93	0.95
Bare-ground/rock outcrop	0.84	0.90	0.87	0.89	0.94	0.91	1.00	0.97	0.99
Overall accuracy	0.87			0.85			0.93		
Kappa index	0.83			0.80			0.91		
30%									
Indigenous forest	0.88	0.55	0.68	0.67	0.72	0.69	0.75	0.90	0.82
Open Bush	0.55	0.72	0.63	0.74	0.65	0.69	0.83	0.71	0.77
Natural grass	0.58	0.63	0.60	0.71	0.71	0.71	0.97	0.91	0.94
Bare-ground/rock outcrop	0.66	0.72	0.69	0.83	0.89	0.86	0.96	1.00	0.98
Overall accuracy	0.65			0.73			0.87		
Kappa index	0.53			0.64			0.83		
	2015			2020			2023		
70%	P	U	F1	P	U	F1	P	U	F1
Indigenous forest	0.88	0.88	0.88	0.91	0.88	0.90	0.83	0.86	0.84
Open Bush	0.86	0.87	0.86	0.87	0.91	0.89	0.85	0.84	0.85
Natural grass	0.91	0.92	0.92	0.89	0.91	0.90	0.84	0.88	0.86
Bare-ground/rock outcrop	0.95	0.92	0.94	0.93	0.91	0.92	0.90	0.85	0.87
Overall accuracy	0.90			0.90			0.86		
Kappa index	0.86			0.87			0.81		
30%									
Indigenous forest	0.76	0.81	0.78	0.61	0.72	0.66	0.76	0.79	0.77
Open Bush	0.77	0.74	0.75	0.60	0.50	0.55	0.81	0.71	0.76
Natural grass	0.92	0.89	0.90	0.70	0.84	0.76	0.60	0.78	0.68
Bare-ground/rock outcrop	0.97	0.97	0.97	0.93	0.78	0.85	0.80	0.69	0.74
Overall accuracy	0.86			0.71			0.74		
Kappa index	0.81			0.61			0.65		

P=Producer's Accuracy

U=User's Accuracy

8.3.6 Average October Evapotranspiration Across Various Land Cover Categories in the Cradle Nature Reserve (2000-2023)

Table 8- 4: Average October Evapotranspiration (ET) Values (mm) for Different Land Covers in the Cradle Nature Reserve (2000-2023)

Year	Indigenous forest	Open bush	Natural grass	bare ground/rock outcrop
2000	45.59	44.79	47.75	48.44
2005	29.78	31.49	31.21	30.93
2010	32.60	32.42	31.89	31.69
2015	32.90	32.21	31.87	32.20
2020	59.89	58.42	56.86	56.95
2023	52.83	51.81	50.29	50.31

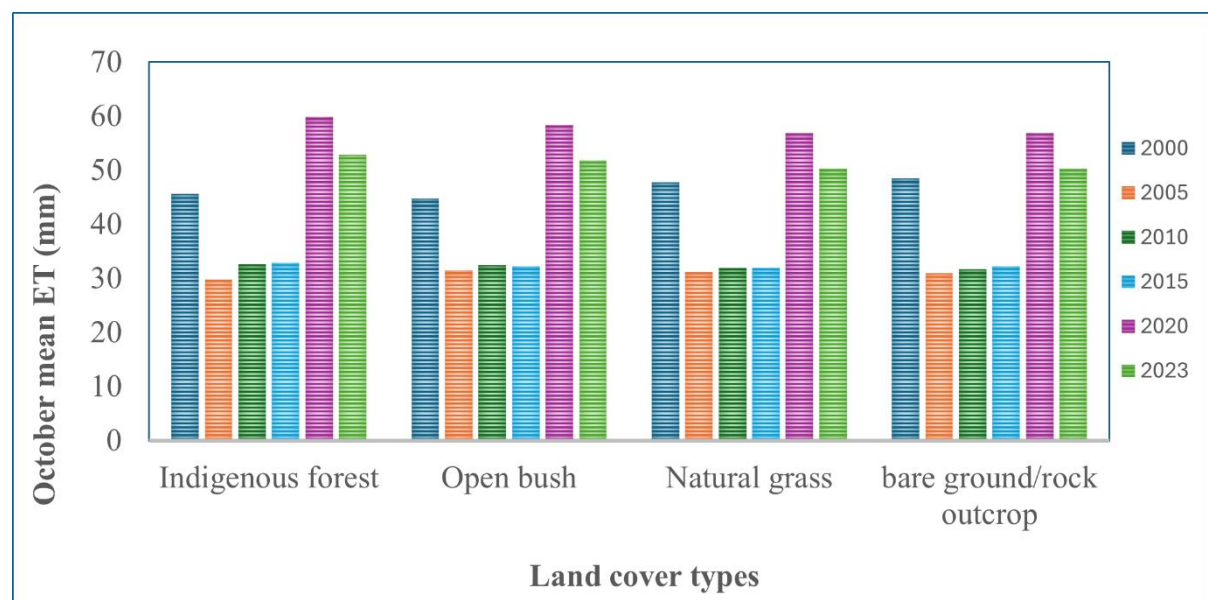


Figure 8- 5: Evapotranspiration (ET) estimates across different land cover types derived using zonal statistics in QGIS version 3.28.3-Firenze.

The analysis of evapotranspiration (ET) data for different land cover types in the Cradle Nature Reserve from 2000 to 2023 (presented in Table 8-4 and Figure 8-5) reveals important trends that highlight ecological changes across the years, especially during the transition from the dry to the wet season. Initially, in 2000, ET values were relatively high across all land cover types, but a significant decline occurred by 2005, possibly due to drought or ecological stress. This trend of low ET values persisted through 2010 and 2015, with only slight variations indicating prolonged periods of poor vegetation health and low water availability. However, by 2020, a marked increase in ET values for all land cover types suggests substantial recovery, likely due to improved vegetation health, water management, and favourable climatic conditions. The

slight reduction in ET values by 2023 indicates that while the recovery continues, some variability remains.

Table 8- 5: Summary of Statistical Analysis

Indigenous forest versus Year							Open bush versus Year						
Regression Equation							Regression Equation						
Indigenous forest = -1481.46 + 0.76 Year							Open bush = -1344.3 + 0.69 Year						
Coefficients													
Term	Coef	SE Coef	T	P			Term	Coef	SE Coef	T	P		
Constant	-1481.46	1189.41	-1.25	0.28			Constant	-1344.30	1121.79	-1.20	0.30		
Year	0.76	0.59	1.28	0.27			Year	0.69	0.56	1.24	0.28		
Summary of Model													
S = 11.69 R-Sq = 29.09% R-Sq(adj) = 11.37%							S = 11.02 R-Sq = 27.63% R-Sq(adj) = 9.53%						
PRESS = 1476.27 R-Sq(pred) = -91.64%							PRESS = 1270.89 R-Sq(pred) = -89.30%						
Analysis of Variance													
Source	DF	Seq SS	Adj SS	Adj MS	F	P	Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	1	224.12	224.12	224.12	1.64	0.27	Regression	1	185.48	185.45	185.48	1.53	0.28
Year	1	224.12	224.12	224.12	1.64	0.27	Year	1	185.48	185.48	185.48	1.53	0.28
Error	4	546.23	46.23	136.56			Error	4	485.89	485.89	121.47		
Total	5	770.35					Total	5	671.37				
Natural grass versus Year							bare ground/rock outcrop versus Year						
Regression Equation							Regression Equation						
Natural grass = -1023.13 + 0.53 Year							bare ground/rock outcrop = -1001.48 + 0.52 Year						
Coefficients													
Term	Coef	SE Coef	T	P			Term	Coef	SE Coef	T	P		
Constant	-1023.13	1175.93	-0.87	0.43			Constant	-1001.48	1197.14	-0.84	0.45		
Year	0.53	0.58	0.91	0.42			Year	0.52	0.59	0.87	0.43		
Summary of Model													
S = 11.5534 R-Sq = 17.01% R-Sq(adj) = -3.74%							S = 11.7618 R-Sq = 15.96% R-Sq(adj) = -5.05%						
PRESS = 1451.48 R-Sq(pred) = -125.61%							PRESS = 1523.65 R-Sq(pred) = -131.41%						
Analysis of Variance													
Source	DF	Seq SS	Adj SS	Adj MS	F	P	Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	1	109.44	109.44	109.44	0.82	0.42	Regression	1	105.06	105.06	105.06	0.76	0.43
Year	1	109.44	109.44	109.44	0.82	0.42	Year	1	105.06	105.06	105.06	0.76	0.43
Error	4	533.93	533.93	133.48			Error	4	553.36	553.36	138.34		
Total	5	643.36					Total	5	658.42				

The statistical analysis (Table 8-5) further supports these observations, though it highlights that the year is not a statistically significant predictor of ET trends for any of the land cover types. With p-values ranging from 0.27 to 0.43, and low R-squared values (15.96% to 29.09%), the regression analysis suggests that other factors—such as climate variations, management practices, or seasonal impacts—may be influencing ET changes more than the passage of time alone. The ecological stress and recovery phases observed in Table 8-4 and Figure 8-5 align with the overall weak statistical trends found in Table 8-5, emphasizing the importance of considering multiple environmental variables in future analyses. These results highlight the importance of continuous monitoring and adaptive management to sustain the ecological health and biodiversity of the Cradle Nature Reserve, particularly as it undergoes cycles of stress and recovery during critical seasonal transitions.

8.3.7 Land Cover Changes in the Cradle Nature Reserve (2000-2023)

Table 8- 6: Area Covered by Land Cover Types in the Cradle Nature Reserve (2000-2023) in Hectares

	Indigenous forest	Open bush	Natural grass	bare ground/rock outcrop
2000	10.09	16.03	39.96	19.90
2005	5.99	8.85	52.71	18.34
2010	1.09	9.79	69.38	5.72
2015	2.41	14.88	53.56	15.13
2020	3.18	18.17	50.95	13.69
2023	2.80	16.30	50.67	16.21

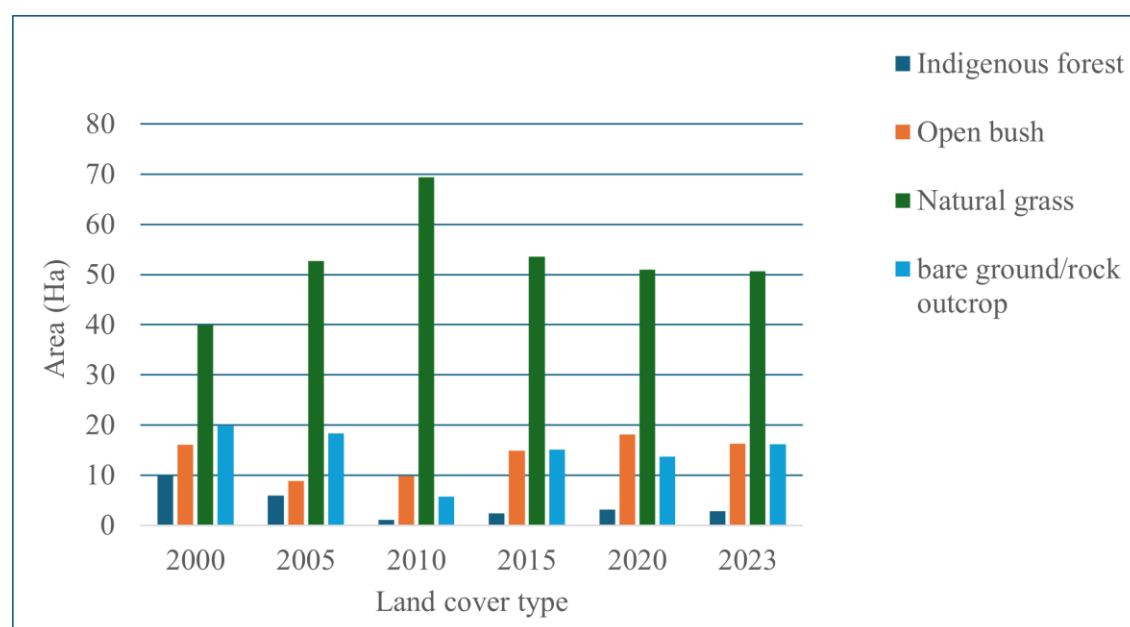


Figure 8- 6: Area covered by land cover types derived using zonal statistics in QGIS version 3.28.3-Firenze.

The analysis of Table 8-6 and Figure 8-6 depicting the land cover types in the Cradle Nature Reserve from October 2000 to October 2023 reveals significant shifts in the areas occupied by different land cover types over the years, reflecting the transition from the dry to wet season. In October 2000, natural grass dominated the land cover with an area of 39.96 hectares, followed by bare ground/rock outcrop at 19.90 hectares, open bush at 16.03 hectares, and indigenous forest at 10.09 hectares. By October 2005, the area of natural grass had significantly increased to 52.71 hectares, while the areas of bare ground/rock outcrop (18.34 hectares), open bush (8.85 hectares), and indigenous forest (5.99 hectares) decreased. In October 2010, natural grass continued to expand, reaching 69.38 hectares, while the areas of indigenous forest (1.09 hectares) and bare ground/rock outcrop (5.72 hectares) significantly declined. Open bush saw a slight increase to 9.79 hectares. October 2015 saw a reduction in the natural grass area to

53.56 hectares and an increase in open bush to 14.88 hectares. The bare ground/rock outcrop and indigenous forest areas were 15.13 hectares and 2.41 hectares, respectively.

By October 2020, the natural grass area slightly decreased to 50.95 hectares, while open bush grew, reaching 18.17 hectares. The bare ground/rock outcrop and indigenous forest areas were 13.69 hectares and 3.18 hectares, respectively. In October 2023, the natural grass and open bush areas were relatively stable at 50.67 hectares and 16.30 hectares, respectively. The bare ground/rock outcrop area increased to 16.21 hectares, and the indigenous forest remained low at 2.80 hectares. Figure 8-6 visually confirms these trends, showing the dominance of natural grass over the years, with significant fluctuations in open bush areas, bare ground/rock outcrop, and indigenous forests. The overall trends indicate that natural grass has consistently occupied the largest area despite some fluctuations, suggesting its resilience or favourable conditions for its growth. The notable decline in indigenous forest areas over the years raises concerns about the loss of this critical habitat, potentially impacting biodiversity. Conversely, the fluctuating open bush and bare ground/rock outcrop areas suggest dynamic ecological processes, possibly influenced by climatic variations, land management practices, and natural succession.

These ecological changes, observed during October—a critical transition period from the dry to the wet season—highlight the importance of continuous monitoring and adaptive management strategies to sustain the biodiversity and ecological health of the Cradle Nature Reserve. Expanding natural grass areas and declining indigenous forest areas could have significant implications for species composition, habitat availability, and overall ecosystem services in the reserve.

8.4 Discussion

8.4.1 Analysis of evapotranspiration fluctuations in the Cradle Nature Reserve from 2000 to 2023 using MODIS data

The analysis of ET maps for the Cradle Nature Reserve from October 2000 to October 2023, based on MODIS sensor data, reveals significant fluctuations in water availability and vegetation health during the transition from the dry to the wet season. These fluctuations are consistent with the impacts of climate variability and changing land management practices (Arnell et al., 2019). In October 2000, the ET values ranged from 28 to 82 mm (Figure 8-3a), indicating healthy vegetation and good water availability. This period likely benefited from favourable climatic conditions, contributing to robust vegetation health. However, by October 2005, ET values dropped significantly to a range of 23 to 41 mm (Figure 8-3b), suggesting a reduction in vegetation health or water availability. This decline can be attributed to adverse climatic conditions or increased vegetation stress, possibly due to prolonged dry periods or other environmental stressors (Allen et al., 1998). The downward trend continued in October 2010, with ET values between 27 and 44 mm (Figure 8-3c), and in October 2015, with values from 27 to 43 mm (Figure 8-3d), indicating stable but suboptimal vegetation health. These years may have experienced inconsistent rainfall patterns or increased temperatures, further stressing the vegetation. Similar findings have been reported by (Gerten et al., 2013), who

noted that climate change intensifies evapotranspiration rates due to rising temperatures and changes in precipitation patterns.

A marked improvement occurred in October 2020, with ET values increasing to a range of 52 to 67 mm (Figure 8-3e), suggesting better water availability and vegetation health. This improvement likely resulted from favourable climatic conditions, effective water management practices, and possibly conservation efforts to restore vegetation health (Arnell et al., 2019). This positive trend continued in October 2023, with ET values between 38 and 69 mm (Figure 8-3f). These recent gains highlight the effectiveness of adaptive management strategies and favourable climatic conditions in enhancing vegetation health and water availability (Arnell et al., 2019; Keenan & Riley, 2018). Spatial patterns also show that high ET areas were more localised in the early years but became more widespread in October 2020 and 2023, indicating overall improvement. These fluctuations point to periods of water stress and recovery, with recent years showing significant gains likely due to better water management, conservation efforts, or favourable climatic conditions. This observation is supported by (Arnell et al., 2019), who emphasised the role of effective water management in mitigating the impacts of climate change on water resources.

The use of MODIS sensor data is essential for effective monitoring and safeguarding of the reserve's ecosystem, as it provides consistent, long-term data on vegetation health and water availability, particularly valuable during seasonal transitions (LP DAAC, 2024; L. Lu et al., 2015; Mu et al., 2011). However, possible limitations of MODIS sensor data include its relatively coarse spatial resolution, which may not capture fine-scale ecological changes, and its dependency on clear skies, which can be problematic in regions with frequent cloud cover (Mu et al., 2011). Despite these limitations, MODIS remains a valuable tool for large-scale environmental monitoring and management (LP DAAC, 2024; Mu et al., 2007a, 2011).

The results of this study have significant implications for biodiversity in the Cradle Nature Reserve. Fluctuations in water availability and vegetation health directly impact the habitat quality of various species. Periods of low ET and reduced vegetation health may lead to habitat degradation, reduced food resources, and increased stress on wildlife populations (Pringle, 2017). Conversely, improvements in ET and vegetation health in recent years suggest enhanced habitat conditions, which can support a more diverse and stable ecosystem, promoting biodiversity conservation in the reserve (Pringle, 2017). These findings align with the observations by (Ha et al., 2024), who highlighted the intricate connections between climate and ecosystem well-being, and Nhamo et al. (2016), who discussed the impacts of climate variability on vegetation stress and land cover changes. The fluctuations in ET values in the Cradle Nature Reserve from October 2000 to October 2023 reflect the complex interplay between climatic conditions, vegetation health, and water management practices. Continuous monitoring and adaptive management are crucial to sustaining the ecological health and biodiversity of the reserve in the face of climate change (Ha et al., 2024).

8.4.2 Interpreting the Relationship Between Evapotranspiration and Elevation in the Cradle Nature Reserve

The linear regression analysis between ET and the DEM in the Cradle Nature Reserve from 2000 to 2023 reveals a significant inverse relationship, where higher elevations generally experience lower ET rates. This relationship is influenced by biophysical and climatic factors (Y. J. Ma et al., 2019), with the intercept values fluctuating from 24.995 in 2005 to 93.6 in 2020, and slope values remaining mostly negative, except in 2005 ($b = 0.0041$). The correlation coefficient (R) ranges from -0.472 in 2020 to 0.0872 in 2005, indicating a generally weak inverse relationship, except in 2005 where a weak positive correlation is observed. These trends are supported by similar studies that demonstrate the sensitivity of ET to elevation and seasonal water availability (Biederman et al., 2018; Mu et al., 2007b; S. Zhou et al., 2018). The mean ET values increased from 47.115 in 2000 to 57.316 in 2020, reflecting an overall rise in ET over time, while the standard deviation of ET values showed notable variability, with significant increases in 2020 and 2023. The strong significance of the regression model in 2020, with an F-statistic of 27,445.55, suggests that specific climatic conditions or land management practices may have amplified the influence of elevation on ET that year, aligning with findings by Li et al. (2024) and other researchers who emphasize the impact of climatic conditions on ET rates. These results underscore the need for adaptive management practices that consider topographical and climatic variability to sustain ecosystem health and resilience (Biederman et al., 2018; H. Li et al., 2024; Mu et al., 2007b; S. Zhou et al., 2018).

8.4.3 Impact of Landsat Sensor Improvements on Land Cover Classification Accuracy in the Cradle Nature Reserve October (2000-2023)

The land cover classification findings of the Cradle Nature Reserve, characterised by karst terrain, demonstrate the increasing precision and dependability of land cover classification from 2000 to 2023, indicating improvements in the quality of Landsat data. The datasets used consist of LANDSAT/LT05/C02/T1_L2 for the years 2000, 2005, and 2010; LANDSAT/LC08/C02/T1_L2 for 2015 and 2020; and LANDSAT/LC09/C02/T1_TOA for 2023. The previous Landsat 5 datasets provide crucial historical surface reflectance data, but they had spectral and radiometric resolution constraints (USGS Earth Explorer, 2024). The introduction of Landsat 8 and 9 brought about significant improvements, including enhanced radiometric resolution, increased signal-to-noise ratio, and improved calibration (Manandhar et al., 2009; Phiri & Morgenroth, 2017). These advances have resulted in more precise and dependable classifications. Progress is seen in the rising levels of accuracy and Kappa index values, especially when the more sophisticated Landsat 8 and 9 datasets were used.

The enhancements to the Landsat images were essential for accurately depicting the intricate topography and varied land cover types of the karst area in the Cradle Nature Reserve. The categorisation accuracy metrics demonstrate this, with notably high Producer's and User's accuracy for classifications such as Bare-ground/Rock Outcrop, especially in the latter years. The presence of diverse and inconsistent data in the testing phase, particularly in earlier years, highlights the difficulties of categorising a landscape with varying characteristics using outdated statistics. Nevertheless, the notable improvements in precision and dependability in

recent times illustrate the influence of upgraded spatial, spectral, and radiometric features of newer Landsat sensors, allowing more accurate monitoring and management of this environmentally delicate area (Manandhar et al., 2009; Phiri & Morgenroth, 2017).

8.4.4 Analysis of Spatial Variation and Assessment of the Effects of Changes in Land Cover

The analysis of ET data for different land cover types in the Cradle Nature Reserve, as presented in Table 8-4 and Figure 8-5 for October from 2000 to 2023, reveals distinct trends and fluctuations across the years, indicating significant ecological changes during the transition from the dry to the wet season (Shoko et al., 2015). In 2000, the ET values were relatively high across all land cover types, with indigenous forest at 45.59 mm, open bush at 44.79 mm, natural grass at 47.75 mm, and bare ground/rock outcrop at 48.44 mm. This period of high ET values is indicative of healthy vegetation and sufficient water availability, aligning with studies that show similar trends in healthy ecosystems (Gerten et al., 2013; Piao et al., 2007).

However, a significant decline was observed in 2005, where the ET values dropped to 29.78 mm for indigenous forest, 31.49 mm for open bush, 31.21 mm for natural grass, and 30.93 mm for bare ground/rock outcrop. This downward trend continued in 2010 and 2015, with only slight variations, indicating a period of relatively low ET values and potentially poor vegetation health and water availability. In 2010, ET values were 32.60 mm for indigenous forest, 32.42 mm for open bush, 31.89 mm for natural grass, and 31.69 mm for bare ground/rock outcrop. By 2015, the ET values were 32.90 mm for indigenous forest, 32.21 mm for open bush, 31.87 mm for natural grass, and 32.20 mm for bare ground/rock outcrop, indicating stability but insignificant improvement. These trends are consistent with findings by (Vicente-Serrano et al. 2010), who reported that adverse climatic conditions and increased vegetation stress due to prolonged dry periods lead to reduced ET rates.

A marked increase in ET values occurs in 2020, with indigenous forest at 59.89 mm, open bush at 58.42 mm, natural grass at 56.86 mm, and bare ground/rock outcrop at 56.95 mm, suggesting substantial recovery in vegetation health and water availability. This improvement is slightly reduced by 2023, with ET values at 52.83 mm for indigenous forest, 51.81 mm for open bush, 50.29 mm for natural grass, and 50.31 mm for bare ground/rock outcrop, indicating sustained but slightly lower ET compared to 2020. The significant recovery in 2020 can be attributed to better water management practices and favourable climatic conditions, as supported by studies from Anderegg et al. (2020) and Bastos et al. (2018), which emphasizes the importance of adaptive management and favourable weather patterns in enhancing ecosystem resilience. The trends illustrated in Figure 8-5 align with the Table 8-4 data, showing the highest ET values in 2000 and 2020 and the lowest in 2005, with gradual increases from 2010 to 2023. These fluctuations reflect periods of water stress and recovery, with recent years showing significant improvements likely due to better water management practices and favourable climatic conditions (Niu et al., 2021; Pringle, 2017). The improved ET values in recent years suggest enhanced habitat conditions, crucial for supporting biodiversity and maintaining the ecological balance in the Cradle Nature Reserve. This observation is supported by Keenan and Riley (2018),

who highlighted the positive impact of recent warming and favourable climatic conditions on vegetation health.

The ecological changes observed through this analysis indicate that the reserve has undergone ecological stress and resilience phases, with recent improvements potentially leading to greater biodiversity and healthier ecosystems. These changes underscore the importance of continuous monitoring and adaptive management to sustain the ecological health of the reserve. These results for October highlight the critical transition period from the dry to the wet season, emphasising the need to understand and manage seasonal impacts on the ecosystem. This is corroborated by Ebrahimi Gatgash and Sadeghi (2024) and Reyer et al. (2015), who discusses adaptive management's role in maintaining ecosystem health and resilience to climate change impacts.

8.4.5 Analysis of changes in land cover and their impact on the health of ecosystems

The study of land cover changes between 2000 and 2023 reveals considerable variations in the extent occupied by several land cover categories, indicating significant ecological transformations. Indigenous forests significantly declined from 13.1 hectares (Ha) in 2000 to 0.7 ha in 2010, indicating a significant forest loss due to deforestation. Despite a partial recovery to 3.7 hectares in 2023, the forest area remains substantially below its original size, indicating persistent conservation difficulties (Mackey et al., 2024; S. K. Roy et al., 2024; Sisay et al., 2024). The open bush areas showed fluctuating patterns, reaching a maximum of 22.3 hectares in 2020, perhaps due to land management techniques such as grazing intensity and bush clearance changes.

The area of natural grasslands had significant growth from 42.6 hectares in 2000 to 74.1 hectares in 2010 but then decreased to 54.5 hectares in 2023. Climate variables, grazing pressures, and fire regimes drive the oscillations in grassland dynamics. The early decrease in bare ground and rock outcrop areas eventually stabilised at around 18 hectares in 2023. The land cover changes have important consequences for soil erosion, water runoff patterns, and habitat quality in the reserve. This highlights the need to use adaptive management measures to preserve the ecological integrity of the reserve (Gilman & Wu, 2023; Saha et al., 2024)

8.4.6 Addressing Uncertainties in Data and Model Predictions

The findings presented in this study offer valuable insights, but they are not without uncertainties that could influence the interpretation of results. A critical evaluation of these uncertainties is essential to enhance the robustness of the conclusions and guide future research directions.

1. **Sensor Resolution Limitations:** The MODIS sensor data utilized, while providing broad spatial and temporal coverage, comes with a coarse resolution of 500 meters. This level of resolution may result in the misclassification of smaller land cover changes, especially in heterogeneous landscapes such as the Cradle Nature Reserve. Features that are below the sensor's resolution threshold may be under- or over-represented in the evapotranspiration (ET) estimates. Integrating higher-resolution

data, such as that from Sentinel-2 (10–20 meters), in future research could mitigate these limitations and offer more precise monitoring of land cover and ET changes (LP DAAC, 2024; L. Lu et al., 2015).

2. **Impact of Atmospheric Conditions:** Cloud cover and atmospheric interference pose significant challenges in remote sensing data acquisition. Although the MOD16A2GF product employs gap-filling techniques to address cloud-related data gaps, some residual uncertainty likely remains, especially during extreme weather conditions. This is particularly important during seasonal transitions when abrupt changes in weather can affect ET measurements. Quantifying the specific impacts of these atmospheric factors would enhance the accuracy of the ET data (Google Earth Engine Team, 2024c; Jamali et al., 2011; LP DAAC, 2024).
3. **Classification Errors in Machine Learning:** The use of the XGBRFCClassifier, while effective, may still introduce classification errors, particularly in land cover types with similar spectral characteristics (e.g., open grasslands and natural grass). The classifier's performance also depends heavily on the quality and coverage of the training data used. Earlier datasets with fewer ground-truth points or misrepresentative samples may result in lower classification accuracy. Employing ensemble learning techniques or incorporating more extensive field validation data could improve the model's robustness and classification accuracy (Gündüz & Orman, 2024; Mehmood et al., 2022).
4. **Temporal Resolution Constraints:** The MOD16A2GF dataset provides ET estimates at an eight-day temporal resolution. While this frequency is sufficient for capturing broad seasonal patterns, it may overlook short-term hydrological events such as flash floods or rapid dry spells that can significantly affect ET rates. Using data from higher temporal resolution sources or combining remote sensing data with ground-based sensors could help capture these short-term variations more effectively (Google Earth Engine Team, 2024c).
5. **Sensitivity to Climate Variability:** The ET trends observed over the study period are influenced by long-term climatic changes, including fluctuations in temperature and precipitation. However, the model may not fully account for extreme events such as droughts or sudden temperature spikes, which can cause rapid changes in ET. Incorporating dynamic climate models and sensitivity analyses could improve the model's ability to predict ET under extreme climate scenarios, thus providing more reliable forecasts for future ecosystem management (Hobeichi et al., 2021; S. Pan et al., 2020).

Addressing these uncertainties is crucial for contextualizing the results of this study. By refining the data acquisition and model methodologies, future research can produce more accurate and reliable insights into evapotranspiration trends and land cover changes in the Cradle Nature Reserve.

8.5 Conclusion

The analysis of evapotranspiration (ET) fluctuations in the Cradle Nature Reserve from 2000 to 2023 using MODIS data reveals significant variations in water availability and vegetation health during the transition from the dry to the wet season. These fluctuations are influenced by climate variability and changing land management practices. Initially, ET values indicated healthy vegetation and good water availability, but a significant decline by 2005 suggested increased vegetation stress and adverse climatic conditions. Although there was some stability

in the subsequent years, the ET values remained suboptimal until a marked improvement in 2020, which continued into 2023, highlighting the positive effects of adaptive management and favourable climatic conditions. The relationship between ET and elevation in the Cradle Nature Reserve, analysed through linear regression, shows a significant inverse relationship, where higher elevations generally experience lower ET rates. This dynamic is shaped by biophysical and climatic factors, with notable variability observed over the years. Specific climatic conditions or land management practices amplified the influence of elevation on ET in certain years, particularly in 2020, emphasising the need for adaptive management practices that account for topographical and climatic variability to maintain ecosystem health and resilience.

Improvements in Landsat sensor technology have significantly enhanced the accuracy of land cover classification in the Cradle Nature Reserve from 2000 to 2023. The enhanced radiometric resolution and improved calibration of Landsat 8 and 9 have led to more precise and reliable classifications, essential for monitoring the karst area's intricate topography and varied land cover types. The study of land cover changes during this period revealed substantial ecological transformations that underscore the importance of adaptive management measures to preserve the ecological integrity of the reserve, as continuous monitoring and effective management strategies are crucial to sustaining its health and biodiversity amidst climate change impacts.

Chapter 9 SYNTHESIS

This chapter consolidates the extensive knowledge acquired throughout the study and provides a cohesive summary of the findings. It highlights the significant role of geospatial technology and remote sensing in environmental monitoring and archaeological research, emphasising their impact on understanding and managing ecological and archaeological landscapes. The synthesis links the findings to the objectives outlined in Chapter 1, showing how integrating advanced geospatial and machine-learning techniques addresses critical research gaps. By exploring the interconnections between land cover transformation, landscape fragmentation, vegetation dynamics, above-ground biomass, the influence of climate variability and topographic on land cover vegetation, and the impacts of land cover change on evapotranspiration, the synthesis underscores this study's essential contributions to geospatial technology and environmental management. Additionally, the chapter discusses the limitations encountered, such as data constraints and technological challenges. It provides recommendations for future research to enhance further the application of these advanced technologies in preserving sensitive ecological and archaeological sites

Objective 1

To investigate the key concepts and themes shaping the use of geospatial technologies in archaeology and to identify potential research gaps and underexplored areas in this field, both globally and in South Africa.

Geographic Information Systems (GIS) emerged as critical tools for capturing, storing, analysing, and visualising geospatial data in archaeology, with their growth driven by open-source software and machine learning algorithms. Specialised spatial analysis functions, spatiotemporal analysis, spatial modelling tools, and spatial databases were identified as less explored, presenting significant research gaps. Remote sensing technologies, including lidar and satellite imagery, were established tools, while aerial photography, optical radar, and UAVs were underutilised, indicating areas for further research. The availability of open data from Earth observation missions and cloud computing platforms is expected to drive future growth in remote sensing applications. In South Africa, GIS and spatial analysis were the primary geospatial tools used in archaeological and cultural heritage investigations, with significant potential for further research and application. Emerging technologies such as virtual reality and augmented reality were highlighted for their role in enabling immersive visualisation and exploration of archaeological sites. Associated tools like 3D modelling, 3D computer graphics, 3D reconstruction, photogrammetry, and artificial intelligence were identified as underexplored, presenting additional research opportunities. The study effectively delineated the current landscape of geospatial technologies in archaeology, identifying notable research gaps and underexplored areas and suggesting these as potential directions for future investigation.

Objective 2

To investigate the key applications of remote sensing in monitoring vegetation, detecting land cover changes, assessing degradation, evaluating topography's impact, and estimating biomass and evapotranspiration.

The study revealed that from 2002 to 2024, there was a significant rise in publications, particularly from 2018 onwards, highlighting the growing importance of integrating remote sensing technologies with advanced analytical methods. Advancements in machine learning algorithms like Random Forests, Support Vector Machines, neural networks, and XGBRFClassifiers have significantly enhanced the ability to analyse vegetation dynamics. Key journals and conferences, notably "Remote Sensing," have played crucial roles in disseminating research, with a notable increase in articles. The study identified vegetation mapping, remote sensing, and machine learning as central themes interconnected with topics such as land use, land cover, climate change, evapotranspiration, aboveground biomass, and accuracy assessment. Despite their importance, evapotranspiration and above-ground biomass remain underexplored, indicating significant research gaps. The study also highlighted the multidisciplinary nature of remote sensing research involving fields like earth and planetary sciences, agricultural and biological sciences, environmental science, and computer science. This research underscores the critical role of advanced remote sensing and machine learning techniques in addressing global environmental challenges, emphasising the need for continuous innovation and research to develop effective environmental management strategies

Objective 3

To investigate which classifier, Naïve Bayes or Extreme Gradient Boosting Random Forest, demonstrates higher accuracy for LULC classification in the Cradle Nature Reserve in 2020 and to determine the land use and land cover changes from 1990 to 2020.

The study employed the XGBRFClassifier, which outperformed Naïve Bayes regarding overall accuracies, Kappa index, and F-score. The detailed classification results revealed significant changes in land use, such as the conversion of 29 hectares of indigenous forests to other landscape classes but mostly to open bush and 359 hectares from the indigenous forest and natural grassland to open bush. Additionally, 780 hectares of natural grassland were lost to other landscape classes, mainly bare ground/rock outcrop, which increased by 449 hectares. The study also meticulously documented LULC changes from 1990 to 2020, highlighting the transformation of natural grasslands into other landscape classes due to factors such as climate change, overgrazing, and the introduction of wild game species. The findings underscored the impacts of landscape fragmentation and invasive species on the ecosystem, providing essential insights for future research and conservation efforts. The study recommended addressing land degradation induced by invasive plants and implementing effective management practices to preserve the ecological and cultural value of the Cradle Nature Reserve.

Objective 4

To investigate the spatio-temporal trends of EVI and environmental factors and examine their statistical associations with climatic factors to inform sustainable grassland management using remote sensing, multilinear correlation, and PCA in the Cradle Nature Reserve.

The study utilised MODIS data to analyse ET fluctuations from 2000 to 2023, revealing significant variations in water availability and vegetation health due to climate variability and land management practices. Notable improvements in ET were observed in 2020 and 2023, suggesting effective water management and favourable climatic conditions, highlighting the critical role of continuous monitoring and adaptive management in maintaining the reserve's ecological health and biodiversity. Linear regression analysis of the relationship between ET and elevation revealed a generally inverse relationship influenced by biophysical and climatic factors, underscoring the need for adaptive management practices that consider topographical and climatic variability. The study also demonstrated the impact of Landsat sensor improvements on land cover classification accuracy, which is essential for precise environmental monitoring. Analysis of land cover changes between 2000 and 2023 showed significant ecological transformations, emphasising the importance of adaptive management to preserve the reserve's ecological integrity. PCA was employed to examine the statistical associations between EVI, ET, and climatic factors. PCA identified key variables influencing vegetation health and helped understand the combined effects of multiple environmental factors. The results indicate that improved habitat conditions in recent years have supported biodiversity, crucial for sustainable grassland management in the face of climate change.

Objective 5

To investigate the factors influencing above-ground biomass in the Cradle Nature Reserve, using RGB drone photos, nDSM vegetation heights, and field-measured chlorophyll analysed with PCA and stepwise regression.

The study demonstrated that the use of RGB drone imagery effectively be used to estimate AGB by capturing detailed vegetation indices and heights. The stepwise regression model incorporating nDSM, GBVI, GRBI, and RBVI explained 65.7% of the variation in AGB for non-riparian forests, highlighting the significant roles of plant height and chlorophyll content. These results align with prior research linking nDSM and chlorophyll with biomass, underscoring the drones' utility in remote sensing applications for forest management and ecological research. In riparian forests, the analysis revealed that the initial model explained 42% of the variation in AGB despite significant multicollinearity issues with variables like nDSM and chlorophyll. Adjustments to the model improved its stability, emphasising the critical roles of vegetation indices in riparian zones. Comparing riparian and non-riparian models highlighted the different environmental conditions influencing AGB, with vegetation height (nDSM) being a stronger predictor in non-riparian areas. The study also identified limitations in RGB drone imagery, such as the lack of near-infrared data and multicollinearity challenges, suggesting future improvements could involve multispectral or hyperspectral

sensors. The research provided valuable insights into using advanced remote sensing and statistical methods to enhance biomass estimation and sustainable grassland management.

Objective 6

To investigate how topographic factors, TWI, EVI, TRI, TPI, and percentage slope gradient collectively affect vegetation growth and changes, moisture distribution, terrain roughness, and habitat suitability in the Cradle Nature Reserve's karst environment

The study successfully investigated the impact of topographic factors such as TWI, EVI, TRI, TPI, and slope gradient on vegetation dynamics in the Cradle Nature Reserve's karst environment. Key findings showed strong correlations between these indices and vegetation health, highlighting that rugged terrain and steep slopes negatively affect plant growth and moisture distribution. Areas with higher TWI values indicated better vegetation health due to higher moisture availability. These insights emphasise the intricate relationship between topography and vegetation, providing essential data for effective land management and conservation strategies in karst landscapes.

Objective 7

To investigate ET's yearly patterns and spatial distribution and to explore how ET correlates with DEM data and land cover changes in the Cradle Nature Reserve.

The study revealed significant yearly fluctuations in ET from 2000 to 2023, highlighting the impacts of climate variability and land management practices on water availability and vegetation health. The analysis identified periods of decline in ET values, notably in 2005, 2010, and 2015, with subsequent improvements in 2020 and 2023, suggesting effective water management and favourable climatic conditions in recent years. These findings underscore the importance of continuous monitoring and adaptive management to sustain the ecological health and biodiversity of the reserve. The relationship between ET and elevation was explored through linear regression, revealing a generally inverse correlation influenced by biophysical and climatic factors. Higher elevations typically experienced lower ET rates, indicating the need for management practices that consider topographical variability. Additionally, the study highlighted improvements in Landsat sensor data, enhancing the accuracy of land cover classification, crucial for monitoring ecological changes. The analysis of land cover changes between 2000 and 2023 demonstrated significant ecological transformations, including deforestation and fluctuations in grassland areas, emphasising the need for adaptive management to maintain the reserve's environmental integrity. Overall, the study effectively utilised advanced remote sensing techniques and statistical methods to achieve its objective, providing valuable insights for sustainable management of the Cradle Nature Reserve.

Reflections

Chapter 1 investigated key concepts and themes in geospatial technologies in archaeology, emphasising the critical role of GIS in capturing, storing, analysing, and visualising geospatial data. It noted that GIS growth is driven by open-source software and machine learning while identifying underexplored areas like spatial analysis functions, spatiotemporal analysis, spatial

modelling tools, and spatial databases. The need for further research in aerial photography, optical radar, UAVs, and emerging technologies like VR, AR, 3D modelling, photogrammetry, and AI was highlighted. Building on the exploration of geospatial technologies, Chapter 2 focused on remote sensing applications in vegetation monitoring and land cover change detection. It revealed a significant rise in publications from 2002 to 2024, especially after 2018, due to advancements in machine learning algorithms enhancing vegetation dynamics analysis. Central themes included vegetation mapping, remote sensing, and machine learning, with research gaps in evapotranspiration and above-ground biomass. The multidisciplinary nature of remote sensing research was emphasised, highlighting the need for continuous innovation in environmental management.

Extending the discussion on vegetation monitoring, Chapter 3 evaluated classifier accuracy for LULC classification in the Cradle Nature Reserve, demonstrating that the XGBRFCClassifier outperformed Naïve Bayes in overall accuracies, Kappa index, and F-score. Significant land use changes were documented, such as converting indigenous forests and natural grassland to open bush. The impacts of climate change, overgrazing, and the introduction of wild game species were highlighted, with recommendations for addressing land degradation from invasive plants and implementing effective management practices. Continuing the analysis of environmental factors, Chapter 4 examined spatiotemporal trends of EVI and environmental factors, analysing ET fluctuations from 2000 to 2023 using MODIS data. Significant variations due to climate variability and land management practices were revealed, with noted improvements in 2020 and 2023, underscoring the need for continuous monitoring. An inverse relationship between ET and elevation was observed, and the importance of Landsat sensor improvements for accurate environmental monitoring was emphasized. Key variables influencing vegetation health were identified through PCA.

Chapter 5 shifted the focus to biomass estimation, exploring factors influencing AGB using remote sensing and statistical methods. It demonstrated the effectiveness of RGB drone imagery in estimating AGB. Stepwise regression models explained significant AGB variation, especially for non-riparian forests. Limitations such as the lack of near-infrared data and multicollinearity challenges were highlighted, suggesting future improvements with multispectral sensors. Insights were provided to enhance biomass estimation and sustainable grassland management using advanced remote sensing and statistical methods. Addressing topographic influences, Chapter 6 investigated the impact of factors like TWI, EVI, TRI, TPI, and slope gradient on vegetation health in the Cradle Nature Reserve's karst environment. Strong correlations were found between these factors and vegetation health, with rugged terrain and steep slopes negatively affecting plant growth. Higher TWI values indicated better vegetation health due to higher moisture availability. These findings are crucial for effective land management and conservation strategies in karst landscapes.

Finally, Chapter 8 examined ET's yearly patterns and spatial distribution, revealing significant yearly fluctuations from 2000 to 2023 linked to climate variability and land management practices. An inverse correlation between ET and elevation indicated the need for management practices that consider topographical variability. Improvements in Landsat sensor data and

significant ecological transformations were highlighted, stressing the need for adaptive management to maintain environmental integrity.

Conclusion

The study highlighted the critical role of GIS in archaeology for data management, identifying significant research gaps in spatial analysis and underutilised remote sensing technologies. It revealed a notable rise in remote sensing publications from 2002 to 2024, driven by advancements in machine learning, with key themes in vegetation mapping. Notable research gaps were identified in evapotranspiration and biomass research. The XGBRFClassifier outperformed Naïve Bayes in LULC classification for the Cradle Nature Reserve in documenting significant land use changes and recommending effective management practices. Analysis of ET fluctuations from 2000 to 2023 emphasised the need for continuous monitoring and adaptive management. RGB drone imagery proved effective in estimating above-ground biomass, with suggestions for future improvements using multispectral sensors. Topographic factors were found to be strongly correlated with vegetation health, which is crucial for land management in karst environments. Overall, the study provided comprehensive insights into geospatial technologies and remote sensing, identifying research gaps and emphasising the need for continuous innovation and adaptive management in environmental management.

Limitations of the study

The absence of near-infrared data, essential for precise evaluations of plant health, limits the use of RGB drone imaging and vegetation indices for biomass estimation. The presence of high reflectance saturation in areas with dense vegetation makes the analysis more difficult and may result in erroneous biomass calculations. The presence of multicollinearity in the nDSM data may compromise the accuracy of biomass calculations, particularly in intricate plant formations. The study's emphasis on a particular geographic region restricts the applicability of its conclusions. When you use MODIS and Landsat satellite data, there may be some errors because of cloud cover and sensor limitations. These errors can affect how accurately you classify land cover and estimate evapotranspiration. The absence of ground truthing data in some of the studies also constrains the verification of remote sensing outcomes, undermining the precision of land cover and vegetation health evaluations. It's important to note that the Scopus database, while a valuable resource, may have inadvertently overlooked pertinent research, potentially limiting the scope of the analysis. Relying solely on bibliometric data also has its drawbacks, as it can hinder the capture of qualitative insights and practical applications, leading to a more general perspective that may overlook specific nuances. While the efficacy of the XGBRFClassifier model was significant, it depended heavily on intricate and time-consuming hyperparameter optimisation, necessitating substantial processing resources. This reliance on resources may limit the practicality of the model for some researchers. In order to improve future studies, it is advisable to include a wider range of datasets, increase the management of keywords, combine qualitative analysis, strengthen efforts to verify accuracy, investigate other machine learning models, and broaden the geographical coverage. Using multispectral or hyperspectral sensors may improve biomass estimates' accuracy, reliability, and land cover classification.

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Appendices

Appendix A: Supplementary Tables

Table A 1: Multicollinearity and Principal Component Analysis Plot 1

Principal Component Analysis:

(a) Eigenvalues:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Eigenvalue	6.13	1.55	1.00	0.24	0.07	0.01	0.00	0.00	0.00
Variability (%)	68.07	17.19	11.10	2.62	0.82	0.15	0.04	0.02	0.00
Cumulative %	68.07	85.26	96.35	98.97	99.79	99.94	99.98	100.00	100.00

(b) Eigenvectors:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.34	-0.12	0.45	-0.45	-0.08	-0.67	-0.06	-0.03	0.00
Chloro	0.34	-0.16	0.45	-0.35	0.10	0.72	0.07	0.05	0.00
AGB	0.30	-0.28	0.41	0.81	-0.08	-0.05	0.01	-0.01	0.00
BGVI	-0.37	-0.31	0.15	-0.02	0.24	-0.09	0.26	0.51	0.60
ExG	0.38	-0.08	-0.32	0.00	-0.16	0.03	-0.52	0.67	0.00
GBVI	0.36	0.29	-0.11	0.10	0.86	-0.11	0.05	0.02	0.00
GRBI	0.38	-0.06	-0.34	-0.02	-0.23	-0.05	0.79	0.18	-0.13
NGRDI	0.27	-0.51	-0.41	-0.06	0.04	0.03	-0.14	-0.51	0.47
RBVI	0.23	0.66	0.09	0.06	-0.31	0.05	0.02	-0.06	0.63

(c) Correlations between variables and factors:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.85	-0.15	0.45	-0.22	-0.02	-0.08	0.00	0.00	0.00
Chloro	0.85	-0.20	0.45	-0.17	0.03	0.08	0.00	0.00	0.00
AGB	0.75	-0.34	0.41	0.39	-0.02	-0.01	0.00	0.00	0.00
BGVI	-0.91	-0.39	0.15	-0.01	0.07	-0.01	0.02	0.02	0.00
ExG	0.94	-0.10	-0.32	0.00	-0.04	0.00	-0.03	0.03	0.00
GBVI	0.89	0.37	-0.11	0.05	0.23	-0.01	0.00	0.00	0.00
GRBI	0.93	-0.08	-0.34	-0.01	-0.06	-0.01	0.05	0.01	0.00
NGRDI	0.66	-0.63	-0.41	-0.03	0.01	0.00	-0.01	-0.02	0.00
RBVI	0.56	0.82	0.09	0.03	-0.08	0.01	0.00	0.00	0.00

(d) Contribution of the variables (%):

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	11.81	1.51	19.94	20.30	0.60	45.43	0.31	0.11	0.00
Chloro	11.84	2.47	19.99	12.54	0.92	51.51	0.49	0.24	0.00
AGB	9.10	7.62	17.07	65.24	0.67	0.28	0.01	0.01	0.00
BGVI	13.42	9.76	2.20	0.06	5.79	0.79	6.50	25.55	35.94
ExG	14.40	0.65	10.44	0.00	2.49	0.07	27.38	44.56	0.00
GBVI	13.02	8.62	1.18	1.02	74.61	1.28	0.22	0.06	0.00

GRBI	14.24	0.41	11.51	0.05	5.33	0.29	63.18	3.36	1.63
NGRDI	7.08	25.67	16.80	0.39	0.18	0.08	1.88	25.75	22.18
RBVI	5.12	43.28	0.88	0.40	9.41	0.27	0.03	0.36	40.25

(e) Squared cosines of the variables:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.72	0.02	0.20	0.05	0.00	0.01	0.00	0.00	0.00
Chloro	0.73	0.04	0.20	0.03	0.00	0.01	0.00	0.00	0.00
AGB	0.56	0.12	0.17	0.15	0.00	0.00	0.00	0.00	0.00
BGVI	0.82	0.15	0.02	0.00	0.00	0.00	0.00	0.00	0.00
ExG	0.88	0.01	0.10	0.00	0.00	0.00	0.00	0.00	0.00
GBVI	0.80	0.13	0.01	0.00	0.05	0.00	0.00	0.00	0.00
GRBI	0.87	0.01	0.11	0.00	0.00	0.00	0.00	0.00	0.00
NGRDI	0.43	0.40	0.17	0.00	0.00	0.00	0.00	0.00	0.00
RBVI	0.31	0.67	0.01	0.00	0.01	0.00	0.00	0.00	0.00

Table A 2: Multicollinearity and Principal Component Analysis Plot 2

Principal Component Analysis:

(a) Eigenvalues:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
Eigenvalue	3.53	1.85	0.97	0.88	0.55	0.48	0.44	0.28	0.03
Variability (%)	39.27	20.55	10.80	9.73	6.08	5.32	4.86	3.11	0.28
Cumulative %	39.27	59.82	70.62	80.35	86.43	91.75	96.61	99.72	100.00

(b) Eigenvectors:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.39	-0.39	-0.39	-0.06	-0.02	-0.04	-0.10	-0.07	0.72
Chloro	0.37	-0.42	-0.42	-0.09	0.00	-0.01	-0.09	-0.12	-0.69
AGB	0.38	-0.06	0.30	-0.18	0.76	0.06	0.19	0.34	-0.01
BGVI	-0.35	-0.40	-0.21	0.15	-0.14	-0.01	0.36	0.71	-0.01
ExG	0.38	0.13	0.08	0.37	-0.25	0.77	-0.01	0.17	-0.02
GBVI	0.38	0.31	0.06	-0.04	-0.30	-0.45	-0.42	0.53	-0.05
GRBI	0.07	-0.40	0.55	-0.57	-0.44	0.11	0.07	-0.02	0.01
NGRDI	0.27	-0.24	0.38	0.62	-0.11	-0.42	0.32	-0.21	-0.02
RBVI	0.27	0.42	-0.27	-0.29	-0.22	-0.09	0.73	-0.06	0.00

(c) Correlations between variables and factors:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.74	-0.53	-0.39	-0.05	-0.01	-0.02	-0.07	-0.04	0.11
Chloro	0.69	-0.57	-0.42	-0.09	0.00	-0.01	-0.06	-0.06	-0.11
AGB	0.72	-0.08	0.30	-0.17	0.56	0.04	0.12	0.18	0.00
BGVI	-0.66	-0.54	-0.21	0.14	-0.10	-0.01	0.24	0.38	0.00
ExG	0.71	0.18	0.08	0.35	-0.19	0.54	-0.01	0.09	0.00
GBVI	0.72	0.42	0.05	-0.04	-0.22	-0.31	-0.28	0.28	-0.01
GRBI	0.13	-0.54	0.55	-0.53	-0.32	0.08	0.04	-0.01	0.00
NGRDI	0.51	-0.33	0.37	0.58	-0.08	-0.29	0.21	-0.11	0.00
RBVI	0.51	0.58	-0.26	-0.27	-0.16	-0.06	0.48	-0.03	0.00

(d) Contribution of the variables (%):

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	15.29	15.46	15.53	0.33	0.03	0.13	1.02	0.52	51.69
Chloro	13.42	17.57	17.83	0.87	0.00	0.01	0.84	1.46	48.01
AGB	14.50	0.35	9.07	3.37	57.48	0.31	3.55	11.37	0.00
BGVI	12.42	15.69	4.41	2.31	1.89	0.02	12.85	50.39	0.01
ExG	14.46	1.69	0.62	13.85	6.46	59.84	0.01	3.05	0.02
GBVI	14.58	9.63	0.31	0.15	8.93	20.46	17.42	28.30	0.21
GRBI	0.46	15.68	30.75	32.15	19.27	1.22	0.43	0.03	0.00
NGRDI	7.47	5.90	14.41	38.75	1.23	17.26	10.40	4.53	0.05
RBVI	7.40	18.04	7.08	8.21	4.70	0.76	53.47	0.34	0.00

(e) Squared cosines of the variables:

	F1	F2	F3	F4	F5	F6	F7	F8	F9
nDSM	0.54	0.29	0.15	0.00	0.00	0.00	0.00	0.00	0.01
Chloro	0.47	0.33	0.17	0.01	0.00	0.00	0.00	0.00	0.01
AGB	0.51	0.01	0.09	0.03	0.31	0.00	0.02	0.03	0.00
BGVI	0.44	0.29	0.04	0.02	0.01	0.00	0.06	0.14	0.00
ExG	0.51	0.03	0.01	0.12	0.04	0.29	0.00	0.01	0.00
GBVI	0.52	0.18	0.00	0.00	0.05	0.10	0.08	0.08	0.00
GRBI	0.02	0.29	0.30	0.28	0.11	0.01	0.00	0.00	0.00
NGRDI	0.26	0.11	0.14	0.34	0.01	0.08	0.05	0.01	0.00
RBVI	0.26	0.33	0.07	0.07	0.03	0.00	0.23	0.00	0.00

(f) Correlation matrix:

Variables	nDSM	Chloro	AGB	BGVI	ExG	GBVI	GRBI	NGRDI	RBVI
nDSM	1.00	0.97	0.44	-0.16	0.37	0.30	0.20	0.38	0.16
Chloro	0.97	1.00	0.41	-0.11	0.32	0.24	0.21	0.33	0.13
AGB	0.44	0.41	1.00	-0.48	0.39	0.38	0.21	0.35	0.25
BGVI	-0.16	-0.11	-0.48	1.00	-0.49	-0.65	0.06	-0.14	-0.51
ExG	0.37	0.32	0.39	-0.49	1.00	0.48	-0.05	0.39	0.35
GBVI	0.30	0.24	0.38	-0.65	0.48	1.00	-0.05	0.25	0.52
GRBI	0.20	0.21	0.21	0.06	-0.05	-0.05	1.00	0.15	-0.18
NGRDI	0.38	0.33	0.35	-0.14	0.39	0.25	0.15	1.00	-0.05
RBVI	0.16	0.13	0.25	-0.51	0.35	0.52	-0.18	-0.05	1.00

(g) Multicollinearity statistics:

Statistic	nDSM	Chloro	AGB	BGVI	ExG	GBVI	GRBI	NGRDI	RBVI
R ²	0.95	0.95	0.42	0.57	0.41	0.54	0.14	0.31	0.38
Tolerance	0.05	0.05	0.58	0.43	0.59	0.46	0.86	0.69	0.62
VIF	20.66	19.28	1.72	2.32	1.70	2.18	1.16	1.45	1.62