Forest Suitability Mapping and Land Use Change Analysis in eThekwini Municipality: Leveraging Remote Sensing and Machine Learning for Forest Restoration and Rehabilitation Efforts

By

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UNIVERSITY OF KWAZULU-NATAL

INYUVESI YAKWAZULU-NATALI

“Lives of great men all remind us

We can make our lives sublime,

And, departing, leave behind us

Footprints on the sands of time;”

-

Henry Wadsworth Longfellow (A Psalm of Life)

Abstract

Ecosystem services are vital in environmental policy, emphasising the crucial role of forests in providing these services. However, urbanisation, deforestation, forest degradation, and climate change continue to threaten forests globally. Moreover, despite international efforts like deforestation and forest degradation in developing countries (REDD+) and growing recognition of their importance, forests continue to face significant threats from deforestation, degradation, and climate change. While regulatory frameworks and incentives are important, they may fall short without advancements in forest restoration processes. As such, this study aimed to streamline forest restoration and rehabilitation by employing remote sensing and machine learning techniques to enhance natural forest monitoring and regional forest suitability modelling.

Objectives included reviewing and analysing global publications on forest rehabilitation and restoration efforts to investigate trends, explore various practices, and identify opportunities for enhancing the success of these initiatives. This was achieved through the usage of a systematic review methodology. Findings for this objective revealed an increasing research activity in recent years, indicating growing interest in forest rehabilitation and restoration. Geographic analysis highlighted regional disparities, with Asian countries leading in research frequency. Policy recommendations underscored the importance of community participation, efficient fire control, and government support in forest rehabilitation efforts. The second objective reviewed and analysed publications on the utilisation of forest suitability models and remote sensing techniques for identifying areas suitable for forest vegetation, also using a systematic review methodology. The findings also indicate a notable increase in research output. Furthermore, the analysis of reviewed articles revealed a preference for medium to high-resolution remote sensing data, with Landsat being the predominant sensor used for forest suitability assessments. Maximum entropy (MaxEnt) was identified as the most utilised model, followed by the increasingly popular random forests (RF). However, the research revealed a significant geographical disparity, with a heavy concentration of publications in the Americas and Asia.

The third objective explored mapping land use and land cover (LULC) changes within the eThekwini Municipality from 2002 to 2022 using remote sensing data from the three most recent Landsat sensors and machine learning algorithms. It utilised RF, support vector machine

(SVM), and extreme gradient boosting (XGBoost) to conduct LULC classifications. The generated maps revealed a significant decrease in cropland and an increase in impervious surfaces. As such, this research established a framework for continuous LULC mapping and highlighted Landsat 9's potential in LULC classifications. The fourth objective assessed land degradation within the eThekwini Municipality by focusing on land cover change and soil organic carbon (SOC) stock using medium-resolution remote sensing data and machine learning algorithms. Variables for land cover change and SOC stock prediction were extracted and analysed using XGBoost, light gradient boosting (LightGBM), RF, and SVM models. LightGBM outperformed other models, revealing a notable land cover shift, with forests and shrubland being converted to cropland and urban areas within the municipality.

The fifth objective sought to provide a framework for monitoring natural forests at a municipal scale using the last three Landsat Missions, focusing on the eThekwini Municipality, to facilitate forest rehabilitation and restoration. Classifications based on Landsat 7 significantly underestimated the extent of natural forests within the study area, whereas Landsat 8 and Landsat 9 data revealed an increase in natural forests from 2015 to 2023. The final objective aimed to model the suitability of areas for forest species within the eThekwini Municipality using species distribution modelling (SDM)/environmental niche modelling (ENM) methodology. The study modelled current forest suitability (2023) using bioclimatic variables from the WorldClim dataset, and elevation and slope data from the Shuttle Radar Topography Mission (SRTM). Remote sensing data was obtained from Landsat 9 and Sentinel-2A. For future forest suitability (2021–2040), bioclimatic variables from two Global Climate Models (GCMs) under four WorldClim shared socioeconomic pathway (SSP)-based representative concentration pathway (RCP) scenarios were used. The models employed were RF, LightGBM, and artificial neural networks (ANN), with data processing conducted via Google Earth Engine (GEE), QGIS, and Python. Currently, 30% of the municipality's land is deemed suitable, primarily concentrated in the central region. Future projections highlight the mountainous north-western region as most suitable, notably under the SSP370 scenario with a projected suitable area of 63%.

Overall, findings from this study highlight the potential of remote sensing and machine learning in supporting forest restoration and rehabilitation efforts, with significant implications for informing policy and prioritising areas for future interventions. Ultimately, this research provides a comprehensive framework for leveraging modern technological advancements to

streamline forest restoration initiatives, ensuring sustainable management and conservation of forest ecosystems amidst escalating environmental challenges.

Keywords: forest, forest rehabilitation, forest restoration, land degradation, remote sensing, machine learning, land cover, land use

DEDICATION

To my best friend and to all of us who face mental health challenges.

ACKNOWLEDGEMENTS

"God willing." When I wrote the previous sentence sometime in 2022, I never imagined I would be here writing this. For that, I am incredibly grateful, both to **God** for guiding me and to **Mr Mzamo Zondi** for his support.

I would like to express my sincere gratitude to my supervisors, **Prof Romano Lottering**, **Dr Kabir Peerbhay**, and **Prof Onisimo Mutanga**. Their guidance, support, and expertise have been invaluable throughout this project.

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I am deeply grateful to my **family** for their unwavering love and support, especially my **mother** for her constant encouragement and prayers. To my **friends** and **colleagues**, thank you for your companionship.

Please note that this list is in no particular order.

PREFACE

The work described in this thesis was carried out in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, from October 2020 to July 2024, under the supervision of Prof Romano Lottering, Dr Kabir Peerbhay, and Prof Onisimo Mutanga.

The research represented in this document is original work by the author and has not otherwise been submitted in any form for any degree or diploma to any tertiary institution. Where use has been made of the work of others it is duly acknowledged in the text.

......[redacted]........... 17 July 2024

Signature (Student) Date

Mr Mthokozisi Ndumiso Mzuzuwentokozo Buthelezi

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

.........[redacted]...................... 17 July 2024

Signature (Supervisor) Date

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Signature (Co-supervisor) Date

Dr Kabir Peerbhay

...[redacted].......... 17 July 2024

Signature (Co-supervisor) Date

Prof Onisimo Mutanga

DECLARATION I - PLAGIARISM

I, Mthokozisi Ndumiso Mzuzuwentokozo Buthelezi declare that

1. The research reported in this thesis, except where otherwise indicated, is my original work.
2. This thesis has not been submitted for any degree or examination at any other university.
3. This thesis does not contain other persons' data, pictures, graphs or additional information unless specifically acknowledged as being sourced from other persons.
4. This thesis does not contain other persons' writing unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:
    a) Their words have been re-written, but the general information attributed to them has been referenced.
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5. This thesis does not contain text, graphics or tables copied and pasted from the internet, unless specifically acknowledged, and the source is detailed in the paper and References sections.

Signed: ....[redacted]...............

DECLARATION II – PUBLICATIONS AND MANUSCRIPTS

1. Buthelezi, M. N. M., Lottering, R., Peerbhay, K., & Mutanga, O. (2024). Exploring forest rehabilitation and restoration: A brief systematic review. *Trees, Forests and People*. Under Review. TFP-D-24-00396.
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LIST OF ACRONYMS

ACIAR	Australian Centre for International Agricultural Research
ANN	Artificial Neural Networks
ARVI	Atmospherically Resistant Vegetation Index
ASTER	Advanced Spaceborne Thermal Emission and Reflection Radiometer
AUC	Area Under the Receiver Operating Characteristic Curve
CALC	Computer Automated Land-Cover
CatBoost	Categorical Boosting
CBD	Convention on Biological Diversity
CFLRP	Collaborative Forest Landscape Restoration Programme
CIFOR	Center for International Forestry Research
CIG	Chlorophyll Index Green
CNN	Convolutional Neural Networks
DEM	Digital Elevation Model
DMOSS	Durban Metropolitan Open Space System
DNN	Deep Neural Networks
DSM	Digital Soil Mapping
EFB	Exclusive Feature Bundling
ENM	Environmental Niche Modelling
EROS	Earth Resource Observation and Science
ETM+	Enhanced Thematic Mapper Plus
EVI	Enhanced Vegetation Index
EVI-2	Enhanced Vegetation Index-2
FABDEM	Forest and Buildings Removed Digital Elevation Model
FAO	Food and Agriculture Organization
FORIG	Forestry Research Institute of Ghana
GAM	Generalised Additive Model
GBMs	Gradient Boosting Machines
GEE	Google Earth Engine
GIS	Geographic Information System
GLM	Generalised Linear Model
GOFC-GOLD	Global Observation for Forest Cover and Land Dynamics

GOSS	Gradient-based One-Side Sampling
GNDVI	Green Normalised Difference Vegetation Index
GNSPI	Geo-statistical Neighbourhood Similar Pixel Interpolator
GRVI	Green-Red Vegetation Index
HWSD	Harmonized World Soil Database
ITTO	International Tropical Timber Organisation
iSDA	Innovative Solutions for Decision Agriculture
ISRIC	International Soil Reference and Information Centre
JRC	Joint Research Centre
LightGBM	Light Gradient Boosting Machine
LULC	Land Use and Land Cover
MaxEnt	Maximum Entropy
MCC	Mathew Correlation Coefficient
MODIS	Moderate Resolution Imaging Spectroradiometer
MNDWI	Modified Normalised Difference Water Index
MSAVI	Modified Soil Adjusted Vegetation Index
NDBI	Normalised Difference Built-up Index
NDII	Normalised Difference Infrared Index
NDSI	Normalised Difference Snow Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NGOs	Non-Governmental Organisations
NIR	Near-Infrared
NLCD	National Land Cover Database
NRMSE	Normalised Root Mean Square Error
OA	Overall Accuracy
OECF	Overseas Economic Cooperation Fund
OLI	Operational Land Imager
OLI2	Operational Land Imager 2
PLS	Partial Least Squares
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PSO	Particle Swarm Optimisation
RBF	Radial Basis Function

REDD	Reducing Emissions from Deforestation and Forest Degradation
REDD+	Reducing emissions from deforestation and forest degradation in developing countries
RF	Random Forest
ROC	Receiver Operating Characteristic
RMSE	Root Mean Square Error
SANLC	South African National Land Cover
SATREPS	Science and Technology Research Partnership for Sustainable Development
SAVI	Soil Adjusted Vegetation Index
SDGs	Sustainable Development Goals
SDM	Species Distribution Modelling
SLC	Scan Line Corrector
SOC	Soil Organic Carbon
SRTM	Shuttle Radar Topography Mission
SVM	Support Vector Machines
SWIR	Shortwave Infrared
TIRS	Thermal Infrared Sensor
TOA	Top-of-Atmosphere
TRMM	Tropical Rainfall Measuring Mission
UAV	Unmanned Aerial Vehicle
UNCCD	United Nations Convention to Combat Desertification
UNLCCS	United Nations Land Cover Classification System
USA	United States of America
USGS	United States Geological Survey
VNIR	Visible and Near-Infrared
XGBoost	Extreme Gradient Boosting

1. CHAPTER ONE: GENERAL INTRODUCTION

1.1 Introduction

Ecosystem services have progressed into a prevailing concept and foundational principle guiding worldwide environmental policy (McElwee and Shapiro-Garza, 2020). As such, this has enhanced forests' importance due to their acknowledgement as critical providers of these services (Aznar-Sánchez *et al.*, 2018; Kelly *et al.*, 2015; Pohjanmies *et al.*, 2017). Forests provide invaluable services essential for human survival, including carbon sequestration, soil fertility maintenance, recreational opportunities and the regulation of air, soil, and water (Triviño *et al.*, 2023). However, the ever-expanding footprint of urbanisation, coupled with ongoing deforestation and forest degradation and the escalating threat of climate change, pose a significant and multifaceted challenge to the extent, health, and resilience of these invaluable ecosystems (Forzieri *et al.*, 2022; Yameogo, 2021). As urban areas expand to accommodate growing populations, they often encroach upon forested areas, leading to deforestation and forest degradation, which not only diminishes the extent of forest cover but also disrupts ecological balance, biodiversity, and ecosystem services (Andreasen *et al.*, 2022; Ortiz *et al.*, 2021). Deforestation and forest degradation are also driven by the immediate incentive land user obtain from exploiting forests, even though societal benefits that would otherwise result from forest conservation outweigh these incentives (Wuepper *et al.*, 2024). Moreover, significant threats to forests posed by climate change, include increased wildfire frequency, pest outbreaks, and shifts in forest structure and composition (Buthelezi *et al.*, 2022; Halofsky *et al.*, 2020). These challenges have resulted in a 3% decline of global forests from the year 1990 (4128 million hectares) to the year 2015 (3999 million hectares) (Buthelezi *et al.*, 2024b).

In Africa, forests face a similar set of challenges. In the case of urbanisation, a study on metropolitan municipalities in South Africa revealed a correlation between employment growth and demographic shifts, indicating that metropolitan municipalities effectively delivered sufficient infrastructure. Nevertheless, the increasing population and household numbers surpassed the supply of affordable housing (Marais and Cloete, 2017). This has allowed for the proliferation of informal settlements (Gambe *et al.*, 2023), which exacerbate the deterioration of vegetated landscapes (Buthelezi *et al.*, 2024b). It has also been postulated by Leaver and Cherry (2020) that although the utilisation of forest resources might not always lead to the depletion of forest habitats, prolonged extraction of these resources has induced alterations in forest structure and the composition of tree species within certain African forests, even when undertaken at moderate levels. As such, there is a need for sustainable forest management practices that consider the impact of urbanisation, deforestation, forest degradation, and climate change to safeguard these vital ecosystems.

Sustainable forest management involves balancing environmental, social, and economic considerations to maintain forest ecosystems' integrity while meeting society's needs for forest products and services (Tampekis *et al.*, 2024; Wang, 2024). This approach emphasises practices such as selective logging, reforestation, and biodiversity conservation to ensure that forests can continue to provide vital ecosystem services (Tischenko *et al.*, 2024). Furthermore, community involvement and stakeholder engagement are integral components of sustainable forest management, as local communities often rely on forests for their livelihoods and cultural heritage (Boiral and Heras-Saizarbitoria, 2017). By empowering communities to participate in decision-making processes and benefit from forest resources sustainably, it is possible to foster greater stewardship and resilience within forest ecosystems. International cooperation and policy frameworks, such as the United Nations' Sustainable Development Goals (SDGs), specifically SDG 15: Life on land and initiatives like Reducing Emissions from Deforestation and Forest Degradation (REDD) and Reducing emissions from deforestation and forest degradation in developing countries (REDD+), also play a crucial role in promoting sustainable forest management practices globally (Baumgartner, 2019). These frameworks provide guidance, resources, and incentives for countries to conserve and sustainably manage their forests, recognising forests' importance in addressing global challenges such as climate change, biodiversity loss, and poverty alleviation.

However, despite SDG 15: Life on land, there are still arguments that deforestation rates worldwide continue to rise, especially in developing countries (Nandasena *et al.*, 2023). In contrast, Aryal *et al.* (2024) argued that the effectiveness of this initiative cannot be quantified given that in the literature, some argue that REDD+ has minimal impact on net forest loss. This conflicting narrative underscores the complexity of tackling deforestation and forest degradation. Stricter regulations and enforcement mechanisms may be needed alongside financial incentives like REDD+ to truly curb forest loss. However, this study posits that while regulatory measures and financial incentives are essential components, they may not suffice without concurrent efforts to streamline forest restoration and rehabilitation processes (Walpole *et al.*, 2017).

Forest rehabilitation aims to restore a forest's productivity and some of its original plant communities (Geldenhuys *et al.*, 2017; Lamb and Gilmour, 2003). New species may also be introduced to enhance ecological functions or provide economic benefits. The forest progressively regains its protective role and ecological services throughout this process. Conversely, forest restoration exclusively targets the complete reinstatement of the original forest's structure, productivity, and species diversity (Brudvig, 2011). The ultimate objective is to align ecological processes and functions with those of the pristine, pre-degraded forest ecosystem. In the broader context of sustainable forest management, both rehabilitation and restoration approaches play vital roles in mitigating forest degradation and promoting biodiversity conservation, contributing to the long-term health and resilience of forest ecosystems. Therefore, this study aims to develop a remote sensing and machine learning-based approach to streamline forest restoration and rehabilitation efforts, focusing on natural forest monitoring and regional forest suitability modelling for enhanced rehabilitation and restoration outcomes.

Forest rehabilitation and restoration involve various planned, financed, implemented, and monitored practices carried out by diverse actors, primarily governments, corporate entities, and non-governmental organisations (NGOs), with governments playing a central role by initiating programmes, providing financial support, and encouraging participation through incentives or policies (de Jong, 2010). These practices include reforestation, afforestation, soil restoration, and biodiversity conservation efforts. However, the achievement of effective forest rehabilitation and restoration hinges on the meticulous examination of various factors before initiating the actual restoration process. The first and most crucial step is clearly defining the existing conditions of the natural forest area, encompassing soil composition, biodiversity, and hydrological patterns (Lewis *et al.*, 2019). This provides an understanding of the history and current state of the area's natural forests. As such, by meticulously assessing these factors stakeholders can comprehensively understand the natural forest area's conditions, laying a solid foundation for effective forest rehabilitation and restoration efforts.

Moreover, forest rehabilitation and restoration success can be enhanced by utilising forest suitability models and remote sensing techniques to identify areas suitable for forest vegetation (Rajaonarivelo and Williams, 2022). By integrating ecological data with geospatial information on factors such as climate, soil properties, and topography, these models can identify areas with optimal conditions for specific tree species or desired forest functions (Buthelezi *et al.*, 2024b;

Zhao, X. *et al.*, 2023). This allows forest managers to prioritise areas for rehabilitation and restoration efforts and predict the potential impacts of climate change on existing forests. Ultimately, regional forest suitability modelling serves as a valuable decision-making tool for establishing and maintaining healthy and resilient forest ecosystems (Lõhmus *et al.*, 2020).

This study focuses on the eThekwini Municipality, which is one of the major municipalities in South Africa, where approximately more than 60% of the population resides in urban areas (Rogerson *et al.*, 2014). This has led to a suggestion that urbanisation within the country is unmanageable and excessive, with significant challenges such as illegal land invasion, social disorder and escalating informal settlements (Nassar and Elsayed, 2018; Turok and Borel-Saladin, 2014). Moreover, urbanisation is further exacerbated in the eThekwini Municipality, given that the municipality faces adverse environmental consequences due to change driven by the attempts to move past the apartheid's discriminative spatial planning (Sutherland *et al.*, 2014). In addition to urbanisation, the municipality is also grappling with frequent and prolonged dry spells, characterised by unpredictable rainfall patterns (Grab and Nash, 2023). These challenging conditions play a significant role in the degradation of forests and other vegetated landscapes within the region (Lutz, 2018). Additionally, there is a lack of comprehensive knowledge and understanding regarding the rate of land use and land cover (LULC) change and land degradation within the municipality and its ramifications for forest ecosystems and ecosystem services.

The dynamics of LULC change and land degradation not only directly impact forest ecosystems but also have far-reaching implications for the provision of ecosystem services that are crucial for human well-being (Debebe *et al.*, 2023; Yu *et al.*, 2024). Therefore, integrating assessments of LULC change and land degradation into forest management strategies is essential for informing targeted decision-making processes and ensuring the sustainability of forest ecosystems in the face of rapid urbanisation and environmental change. As such, this study also leveraged remote sensing and machine learning techniques to enhance the understanding of LULC dynamics and land degradation processes within the eThekwini Municipality.

LULC change significantly impacts sustainable forest management practices, which poses significant challenges to forest ecosystem health (Muche *et al.*, 2023). The conversion of forested areas for agricultural expansion, urbanisation, and industrial development alters land cover patterns, leading to habitat fragmentation, loss of biodiversity, and compromised forest health (Li *et al.*, 2022). Unsustainable practices such as deforestation for timber extraction and conversion of natural habitats into monoculture plantations exacerbate soil erosion, water pollution, and loss of soil fertility, undermining the resilience of forest ecosystems (Kelly *et al.*, 2015).

Land degradation entails the continuous and accelerated decline in land productivity stemming from a combination of anthropogenic activities and natural causes (Reith *et al.*, 2021). Approximately 75% of the land globally has been degraded already (Prăvălie, 2021; Yu and Deng, 2022). In most regions, land degradation is induced by human activities such as urbanisation and agricultural intensification (Egidi *et al.*, 2021). These activities are a response to the rapid growth of the world population (Yu and Deng, 2022). Projected estimates indicate that by 2050, there will be a necessity to double agricultural production to fulfil the rising demands of the expanding global population (Skendžić *et al.*, 2021). These estimates imply that degraded landscapes will expand further than the current estimates of 75%. Perović *et al.* (2021) reported that more than 90% of the land will be degraded globally by 2050 without any intervention. Therefore, the United Nations Convention to Combat Desertification (UNCCD) expressed the need to prevent further degradation and to restore degraded lands at the 2012 United Nations Conference on Sustainable Development (RIO + 20), where the target of zero net land degradation was set (Sutton *et al.*, 2016). Addressing land degradation is integral to the SDGs, as reflected in the third indicator of SDG 15: Life on Land. This indicator strives to safeguard, restore, and sustainably manage terrestrial ecosystems, forests, and biodiversity while also combating desertification and land degradation (Keesstra *et al.*, 2021b). Therefore, a comprehensive understanding of degraded lands and LULC change is imperative for effective forest management, as it allows for targeted interventions to restore ecosystem health, conserve biodiversity, and mitigate the adverse impacts of forest degradation.

As aforementioned, this study leverages the capabilities of remote sensing and machine learning to streamline forest rehabilitation and restoration efforts. Remote sensing technology offers invaluable capabilities in forest management by providing a powerful toolset for monitoring and assessing forest ecosystems at various spatial and temporal scales (Fassnacht *et al.*, 2024). By leveraging satellite, airborne, and ground-based sensors, remote sensing enables the acquisition of detailed information on forest structure, composition, and dynamics over large areas (Hwang *et al.*, 2023; Mahanta *et al.*, 2024). Additionally, this technology facilitates the identification of forest cover changes, including deforestation, degradation, and regrowth, allowing for timely interventions to mitigate forest loss and promote sustainable management practices (Haq *et al.*, 2024). Moreover, remote sensing data can inform forest inventory and mapping efforts, supporting decision-making processes related to timber harvesting, biodiversity conservation, and ecosystem services assessment (Abad-Segura *et al.*, 2020). Overall, the capabilities of remote sensing play a crucial role in enhancing the efficiency, accuracy, and sustainability of forest management practices.

Remote sensing can effectively capture LULC change information by integrating spectral-temporal metrics and a diverse set of features to monitor changes in various LULC classes (Liang *et al.*, 2022; Nkundabose, 2021). Significantly, substantial advancements have been achieved in monitoring the sub-indicators of land degradation, with remote sensing emerging as a dependable alternative to conventional methods (Buchhorn *et al.*, 2020b; Liping *et al.*, 2018). These sub-indicators include vegetation productivity, land cover, and soil organic carbon (SOC) stock. It has also been noted by Odebiri *et al.* (2022) that remote sensing techniques provide a robust alternative to in situ and laboratory methods for estimating SOC stock, offering adequate information for accurate digital soil mapping (DSM).

Leveraging remote sensing data within forest suitability modelling offers a powerful approach to identifying areas with high potential for successful restoration initiatives (Buthelezi *et al.*, 2024b). Researchers can create detailed spatial maps that predict the likelihood of tree establishment and growth across a landscape by integrating information on factors such as soil moisture, topography, and existing vegetation cover derived from satellite and airborne sensors (Ndao *et al.*, 2022). This approach offers a significant advantage over traditional field-based methods, enabling the rapid and cost-effective assessment of large spatial extents for restoration suitability. Therefore, to enhance the effectiveness of forest rehabilitation and restoration research, it is recommended to further explore the capabilities of remote sensing technologies, particularly those with proven effectiveness and easy access, such as Landsat.

Machine learning algorithms have revolutionised the extraction of information from remote sensing data, enabling the automated analysis of large volumes of complex spatial data (Han *et al.*, 2023). These algorithms, ranging from traditional classifiers like random forest (RF) and support vector machines (SVM) to more advanced techniques like convolutional neural networks (CNN), leverage patterns and relationships within the data to classify land cover, detect changes, and extract valuable information about environmental conditions (Azedou *et al.*, 2023; Boston *et al.*, 2022; Shao and Lunetta, 2012). By training these algorithms on labelled datasets, they can learn to recognise patterns indicative of different land cover types, vegetation health, and other relevant features present in remote sensing imagery. Machine learning approaches significantly accelerate the analysis process and enhance the accuracy of results compared to manual interpretation (Javaid *et al.*, 2022). Additionally, these algorithms can adapt and improve their performance over time as they are exposed to more data, making them well-suited for handling the dynamic and diverse nature of remote sensing datasets (Peng *et al.*, 2023). As a result, machine learning algorithms have become increasingly prevalent in various remote sensing applications, including land cover mapping, vegetation monitoring, and environmental change detection, facilitating more efficient and comprehensive analysis of Earth's surface dynamics.

Nonetheless, despite international efforts and growing recognition of the critical importance of forests, they continue to face significant threats from deforestation, degradation, and climate change (Flores *et al.*, 2024). Initiatives like REDD+ aim to incentivise forest conservation, but their effectiveness remains debated, revealing the complexity of addressing these issues. While crucial, regulatory frameworks and financial incentives may be insufficient without advancements in forest restoration and rehabilitation processes. This gap in effective solutions highlights the need for innovative approaches. Therefore, this study proposes a novel method to streamline forest restoration and rehabilitation using remote sensing and machine learning techniques. By focusing on natural forest monitoring and regional forest suitability modelling, the study aims to enhance the effectiveness and efficiency of restoration efforts in the eThekwini Municipality.

It should be noted that this study does not overlook the significant advancements in forest rehabilitation and restoration research globally. However, key gaps persist in the context of urbanised and expanding municipalities like the eThekwini Municipality. Specifically, there is a lack of long-term LULC change data that captures the impacts of rapid urbanisation on local environments (Siddik *et al.*, 2022). The unique challenges of urban sprawl, deforestation, and shifting land use patterns create a complex landscape where forests are at high risk of degradation and fragmentation. Without targeted, long-term data, it becomes difficult to quantify these impacts accurately, which limits the effectiveness of restoration and rehabilitation initiatives. By analysing LULC changes, this study addresses the need for consistent monitoring to better understand how these evolving land patterns influence forest loss, ecosystem resilience, and potential areas for rehabilitation.

Another important research gap involves the assessment of land degradation within urban municipalities, which remains underexplored despite its significant implications for forest restoration and rehabilitation. Land degradation including soil erosion, nutrient depletion, and loss of SOC poses serious challenges to the success of forest restoration and rehabilitation efforts, especially in urbanised areas where natural landscapes are increasingly fragmented and degraded due to human activities (AbdelRahman, 2023; Deeb *et al.*, 2024). Existing degradation studies are often conducted at regional or national scales, which do not provide the specificity needed to understand localised impacts within municipalities like the eThekwini Municipality. The lack of detailed municipal-level data on land degradation restricts the ability of local authorities to identify priority areas for intervention and to measure the underlying conditions that affect forest regrowth potential. This study addresses the gap by employing machine learning algorithms with remote sensing imagery to evaluate land degradation indicators, particularly focusing on SOC stocks and land cover changes. By doing so, it aims to generate a more refined understanding of land degradation patterns within the eThekwini Municipality, identifying areas where degradation is most severe and where forest restoration and rehabilitation efforts are likely to be most impactful.

There is also a notable research gap in mapping natural forests within urban municipalities like the eThekwini Municipality. Natural forests are essential for biodiversity conservation and ecosystem resilience (Brockerhoff *et al.*, 2017), yet their distribution within rapidly urbanising areas remains poorly documented. Existing mapping efforts often lack the spatial resolution and specificity needed to distinguish natural forests from other vegetative cover (Fassnacht *et al.*, 2024), which is crucial for effective conservation planning. Without accurate maps, it is challenging to monitor changes in natural forest extent, prioritise areas for protection, or implement targeted restoration and rehabilitation measures. This study addresses this gap by using advanced remote sensing data combined with machine learning algorithms to map natural forests at a municipal level, ensuring that conservation and restoration efforts are based on precise, up-to-date information.

Although broader, regional models provide valuable insights, they often overlook the granularity required for municipal-scale decision-making, where factors like specific land ownership, microclimates, and unique socio-economic conditions play crucial roles. This study seeks to bridge this gap by employing machine learning algorithms and remote sensing imagery to develop localised suitability maps for forest vegetation. These maps can guide more accurate and effective forest rehabilitation efforts by identifying suitable areas and predicting future conditions, thus addressing the limitations of generalised, large-scale models. Together, these insights support the study's objectives to enhance the precision and applicability of restoration approaches within the eThekwini Municipality.

Another critical research gap lies in the limited application of machine learning and remote sensing at the municipal level to support local forest restoration and rehabilitation. While machine learning and remote sensing have been effective in broad-scale environmental monitoring and forest management, they are often applied on national or regional scales, overlooking the finer spatial and contextual details necessary for municipal-level management (Yu and Fang, 2023). Localised forest restoration and rehabilitation requires data that accurately reflects smaller spatial units and considers diverse, site-specific variables, such as local land ownership patterns, microclimates, and urban development pressures that influence forest growth and ecosystem resilience (Marques *et al.*, 2016).

The absence of such fine-scale applications restricts municipalities from making fully informed decisions regarding forest restoration priorities and strategies. This study addresses this gap by utilising machine learning algorithms along with remote sensing data to produce detailed suitability models, LULC and natural forest extent change maps. These tools allow for precise identification of areas most suitable for forest restoration and rehabilitation within the municipality, while also monitoring how urban expansion and land use changes impact potential restoration and rehabilitation sites. By providing a tailored approach to forest monitoring, this study aims to enhance local restoration initiatives with data-driven insights that are often unavailable at the municipal level.

As such, by addressing these research gaps, the effectiveness and efficiency of forest restoration and rehabilitation initiatives can be enhanced, ultimately contributing to the conservation and sustainable management of forest ecosystems.

1.2 Aim of the Study

This study aimed to develop and implement a remote sensing and machine learning-based approach for streamlining forest restoration and rehabilitation in the eThekwini Municipality, focusing on regional forest suitability modelling and natural forest monitoring.

1.3 Objectives of the Study

Therefore, to meet the above aim, the following objectives were determined:

i. To review and analyse global publications on forest rehabilitation and restoration efforts to investigate trends, explore the utilisation of various practices, and identify opportunities for enhancing the success of forest rehabilitation initiatives.
ii. To review and analyse publications on the utilisation of forest suitability models and remote sensing techniques for identifying areas suitable for forest vegetation.
iii. To map LULC change within the eThekwini Municipality from 2002 to 2022 using remote sensing data from the three most recent Landsat sensors and machine learning algorithms.
iv. To assess land degradation within the eThekwini Municipality by focusing on land cover change and SOC stock using medium-resolution remote sensing data and machine learning algorithms.
v. To provide a framework for monitoring natural forests at a municipal scale using remote sensing, focusing on the eThekwini Municipality, to facilitate forest rehabilitation and restoration.
vi. To model the suitability of forest species within the eThekwini Municipality using species distribution modelling (SDM)/environmental niche modelling (ENM) methodology.

1.4 Research Questions

Based on the specific objectives of this study, the following research questions have been derived:

i. What are the key challenges, opportunities, and predominant practices identified in enhancing the success of forest rehabilitation and restoration initiatives globally?
ii. What existing forest suitability models and remote sensing techniques are utilised to identify areas suitable for forest vegetation, and how effectively can remote sensing data be integrated with these models to improve the identification of suitable areas?
iii. How accurate are the LULC change maps generated using remote sensing data from Landsat sensors and machine learning algorithms?

iv. What is the extent of land degradation within the eThekwini Municipality based on land cover change and SOC stock, and how effective are medium-resolution remote sensing data and machine learning algorithms in assessing this degradation?

v. How can remote sensing technology effectively monitor natural forests at a municipal scale, and how can the developed framework facilitate forest rehabilitation efforts in the study area?

vi. How can the SDM/ENM methodology be applied to model the suitability of forest species within the eThekwini Municipality, and how accurate are these models in predicting suitability for afforestation and reforestation?

1.5 Study Area

The eThekwini Municipality is located within the province of KwaZulu-Natal, South Africa (Figure 1.1). Based on the Köppen classification, this area features a humid subtropical climate (Cwa) with distinct seasonal variations: hot and wet summers (November-April) and cool and dry winters (May-October) (Mushore *et al.*, 2023). The municipality covers 2297 km^2, representing a modest 1.4% of KwaZulu-Natal's landmass and is South Africa's third-largest metropolis with the busiest port on the African continent (Zungu *et al.*, 2020b). Zungu *et al.* (2020b) added that the eThekwini Municipality’s landscape was dominated initially by natural forests (65%). However, urbanisation has extensively altered the terrestrial habitat in the municipality, with major threats from invasive plant species, pollution, and climate change (Odindi *et al.*, 2015). As such, 53% of the initial vegetation has been converted for human activities such as agriculture, construction, roads, and settlements, and an additional 17% is classified as highly degraded (Zungu *et al.*, 2020b). Conservation efforts through controlled development, environmental servitudes, and land acquisition have preserved some portions of the green environment in near-pristine conditions in the municipality (Odindi *et al.*, 2015). One example is the Durban Metropolitan Open Space System (DMOSS), a network of designated areas aimed at preserving the native fauna and flora, which the municipality implemented (Buthelezi *et al.*, 2024a). However, these conservation efforts have continuously ignored natural forest rehabilitation and restoration.

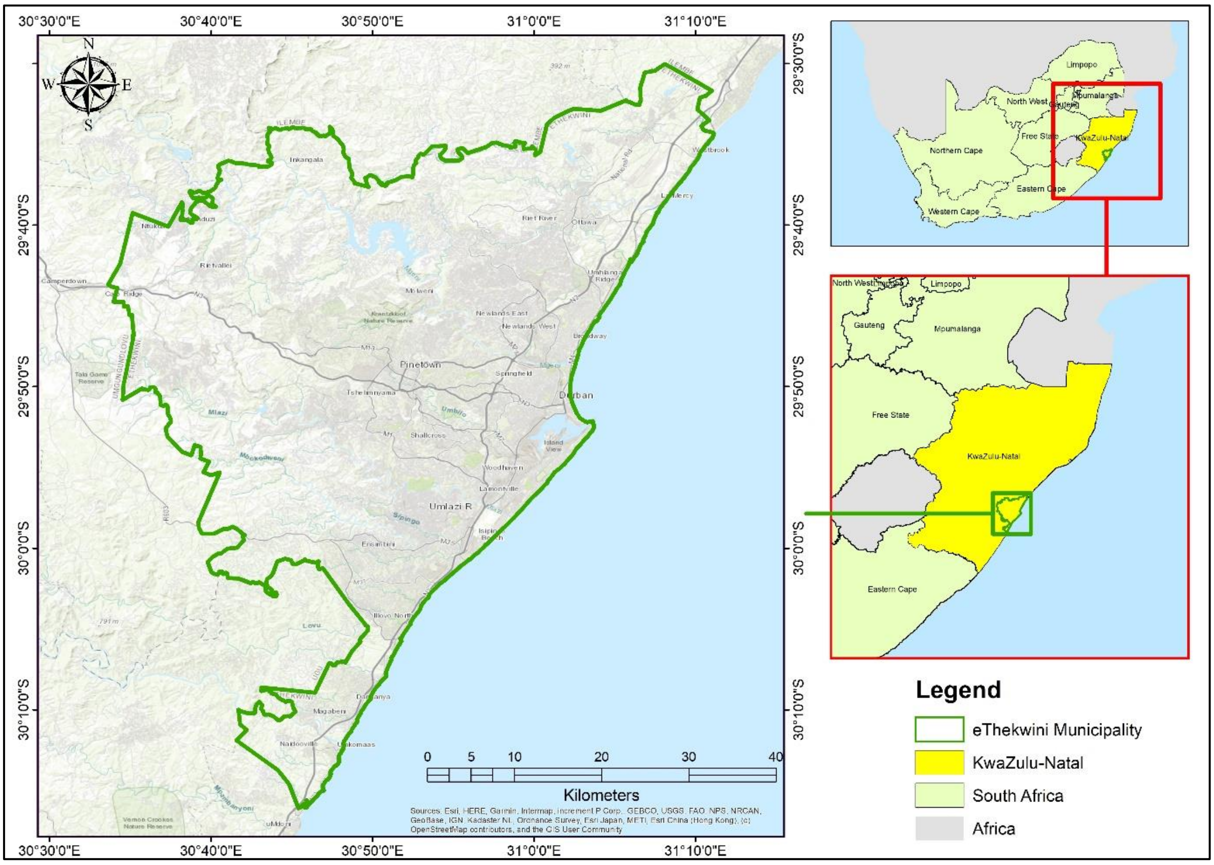

Figure 1.1. Location of the eThekwini Municipality in the province of KwaZulu-Natal, South Africa.

1.6 Scientific Scope

This study aims to analyse forest rehabilitation and restoration in the eThekwini Municipality using remote sensing and machine learning techniques. By leveraging data from the three most recent Landsat missions and Sentinel-2, the research focuses on land use and land cover (LULC) mapping, land degradation assessment, and species suitability modelling. Specifically, the study applies machine learning algorithms to analyse historical land cover changes, assess shifts in forest ecosystems, and predict suitable areas for forest rehabilitation. The results will contribute to more efficient forest monitoring and inform strategic planning for restoration initiatives.

1.7 Thesis Outline

This thesis consists of eight chapters, including the introductory chapter, which provides an overview, and chapter eight, which serves as the synthesis. Excluding these two chapters, this thesis comprises six research papers aligned with the objectives outlined in subsection 1.3.

Among these, five have been published in peer-reviewed journals and the remaining chapter is under review. Furthermore, each research paper constitutes a separate chapter, resulting in some overlap in theoretical content across the chapters. The literature review and methodology are thoroughly discussed in the aforementioned chapters.

Chapter Two: This chapter investigates forest rehabilitation and restoration efforts globally. The methodology employs a systematic review approach focusing on publications before 2024. The review searches Scopus, ScienceDirect, and Web of Science for publications containing the keywords "forest rehabilitation" and “forest restoration”. Inclusion and exclusion criteria are used to select relevant studies. Data extraction and analysis include frequency analysis, bibliometric analysis, geographical analysis, a thematic analysis of rehabilitation practices, ecosystems, remote sensing applications, funding, policy recommendations, and future research avenues.

Chapter Three: This chapter reviews the use of suitability models and remote sensing techniques by employing a systematic review methodology to analyse relevant literature published between 2008 and 2022. This review offers a comprehensive analysis of the effectiveness of diverse suitability models and remote sensing methodologies, the geographical emphasis of this research, collaborative patterns among researchers contributing to this domain, and the array of methods utilised, and the scales at which the studies were undertaken.

Chapter Four: This chapter delves into the complex interplay of environmental, social, economic, and political factors that shape the spatial configuration of a region, shedding light on how this matrix influences changes on the Earth's surface. It emphasises the importance of LULC maps in illustrating these dynamics, highlighting their role in understanding the relationship between humans and the environment and in implementing sustainable land management practices. The chapter aims to map LULC changes within the municipality by utilising remote sensing and machine learning techniques, offering valuable insights for decision-making and policy development to address environmental challenges effectively.

Chapter Five: This chapter utilises remote sensing data from Landsat 7, Landsat 8, and Landsat 9 and employs extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), random forest (RF), and support vector machine (SVM) to assess land degradation based on land cover change and soil organic carbon (SOC) stocks. The accuracy of the models is evaluated using various metrics, including overall accuracy, sensitivity, specificity, quantity and allocation disagreements, and the F1 Score.

Chapter Six: This chapter analyses the extent of natural forest in the eThekwini Municipality, aimed at facilitating rehabilitation and restoration efforts. It leverages remote sensing data obtained from Landsat 7, Landsat 8, and Landsat 9 to delineate the historical and current distribution of natural forests. Machine learning algorithms, namely, LightGBM and artificial neural networks (ANN), are harnessed and trained on reference data to categorise forest cover based on spectral indices extracted from the satellite imagery. Moreover, feature importance analysis is conducted to pinpoint the most significant factors influencing forest cover classification. Subsequently, the performance of the machine learning models is evaluated using accuracy assessment metrics such as the receiver operating characteristic (ROC) area under the curve (AUC) and the F1 score.

Chapter Seven: This chapter identifies suitable areas for forest restoration and rehabilitation within the study area. To achieve this, the chapter employs SDM using three algorithms: RF, LightGBM, and ANN. These models considered various environmental variables, including bioclimatic data, topography, remote sensing data, and land ownership. The results of the models were used to create maps highlighting areas suitable for forest restoration and rehabilitation, considering not only ecological suitability but also practical limitations like land ownership. This information can be a valuable tool for informing targeted rehabilitation and restoration strategies within the municipality.

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2. CHAPTER TWO: EXPLORING FOREST REHABILITATION AND RESTORATION: A BRIEF SYSTEMATIC REVIEW

This chapter is based on:

Buthelezi, M. N. M., Lottering, R., Peerbhay, K., & Mutanga, O. (2024). Exploring forest rehabilitation and restoration: A brief systematic review. *Trees, Forests and People*. Under Review. TFP-D-24-00396.

Abstract

Ecosystem services are essential to global environmental policy, highlighting the critical role of forests as providers of these services. However, extensive deforestation threatens access to these vital services. This study emphasised the urgent need for comprehensive forest management practices, identifying forest rehabilitation and restoration as crucial strategies. These approaches require context-specific planning and consideration of various factors outlined in existing literature. Using a systematic review methodology, this study investigated trends in forest rehabilitation and restoration efforts up to 2023, examined the utilisation of different practices, and identified opportunities for enhancing the success of efforts globally. An analysis of 117 publications revealed increasing research activity in recent years, with notable peaks between 2019 and 2023, indicating growing interest in the field. Geographic analysis showed regional disparities, with Asian and South American countries leading in research frequency. Policy recommendations underscored the importance of community participation and government support in forest rehabilitation and restoration efforts. The reviewed publications predominantly focused on tropical forests and reforestation/natural succession/nucleation as primary practices, highlighting the significance of these ecosystems and strategies in current research. Given the critical role of forests and the threats they face, this study aimed to inform effective global forest rehabilitation policies and interventions by analysing existing research on forest rehabilitation and restoration techniques.

Keywords: rehabilitation, restoration, forest, policy, ecosystem services, ecosystem

2.1 Introduction

Ecosystem services have evolved into a prevailing concept and foundational principle guiding worldwide environmental policy (McElwee and Shapiro-Garza, 2020). As such, this has enhanced forests' importance due to their acknowledgement as critical providers of these services (Aznar-Sánchez *et al.*, 2018; Pohjanmies *et al.*, 2017). Ecosystem services encompass the naturally occurring environmental conditions, functions, and processes established and sustained by the ecosystem, which are crucial for human survival (Liu *et al.*, 2020). Ecosystem services provided by forests include the provision of timber, non-timber products, and food while also playing crucial roles in climate regulation, soil retention, water quality improvement, natural hazard mitigation, biodiversity enhancement, and providing recreational and aesthetic values in rural and peri-urban landscapes (Buchelt *et al.*, 2024; Grammatikopoulou and Vačkářová, 2021).

However, to fulfil their daily requirements, humans have continuously cleared and fragmented extensive expanses of forested areas globally, threatening the accessibility of ecosystem services they provide (Jebiwott *et al.*, 2019). Moreover, between 1990 and 2020, the global forest area decreased by 4.4%, indicating a net loss of 178 million hectares (ha) (Debebe *et al.*, 2023). These trends underscore the urgent need for comprehensive and sustainable forest management practices. This is also highlighted in the Sustainable Development Goals (SDGs). Specifically, SDG 15: Life on Land, which aims to safeguard, restore, and promote sustainable management of terrestrial ecosystems, forests, and biodiversity and combat desertification and land degradation (Keesstra *et al.*, 2021a).

One strategy to address the issue of deteriorated forests involves the rehabilitation and restoration of these ecosystems (Dharmawan and Pratiwi, 2023). Forest rehabilitation and restoration involves various planned, financed, implemented, and monitored practices carried out by diverse actors, primarily governments, corporate entities, and non-governmental organisations (NGOs). Governments play a central role by initiating programmes, providing financial support, and encouraging participation through incentives or policies (de Jong, 2010). These practices include reforestation, afforestation, soil restoration, and biodiversity conservation efforts. However, the achievement of effective forest rehabilitation and reforestation hinges on the meticulous examination of various factors before initiating the actual restoration process.

Lewis *et al.* (2019) outlined some of the variables that should be considered before a forest rehabilitation or restoration project commences. First, the existing conditions of the natural forest area, encompassing soil composition, biodiversity, and hydrological patterns, must be clearly defined. Second, a comprehensive historical analysis that employs historical maps, satellite imagery, and available records using remote sensing and a Geographic Information System (GIS). Subsequently, well-defined rehabilitation and restoration goals, aligned with conservation and sustainability objectives, should be established, accompanied by measurable success criteria. Drawing from proven techniques based on historical lessons, the rehabilitation and restoration process should leverage approaches with a track record of success. Implementing a robust monitoring programme is crucial, allowing for the ongoing assessment of progress against defined criteria and facilitating adaptive management. Finally, knowledge sharing is paramount, with documented outcomes contributing to a collective understanding of effective strategies for rehabilitating and restoring forests.

As such, this review aimed to investigate the trends in forest rehabilitation and restoration efforts, explore the utilisation of various rehabilitation and restoration practices, and identify opportunities for enhancing the success of forest restoration initiatives globally. Moreover, the specific objectives of this systematic review were to identify knowledge gaps and inform future research and policy decisions. The systematic review methodology was adopted because it offers a reliable approach that allows management decisions to be supported by precise and current information (Thompson *et al.*, 2023). As such, using this methodology, a comprehensive search using "forest rehabilitation" OR "forest restoration" on Scopus, ScienceDirect, and Web of Science was conducted. Robust inclusion and exclusion criteria were developed to select the relevant publications. This review stands out as one of the few, if not the only, systematic reviews of global publications on forest rehabilitation and restoration. Notably, the analysis included studies addressing both forest rehabilitation and restoration.

2.2 Methods and Materials

This systematic review follows the framework outlined by Pullin and Stewart (2006). This framework involves a step-by-step process for conducting a rigorous review. It includes tasks such as protocol development, creating a search strategy, determining the inclusion criteria, extracting data, and performing the analysis. It also aligns with the PRISMA protocol 17-item checklist developed by Moher *et al.* (2015). As such, the methodology has four steps, which encompass recommendations from the adopted framework and protocol.

2.2.1 Step 1: Literature search

This review had no geographic limitation. However, the ecosystem scope was limited to forest ecosystems. Moreover, it should be noted that studies focusing on the rehabilitation and restoration of commercial forest plantations were also included in the scope. That is because outcomes from these studies can provide crucial information for rehabilitation studies focused on regions where commercial plantation forests dominate.

Scopus, ScienceDirect, and Web of Science were the primary literature repositories where "forest rehabilitation" OR "forest restoration" was the Boolean code. The selection of these three platforms as the primary literature repositories was based on their comprehensive coverage, academic credibility, and multidisciplinary scope. These databases are among the most reputable and widely used in scholarly research, ensuring access to high-quality, peer-reviewed literature across various fields relevant to forest restoration, remote sensing, and machine learning. Using two keywords, this systematic review ensured clarity and consistency throughout the search and analysis phases. This approach facilitated the development of a precise search strategy and streamlined data extraction procedures. Moreover, by focusing on two terms, ambiguity and potential confusion regarding the review scope were minimised. This enhanced the efficiency of the review process, enabling the identification of key studies with greater effectiveness and promoting a more comprehensive understanding of the chosen topic, ultimately leading to the generation of insightful findings and robust conclusions.

2.2.2 Step 2: Screening (inclusion and exclusion)

Table 2.1 presents the inclusion and exclusion criteria used to screen publications for this review. The inclusion criteria for the literature search required publications to be in English, focus on forest rehabilitation and restoration with a well-defined methodology, be published before January 1, 2024, and be accessible without a paywall. Exclusion criteria ruled out books, reviews, conference papers, publications unrelated to the forest ecosystem, and duplicates. Books and conference papers were excluded to maintain a focus on peer-reviewed, empirical research, as books often provide broad overviews or theoretical discussions rather than primary data and may lack the rigorous peer-review process characteristic of journal articles. Conference papers, while valuable for presenting emerging ideas, frequently lack the depth, methodological detail, and validation needed for systematic analysis. This review aimed to prioritise high-quality, detailed studies that are essential for accurate synthesis and reproducibility. Review papers were excluded because they synthesise findings from multiple primary studies, leading to potential duplication of data if those primary studies are also included. This double counting can distort the analysis. Additionally, review papers may introduce biases based on the authors' interpretations and the specific studies they chose to include which this systematic review aims to minimise through a rigorous, predefined methodology for study selection and data extraction. As such, by concentrating on primary studies, this review ensured a more uniform application of the inclusion criteria.

However, the inclusion and exclusion criteria used in this systematic review has an inherent limitation, which is the exclusion of studies for which full text was unavailable or restricted by paywalls. This exclusion, while necessary to ensure consistent data accessibility, may introduce a bias toward studies from developed countries, where research is more frequently published in open-access or widely accessible journals. Consequently, this could lead to an overrepresentation of themes, methodologies, and findings from developed regions, while underrepresenting insights from developing countries, where barriers to open-access publishing are often higher.

The impact of this limitation is twofold. First, the geographical distribution of the findings may be skewed, potentially highlighting practices and challenges that are more relevant to forest rehabilitation and restoration in developed nations while overlooking context-specific factors critical in developing regions. Second, the thematic focus could be affected, as topics prioritised in more accessible journals may differ from those in restricted-access studies. For example, research on community-driven or low-cost restoration techniques, which are particularly relevant in developing countries, might be underrepresented, leading to a less comprehensive understanding of global practices. By acknowledging this constraint, the study provides a more transparent view of its scope and emphasises the need for further research that includes a broader array of publications to capture a more balanced perspective on forest rehabilitation and restoration practices worldwide.

All publications retrieved from the three databases were added to a Scopus list, where duplicates were automatically discarded. This was followed by an initial screening of publications, using their titles and abstracts to determine if they met the inclusion criteria. All publications that met the inclusion criteria were exported to EndNote 21 for full text screening. Publications that did not meet the criteria were discarded, and the remaining ones were used to extract data for analysis in this review.

Table 2.1. The criteria for selecting and excluding publications to be included in the review.

Inclusion criteria	Exclusion criteria
The publication is in English.	Publication is a book, a review, and a conference paper.
The publication focuses on forest rehabilitation and restoration with a well-defined methodology.	The publication does not include the forest ecosystem.
Publication is made before January 1, 2024.	The publication is a duplicate.
The publication is not locked behind a paywall.	

2.2.3 Step 3: Data extraction

The information extracted from the publications that met the inclusion criteria after full text screening included the publication year, author details (name, address, and affiliation), study location(s) and scale, and keywords. Furthermore, information on rehabilitation and restoration practices, forest ecosystem type, funding details, remote sensing applications, policy recommendations, and avenues for future research was extracted from the publications.

2.2.4 Step 4: Data analysis

First, a frequency analysis was executed based on the annual count of publications. Subsequently, a bibliometric analysis was conducted, exploring author patterns by scrutinising intra-author connections. To visualise these author patterns in the review, VOSviewer version 1.6.16, a widely used software tool for creating and presenting collaboration or network-based maps (Van Eck and Waltman, 2011), was utilised. Third, a geographical analysis was conducted, considering the study's scale and the precise locations of the study areas. It is crucial to note that in cases where a study covered multiple countries, all those countries were included in the count. Finally, a comprehensive analysis was conducted, delving into forest rehabilitation and restoration practices, forest ecosystem type, remote sensing applications, funding organisations, policy recommendations, and potential avenues for future research in the field of forest rehabilitation and restoration.

2.3 Results

2.3.1 Search results

The initial search across the three databases yielded 1975 publications (Figure 2.1). These publications were added to a Scopus list, where 138 duplicates were discarded. Publications that were not duplicates were screened based on their titles and abstracts, applying the inclusion and exclusion criteria. This resulted in 283 publications being deemed eligible for inclusion. Subsequent screening of full text publications resulted in 117 publications meeting the inclusion criteria, with the earliest publication dating back to 1984. These publications were distributed across 73 journals, with *Forests* having the most publications (15), followed by *Forest Ecology and Management* and *PLoS ONE*, with 10 and four journal articles, respectively.

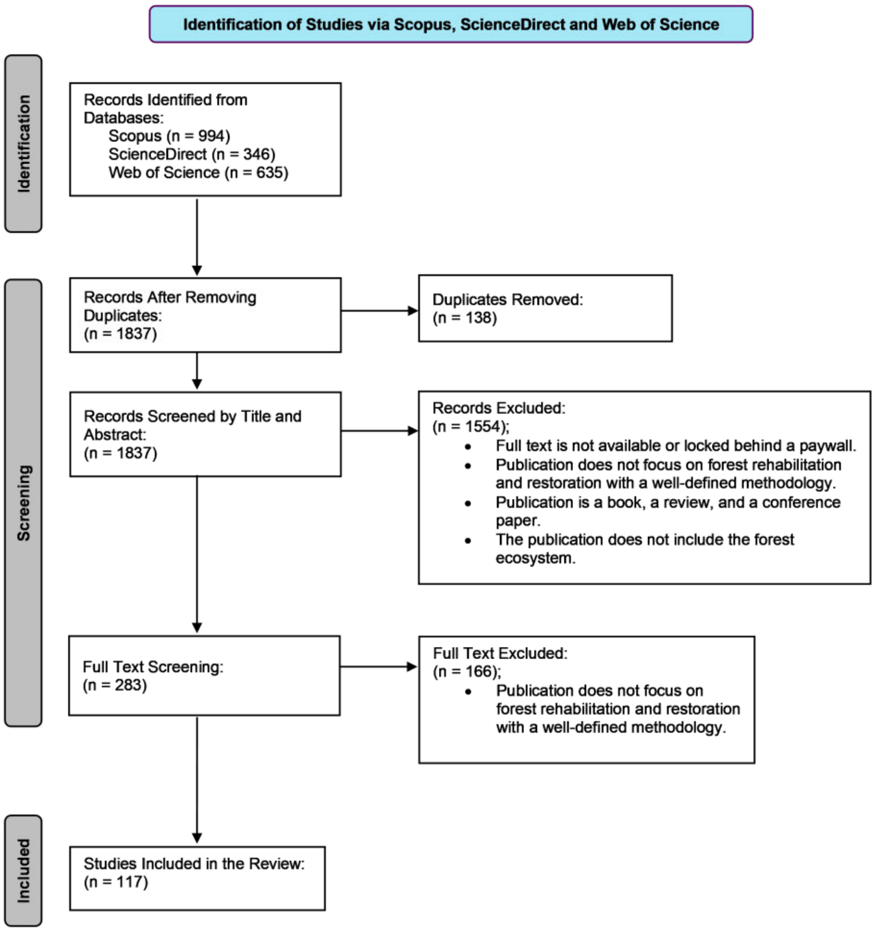

Figure 2.1. Summary of database search results for forest rehabilitation and restoration publications using a PRISMA flow diagram for a systematic review (Page *et al.*, 2021).

2.3.2 *Frequency analysis*

Figure 2.2 presents the distribution of the 117 publications selected for this review across different years. The analysis reveals varying levels of research activity over time, with peaks observed in recent years. Peaks in research output are notably evident in recent years, particularly in 2022 and 2023 (16 publications each), 2019 (13 publications), and 2021 (10 publications), suggesting a heightened interest or focus on forest rehabilitation and restoration during these periods. In contrast, the earlier period from 1985 to 2007 reveals a distinct lack of publications, suggesting a comparatively lower level of research activity during those years. This is particularly evident with the complete absence of publications between 1986 and 1993, along with isolated gaps in 1995, 1998, 2002, 2007, and 2015.

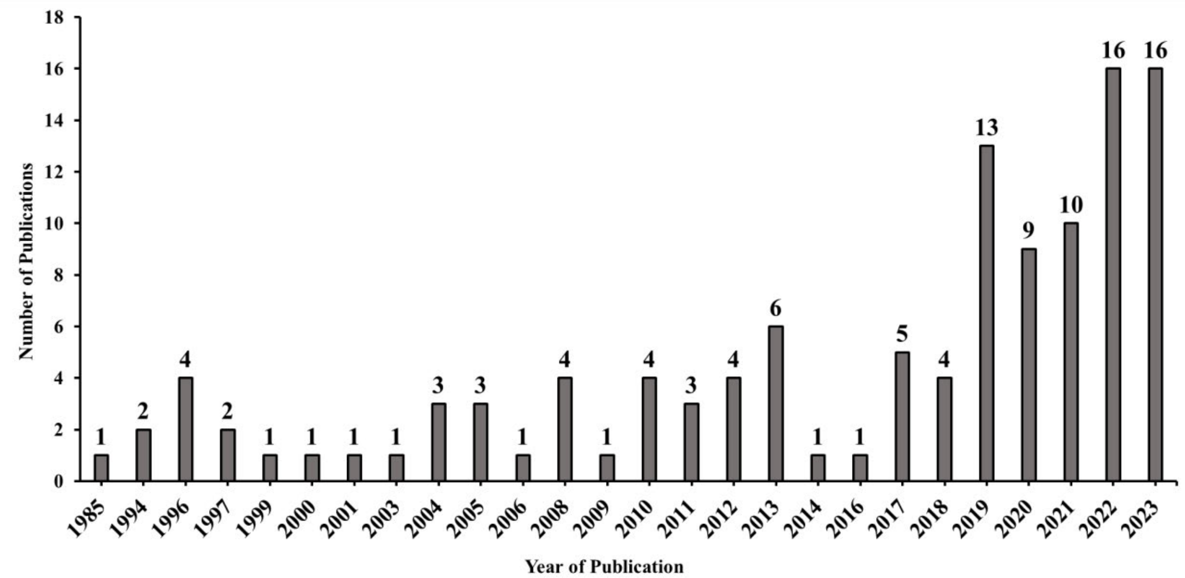

Figure 2.2. Annual distribution of the 117 publications that met the inclusion criteria for this review.

Overall, there is a trend of increasing research interest in forest rehabilitation and restoration, with a notable increase in the number of publications in recent years, possibly influenced by technological advancements and evolving research priorities.

2.3.3 *Bibliometric analysis*

2.3.3.1 Keywords

Figure 2.3 presents the network analysis conducted on keywords extracted from the titles and abstracts of the 117 reviewed publications using VOSviewer. The selection of these keywords in VOSviewer prioritised terms within the top 60% of relevance and appeared at least 10 times within the dataset. The size of the terms corresponds to the number of occurrences or instances within the text of the titles and abstracts of the reviewed publications. From an initial pool of 4215 terms, 83 met the criteria, and 50 were selected based on the 60% relevance threshold. The terms that appeared most frequently included "restoration" (79 occurrences), "community" (68), "treatment" (65), "plantation" (53), and "forest restoration" and "regeneration" (48 each).

The term "restoration" was identified within the red cluster, which consisted of 16 items. This cluster includes terms that are thematically related, indicating a strong association between them within the context of the reviewed publications. Notable terms in this cluster include "biodiversity," "community," "farmer," "forest restoration," "perception," and "livelihood." The presence of these terms suggested that discussions around forest restoration often intersect with themes such as biodiversity conservation, community involvement, agricultural practices, forest recovery efforts, stakeholders' perceptions, and impacts on livelihoods. This thematic clustering highlighted the multifaceted nature of forest rehabilitation and restoration efforts, emphasising their ecological, social, and economic dimensions.

The term "regeneration" was detected within the green cluster, encompassing 12 items. Among these items were terms such as "growth," "development," "tree species," "species richness," and "seedling." These terms indicate a focus on the biological and ecological processes of regeneration, emphasising the stages of growth and development. The cluster also highlighted an interest in biodiversity, particularly in the variety and abundance of tree species within regenerating forest ecosystems. The term "seedling" underscores the importance of early plant development and survival in successful regeneration efforts.

The blue cluster, comprised of 12 items, encompassed terms such as "rehabilitated forest," "soil," "soil property," and "secondary forest." This cluster highlights the importance of soil characteristics and the distinction between rehabilitated and secondary forests in ecological research and conservation efforts. The yellow cluster, consisting of five items, included terms such as "treatment," "control," and "fire," indicating a focus on experimental methodologies and the role of fire in forest management. Meanwhile, the purple cluster, also comprised of five items, included terms like "native forest," "plantation," "establishment," and "native species."

As such, this cluster underscored the significance of promoting native biodiversity and the challenges associated with establishing native species in managed or altered landscapes.

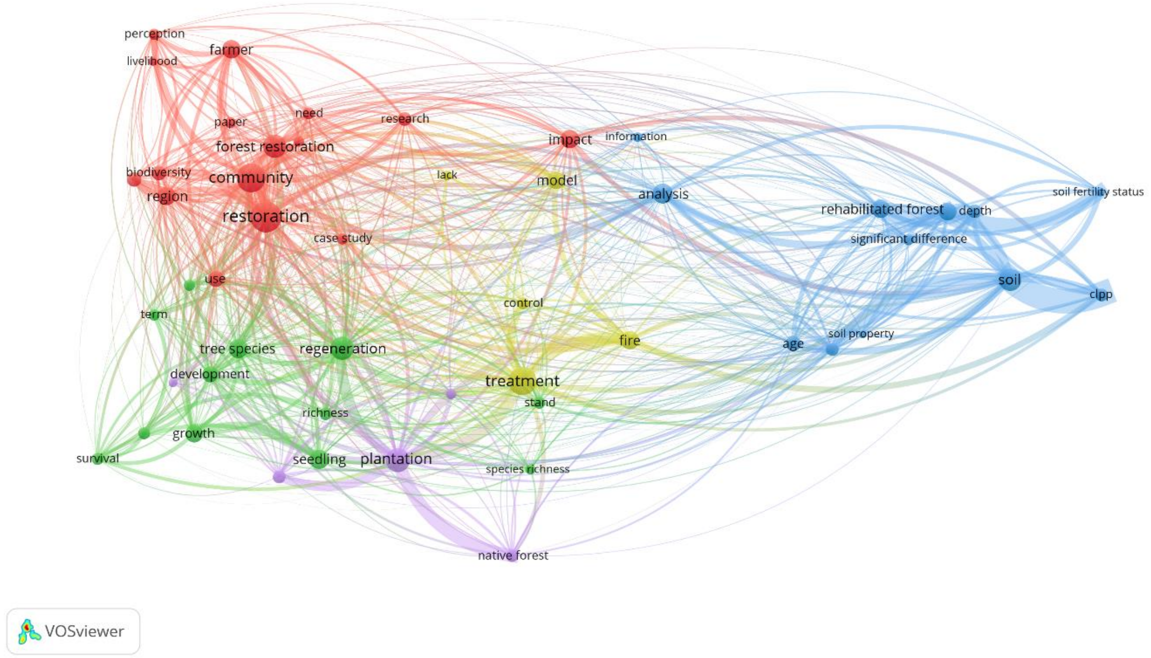

Figure 2.3. Network analysis of keywords extracted from the titles and abstracts of the 117 reviewed studies using VOSviewer.

2.3.3.1 Co-authorship

Figure 2.4 illustrates the analysis of collaborative relationships between authors based on their joint publication of research articles in VOSviewer. In the examination of co-authorship within the 117 reviewed publications, a total of 489 authors were identified, with the largest network comprising 50 connected authors. Notably, Ahmed O. H. emerged as a prominent collaborator, contributing to four documents and demonstrating a link strength of 18 within the network. The largest cluster in the co-authorship network included 11 authors, indicating a cohesive and active collaboration among these researchers.

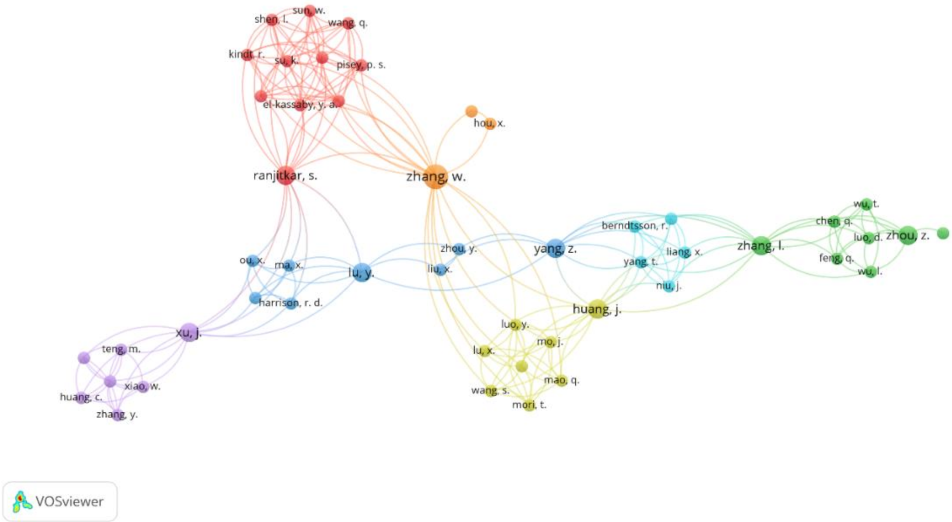

Figure 2.4. Network analysis of collaborative relationships among authors who contributed to the publication of the 117 publications.

2.3.4 Geographic analysis

2.3.4.1 Study area locations

The distribution of publications across various countries highlights a significant concentration of research activity in certain regions (Figure 2.5). China leads with 16 publications, followed by the United States of America (USA) with 14 publications and Brazil with 13 publications, indicating strong research presence and investment in these countries. Mid-level contributors like Indonesia (10), Malaysia (9), and Australia (7) also show considerable engagement. In terms of continental contributions, Asia and South America are prominent, with countries like China, Indonesia, and Brazil leading in publications. North America is also well represented, primarily through the USA and Canada. Conversely, African countries show a notable lack of publications, with only Ethiopia, Ghana, Madagascar, South Africa, Sudan, and Uganda each contributing two publications, and Burkina Faso with just one. This suggests limited research activity or resources dedicated to forest rehabilitation and restoration on the African continent. Overall, the data reveals a global interest in forest rehabilitation and restoration with varying levels of research activity, highlighting regions with strong engagement and those with potential for increased focus and support.

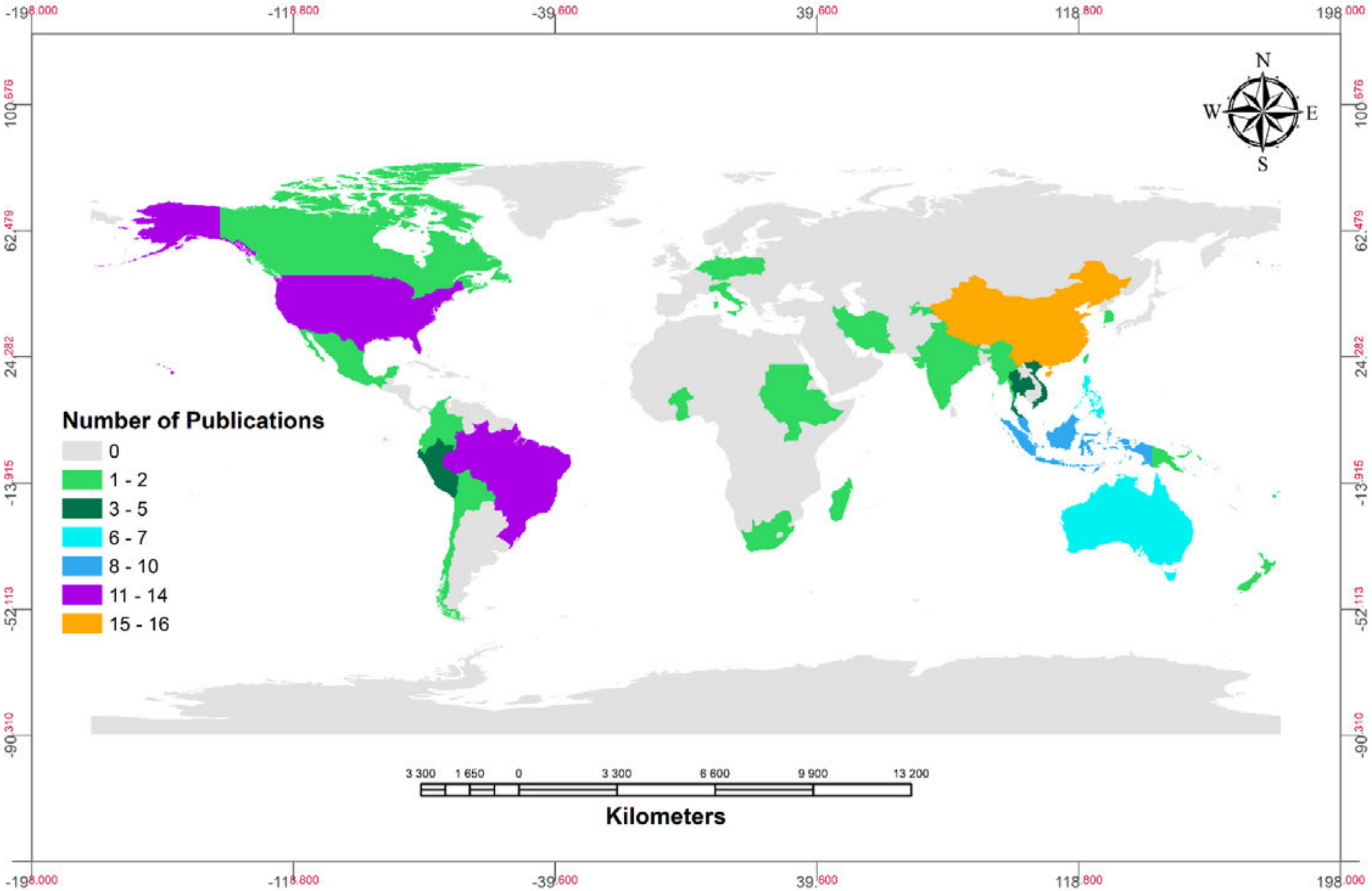

Figure 2.5. The distribution of the reviewed publications based on the geographic location of their study areas.

2.3.4.2 Study scales

Figure 2.6 illustrates the distribution of reviewed publications based on the scale at which they were conducted, where most of the publications (108) focused on the subnational scale, whereas only six publications examined national-scale dynamics. Three publications delved into continental-scale analyses, while none were conducted globally. This distribution highlights a significant emphasis on localised efforts in forest rehabilitation and restoration research.

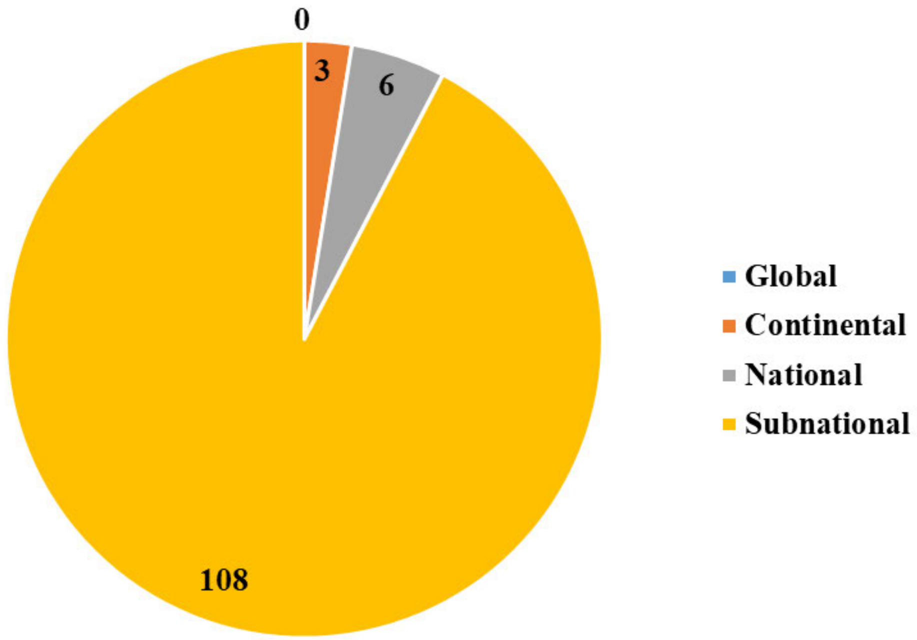

Figure 2.6. The distribution of reviewed publications based on the scale at which they were conducted.

2.3.5 Forest ecosystem types

This study investigated the distribution of publications across various forest ecosystem types, revealing noticeable variability in research focus. Tropical forests dominated the analysis with 71 publications, reflecting their ecological significance and pressing conservation challenges. Temperate and dryland forests also received notable attention, with 14 and 10 publications, respectively, indicating strong research interest in these ecosystems. Mangrove forests garnered moderate attention with six publications. In contrast, subtropical forests, montane forests, mixed hardwood-conifer forests, and commercial forests each had three to four publications, suggesting these are niche areas of current research. Coastal dune forests, cloud forests, and peat-swamp forests were minimally represented, with only one publication each. This distribution highlights the need for increased research on less-studied ecosystems to better understand and manage these unique environments.

2.3.6 Rehabilitation and restoration practice

This study assessed the distribution of publications on various forest rehabilitation and restoration practices, uncovering significant disparities in research focus (Figure 2.7). Planting/natural succession/nucleation was the most researched practice, with 87 publications, highlighting its fundamental role in forest rehabilitation and restoration and broad applicability across ecosystems. Agroforestry had 13 publications, indicating considerable interest in integrating trees into agricultural landscapes for ecological and economic benefits. Practices like herbicide treatment, fire management, and thinning were each used in five publications, highlighting moderate research interest due to their importance in managing vegetation, reducing wildfire risk, and improving forest structure. Rangeland regeneration and management of invasive plant species each had three publications, suggesting emerging areas of interest crucial for maintaining ecosystem balance and preventing biodiversity loss. Sustainable logging practices and salvage harvesting were each used in two publications, reflecting limited research into methods balancing economic activities with ecological sustainability. Regeneration on dead wood and propagule addition were the least studied practices, each with only one publication, indicating potential gaps in understanding and applying these specific techniques.

Overall, the data reveals a substantial emphasis on planting/natural succession/nucleation, underscoring their perceived effectiveness in restoration practices. Agroforestry also receives significant attention, reflecting its dual benefits for productivity and ecological restoration. However, the relatively lower number of publications on other practices like herbicide treatment, fire management, and thinning suggests these methods, while important, are either more specialised or require further research to optimise their application. The limited focus on practices like regeneration on dead wood and propagule addition highlights areas where further investigation could enhance restoration efforts. This distribution underscores the need for a balanced research approach, addressing both well-studied and underrepresented practices, to develop comprehensive and effective forest rehabilitation and restoration strategies.

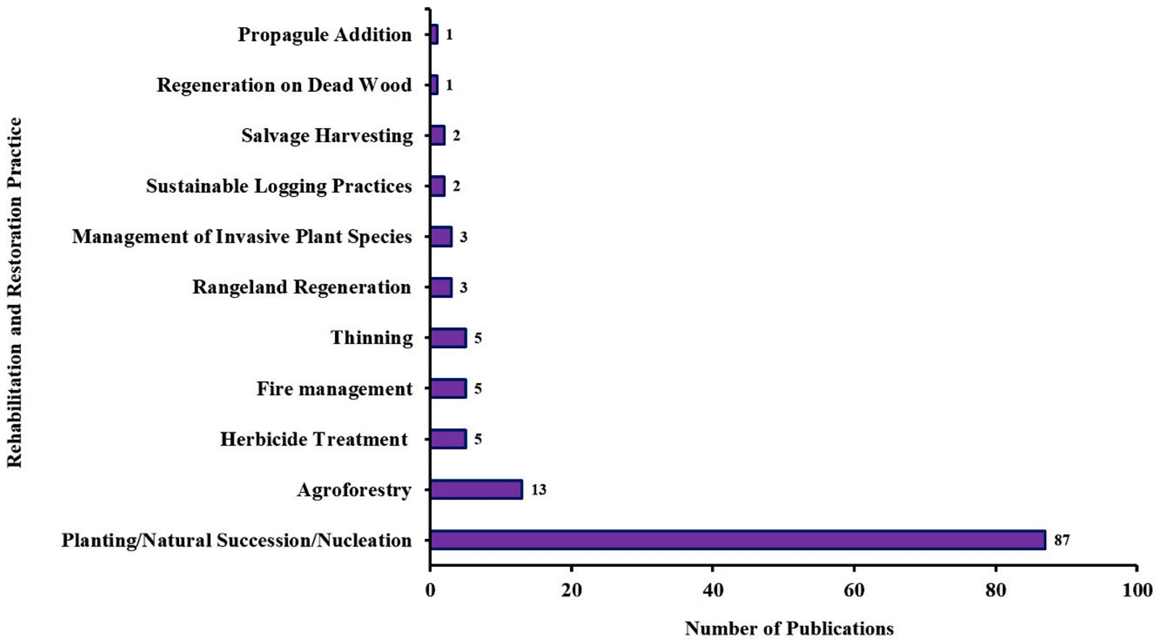

Figure 2.7. The number of publications for each rehabilitation and restoration practice. Publications with multiple rehabilitation and restoration practices meant all those practices were included in the count each time.

2.3.7 Remote sensing

This study analysed the distribution of the 11 publications that used various remote sensing tools, revealing distinct preferences in research focus (Figure 2.8). Landsat emerged as the most frequently used data source, with seven publications, highlighting its widespread application in forest rehabilitation and restoration studies due to its long-term data availability and detailed imagery. The Moderate Resolution Imaging Spectroradiometer (MODIS) was employed in two publications. Other tools like Google Earth, the Tropical Rainfall Measuring Mission (TRMM), Formosat-2, and the Shuttle Radar Topography Mission (SRTM) were each used in one publication. This distribution suggests that while Landsat remains a cornerstone in remote sensing for forest studies, there is growing interest in exploring the capabilities of various other tools to enhance the understanding and management of forest ecosystems.

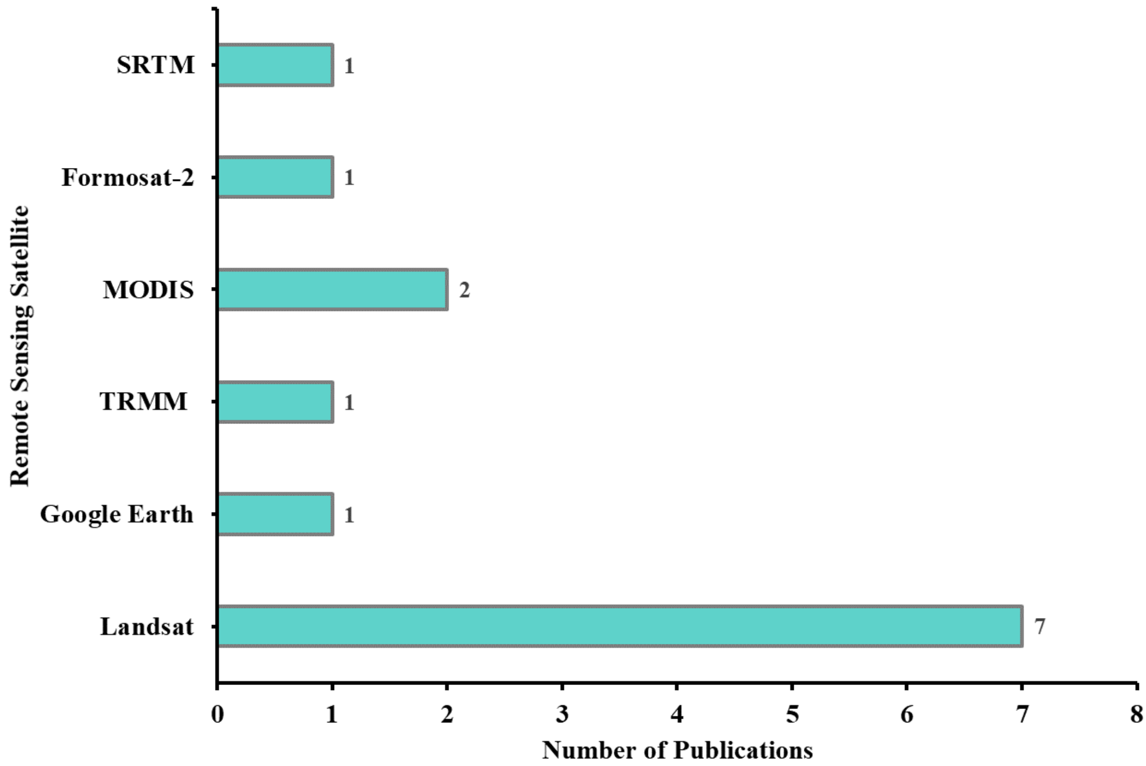

Figure 2.8. The number of publications for each remote sensing satellite. Publications with multiple remote sensing satellites meant all those satellites were included in the count each time.

2.3.8 Funding

The analysis of funding bodies associated with publications on forest rehabilitation showed a diverse range of contributors. While government funding was the most prevalent, with six publications acknowledging governmental support, various other organisations and entities also made notable contributions. The Asian Development Bank (ADB), the Mitsubishi Corporation, and the Science and Technology Research Partnership for Sustainable Development (SATREPS) were among those mentioned, each funding two publications. Other funding bodies, such as the Overseas Economic Cooperation Fund (OECF), Alcoa of Australia Limited, the Centre for International Forestry Research (CIFOR)/Japan, the Forestry Research Institute of Ghana (FORIG), the International Tropical Timber Organisation (ITTO), the National Natural Science Foundation of China, the Kamprad Family Foundation, the Australian Centre for International Agricultural Research (ACIAR), and Bosques Amazónicos BAM, were associated with one publication each.

2.3.9 Policy recommendations

The analysis of policy recommendations for forest rehabilitation initiatives reveals several key themes emphasised in the reviewed publications (Table 2.2). Firstly, there is a strong emphasis on the importance of community participation and engagement at various levels of forest rehabilitation projects (Etongo *et al.*, 2021). The authors argued that involving local communities enhances project effectiveness and ensures equitable distribution of benefits, contributing to project sustainability (Blay *et al.*, 2008). Additionally, transparency in decision-making processes is advocated for, with procedures promoting transparency and participation highlighted as beneficial (Apan, 1996a). Efficient fire control emerged as another critical aspect, underscoring the necessity of proactive fire prevention measures to accelerate forest rehabilitation efforts (Zhuang, 1997). Government support is also deemed crucial, with governments urged to back international forestry initiatives and promote rehabilitation aligned with rural development objectives (de Jong, 2010). Furthermore, the potential of carbon market funds to support rainforest rehabilitation and carbon protection efforts is emphasised, suggesting a significant role for these funds in future agreements such as Reducing emissions from deforestation and forest degradation in developing countries (REDD+) (Ansell *et al.*, 2011). Concerns regarding distributive justice in forest policies are raised, emphasising the need for equitable distribution of benefits to communities (Royer *et al.*, 2018). Managing diverse interest positions is vital to incentivise stakeholder participation and promote engagement in forest rehabilitation initiatives (Park, 2018).

Additionally, effective forest rehabilitation and restoration also hinge on addressing system-level issues and setting clear goals (Bateman *et al.*, 2012; Wilkinson *et al.*, 2005). The continuous revaluation and mitigation of system-level issues are crucial for the success of ecological rehabilitation, as they allow for dynamic adaptation to emerging challenges and opportunities. As such, establishing clear and specific goals from the outset is paramount. This strategic clarity prevents unintended consequences and provides a framework for adaptive management, ensuring that rehabilitation and restoration activities remain aligned with broader environmental and social objectives. By integrating these components, restoration efforts can be more effectively tailored to achieve long-term ecological and human benefits. Overall, these policy recommendations provide valuable insights into the multifaceted approaches advocated in the forest rehabilitation literature.

Table 2.2. Summary of policy recommendations for forest rehabilitation initiatives, highlighting key strategies and approaches recommended in the reviewed publications.

Policy Recommendation	**Description**	**Reference**
Community participation	Suggests that greater involvement of local communities is essential for successful forest rehabilitation, indicating that their participation not only enhances project effectiveness but also ensures equitable distribution of benefits.	Blay *et al.* (2008)
Community engagement across levels	Advocates for the involvement of local communities at all stages of forest rehabilitation, from planning to monitoring, to ensure sustainability and capacity building across different levels, acknowledging the multifaceted influences on community engagement.	Etongo *et al.* (2021)
Transparency	Advocates for the use of procedures that promote transparency and participation in decision-making processes.	Apan (1996a)
Efficient fire control	Stresses the importance of efficiently controlling fires to accelerate forest rehabilitation efforts in degraded areas, underscoring the critical role of fire prevention in ecosystem restoration.	Zhuang (1997)
Government support	Highlights the role of governments in supporting international forestry initiatives and promoting forest rehabilitation aligned with rural development objectives, emphasising the significance of governmental backing for such projects.	de Jong (2010)
Carbon market funds	Proposes that rainforest rehabilitation should play a significant role in future agreements like REDD+ and advocates for the utilisation of carbon market funds to support carbon protection and enhancement efforts.	Ansell *et al.* (2011)
Managing interest positions	Acknowledges the importance of managing diverse interests to incentivise participation from various stakeholders, emphasising the need for strategies to motivate engagement in forest restoration initiatives.	Park (2018)
Distributive justice	Raises concerns about distributive justice in forest policies, suggesting that existing policies often fail to devolve new rights or benefits to communities, highlighting the need for equitable distribution of benefits.	Royer *et al.* (2018)
Revaluation of system-level issues	Mentions that successful ecological rehabilitation and restoration hinge on the continuous revaluation and mitigation of system-level issues.	Wilkinson *et al.* (2005)
Clear and specific goals	Highlights that effective rehabilitation and restoration go beyond just achieving stated goals. Setting clear and specific goals upfront is essential to avoid unintended consequences and ensure adaptability in managing the restoration process.	Bateman *et al.* (2012)

2.3.10 Avenues for future research

The results in Table 2.3 highlight various avenues for future research to advance forest rehabilitation efforts. Firstly, there is a need for further exploration of digital analysis techniques for remote sensing imagery to enhance the rapid assessment of forest conditions and the delineation of damage classes (Lewis *et al.*, 2016). Additionally, future research should focus on optimising the use of indigenous species in rehabilitation projects while also considering the role of exotic species in specific ecological contexts (Lamb and Tomlinson, 1994). Addressing the constraints related to the availability and quality of datasets for digital analysis is crucial for adopting such approaches (Apan, 1996b). Moreover, there is a call for in-depth investigations into plantation management strategies to maximise the effectiveness of nurse-crop practices and mitigate post-logging environmental impacts (Fimbel and Fimbel, 1996). Wildlife conservation efforts should be further studied to better understand their role in facilitating natural forest succession processes (Zhuang, 1997). Cultural practices that enhance nutrient availability on degraded sites warrant attention to improve seedling establishment and growth (Gardiner *et al.*, 2001). Evaluating the long-term impact of forest restoration projects on ecosystem functions and services is essential for informing future rehabilitation efforts (Raymond *et al.*, 2020).

Additionally, assessing the coupling strength between land cover changes and atmospheric processes can provide insights into the broader environmental implications of rehabilitation interventions (Haghtalab *et al.*, 2022). Research focusing on the provision of straightforward, evidence-based methods for selecting native tree species will significantly support and enhance local restoration initiatives (Lu *et al.*, 2017). By offering clear guidelines grounded in scientific research, these methods empower communities and practitioners to make informed decisions that align with ecological best practices. This approach not only improves the success rates of forest rehabilitation and restoration projects but also fosters greater engagement and confidence among local stakeholders, ensuring that restoration efforts are both effective and sustainable in the long term. Future research should explore strategies for enriching biodiversity by introducing multipurpose tree species, contributing to ecosystem resilience and sustainability (Hemida *et al.*, 2022). Lastly, utilising a land suitability approach to target priority areas for rehabilitation and restoration significantly enhances both ecosystem biodiversity and human well-being, ensuring that resources are directed to the most impactful areas (Rajaonarivelo and Williams, 2022). These avenues for future research underscore the interdisciplinary nature of forest rehabilitation and the need for comprehensive approaches to address current challenges and uncertainties in the field.

Table 2.3. Summary of recommendations for future research in forest rehabilitation initiatives from the reviewed publications.

Recommendation	Description	Reference
Digital analysis of remote sensing imagery	More research is required in the provision of rapid assessments of forest conditions using satellite imagery.	Lewis *et al.* (2016)
Utilisation of indigenous species	Research towards optimising the utilisation of indigenous species while acknowledging that specific exotic species will invariably contribute to ecological or economic contexts.	Lamb and Tomlinson (1994)
Availability of reliable datasets	Research aimed at addressing the constraints related to the availability and quality of datasets for digital analysis is crucial for the widespread adoption of forest rehabilitation.	Apan (1996b)
Identifying suitable areas	Research towards utilising a land suitability approach to target priority areas for forest rehabilitation and restoration.	Rajaonarivelo and Williams (2022)
Plantation management strategies	Further investigation is needed in plantation management to optimise the potential for rehabilitating and restoring native forests through the implementation of nurse-crop techniques.	Fimbel and Fimbel (1996)
Wildlife conservation	Extending the monitoring period for wildlife conservation efforts to better understand their role in facilitating natural forest succession processes.	Zhuang (1997)
Cultural practices for nutrient enhancement	Investigating approaches to improve nutrient availability for seedling establishment and growth on degraded agricultural sites through cultural practices.	Gardiner *et al.* (2001)
Evaluation of forest restoration projects	Investigating the long-term impact of forest restoration projects on ecosystem functions and services is essential for informing future rehabilitation efforts.	Raymond *et al.* (2020)
Assessment of land cover changes	Research aimed at analysing the strength of the connection between alterations in land cover and atmospheric processes offers valuable insights into the wider environmental consequences of rehabilitation efforts.	Haghtalab *et al.* (2022)
Evidence-based methods for native tree species selection	Research on straightforward, evidence-based methods for selecting native tree species will support and enhance local rehabilitation and restoration initiatives.	Lu *et al.* (2017)
Enriching biodiversity	Further investigation is warranted into introducing multipurpose tree species to enhance biodiversity.	Hemida *et al.* (2022)

Overall, the analysis of forest rehabilitation and restoration literature underscores the multidimensional nature of research in this field, highlighting the need for continued interdisciplinary efforts to address emerging challenges such as forest degradation and advance sustainable practices globally.

2.4 Discussion

The analysis of the 117 publications that met the inclusion criteria unveils noteworthy insights into the trends and patterns observed in forest rehabilitation and restoration research, prompting a comprehensive discussion on the implications and future directions within the field.

2.4.1 Frequency and geographic analysis

The frequency analysis showed fluctuating trends in forest rehabilitation research outputs over time, as evidenced by the distribution of publications across different years in Figure 2. The observed peaks in recent years, particularly between 2019 and 2023, suggest a growing interest and focus on forest rehabilitation, possibly driven by emerging environmental concerns, technological advancements, or shifts in research priorities. This was also noted by Mansourian and Vallauri (2014), who found that initiatives such as the United States Forest Service's Collaborative Forest Landscape Restoration Programme (CFLRP), the guidelines set forth by the ITTO, and the directives outlined by the Convention on Biological Diversity (CBD) have stimulated interest in forest landscape restoration. These initiatives underscore the importance of ecological, economic, and social sustainability, as well as the role of forest rehabilitation and restoration in mitigating climate change and addressing challenges like food security and disaster mitigation.

Additionally, initiatives aimed at developing nations, such as REDD+, strive to enhance carbon stocks and reduce deforestation while also seeking to benefit local communities (Alusiola *et al.*, 2021; Corbera and Schroeder, 2011). Moreover, it is noteworthy that the establishment of this initiative aimed to make significant contributions to mitigating climate change at a relatively low cost, with anticipated benefits extending not only to developing nations but also to developed countries (Morita and Matsumoto, 2023). REDD+ operates by incentivising countries and communities to reduce deforestation and forest degradation through financial rewards tied to carbon sequestration and conservation efforts (Bluffstone *et al.*, 2013). Since 2008, the total approved funding for REDD+ activities has amounted to USD 2.4 billion, with USD 260 million approved in 2018 alone (Alusiola *et al.*, 2021). Given these sums of money, multiple studies, such as Guizar-Coutiño *et al.* (2022), Aryal *et al.* (2024), and Malan *et al.* (2024), have investigated the effectiveness of this initiative. Both Guizar-Coutiño *et al.* (2022)

and Malan *et al.* (2024) found REDD+ to have reduced deforestation, while Aryal *et al.* (2024) pointed out issues regarding the quantification of the effectiveness of this initiative, as some sources in the literature argue that REDD+ has a minimal impact on net forest loss. As such, more research is needed to evaluate further the effectiveness of REDD+ and other similar initiatives in reducing deforestation and instilling interest in forest rehabilitation and restoration projects.

Moreover, the frequency of research publications on forest restoration and rehabilitation has also been significantly influenced by the growing impacts of climate change and the increasing focus on international climate agreements such as the Paris Agreement aimed at mitigating these effects (Maleknia and Salehi, 2024; Psistaki *et al.*, 2024). In recent years, climate change has led to more frequent and severe environmental disturbances, including prolonged droughts, wildfires, and biodiversity loss, which have highlighted the urgent need for forest restoration and rehabilitation efforts to enhance ecosystem resilience (Girona *et al.*, 2023).

As such, the lower publication outputs in earlier years probably reflect lesser attention to this field or limitations in data availability and research methodologies during those periods. As such, these findings underscore the dynamic nature of forest rehabilitation and restoration research and emphasise the need for continued exploration and innovation to address contemporary environmental challenges effectively.

However, the observed increase in publications should be normalised to confirm whether this trend truly reflects a rising interest in forest rehabilitation and restoration, rather than simply a general growth in publication accessibility or overall research output. Normalising the data would entail comparing the growth rate of publications on r forest rehabilitation and restoration with the general rise in publication numbers across related fields over the same period. This approach would clarify whether the trend observed is genuinely specific to heightened interest in these topics or merely indicative of broader publishing patterns. Such normalisation is essential for accurately interpreting the research landscape and tracking the field's development, ensuring that the observed growth indeed signifies a focused increase in scientific attention to these technologies.

The reviewed publications were also analysed based on the locations where they were conducted. This underscores significant regional disparities in forest rehabilitation and restoration research, with Asia and South American countries being more prominent, with countries like China, Indonesia, and Brazil leading in reviewed publications. North America was also well represented, primarily through publications conducted in the USA and Canada. In contrast, Africa exhibited lower research intensity, while Europe displayed moderate activity. These findings are similar to those from Matiza *et al.* (2023), who also found Africa lagging behind other continents in forestry research. As such, these findings accentuate the importance of addressing regional imbalances and fostering broader global research efforts in forest rehabilitation. Additionally, the distribution of publications based on scale indicates a predominant focus on localised efforts, with most studies conducted at the subnational level. This highlights the need to expand the research scope to encompass national and continental scales, facilitating a more comprehensive understanding of forest rehabilitation dynamics and contributing to more effective global conservation strategies.

2.4.2 Bibliometric analysis

The network analysis conducted on keywords extracted from the titles and abstracts of the 117 reviewed studies using VOSviewer revealed distinct thematic clusters, shedding light on the prevailing topics in forest rehabilitation research. Terms such as "restoration," "soil," "plantation," "community," and "treatment" signify the diverse facets explored within the literature, ranging from soil properties and forest management practices to community engagement and perceptions. The prevalence of soil properties in the reviewed literature stems from the fact that soils play a crucial role in ecosystem functioning and are crucial for the effectiveness of forest ecosystem restoration efforts (Gatica-Saavedra *et al.*, 2023). However, vegetation restoration strategies frequently overlook soils, with studies predominantly concentrating on recovering vegetation composition and structure (Callaham Jr *et al.*, 2008; Farrell *et al.*, 2020; Gatica-Saavedra *et al.*, 2023). Therefore, future studies must prioritise incorporating soil properties into forest rehabilitation and restoration initiatives.

The reviewed publications also revealed the importance of community engagement and perceptions in forest rehabilitation initiatives. That is because local communities can play a crucial role in shaping the success and sustainability of such initiatives through their active participation, knowledge, and attitudes towards forest management practices. Additionally, the findings highlighted the need for a deeper understanding of the diverse perspectives and perceptions held by various stakeholders, including residents, policymakers, and conservation practitioners, towards forest rehabilitation and restoration projects. Understanding and addressing these perceptions can foster stronger partnerships, enhance project acceptance and support, and ultimately contribute to the long-term success of forest rehabilitation endeavours. Sattayapanich *et al.* (2022) recommended that to foster community engagement throughout the development stages of forest management initiatives, it is essential to improve community members perceived ecological values. Moreover, educating community members about the importance of forests can encourage their involvement in the monitoring phase.

2.4.3 Forest ecosystem types

The analysis of the 117 publications on forest rehabilitation reveals a notable focus on tropical forests, with 71 out of 117 publications centred on this ecosystem type. This emphasis is likely driven by the high biodiversity and ecological significance of tropical forests (Maurent *et al.*, 2023). Pillay *et al.* (2022) further corroborated this notion, revealing that tropical forests serve as habitats for 62% of the global terrestrial vertebrate species, exceeding the count found in any other terrestrial biome on Earth by more than twofold. Temperate and dryland forests also received considerable attention, with 17 and 10 publications dedicated to them, respectively. This reflected their prevalence and the intensive management they often undergo.

However, certain forest ecosystems, such as cloud forests and peat-swamp forests, received minimal attention, with only one to four publications each. This underscores the need for broader research efforts to encompass a more diverse range of forest types, ensuring a comprehensive understanding of forest rehabilitation dynamics across different ecosystems. Given that all forests face threats, it is crucial to prioritise rehabilitation and protection efforts for all forest types (Randhir and Erol, 2013).

2.4.4 Rehabilitation and restoration practice

The 117 reviewed publications showed a preference for reforestation/natural succession/nucleation, with 87 publications focusing on this method. It is noteworthy that while reforestation using indigenous trees is a widely employed practice, two of the studies included in this category utilised alien species, indicating potential risks associated with this approach. The trend towards utilising indigenous trees in reforestation initiatives reflects a transition from prioritising timber production, which prevailed from 1949 to the late 1970s, to addressing environmental concerns and meeting the growing demand for other ecological benefits from forest ecosystems such as carbon sequestration and catchment protection (Wang and Meng, 2018). Additionally, Sithole *et al.* (2018) posited that reforesting with diverse indigenous tree species helps counteract biodiversity decline by expanding habitat diversity and fostering a broader array and greater abundance of plant and animal species.

Agroforestry emerged as another significant focus, with 13 publications discussing its application in forest rehabilitation and restoration. This suggests a growing interest in integrating agricultural and forestry practices to achieve both ecological and socio-economic objectives in degraded forest areas. Developing countries generally employ agroforestry as a strategy to alleviate the impacts of climate change (Tega and Bojago, 2023). That is because recent evidence suggests that forest and grassland cover types mitigate net greenhouse gas emissions from agricultural soils; as such, agroforestry systems have been shown to enhance aboveground and soil carbon stocks, serving dual roles in climate change adaptation and mitigation (Getnet *et al.*, 2023; Mngadi *et al.*, 2021).

However, less attention was given to practices such as sustainable logging, herbicide frill treatment, and salvage harvesting, each represented by only one to five publications. Rangeland regeneration, while addressed in three publications, also received relatively limited focus. That is despite evidence demonstrating positive outcomes from rangeland regeneration, as indicated in studies by Leverkus *et al.* (2020), DeLuca and Hatten (2024), and Bousfield *et al.* (2020). Moreover, the review of 117 publications highlighted the minimal coverage of herbicide treatment and fire management, with only five publications mentioning these practices. However, their limited appearance hides their critical roles in forest restoration and rehabilitation. Herbicide treatment serves as a crucial tool for controlling invasive species and managing competitive vegetation, thereby promoting biodiversity and ecosystem health (Tataridas *et al.*, 2022). Similarly, fire management, through controlled burns, helps maintain ecological balance, prevent wildfires, and foster habitat diversity (Jacoby, 2023). Despite their underrepresentation in the literature, these practices offer targeted solutions to ecological challenges, emphasising their significance in achieving restoration and rehabilitation objectives.

As such, these findings underscore the predominant emphasis on reforestation/natural succession/nucleation and agroforestry in the reviewed literature, suggesting a need for further exploration and evaluation of the mentioned forest rehabilitation practices and alternative or complementary approaches to address the complex challenges of forest ecosystem rehabilitation and restoration. Complementary approaches to natural succession, nucleation, and agroforestry in forest restoration include Assisted Natural Regeneration (ANR), which supports natural vegetation growth, and enrichment planting, where diverse species are added to improve biodiversity and ecosystem structure (Oluwajuwon *et al.*, 2024). Other methods like silviculture systems and soil and hydrological restoration focus on sustainable forest management and improving soil and water systems (Meli *et al.*, 2024; Royo *et al.*, 2023). Integrated Landscape Approaches address broader ecological and social needs, combining forestry with agriculture and community needs to restore ecological integrity while enhancing human well-being (Bayala, 2024). Together, these approaches offer diverse, adaptable solutions to the complex challenges of forest rehabilitation and restoration.

2.4.5 Remote sensing applications

Among the reviewed publications, Lewis *et al.* (2016) recognised remote sensing as pivotal in forest monitoring and preventing additional forest degradation. However, there was limited utilisation of remote sensing tools in the reviewed publications, with only 11 out of 117 studies employing the technology. Landsat emerged as the most used data source among these 11 publications, featuring in seven publications, while MODIS was used in two publications and Google Earth, TRMM, Formosat-2, and SRTM were each employed in one publication. This indicates potential areas for exploring and expanding remote sensing applications in forest rehabilitation and restoration studies.

The distribution of remote sensing platform usage among the reviewed publications likely reflects accessibility, data availability, and spatial resolution requirements in forest rehabilitation and restoration studies. Landsat is the most frequently used data source due to its long time series, free access, and moderate spatial resolution, which is suitable for monitoring forest cover changes and degradation over time. The free access to Landsat is a result of the decision by the US government to make Landsat satellite imagery freely available online in 2008, leading to a surge in scientific and practical uses (Zhu *et al.*, 2019). Additionally, the global data archive of Landsat now spans over 50 years, constituting a comprehensive record in remote sensing (Crawford *et al.*, 2023). MODIS, with its higher temporal resolution but coarser spatial detail, is often used for tracking broader vegetation trends and detecting seasonal changes, explaining its limited but specific application in forest monitoring studies (Gong *et al.*, 2024). TRMM and Formosat-2 serve more specialised functions, such as precipitation data and high-resolution imagery, often used in niche applications within forest restoration research (Chang *et al.*, 2009; Thanabalan *et al.*, 2023).

To enhance the effectiveness of forest rehabilitation and restoration research, it is recommended to further explore the capabilities of remote sensing technologies, particularly those with proven effectiveness and easy access, like Landsat. Further, Sentinel-1 and Sentinel-2 offer significant opportunities for forest monitoring, with Sentinel-2's Red Edge bands providing enhanced capability to detect vegetation health, stress, and growth phases, factors critical to evaluating forest recovery (Blickensdörfer *et al.*, 2024; Radeloff *et al.*, 2024). Sentinel platforms, part of the European Space Agency's Copernicus Programme, also provide freely accessible data with higher spatial and spectral resolutions than many other platforms, making them highly beneficial for detailed analysis in forest rehabilitation studies (Occhipinti *et al.*, 2024). Researchers could benefit from incorporating these tools into their methodologies to gain valuable insights into forest dynamics, landscape changes, and ecosystem health (Lewis *et al.*, 2019). Moreover, promoting user-friendly platforms like Google Earth could facilitate broader adoption among researchers, enabling easier visualisation and analysis of spatial data crucial for forest rehabilitation (Amani *et al.*, 2020).

Additionally, considering the potential of emerging technologies such as unmanned aerial vehicles (UAVs) and hyperspectral imaging, this could open new avenues for detailed and precise monitoring of forest ecosystems. Overall, integrating remote sensing techniques more comprehensively into forest rehabilitation studies could lead to more informed decision-making and more effective conservation and restoration efforts.

2.4.6 Funding and policy recommendations

Extracting funding information from the 117 reviewed publications proved to be a challenge, given that most publications did not mention the funding details for the forest rehabilitation projects their research was based on. The publications that did mention the funding details revealed a diverse array of contributors, with government funding being the most common. Various organisations and entities, such as the Asian Development Bank, Mitsubishi Corporation, SATREPS, and the Bosques Amazónicos BAM, also made contributions. The reason for governments being the most common funders is due to international agreements, such as the United Nations Framework Convention on Climate Change (UNFCCC) and the CBD, which mandate governments to engage in forest restoration initiatives to fulfil their obligations and achieve international targets (Muthee *et al.*, 2022).

Moreover, Mansourian *et al.* (2022) found that a comprehensive policy framework comprising plans for forest restoration, financial incentives, collaborative arrangements, tenure rights to forests and trees, and specific goods and services derived from them, alongside the involvement of specialised agencies, external stakeholders, local communities, and authorities, is one of the factors that facilitate the implementation of forest rehabilitation and restoration. As such, policy recommendations from the 117 reviewed publications were analysed. These publications emphasised several key themes, including community participation, transparency in decision-making processes, and government support for international forestry initiatives aligned with rural development objectives. Additionally, the potential role of carbon market funds in supporting rainforest rehabilitation efforts and concerns regarding distributive justice in forest policies were highlighted, emphasising the need for equitable distribution of benefits and effective management of diverse stakeholder interests to incentivise engagement in forest restoration initiatives.

2.4.7 Opportunities for future research

The analysis of avenues for future research in forest rehabilitation, as outlined in Table 3, underscores several critical areas for advancement in this field. These include exploring digital analysis techniques for remote sensing imagery to assess forest conditions and delineate damage classes, along with efforts to optimise the utilisation of indigenous species while considering the role of exotic species in specific ecological contexts. However, Fassnacht *et al.* (2024) noted that the integration of remote sensing into operational forest management and monitoring exhibits significant variability across different regions and applications, with some countries addressing this challenge through enhanced communication and collaboration among researchers, forest industry stakeholders, and regulators, including close coordination between remote sensing and forest science experts. This underscores the importance of enhanced collaboration among researchers, industry stakeholders, and regulators to overcome this challenge and ensure effective global forest monitoring and management practices.

Another crucial area for future research is addressing constraints related to dataset availability and quality for digital analysis. This will facilitate the broader adoption of forest rehabilitation approaches. Additionally, further investigation into plantation management strategies, wildlife conservation, cultural practices for nutrient enhancement, and the evaluation of the long-term impacts of restoration projects on ecosystem functions is imperative for informing future rehabilitation efforts. Moreover, evaluating the correlation between land cover changes and atmospheric processes within the context of forest rehabilitation can offer valuable insights into broader environmental implications. Additionally, integrating strategies to enhance biodiversity through the introduction of multipurpose tree species is imperative for bolstering ecosystem resilience and sustainability within forest rehabilitation efforts (Iiyama *et al.*, 2018).

However, the most crucial avenue for research lies in the utilisation of a land suitability approach, integrating ecological principles with socio-economic considerations, to strategically target priority areas for forest rehabilitation and restoration (Bateman *et al.*, 2012). In the reviewed publications, only two publications from 117 utilised this approach. Suitability mapping allows researchers to identify areas where restoration efforts are most likely to succeed in enhancing both ecosystem biodiversity and human well-being (Schulz and Schröder, 2017). This approach involves assessing various factors such as soil quality, topography, hydrology, and land use history, as well as considering the needs and preferences of local communities (Dornik *et al.*, 2022). By aligning restoration efforts with areas that have the highest potential for ecological and societal benefits, researchers can maximise the effectiveness and efficiency of restoration projects, ultimately contributing to the long-term sustainability of forest ecosystems and the well-being of surrounding communities.

2.5 Conclusion

This systematic review of 117 publications on forest rehabilitation and restoration provided valuable insights into the trends, patterns, and challenges within this field. The frequency analysis revealed fluctuating trends over time, with a growing interest in forest rehabilitation and restoration, particularly between 2019 and 2023, likely driven by emerging environmental concerns and global initiatives such as the Collaborative Forest Landscape Restoration Programme (CFLRP) and REDD+. However, significant regional disparities in research outputs underscore the need for broader global research efforts. As such, policymakers should prioritise funding for forest rehabilitation and restoration efforts in underrepresented regions such as, Africa, to address global disparities in research and implementation.

The predominant focus on tropical forests highlighted their ecological significance, while the minimal attention given to other forest ecosystems, such as cloud forests and peat-swamp forests, emphasised the necessity for more inclusive research efforts. The preference for reforestation/natural succession/nucleation and agroforestry practices indicated the need for further exploration and evaluation of alternative or complementary approaches. Moreover, the limited use of remote sensing and the land suitability approach suggested significant potential for their expanded application in forest monitoring and targeted rehabilitation efforts.

This review also noted that funding for forest rehabilitation and restoration efforts is primarily driven by governmental support, which underscored the pivotal role that governments play in initiating and sustaining these efforts. This support is often a result of international agreements and commitments, which mandate countries to engage in activities that promote forest conservation and restoration. Comprehensive policy frameworks at both national and international levels are crucial in this context, as they provide the necessary guidelines, financial incentives, and regulatory support to ensure the effective implementation of rehabilitation and restoration projects. As such, this review highlights that without such robust support structures, the scale and impact of forest restoration projects would be significantly limited, emphasising the need for continued and enhanced governmental commitment and international cooperation to achieve meaningful progress in forest rehabilitation and restoration.

Therefore, future research should focus on exploring digital analysis techniques for remote sensing imagery, suitability mapping, optimising species selection, addressing dataset limitations, and evaluating the long-term impacts of restoration efforts on ecosystem functions. Emphasising interdisciplinary approaches and enhancing collaboration among researchers, industry stakeholders, and policymakers is crucial for addressing the complex challenges and uncertainties in forest rehabilitation and restoration. Ultimately, this review underscores the multifaceted nature of forest rehabilitation and restoration research, emphasising the need for comprehensive, globally coordinated efforts to advance sustainable practices and effectively address forest degradation. The success and sustainability of forest rehabilitation and restoration initiatives worldwide can be enhanced by integrating technological advancements, policy support, and community engagement.

2.6 Summary

This chapter provided an extensive analysis of trends and practices in forest rehabilitation and restoration up to 2023. It emphasised the vital role of forests in providing ecosystem services and the urgent need for effective forest management to combat deforestation. Using a systematic review methodology, 117 publications were analysed, noting increased research activity in recent years, particularly in Asia and South America. Key rehabilitation and restoration practices identified included reforestation/natural succession/nucleation, agroforestry, herbicide treatment, and fire management, focusing predominantly on tropical forests. This chapter further highlighted the importance of community participation and government support in successful rehabilitation efforts. It underscored the need to address regional disparities and underrepresented ecosystems, such as cloud and peat-swamp forests, to develop comprehensive and effective strategies for global forest rehabilitation and restoration. Ultimately, the chapter called for further research in remote sensing, suitability mapping, indigenous species utilisation, and comprehensive policy frameworks to enhance global forest rehabilitation and restoration initiatives.

3. CHAPTER THREE: THE USE OF MODELS AND REMOTE SENSING TO MAP AREAS SUITABLE FOR FOREST VEGETATION: A SYSTEMATIC REVIEW

This chapter is based on:

Buthelezi, M. N. M., Lottering, R. T., Peerbhay, K. Y., & Mutanga, O. (2024). The use of suitability models and remote sensing to map forest suitability: a systematic review. *Southern Forests: A Journal of Forest Science*, 1–16. https://doi.org/10.2989/20702620.2024.2373749

Abstract

The rapid decline of vegetated landscapes jeopardises vital ecosystem services underpinning climate change mitigation efforts. Restoring and repurposing these landscapes presents a powerful opportunity to recover lost services and strengthen the fight against climate change. This study undertook a comprehensive systematic review of the scientific literature, focusing on suitability models and remote sensing sensors used to identify areas suitable for forest vegetation. An exhaustive search and analysis of publications across the globe made over a 15-year period from 2008 to 2022 across three major databases (Scopus, ScienceDirect, and Web of Science) yielded 80 relevant publications. This analysis revealed a significant upward trend in research output, particularly since 2020. This surge reflects the increasing urgency of global landscape restoration initiatives. Additionally, the analysis of the reviewed articles revealed a rising preference for medium- to high-resolution remote sensing data, with Landsat emerging as the dominant sensor for forest suitability assessments. Notably, Maximum Entropy (MaxEnt) emerged as the most widely used model, followed by the increasingly popular Random Forest (RF). However, a concerning geographical disparity in research was identified. Publications were concentrated in the Americas and Asia, while developing nations showed a significant research gap. This discrepancy highlights the critical need for increased research efforts in developing countries to equip them with the robust suitability models and advanced sensor technologies necessary for effective and targeted forest rehabilitation and restoration initiatives. Investing in research capacity building within developing nations holds immense potential to accelerate global landscape restoration efforts.

Keywords: suitability models, remote sensing, machine learning, forestry, ecosystem services

3.1 Introduction

The geographical distribution of forest species is primarily influenced by a combination of climatic factors and soil properties (Zuquim *et al.*, 2020). However, climate change has accelerated the creation of unsuitable climatic environments, leading to increased forest degradation and reduced species diversity (Mothes *et al.*, 2020). Climate change-induced novel stresses, such as increased incidence of diseases and the encroachment of invasive pests, are confronting forests with unprecedented challenges (Trumbore *et al.*, 2015). Collectively, these factors threaten the overall health and vitality of forest ecosystems. Consequently, the literature anticipates that climate change will significantly impact the abundance of forests and rapidly shift the areas suitable for these ecosystems (del Río *et al.*, 2021; Fyllas *et al.*, 2022; Harrison, 2021). Moreover, with the continued spread of urban expansion worldwide, over 80% of natural habitats, including forests, have already been lost (Ren *et al.*, 2023).

In South Africa, over 60% of the population resides in urban areas (Rogerson *et al.*, 2014). The surge in urban populations has led to the notion that the level of urbanisation within South Africa has become unmanageable and excessively rapid. As a result, substantial challenges have arisen, including unlawful land encroachments and the rapid growth of informal settlements (Nassar and Elsayed, 2018; Turok and Borel-Saladin, 2014). Unlawful land encroachments and informal settlements have both contributed to the degradation of forests in the country (Bikis and Pandey, 2023).

The loss of forests and areas suitable for these ecosystems results in the loss of the natural ecosystem services they provide (Tew, 2019). This is because ecosystem services play a vital role by offering regulatory, provisioning, supportive, and cultural benefits that are essential for human survival and well-being (Deng *et al.*, 2023). Therefore, identifying the areas suitable for forests is essential for rehabilitating and restoring lost and degraded forests, facilitating the recovery of the ecosystem services they provide. Furthermore, locating areas suitable for forest vegetation is vital, given the extensive urban expansion and the growing impact of climate change.

In the literature, it is suitability models that have been extensively utilised for predicting areas suitable for forest vegetation and that are best fitted for reforestation (Casalegno *et al.*, 2011; Kaminski *et al.*, 2013; Karami *et al.*, 2022; Yousaf *et al.*, 2022). These models assume that environmental factors determine the distribution of vegetation and species’ responses are limited to environmental gradients (Austin, 2007). The use of suitability models has improved with the increase in remote sensing satellites and easy access driven by the free and open data policy (Zhu *et al.*, 2019). These satellites provide a vast number of geographic images, covering nearly the entire Earth's surface at all times (Zhang *et al.*, 2016). Thus, remote sensing aids in the building of accurate suitability models by providing a comprehensive and high-resolution view of the landscape, capturing a wide range of environmental variables such as vegetation cover, land use, topography, and climate patterns (Kellner *et al.*, 2019).

However, successful utilisation of the information provided by remote sensing satellites necessitates accurate and reliable image-analysis methods for extracting the desired information (Serpico *et al.*, 2012). This necessity has attracted the application of machine and deep learning approaches (Camps-Valls *et al.*, 2014). Some of the most popular and widely used machine and deep learning models include random forest (RF), extreme gradient boosting (XGBoost), support vector machines (SVM), and artificial neural networks (ANN). These models can extract comprehensive and high-dimensional information, thereby offering an efficient tool for high-precision classification and recognition across various fields (Han *et al.*, 2023). These approaches have also proven more efficient than handcrafted classification methods (Zhang *et al.*, 2016).

Given the need to rehabilitate and restore forests, it is essential to review the use of suitability models and remote sensing to determine areas suitable for forest vegetation. This review will help identify opportunities, gaps, and progress that has been made in mapping forest suitability using suitability models and remote sensing. Therefore, this review paper employed a systematic review methodology to review the literature incorporating forest suitability models and remote sensing, published between 2008 and 2022. This period includes all the years since the inception of the United Nations Programme on Reducing Emissions from Deforestation and Forest Degradation (UN-REDD), which later extended in 2013 to Reducing Emissions from Deforestation and Forest Degradation and the role of conservation, sustainable management of forests, and enhancement of forest carbon stocks in developing countries (REDD+).

This review assists in ascertaining preferred forest suitability models and remote sensing satellites. Investigating the locations where the studies were conducted will help determine the extent the extent to which developing countries are taking reforestation initiatives, given that they are also facing increased ecosystem service losses (Chen *et al.*, 2020). This review further investigates the origins and collaborations of the researchers, the methods used, and the scales at which the studies were conducted.

3.2 Methods and Materials

This review utilised a systematic review methodology similar to Kumar and Mutanga (2018), Wang and Yang (2019), and Masenyama *et al.* (2022). Moreover, it aligns with the Preferred Reporting Items for Systematic Review and Meta-Analysis (PRISMA) protocol, a 17-item checklist developed by Moher *et al.* (2015). Unlike alternative review methods, the systematic review approach is founded upon a replicable protocol, elevating its methodological precision and guaranteeing the strength and applicability of its results (Rao *et al.*, 2023). Therefore, this study employed a four-step procedure to achieve replicability and obtain robust findings. The four-step procedure was also adopted by Bangira *et al.* (2023).

3.2.1 Step 1: Literature search

A comprehensive search of peer-reviewed journal articles published in English was conducted in Scopus, ScienceDirect, and Web of Science. These three platforms were selected as the primary literature repositories due to their extensive coverage, academic reliability, and multidisciplinary range. They are among the most frequently used sources in scholarly research, providing access to high-quality, peer-reviewed literature across diverse fields essential to forest suitability modelling.

The search query used for retrieving articles in all three repositories involved a set of keywords ("forest" OR "reforestation" OR "afforestation") AND ("suitability modelling" OR "ecological niche modelling") AND "remote sensing", further filtered by publication years between 2008 and 2022, as well as the restriction to articles published in the English language. The inclusion of “reforestation” and “afforestation” helped remove irrelevant literature that does not address the suitability of forest vegetation. Additionally, the keyword "ecological niche modelling" was included because it can be used interchangeably with "suitability modelling". The Scopus search yielded 1296 results, while Science Direct provided 108 articles, and Web of Science produced 44 relevant articles.

3.2.2 *Step 2: Screening (inclusion and exclusion)*

Books and conference papers were excluded to ensure a focus on peer-reviewed, empirical studies. Books typically offer general overviews or theoretical perspectives rather than primary data and may not undergo the rigorous peer-review process typical of journal articles. Although conference papers can introduce new ideas, they often lack the depth, methodological rigour, and validation required for systematic analysis. This review prioritised high-quality, detailed studies that are crucial for accurate synthesis and reproducibility.

In total, there were 1448 articles retrieved from the combined searches in Scopus, ScienceDirect, and Web of Science. Thus, the screening of the 1448 journal articles followed the inclusion and exclusion criteria presented in Table 3.1. To remove duplicates, all the journal articles (n = 1448) were added to a list in Scopus, which automatically removed the duplicates (n = 64). After removing duplicates, the journal articles (n = 1384) were screened using their titles and abstracts, and the articles that did not fit the inclusion criteria were discarded (n = 1263). The articles (n = 121) that met the inclusion criteria were exported to EndNote 21 and underwent a revaluation through a meticulous examination of their full texts. This resulted in the exclusion of 41 articles, leaving 80 journal articles that satisfied the inclusion criteria. Thus, the 80 journal articles were used for data extraction.

However, the inclusion and exclusion criteria applied in this systematic review carry an inherent limitation. This is the exclusion of studies for which full text was inaccessible or restricted by paywalls. While necessary to maintain consistent access to data, this exclusion may introduce a bias favouring studies from developed countries, where research is more often available in open-access or widely accessible journals. As a result, this could lead to an overrepresentation of themes, methodologies, and findings from developed regions, potentially underrepresenting insights from developing countries where open-access barriers are more common.

This limitation impacts this systematic review in two ways. First, the geographical distribution of findings may be skewed, highlighting practices and challenges more pertinent to developed nations while potentially overlooking critical, context-specific issues in developing regions. Second, the thematic scope may be affected, as topics commonly covered in accessible journals may differ from those in restricted-access studies. Acknowledging this constraint helps clarify the study’s scope and underscores the importance of future research that includes a wider range of publications to provide a more balanced perspective on forest rehabilitation and restoration practices worldwide.

Table 3.1. The criteria followed for the inclusion and exclusion of publications to be used for review.

Inclusion criteria	Exclusion criteria
1. Publications addressing forest vegetation suitability.	1. Publications do not address the main areas of interest, which are forest vegetation suitability and remote sensing.
2. Publications utilising suitability models.	2. Full text is not available or locked behind a paywall.
3. Publications utilising remote sensing.	
4. Publications made between 2009 and 2022.	3. Conference papers, working papers, book chapters, review papers, and technical reports, are excluded.
5. Publications made in English.	

3.2.3 Step 3: Data extraction

This review identified 80 relevant articles from an initial pool of 1448 articles through a rigorous selection process aligned with the predefined inclusion and exclusion criteria outlined in Table 3.1. The full texts of these 80 journal articles were thoroughly studied to retrieve all the information required to meet the objectives of this review. These objectives included identifying the opportunities, gaps, and progress that has been made in the mapping of forest suitability using suitability models and remote sensing. The information extracted included the year of publication, author information (name, address, and affiliation), location(s) where the study was conducted, the scale at which the study was conducted, keywords from each publication, and remote sensing satellites used. Additionally, the publications were scanned for the machine and deep learning algorithms they used.

3.2.4 Step 4: Data analysis

The analysis of information extracted from publications in Step 3 followed the approaches used by Kumar and Mutanga (2018) and Bangira *et al.* (2023). First, the frequency analysis was conducted using the number of publications made per year. Second, a bibliometric analysis was performed, delving into author patterns by analysing intra-author connections. For visualisation of these author patterns, the review used VOSviewer version 1.6.16, a software tool commonly used for generating and presenting collaboration or network-based maps (Van Eck and

Waltman, 2013). Additionally, VOSviewer was used to create visual maps highlighting the most frequently used keywords in publications on mapping forest suitability and remote sensing. Third, a geographical analysis was conducted, considering the study's scale (global, continental, national, or sub-national) and the specific study areas' locations. However, it is important to note that if a study encompassed multiple countries, all those countries were included in the count. Finally, a detailed analysis of remote sensing sensors used in forest suitability was conducted by looking at the number of times each satellite was used and the years they were used. Furthermore, an analysis was conducted on the variables selected, methods utilised, and criteria used to evaluate their performance. Figure 3.1 presents the overall methodology of this review.

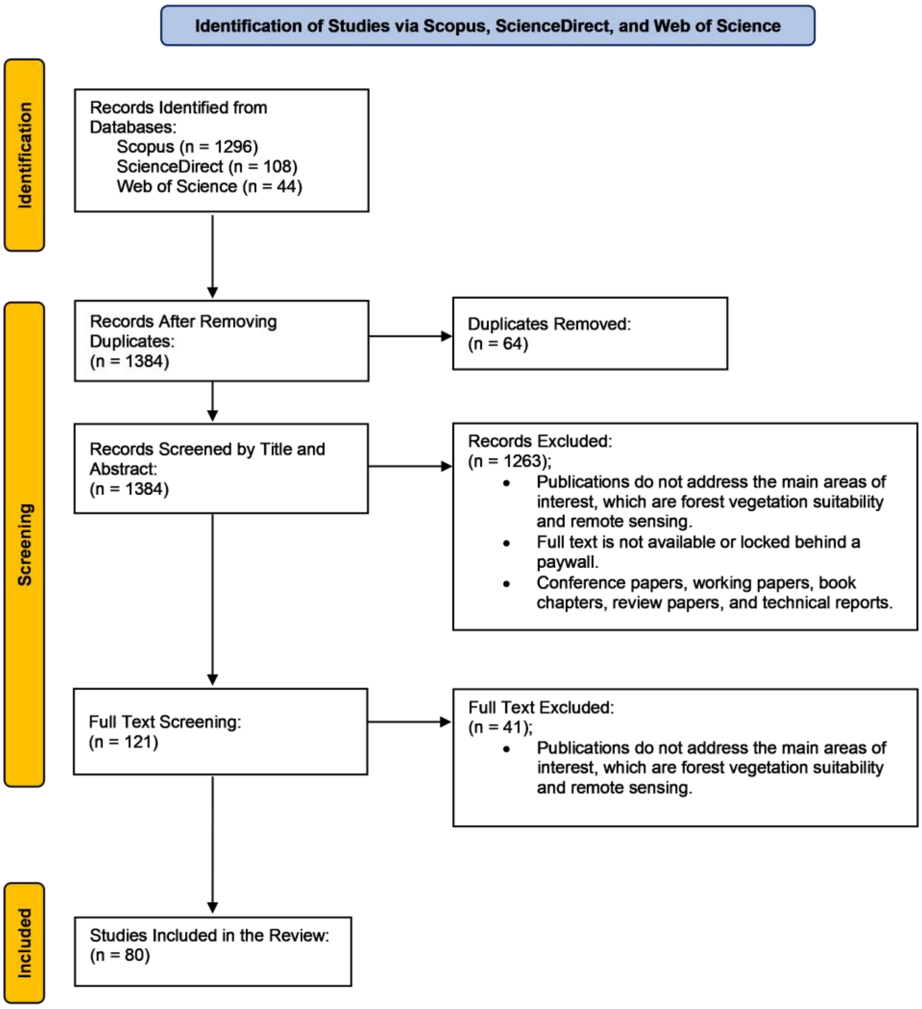

Figure 3.1. The PRISMA flow diagram for a systematic review outlining the database search process, the screening of publication records, and the number of full text articles that were included (Page *et al.*, 2021).

3.3 Results

3.3.1 Frequency analysis

Figure 3.2 presents the distribution of publications over the years. No articles published between 2008 and 2009 met the inclusion criteria. During the 2010 to 2012 period, the number of publications remained consistently low, with two publications each year. A slight increase was observed in 2013, with three publications, followed by a relatively stable period until 2016, with the number of publications ranging from one to three per year. Starting in 2017 onward, there was a noticeable upward trend in the number of publications. The year 2020 saw a significant increase, with 19 publications indicating heightened interest in the subject. This upward trend continued in 2021, with 15 publications, and peaked in 2022 with 22 publications. The increasing number of publications in recent years, particularly in 2020, 2021, and 2022, suggests a growing research interest in exploring the use of remote sensing and suitability models. This could be attributed to the evolving significance of the topic, advancements in technology, and the recognition of its practical applications.

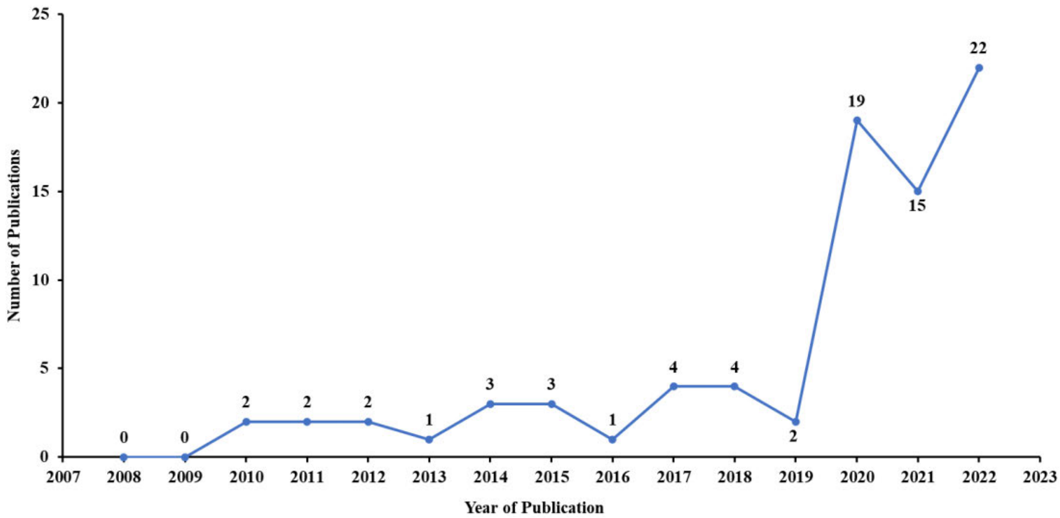

Figure 3.2. Temporal trend of publications utilising suitability models for reforestation and/or forest rehabilitation.

3.3.2 Bibliometric analysis

3.3.2.1 Co-authorship

The clusters in VOSviewer represent collaborations or connections between authors in one or more publications. Across the span of 80 publications, a total of 391 authors contributed to their creation. The cluster with the most links had 21 authors collaborating (Figure 3.3). The initial instances of collaboration were noted in 2020, as depicted by the blue cluster involving authors Clark J., August P.V., and Wang Y. Subsequent collaborations are represented by the green and yellow clusters, corresponding to 2021 and 2022, respectively. Wang Y. stands out with the highest contribution count of four publications, resulting in the author having the most connections within the graph.

3.3.2.2 Keyword analysis

Figure 3.4 presents the key terms extracted from the titles and abstracts of the screened journal articles used in this review. The five predominant key terms were "species" (229 occurrences), "forest" (86), "data" (63), "climate change" (62), and "suitable area" (39). The presence of "India" and "China" suggests that a substantial portion of the studies were conducted within these countries. In terms of modelling algorithms, the prevalence of "MaxEnt" (Maximum Entropy) indicates that it is the most frequently used method for general suitability modelling.

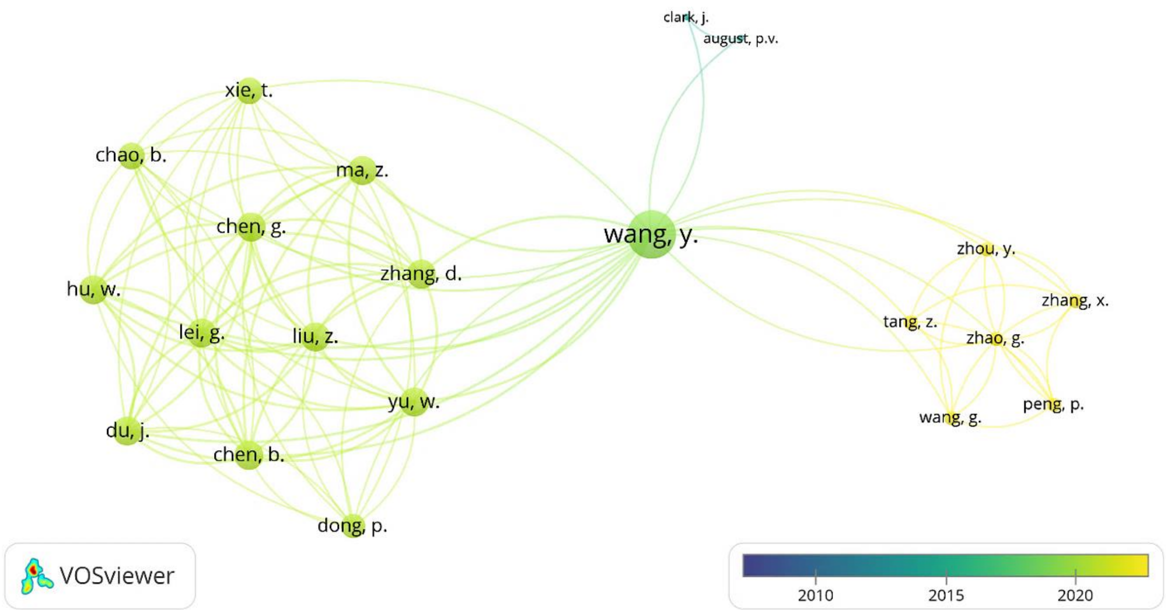

Figure 3.3. Cluster graph produced in VOSviewer showcasing the collaborative relationships among authors throughout the years.

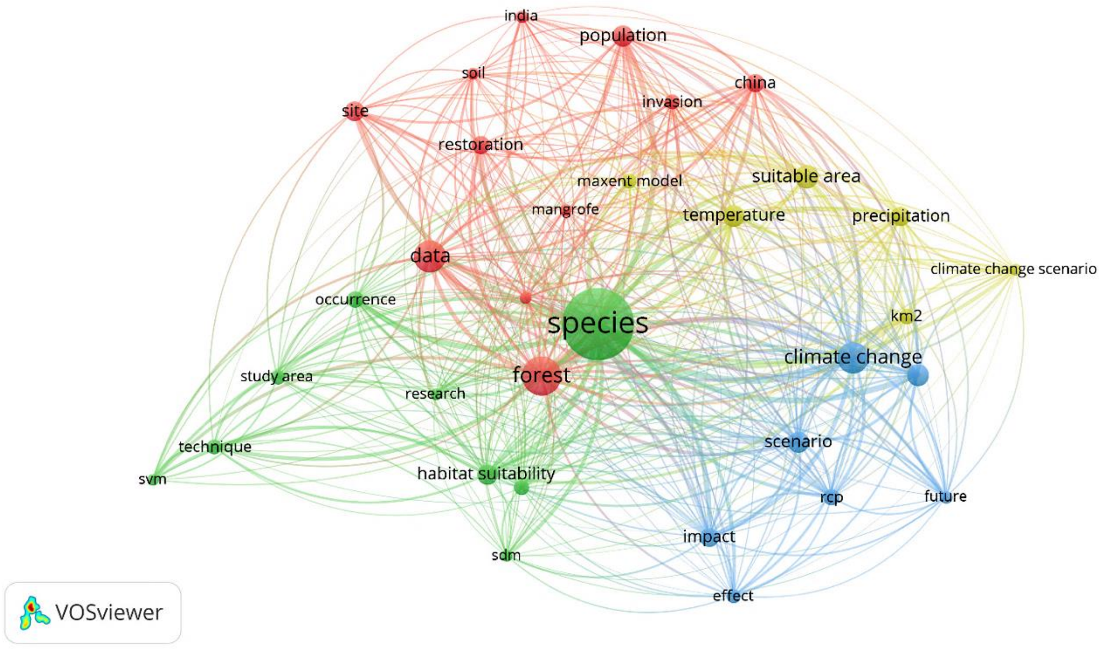

Figure 3.4. Cluster graph produced in VOSviewer showcasing the key terms appearing the most in the screened publications.

3.3.3 Geographic analysis

3.3.3.1 Study area locations

Figure 3.5 shows the distribution of the screened journal articles across various countries and provides insights into the geographic focus of the research. India and China stand out with twelve and ten occurrences, respectively, indicating that a significant number of studies were conducted in these nations. Other countries like Mexico, the United States of America (USA), and Pakistan also had notable representation. Several countries appeared in one or two studies, highlighting their engagement with the subject. Suitability modelling research spans a diverse range of nations across different continents, indicating the global significance of the topic. It is important to acknowledge that both Asia and the Americas have made substantial contributions, whereas Africa's representation appears relatively limited. Additionally, it is worth noting that two studies were omitted from the count: one conducted on a global scale and the other examining the entirety of Sub-Saharan Africa.

3.3.3.2 Study scales

The distribution of publications across different study scales in Table 3.2 provides valuable insights into the extent to which different studies focused their research. Notably, a single publication adopted a global perspective, indicating a comprehensive analysis spanning the entire planet. The absence of studies conducted on a continental scale suggests potential for broader regional investigations that encompass multiple countries within a continent. Furthermore, there were seven and eight studies conducted at sub-continental and national levels, respectively. These scales allow for more detailed analysis within specific regions or countries. Most notably, the sub-national scale garnered the highest number of publications at 61. This indicates a strong emphasis on localised research.

Table 3.2. The distribution of study scales at which the screened publications were conducted.

Study Scale	**Number of Publications**
Global	1
Continental	0
Sub-continental	7
National	11
Sub-national	61

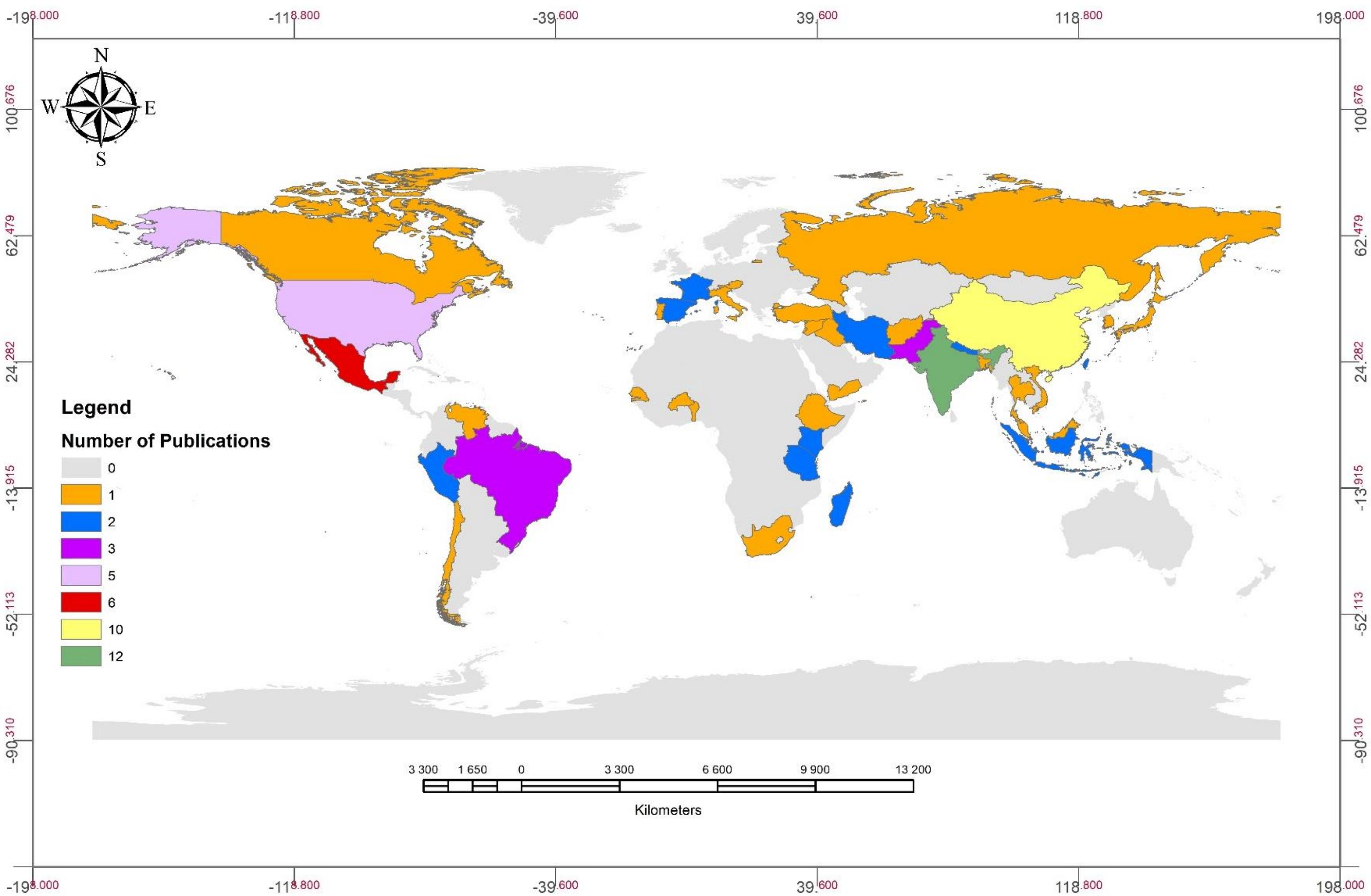

Figure 3.5. The breakdown of countries where the 80 publications utilising suitability models and remote sensing to map forest vegetation suitability. Publications that included several countries meant all those countries were included in the count each time.

3.3.4 Variables used in modelling forest suitability

One of the most crucial steps in suitability modelling is the selection and preparation of relevant input variables. Forest suitability modelling is primarily influenced by climatic, topographic, soil, land cover, and remote sensing-derived variables. The accuracy of suitability mapping outcomes heavily depends on the selection and quality of these variables. Table 3.3 presents all the data sources used by the screened publications to derive climatic, topographic, land cover, and soil variables. The remote sensing satellites used by the reviewed publications, along with the variables derived from the remote sensing data, are presented in Figures 3.6 and 3.7 and Table 3.4, respectively.

Climatic variables include factors such as temperature, precipitation, humidity, and solar radiation. The WorldClim dataset stood out as a prominent data source, as it was referenced in 52 publications. Topographic variables include elevation, slope, and aspect, which influence factors like water availability, sunlight exposure, and soil properties. In the screened publications, the Shuttle Radar Topography Mission (SRTM) data played a pivotal role, appearing prominently in 41 publications. Other datasets, such as the Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Earth Topography 1 (ETOPO1), also made notable contributions, featuring in five and two publications, respectively. Soil data are among the crucial determinants of the current distribution of plant species (Zuquim *et al.*, 2020). Thus, it was anticipated that soil datasets would appear in the literature. The International Soil Reference and Information Centre (ISRIC) was used in eight of the 15 studies that incorporated soil data to map forest suitability. The diversity of data sources for topographic variables underscores the significance of accessing accurate and diverse topographic information to enhance the precision and comprehensiveness of forest suitability assessments.

Among the eleven studies that integrated land cover data, the National Land Cover Database (NLCD) appeared in two publications, representing the most significant contribution from a single data source.

Table 3.3. Data sources and the number of publications for various variable types.

Variable Type	Data Source	Number of Publications
Climatic	AfriClim	2
	Bangladesh Meteorological Department (BMD)	1
	Climatologies at high resolution for the earth's land surface areas (CHELSA)	7
	Climate Hazards Group InfraRed Precipitation with Stations version 2.0 (CHIRPS v.2.0)	1
	European Center for Medium-Range Weather Forecasts (ECMWF)	1
	Fars Meteorological Bureau (FMB)	1
	Neotropical Bioclimate Database (NBD)	1
	Terrestrial Observation and Prediction System (TOPS)	1
	WorldClim	52
Topographic	ALOS Phased Array type L-band Synthetic Aperture Radar (ALOS PALSAR)	2
	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	5
	Earth Topography 1 (ETOPO1)	2
	Global 30 Arc-Second Elevation (GTOPO30)	1
	Shuttle Radar Topography Mission (SRTM)	41
	WorldClim	2
Land Cover	National Land Cover Database (NLCD)	2
	Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER)	1
	Environment Data Cloud Platform of the Chinese Academy of Sciences	1
	Moderate Resolution Imaging Spectroradiometer (MODIS)	1
	Landsat Enhanced Thematic Mapper Plus (ETM+)	1
	Landsat Operational Land Imager (OLI)	1
	National Institute of Statistics and Geography of Mexico	1
	Sentinel-2	1
	SPOT-VEGETATION	1
	United Nations Land Cover Classification System (UN-LCCS)	1
Soil	United States Soil Survey Database (USSOILS)	1
	AfSoilGrids	1
	Center for Sustainability and the Global Environment (SAGE)	1
	Food and Agriculture Organization (FAO) Geo Network	5
	Harmonised World Soil Database (HWSD)	1
	International Soil Reference and Information Centre (ISRIC)	8
	National Soil Maps of Vietnam of Ministry of Natural Resources and Environment	1

Figure 3.6 shows various remote sensing satellites along with the corresponding frequency of their usage in the screened publications, whereas Figure 3.7 shows how the use of these

satellites has progressed over the years. These two figures offer valuable insights into the patterns of remote sensing data utilisation within the field of forest suitability modelling. Most satellites are featured in a limited set of publications, suggesting that these are specialised or infrequently employed platforms in suitability modelling. Of note is the fact that the SRTM stands out with the highest frequency, appearing in 41 publications. This prominence likely stems from the global coverage and high-quality elevation data provided by this platform, making it an invaluable resource for modelling studies across diverse landscapes.

Other well-utilised satellites include the MODIS (18 publications), Landsat 8 OLI (9 publications), and the ASTER (eight publications). These satellites are known for their versatility, as they are also applicable for tasks such as land surface temperature analysis (MODIS), multispectral imagery (ASTER), and land cover mapping (Landsat 8 OLI). The satellites have also been in operation for multiple decades, which has made them more reliable (Bangira *et al.*, 2023). The distribution of satellite usage underscores the varied preferences and requirements of researchers when selecting remote sensing data sources for their studies. This mix of specialised and widely adopted platforms reflects the dynamic landscape of resources harnessed for forest suitability analysis. Figure 7 also illustrates a trend where emerging satellite missions were gradually adopted in forest suitability modelling within the studied publications.

Furthermore, the reviewed articles only incorporated a specific set of vegetation indices for the modelling aspect. These indices, which are derived from remote sensing data and summarised in Table 3.4, include the Normalised Difference Vegetation Index (NDVI), Soil-Adjusted Vegetation Index (SAVI), Normalised Difference Infrared Index (NDII), Enhanced Vegetation Index (EVI), Green-Red Vegetation Index (GRVI), Normalised Difference Water Index (NDWI), Normalised Difference Snow Index (NDSI), and Simple Ratio Vegetation Index (SR). Additionally, the Atmospherically Resistant Vegetation Index (ARVI) was also considered in this context. These variables were mainly derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) and Landsat 8 Operational Land Imager (OLI), which were featured in 17 and 12 publications, respectively.

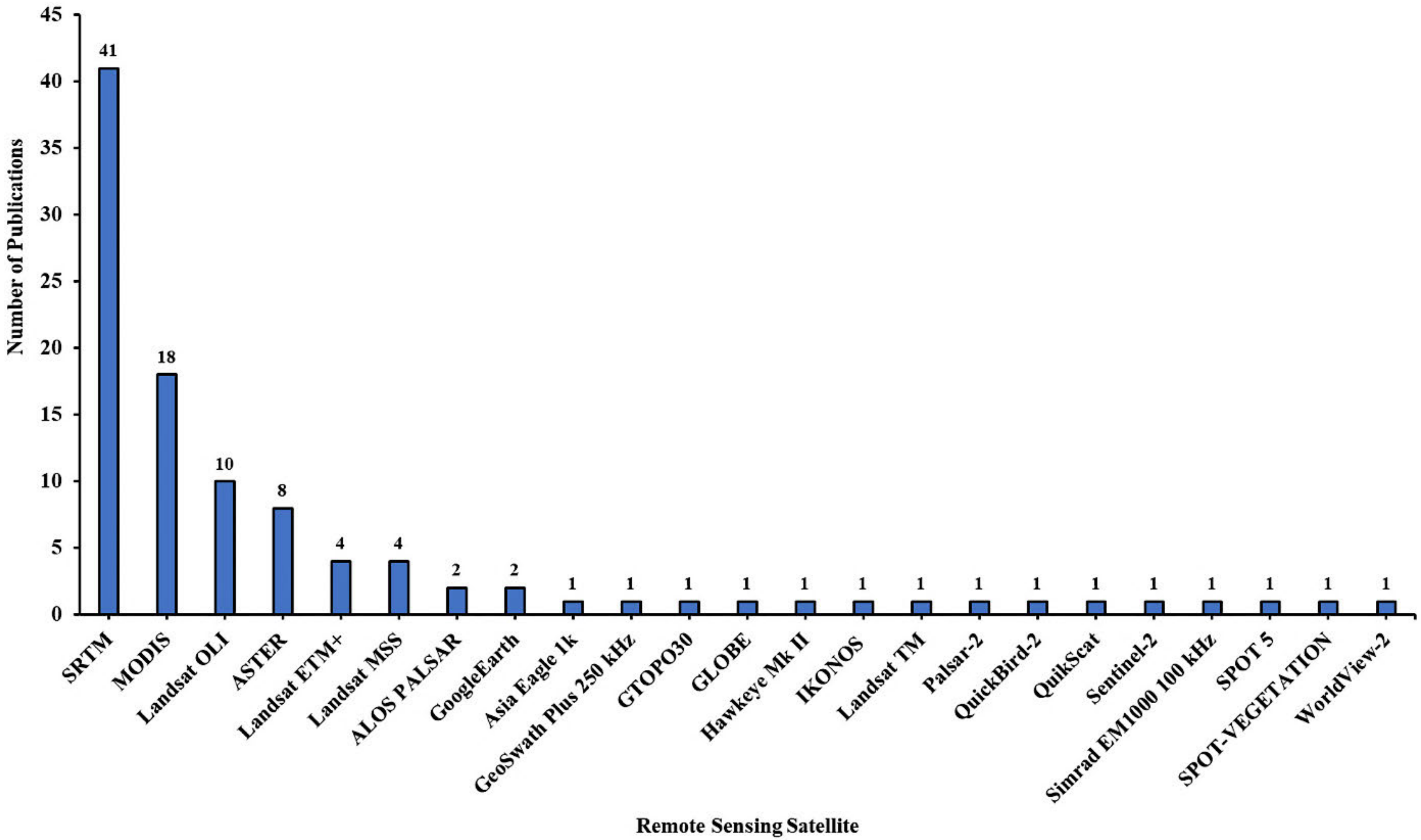

Figure 3.6. The distribution of remote sensing satellites used for mapping forest suitability.

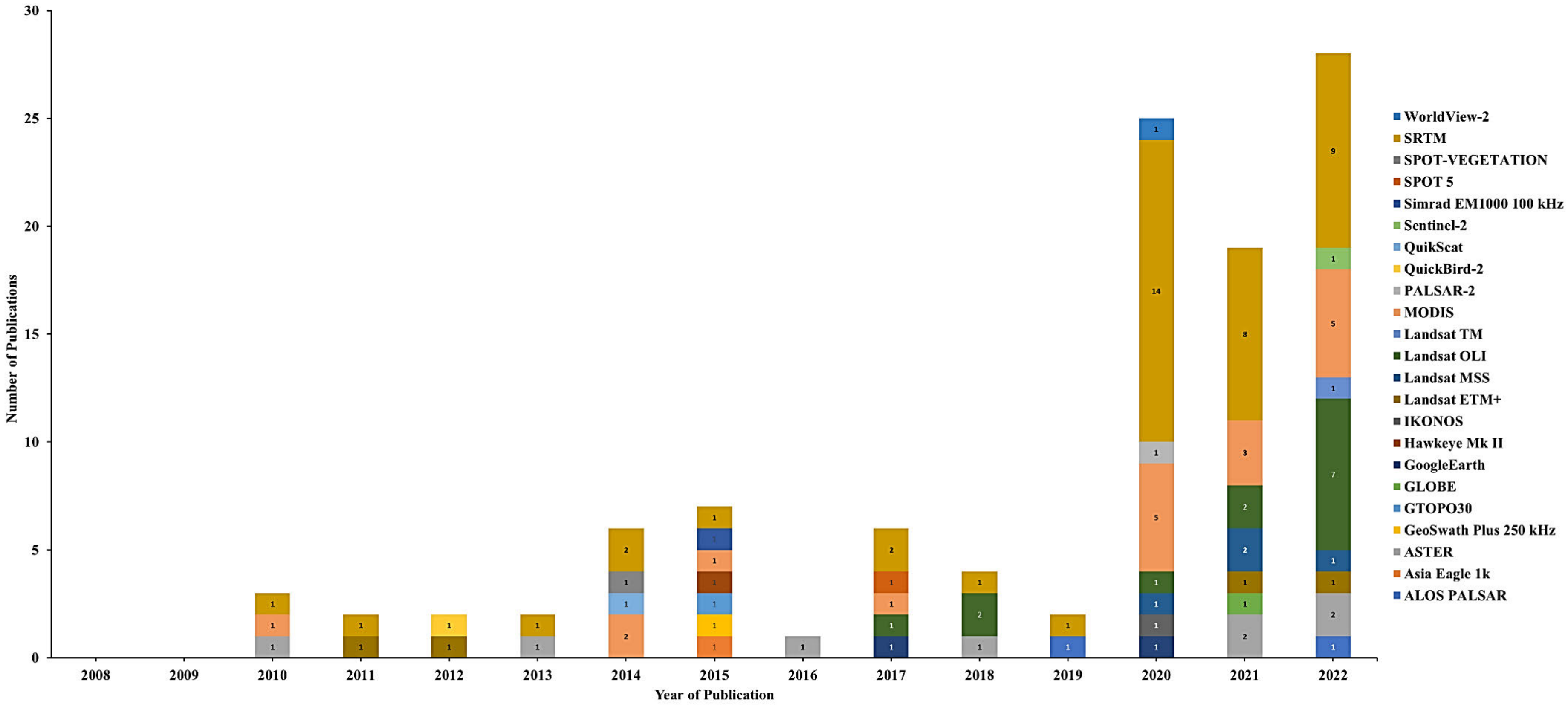

Figure 3.7. The temporal distribution of remote sensing satellites employed in the process of mapping forest suitability by the screened publications.

Table 3.4. Summary of vegetation indices used for modelling forest suitability.

Index	Formula	Equation	Reference
Normalised Difference Vegetation Index (NDVI)	$\frac{(NIR - Red)}{(NIR + Red)}$	1	Tucker and Sellers (1986)
Simple Ratio Vegetation Index (SR)	$\frac{NIR}{Red}$	2	Carlson and Ripley (1997)
Enhanced Vegetation Index (EVI)	$\frac{[(2.5 \text{ X } (NIR - Red)]}{[(NIR + (6 \text{ X } Red) - (7.5\ X\ BLUE) + 1]}$	3	Huete *et al.* (2002)
Normalised Difference Water Index (NDWI)	$\frac{(Green - NIR)}{(Green + NIR)}$	4	Gao (1996)
Normalised Difference Infrared Index (NDII)	$\frac{(NIR - SWIR)}{(NIR + SWIR)}$	5	Hunt and Rock (1989)
Soil Adjusted Vegetation Index (SAVI)	$(\frac{(NIR - RED)}{(NIR + RED + 0.5)}) \times (1 + 0.5)$	6	Huete (1988)
Atmospherically Resistant Vegetation Index (ARVI)	$\frac{(\text{NIR} - (\text{Red} - 1 \times (\text{Blue} - \text{Red}))}{(\text{NIR} + (\text{Red} - 1 \times (\text{Blue} - \text{Red}))}$	7	Kaufman and Tanre (1992)
Normalised Difference Snow Index (NDSI)	$\frac{(Green - SWIR)}{(Green + SWIR)}$	8	Salomonson and Appel (2004)

3.3.5 Methods used in modelling forest suitability

The choice of method and algorithm also plays a pivotal role in suitability modelling. Selecting the appropriate modelling approach, whether it is a statistical method like linear regression (LR) (Baturynska and Martinsen, 2021), machine learning algorithms like RF and MaxEnt (Fitzgibbon *et al.*, 2022), or other techniques, directly impacts the accuracy and robustness of the model's predictions. As such, the publications that met the inclusion criteria were screened for methods used to map forest vegetation suitability, and the findings are presented in Figure 3.8. MaxEnt was the most utilised method, featured in 62 publications, indicating its wide adoption for forest suitability analysis. Other methods that featured prominently included RF, which was used in 15 publications, followed by the Generalised Linear Model (GLM), which was used in 12 publications, and the Generalised Additive Model (GAM), which appeared in eight publications. Several other methods were employed with varying frequencies, each contributing to the diverse toolkit of approaches that present the possibility of mapping forest suitability.

The adoption of these methods over time is presented in Figure 3.9, where it can be observed that Maxent had been a dominant approach throughout the study period. However, starting in 2020, other machine learning approaches started gaining traction, especially the use of RF. While deep learning methods like ANN and deep neural networks (DNN) have found applications in suitability modelling, their utilisation has been relatively less prominent compared to conventional machine learning approaches.

3.3.6 Evaluation criteria

Table 3.5 highlights various evaluation methods utilised in the reviewed publications. Notably, 56 publications utilised the area under the receiver operating characteristic curve (AUC), highlighting its significance as a measure of accuracy. Other commonly used evaluation methods included measures of accuracy, statistical significance, and model fitting. Accuracy measures included the root mean square error (RMSE) and overall accuracy. RMSE quantifies the average magnitude of the difference between predicted and actual values, while overall accuracy indicates the proportion of correct predictions. Statistical significance was mainly measured by p-Values in the reviewed publication, with a low p-value suggesting that the observed effect is unlikely due to chance. Model fitting was primarily assessed by R^2, which indicates the proportion of variance in the data explained by the model. These methods suggest a comprehensive approach to evaluating models and analysis, as highlighted by the reviewed publications. Furthermore, error metrics like mean absolute relative error (MARE) and normalised root mean square error (NRMSE) highlighted the attention given to precision in forest suitability modelling.

Table 3.5. Comparison of evaluation methods in publications utilising suitability models and remote sensing to map forest suitability.

Evaluation Method	Number of Publications
R^2	4
Jackknife Tests	1
p-Value	4
Root Mean Square Error (RMSE)	3
Area Under the Receiver Operating Characteristic Curve (AUC)	56
Cohen's Kappa	5
Overall Accuracy	4
Mean Absolute Relative Error (MARE)	1
Normalised Root Mean Square Error (NRMSE)	1

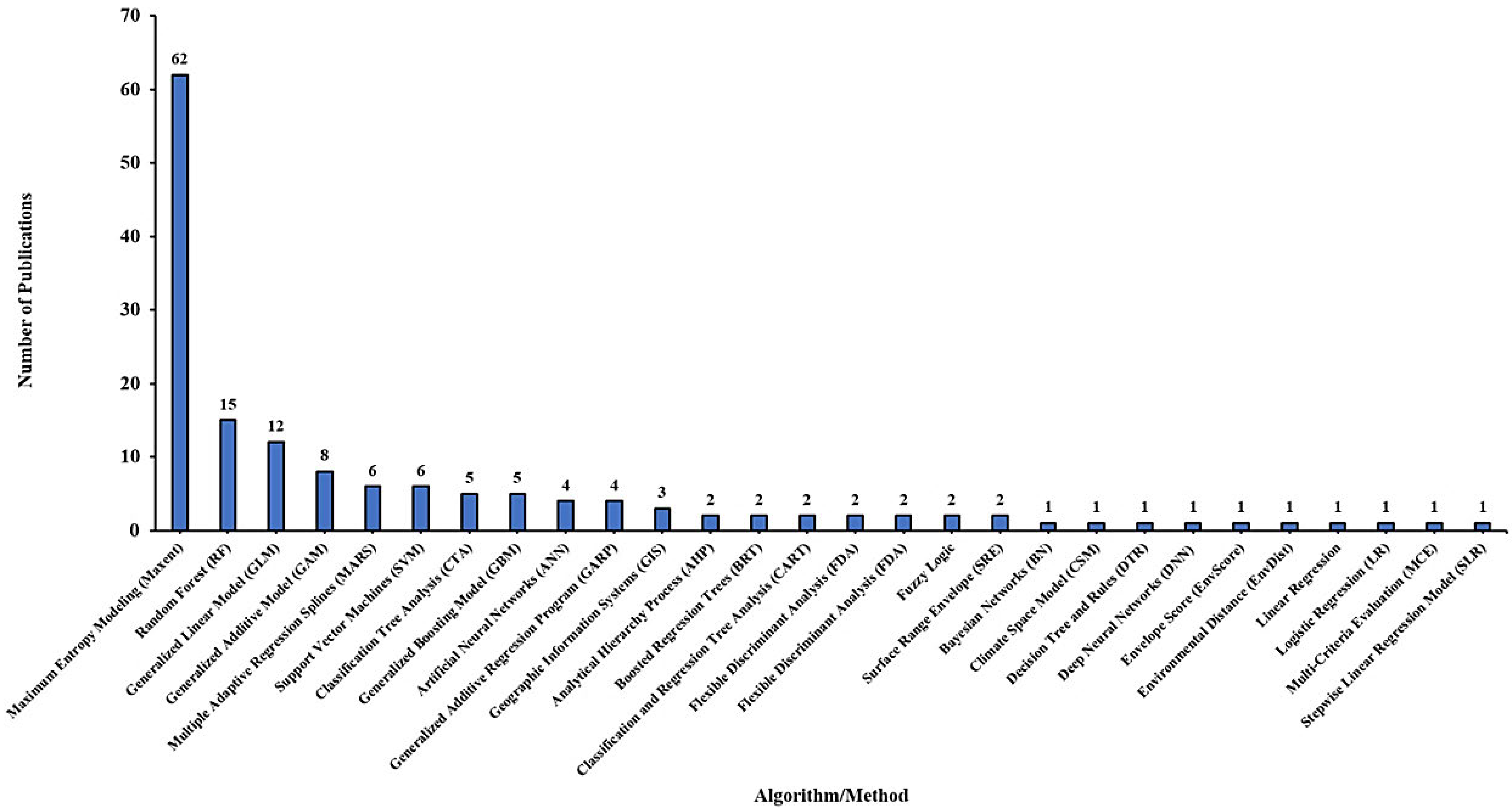

Figure 3.8. The distribution of methods used to model forest suitability.

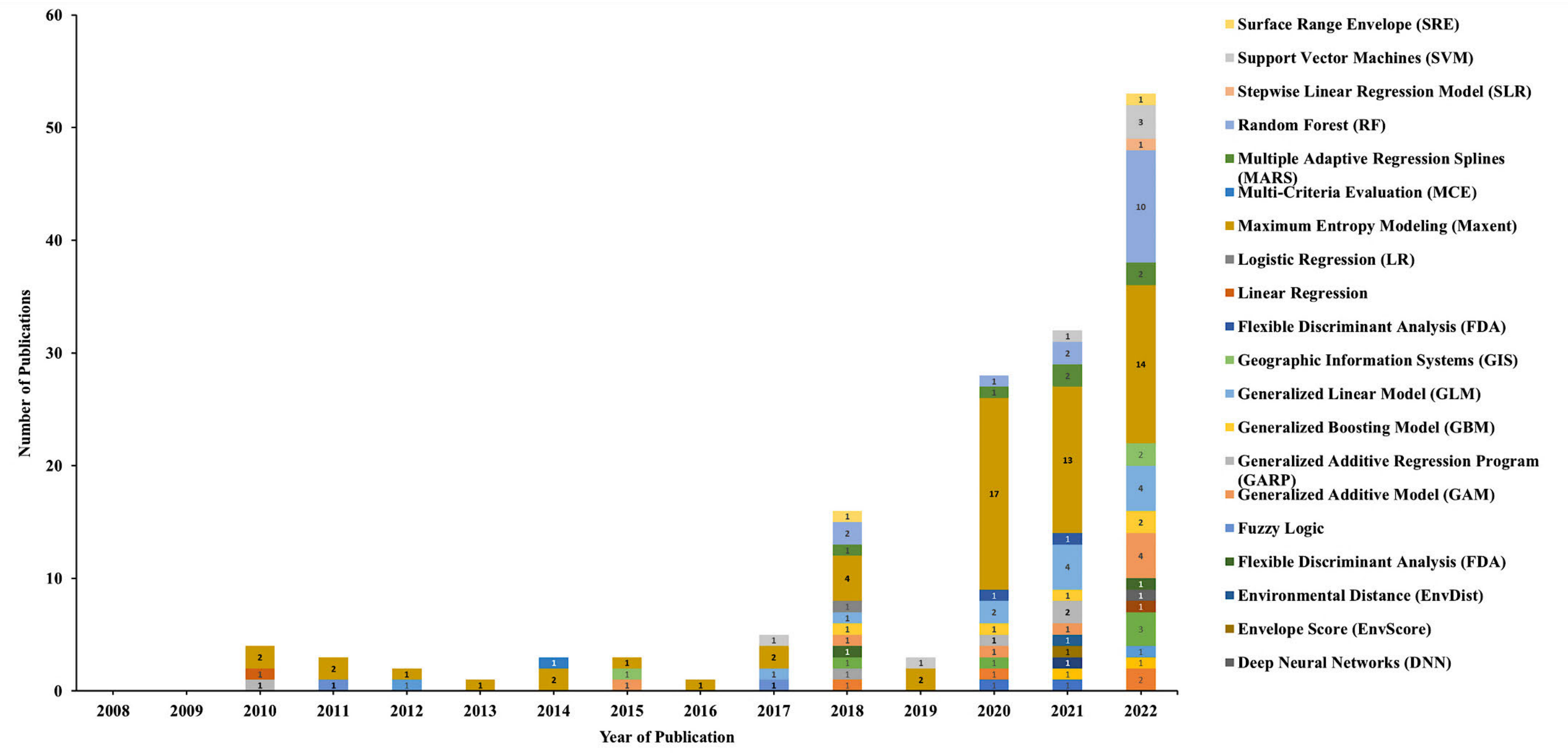

Figure 3.9. The temporal distribution of approaches employed in the process of mapping forest suitability by the screened publications.

3.4 Discussion

3.4.1 Frequency and geographic distribution of publications

This review paper identified 80 publications for review and analysed the temporal and spatial trends of these studies on forest suitability modelling. The results showed an increase in the number of publications starting from 2010 to 2022, with no publications identified in 2008 and 2009. This increase can be linked to the 2010 UN Convention on Biological Diversity (CBD) that requested the restoration of at least 15% of ecosystems that are degraded under Aichi Biodiversity Target 15, a goal that approximately 49 countries have committed to achieving (Marques *et al.*, 2014). Additionally, international climate agreements like the Kyoto Protocol and the Paris Agreement have played a significant role in driving this trend, as these frameworks encourage reforestation, afforestation, and ecosystem restoration as part of broader climate mitigation strategies (Psistaki *et al.*, 2024). Both agreements have mobilised resources and policy support for forest restoration, prompting an increase in research to support the restoration of at least 150 million hectares (ha) of deforested and degraded land by 2020, with a goal to expand this to 350 million ha by 2030 (Kemppinen *et al.*, 2020).

However, the observed increase in publications should be normalised to verify that this trend reflects a genuine rise in interest in exploring remote sensing and suitability models for forest rehabilitation, rather than a general increase in publication accessibility or overall research output. Normalising the data would involve comparing the growth rate of publications on remote sensing and suitability models with the general publication growth across related fields during the same period. This approach would help distinguish whether the observed trend is specific to increased interest in these topics or simply a reflection of broader publication trends. Such normalisation is crucial for accurately interpreting the research landscape and understanding the field’s progression, ensuring that the apparent growth truly represents a focused increase in scientific engagement with these technologies.

Most publications were concentrated in Asia and the Americas, with less representation observed in Europe. Significantly, the results indicated that developing countries, mainly those in Africa, still lack publications focusing on restoring forest vegetation. This is particularly significant given the establishment of REDD+, which aims to reduce or stop land-use change in developing countries (Corbera and Schroeder, 2011). REDD+ also aims to include developing countries in climate change mitigation endeavours. Bamwesigye *et al.* (2020)

emphasised that in Africa, particularly East Africa, where wood biomass serves as the primary household fuel, REDD+ faces challenges such as conflicting land-use policies, corruption, and occasional information gaps, resulting in significant forest degradation and deforestation. Agreeing with Bamwesigye *et al.* (2020), Kumar and Mutanga (2018) suggested that the lack of publications from developing countries can be due to several factors, which include limited data accessibility, opportunities for research, and the technological and the technical skills to process the data required to implement reforestation projects, which are in contrast with the developed countries. Therefore, it can be concluded that developing countries, particularly African countries, are still lagging behind developed countries in reforestation and climate change mitigation efforts.

3.4.2 Variable selection in forest suitability modelling

There is a consensus that bio-physical factors are crucial for determining suitable areas for reforestation. Thus, nearly all publications encompassed a range of bio-physical factors, including but not limited to climate, soils, and topography. Therefore, the selection of a reliable data source is also crucial, as these variables may significantly affect model performance (Zhang *et al.*, 2023). The WorldClim dataset was used by 65% of the publications to extract bioclimate information. Additionally, some of the publications only used climate and topographical information to map forest vegetation suitability. This highlighted the importance of selecting a reliable climate dataset was elevated. WorldClim provides global information for 19 distinct bioclimatic variables at varying resolutions, effectively capturing the characteristics of all global environments for both historical and future time horizons (Lo Parrino *et al.*, 2023). The first version of WorldClim was developed by Hijmans *et al.* (2005) and released in 2005, followed by a second version released in 2020 by Fick and Hijmans (2017).

Cerasoli *et al.* (2022) compared both versions of WorldClim in suitability modelling. They found both versions to be generally accurate when estimating areas of suitability. However, they noted that models that incorporated a narrow combination of climatic conditions failed to accurately retrieve the simulated climate-occurrence relationships for the climate-tolerant species. They also observed a mismatch between the two versions when predicting species whose suitability mainly depended upon diurnal or yearly variability in temperature. Therefore, they recommended a revaluation of previous biodiversity-related studies that relied on geographical predictions from WorldClim-based suitability models. However, Fraga *et al.*

(2022) did advocate for the use of the second version of WorldClim as an alternative to in situ data sources.

DEMs also played a significant role in modelling forest vegetation suitability, as they were incorporated in 66% of the reviewed publications. That is because DEMs provide crucial spatial information for understanding the complex interactions between topography, climate, hydrology, and vegetation dynamics in forest ecosystems (Odebiri *et al.*, 2020; Okolie and Smit, 2022). As such, incorporating DEM-derived variables such as slope and aspect into forest suitability assessments enhances the accuracy and robustness of SDMs, ultimately supporting informed decision-making for forest management, conservation, and restoration initiatives (Yi *et al.*, 2022). Slope influences factors such as water runoff, soil erosion, and microclimate conditions, affecting forest vegetation's distribution and growth (Cheng *et al.*, 2023). Whereas, the aspect determines the direction of slope faces, influencing sunlight exposure, temperature gradients, moisture levels, and consequently, vegetation growth and species distribution (Måren *et al.*, 2015). Additionally, DEMs provide essential topographic information that is used in various climatic modelling processes, including interpolating temperature and precipitation data to produce global climate datasets like WorldClim (Antal *et al.*, 2023).

SRTM was used by 41 publications to derive elevation data. The prevalent use of SRTM is mostly due to its ability to outperform other DEMs. For example, Saberi *et al.* (2023) conducted a comparative study wherein they assessed the performance of various DEMs, including ASTER, Copernicus DEM with forest and buildings removed (FABDEM), and multi-error-removed improved-terrain (MERIT), in contrast with SRTM. This assessment was carried out using the particle swarm optimisation (PSO) algorithm. Their findings indicated that SRTM outperformed the other DEMs. Additionally, the extensive use of SRTM in the reviewed publications stems from the fact that it was one of the first sensors to offer a nearly global high-resolution DEM characterised by high accuracy and free accessibility (Yang *et al.*, 2011). The SRTM DEM additionally provides temporally consistent sampling and early acquisition time (Liu *et al.*, 2024).

However, Ouyang *et al.* (2023) argued that SRTM’s accuracy is constrained by topography and vegetation. This is due to limitations in radar side-view imaging (Sun *et al.*, 2023). As such, machine learning algorithms have been recommended for improving SRTM’s accuracy using high-accuracy reference elevation observed data (Kandil *et al.*, 2024). However, many of the methodologies incorporating reference observations primarily employ either parametric or non-parametric regression (such as a single machine learning model), potentially resulting in overfitting or underfitting issues, thereby constraining enhancements in the accuracy of SRTM DEM outputs (Ouyang *et al.*, 2023). Meadows and Wilson (2021) found that models tend to exhibit bias towards the predominant land cover and terrain characteristics present in their training datasets, highlighting the need for additional investigation into the significance of restricting training data inputs to those that best reflect the intended application area(s). As such, more research is still required on the methods used to improve the accuracy of DEMs using machine learning methods.

Other than elevation, remote sensing-derived variables included the NDVI, SAVI, NDII, EVI, GRVI, NDWI, NDSI, SR, and ARVI. NDVI was the most prominent index in the reviewed publications. This index was developed by Tucker and Sellers (1986), who normalised the spectral reflectance from the red and NIR bands. Despite NDVI's widespread popularity, it has been established that the index becomes saturated at elevated biomass levels (to moderate-dense canopy conditions), resulting in a loss of its capacity to effectively capture biophysical information (Mutanga *et al.*, 2012; Mutanga *et al.*, 2023). As such, multiple indices have been explored as alternatives to overcome the saturation effect, including the Modified Normalised Difference Vegetation Index (MNDVI), EVI, SR, and SAVI (Masenyama *et al.*, 2022). Gao *et al.* (2023) compared 36 vegetation indices to determine the one with the best resistance to the saturation effect, where SR showed the best performance, followed by Modified Simple Ratio (MSR), Soil-Adjusted Vegetation Index 2 (SAVI2), Near-Infrared Reflectance of Vegetation (NIRv), and EVI. Therefore, it is recommended that future studies consider the saturation effect when selecting remote sensing variables for modelling forest vegetation suitability.

Land cover and soil data were mostly accessed from data sources local to the study areas. This is attributed to the fact that local data sources offer an elevated degree of precision and accuracy tailored to the specific study area. Soils and land cover can exhibit significant variations over relatively short distances, which may not be adequately captured by global or generalised datasets (Ayele *et al.*, 2022; Wendroth *et al.*, 2011).

3.4.3 Remote sensing satellites for forest suitability

SRTM, MODIS, Landsat sensors, and ASTER were the most used satellite sensors by the 80 publications reviewed. As previously asserted, DEMs play a significant role in modelling forest vegetation suitability. As such, SRTM and ASTER remain crucial in advancing the understanding of forest ecosystems and informing conservation and management strategies.

The extensive use of MODIS and the three Landsat sensors in the studies reviewed concurs with multiple studies that came to a similar conclusion, such as Masenyama *et al.* (2022); Zhao *et al.* (2022), and Bangira *et al.* (2023). The popularity of these sensors stems from their open accessibility and extensive time in orbit, spanning multiple decades. The first Landsat mission was launched on July 23, 1972, as the Earth Resources Technology Satellite (ERTS), carrying the Return Beam Vidicon (RBV) and the Multispectral Scanner (MSS), before being renamed Landsat 1 (Lulla *et al.*, 2021). Since that first Landsat mission, the succeeding missions have ensured that sensor specifications remain constant over time (Roy *et al.*, 2014). This allows for a more accurate analysis of temporal changes in land cover and vegetation dynamics, facilitating long-term monitoring and assessment of environmental changes. As such, Adams *et al.* (2020) added that the Landsat time series analysis allows for the quantification of seasonal patterns and long-term trends across various types of forests, which can be utilised to create diverse feature sets for mapping forest vegetation. The inaugural MODIS instrument was deployed aboard the Earth Observing System's (EOS) Terra satellite in December 1999 (Masuoka *et al.*, 2001). The MODIS time series analysis has also demonstrated its usefulness in vegetation monitoring, as demonstrated by studies such as Dai, R. *et al.* (2023), Hosen *et al.* (2023), and Das and Mondal (2024).

Zhao *et al.* (2022) added that another pivotal factor contributing to the widespread utilisation of Landsat and MODIS data is their provision of a large amount of analysis-ready data (ARD). Data from these sensors are freely available from the United States Geological Survey (USGS) EarthExplorer (https://earthexplorer.usgs.gov/) (Deutsch *et al.*, 2021). However, these sensors offer medium to coarse spatial resolution. As such, Cisneros-Araujo *et al.* (2021) asserted that Sentinel-2 imagery is a great alternative to these two sensors due to its higher spatial resolution (10 meters) and its robustness in estimating vegetation variables for suitability modelling. The Sentinel satellite constellation is part of the European Space Agency's Copernicus programme and has the capability to provide data on land cover, land use, and vegetation health. Sentinel-2, for instance, offers high-resolution multispectral imagery suitable for forest suitability analysis, as was demonstrated by one publication in this review, Nasiri, Darvishsefat, *et al.* (2022). It should be noted that, although Sentinel-2 offers a higher resolution compared to MODIS and Landsat missions, its data might be less suitable for studies requiring historical trends given that it was only launched in 2014 (Schmidt *et al.*, 2023). Additionally, Sentinel-3, with a coarser spatial resolution of 300 m, lacks the finer detail of Sentinel-2's 10-20 m resolution, limiting its applicability for studies focused on detailed land cover analysis.

Moreover, the increasing ease of access to remote sensing data has been the main driver of the increased application of remote sensing imagery (Thakur *et al.*, 2020). However, in this review, the utilisation of remotely sensed imagery has not contributed significantly to improving the number of publications coming from African countries. That is because only ten publications were produced in these countries. This discrepancy underscores the need for greater capacity-building efforts and resource allocation towards remote sensing research and education in African nations, aiming to foster indigenous expertise and facilitate greater participation in the global scientific discourse on remote sensing applications. Additionally, creating regional data repositories, fostering collaboration with international research groups, or developing training programmes focused on applying remote sensing to local forestry challenges could encourage more research from African countries.

However, a critique of the reviewed studies is the limited use of Sentinel-1 and Sentinel-2 data, despite these platforms offering open-source access, higher spatial resolution, and additional red edge bands (De Luca *et al.*, 2022). Sentinel-2, in particular, provides relatively high-resolution multispectral imagery with red edge bands, which are highly beneficial for assessing vegetation health, monitoring growth stages, and detecting subtle changes in forest cover (Adiningrat *et al.*, 2024). Sentinel-1, with its radar capabilities, is equally valuable for penetrating cloud cover and providing consistent imagery in various weather conditions, an advantage for continuous forest monitoring (Schellenberg *et al.*, 2023). The limited inclusion of these platforms by the authors of the reviewed studies represents a missed opportunity to leverage advanced remote sensing technologies that could significantly enhance the accuracy and depth of forest rehabilitation and restoration analysis. This critique highlights the need for broader adoption of these Sentinel platforms in future research to fully utilise their capabilities for detailed and resilient forest monitoring.

3.4.4 Methods used in determining forest suitability

MaxEnt emerged as the predominant choice, employed in 62 publications, while RF ranked second with 15 studies adopting this algorithm. MaxEnt's popularity largely stems from its user-friendly software and its consistent track record of outperforming other methods in terms of predictive accuracy (Merow *et al.*, 2013). The utilisation of RF as a machine learning algorithm is driven by its better suitability for sparse or noisy data compared to many well-established models (Li *et al.*, 2015). RF also produces superior performances in recognising data patterns and possesses user-friendly parameters, the ability to easily address the interactions between predictive variables, and a lack of assumptions related to the properties of the data (Luan *et al.*, 2020).

Furthermore, deep learning, which is a subset of machine learning, has demonstrated promise in forest suitability modelling (Kalinaki *et al.*, 2023). In this study, deep learning algorithms appeared in five (four utilised ANN and one utilised DNN) publications, indicating a gap in the application of these algorithms. Increased computational power, the availability of large datasets, and storage capacities have paved the way for adopting deep learning (Ahmad *et al.*, 2023). Deep learning approaches behave like a human brain in that they utilise artificial neural networks, which are made up of many interconnected nodes that work together to process information (Christin *et al.*, 2019). Therefore, it is recommended that future studies employ deep learning approaches in modelling forest suitability.

Ultimately, this review shared a similar sentiment with that shared by Kumar and Mutanga (2018), who mentioned that the lack of publications and collaborations from developing countries, particularly African countries, does not imply that the researchers from these countries are not engaged with science. Matthews *et al.* (2020) postulated that researchers in developing countries face many barriers that are not well-researched. These researchers are not privileged with easy access to prestigious journals; thus, they have to publish their research in a foreign language and country or develop their journals, which must first gain credibility and prestige within the disciplines (Lund, 2021). However, as previously stated, the lack of publications in developing countries per this review is also due to most developing countries not being highly forested and located in deserts. It should also be noted that this review's findings only captured studies primarily aimed at the scientific publication domain. There may be many reforestation or forest rehabilitation projects that might have utilised suitability models that are not published.

3.5 Conclusion

Reforestation and afforestation are crucial for socio-economic benefits and the revival of ecosystem services (Nunes *et al.*, 2020). These services are important for sustaining livelihoods and combating climate change in developing countries. As such, it is a necessity for more research to go into reviving and establishing new forests in these countries. This review rigorously applied a systematic methodology to assess the literature published from 2008 to 2022. The primary focus was on studies that leveraged both suitability models and remote sensing techniques to effectively model the suitability of forest vegetation. As such, the review explored the temporal and spatial trends of publications and their methodological preferences. Results from this review indicated an increasing trend in publications indicating a positive influence of the UN-REDD Programme over its first 10 years. International collaborations are also evident in the reviewed publications. Encouraging further collaboration, particularly with researchers from underrepresented regions, can offer valuable insights. That is because these publications were mostly concentrated in developed countries. This meant that the extension of UN-REDD to REDD+ to aid developing countries in mitigating climate change through reforestation and reducing deforestation has not stimulated forestry research in these countries.

Therefore, researchers in developing countries need more opportunities to publish impactful work on reforestation and afforestation. International collaboration, funding, and training programmes can empower them with the skills and resources to achieve this. Additionally, future research should aim to include a wider geographic focus, particularly targeting underrepresented regions, to capture unique challenges and opportunities associated with reforestation and afforestation in different ecological and socio-economic contexts. This broader perspective will lead to more globally inclusive and effective forest management strategies.

While the keywords "forest, reforestation, afforestation, suitability modelling, ecological niche modelling, and remote sensing" were pivotal in this research, future studies may benefit from incorporating alternative sets of keywords to capture a broader spectrum of related literature and emerging trends. Suggested keywords include "forest restoration, habitat restoration, ecological modelling, remote sensing applications, climate change impacts, and forest management practices." These alternatives can help in obtaining a more comprehensive understanding of the state of the art and potentially uncover new insights and methodologies in the field. Furthermore, integrating advanced technologies like machine learning, big data analytics, and drone-based remote sensing can significantly improve the accuracy and efficiency of suitability models for reforestation projects.

In conclusion, advancing reforestation and afforestation research requires a multi-pronged approach: building research capacity in developing countries, expanding geographic focus, and leveraging advanced technologies. By addressing these areas, researchers can make a significant contribution to the fight against deforestation and forest degradation on a global scale.

3.6 Summary

This chapter provided a comprehensive review of scientific literature focusing on the application of suitability models and remote sensing to identify areas suitable for forest vegetation. The study analysed 80 relevant publications from 2008 to 2022 across three major databases (Scopus, ScienceDirect, and Web of Science), highlighting a significant increase in research output since 2020. The findings reveal a preference for medium- to high-resolution remote sensing data, with Landsat being the most used sensor and MaxEnt the most popular model, followed by RF. The review also identified a geographical disparity in research, with a concentration in the Americas and Asia, and a notable gap in developing nations (similar to chapter two). The study emphasised the need for increased research efforts and capacity building in developing countries to enhance forest rehabilitation and restoration initiatives.

4. CHAPTER FOUR: PREDICTING LAND USE AND LAND COVER CHANGE DYNAMICS IN THE ETHEKWINI MUNICIPALITY: A MACHINE LEARNING APPROACH WITH LANDSAT IMAGERY

This chapter is based on:

Buthelezi, M. N. M., Lottering, R. T., Peerbhay, K. Y., & Mutanga, O. (2024). Predicting land use and land cover change dynamics in the eThekwini Municipality: a machine learning approach with Landsat imagery. *Journal of Spatial Science*, 1–23. https://doi.org/10.1080/14498596.2024.2378362

Abstract

Monitoring and providing accurate land use and land cover (LULC) change information is crucial for understanding the impacts of accelerated Earth surface changes. This information guides sustainable environmental planning and development efforts, particularly in vulnerable areas like the eThekwini Municipality. As such, this study utilised Landsat imagery from 2002 to 2022 to generate updated LULC change maps for the eThekwini Municipality, integrating Enhanced Vegetation Index (EVI), Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Modified Normalised Difference Water Index (MNDWI), and Normalised Difference Built-up Index (NDBI). Random forest (RF), support vector machine (SVM), and extreme gradient boosting (XGBoost) were used to conduct these LULC classifications, with XGBoost achieving the highest accuracy (80.57%). The generated maps revealed a significant decrease in cropland and an increase in impervious surfaces. As such, this research established a framework for continuous LULC mapping and highlighted Landsat 9's potential in LULC classifications.

Keywords: land cover, land use, remote sensing, machine learning, Landsat

4.1 Introduction

The complex environmental, social, economic, and political matrix is the primary driver of a territory's spatial arrangement (Trujillo-Jiménez *et al.*, 2022). This matrix has also accelerated the natural Earth surface changes through increased resource consumption to accommodate increased human populations and accelerated economic development (Digra *et al.*, 2022; Kafy *et al.*, 2021). Land use and land cover (LULC) maps serve as excellent depictions of this matrix (Trujillo-Jiménez *et al.*, 2022), primarily because producing up-to-date and accurate LULC change information provides an understanding of human-environment relationships and the adverse impacts of global change (Chakraborty *et al.*, 2016; Nasiri, Deljouei, *et al.*, 2022). Moreover, this updated information also provides crucial insights for implementing sustainable land management practices, conserving natural resources, and enhancing resilience to climate-related hazards (Effiong *et al.*, 2024). Therefore, LULC change information, especially at the regional scale, aids decision-makers in mitigating the persistent challenges of global change that results from LULC change through appropriate environmental management policies and strategies (Ai *et al.*, 2020; Tadese *et al.*, 2020). Thus, LULC maps are the key to sustainable environmental planning and development (González-González *et al.*, 2022). This primarily pertains to impoverished rural regions, some of which are key areas for ecological and biodiversity significance (Musetsho *et al.*, 2021).

The eThekwini Municipality has attempted to protect and manage its biodiversity and ecological hotspots that supply ecosystem services crucial for human well-being by establishing the Durban Metropolitan Open Space System (DMOSS) (Boon *et al.*, 2016). This was due to the increased degradation and loss of the vegetated landscapes within the municipality (Zungu *et al.*, 2020a). However, the eThekwini Municipality is still susceptible to adverse environmental consequences due to the change driven by the municipality's attempts to move past the apartheid's discriminative spatial planning (Sutherland *et al.*, 2014). Additionally, there is a lack of comprehensive knowledge and understanding regarding the rate of LULC change within the municipality and its ramifications for ecosystems and ecosystem services. Therefore, by providing updated LULC change maps, the eThekwini Municipality can implement appropriate environmental or spatial management policies and strategies. These maps will also inform an update to the DMOSS layer, which was last updated in 2018.

Generating LULC change maps previously relied on in situ monitoring techniques (Buchhorn *et al.*, 2020a). However, the prominence of remote sensing over the past decades and the improved accessibility and development of various methods for extracting remotely sensed data has seen more LULC mapping studies utilising remote sensing (Amini *et al.*, 2022). Remote sensing presents the ability to effectively capture LULC change information (Nkundabose, 2021) by making it possible to integrate spectral-temporal metrics and a diverse set of features to capture changes in various LULC classes (Liang *et al.*, 2022). Most studies have utilised medium-resolution sensors such as Landsat (30 m) and Sentinel 2 (10 m), given that these sensors can detect most human-nature interactions (Chen *et al.*, 2015). These sensors also provide revisit time of 16 days and vast spectral configurations (Nasiri, Deljouei, *et al.*, 2022). Hence, this research utilised imagery from Landsat 7 (Enhanced Thematic Mapper - ETM+), Landsat 8 (Operational Land Imager 1 - OLI 1), and Landsat 9 (Operational Land Imager 2 - OLI 2) with a spatial resolution of 30 m to analyse the changes in LULC within the eThekwini Municipality. The selection of these three sensors is also based on the consistency of the Landsat data record across the entire Landsat sensor series (Roy *et al.*, 2016).

The utilisation of remote sensing in mapping LULC change has attracted the application of machine and deep learning approaches. These approaches are applied to reduce spectral and spatial limitations associated with medium and low-resolution LULC classifications, which should result in more precise LULC maps (Talukdar *et al.*, 2020). Some of the most popular algorithms in LULC change classification include Artificial Neural Networks (ANN), random forests (RF), Cellular Automata (CA), support vector machines (SVM), Markov Chain, and extreme gradient boosting (XGBoost) (Abdi, 2020; Kafy *et al.*, 2021). However, RF and SVM tend to produce more accurate LULC maps compared to the algorithms aforementioned (Abdi, 2020; Ali *et al.*, 2022; Talukdar *et al.*, 2020).

Therefore, this research investigated the effectiveness of three machine learning algorithms, specifically, SVM, RF, and XGBoost in mapping changes in LULC. However, it should be noted that remote sensing based LULC change classifications can be limited by the requirement to access and store large remote sensing data and high computational costs. Platforms, such as the Google Earth Engine (GEE), which is cloud-based, have overcome these limitations (Tassi and Vizzari, 2020). GEE allows scientists and independent researchers to access large data banks for change detection freely and quantify resources on the Earth's surface (Mutanga and Kumar, 2019). Therefore, Landsat data were obtained and processed in GEE.

Overall, the objective of the study was to map LULC change from 2002 to 2022 within the eThekwini Municipality using the three most recent Landsat sensors and machine learning algorithms. The justification for starting in 2002 stems from the consolidation of smaller municipalities and ex-homeland areas into a single metropolitan municipality at the end of 2000, which increased the municipal area by 68% and significantly altered its land use patterns (Sim et al., 2016). Analysing this 20-year period allows the study to capture the long-term effects of this expansion on land use, providing critical insights into urbanisation, deforestation, and environmental shifts. This timeframe is also ideal for identifying meaningful trends in land conversion and assessing the current rate of LULC change. Furthermore, the study helps to pinpoint the key drivers of these changes, informing more effective land management and restoration strategies.

The absence of comprehensive knowledge on the rate of LULC change and the lack of understanding of the consequences of LULC change for ecosystems and ecosystem services within the eThekwini Municipality highlight the critical need for updated LULC change maps to inform decision-making and policy development. This research addresses these gaps by providing enhanced accuracy and efficiency in LULC mapping by employing machine learning algorithms. Such advanced methodologies bring significant advancement to the fields of remote sensing and spatial science, enabling more precise monitoring and analysis of land use and cover dynamics. Furthermore, including Landsat 9 imagery expands the temporal scope of the study. It also enhances the accuracy of LULC change detection, emphasising its importance in improving the understanding of landscape dynamics over time. Consequently, the generated maps will not only facilitate the identification of areas for vegetation restoration within the eThekwini Municipality but also contribute to developing appropriate environmental or spatial management policies and strategies. Thus, the study's findings will provide policymakers with invaluable insights to make decisions that are well-aligned with practical realities and sustainability goals.

Furthermore, in this study, "prediction" should be understood solely in the context of classifying LULC across historical timeframes, rather than as a method for forecasting future changes.

4.2 Methods and Materials

4.2.1 Study area

The eThekwini Municipality, established in 2000, is located in the South African province of KwaZulu-Natal (Figure 2.1), along the Indian Ocean’s western coast (Musvoto *et al.*, 2016; Shivambu *et al.*, 2020). The municipality is a key economic centre in South Africa, primarily attributed to its port, recognised as the busiest port on the African continent (Zungu *et al.*, 2020a). The municipality is consists of 103 wards with an approximate population of 3.5 million, which grows by one percent annually (Zungu *et al.*, 2019). The municipality’s mainland is primarily characterised by urban areas that form the city of Durban, which is surrounded by peri-urban residential areas and informal and rural communities (Hellberg, 2014). With the population and rural-urban migration increasing and more residential spaces being required, the municipality established the DMOSS, a network of areas reserved for conserving native fauna and flora (Khumalo and Sibanda, 2019; Zungu *et al.*, 2019). DMOSS also aimed to limit the conversion of native vegetation for anthropogenic purposes, which include agriculture, residential areas, and roads. As of 2019, 53% of native vegetation had already been converted for human benefit (Zungu *et al.*, 2020a).

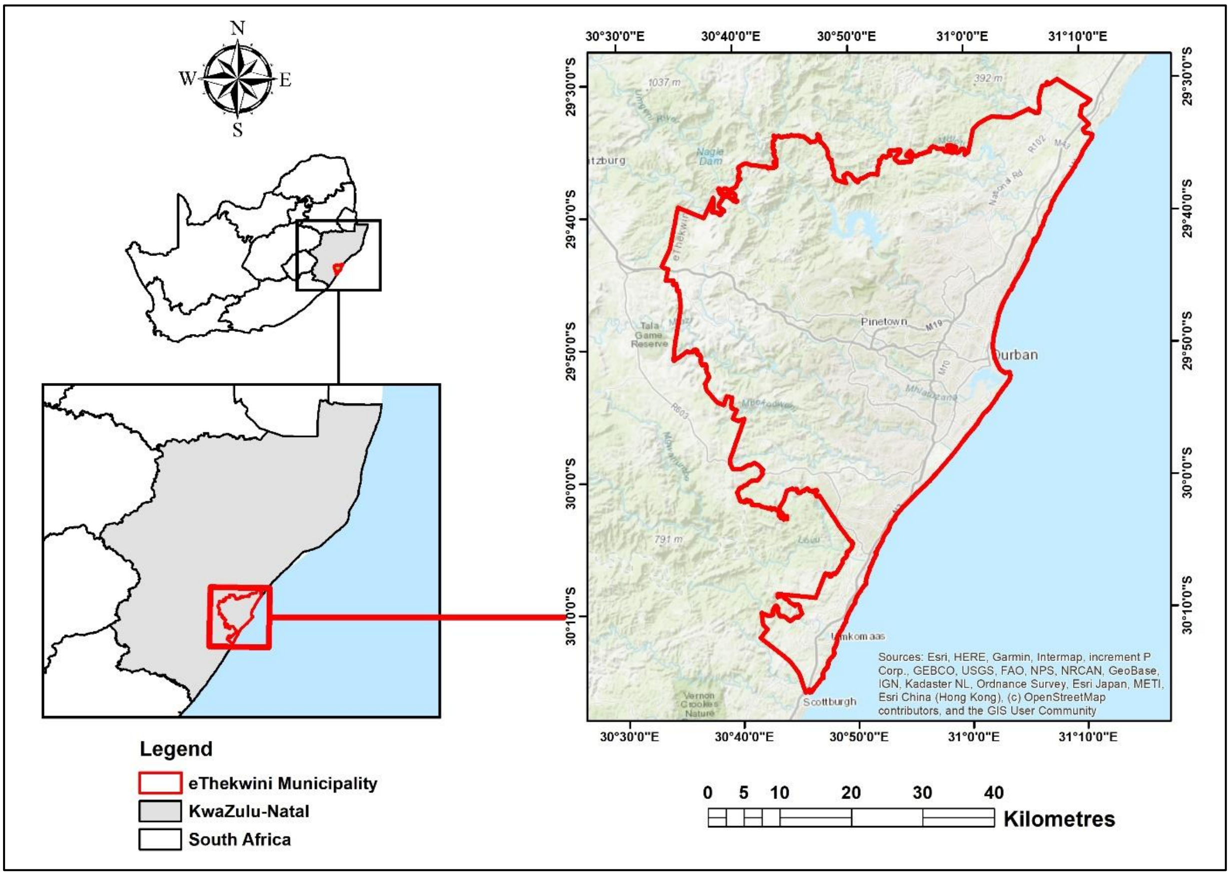

Figure 4.1. The eThekwini Municipality's location in KwaZulu-Natal, South Africa.

4.2.2 Data acquisition and pre-processing

4.2.2.1 Reference data

The 2017 Finer Resolution Observation and Monitoring-Global Land Cover-Segmentation at 10 m (FROM – GLCS10) was used as a reference. FROM – GLCS10 offers a fundamental land cover scheme that incorporates continuous field layers for all primary land cover classes. These classes provide proportionate estimates of vegetation/ground cover for the respective land cover types. Classes in land-cover products generally utilise a hierarchical structure and, thus, this is also the case in FROM – GLCS10 (Zhu *et al.*, 2021). The classes in FROM – GLCS10 found within the eThekwini Municipality are presented in Table 4.1. The LULC class descriptions are derived from the descriptions provided by Wei *et al.* (2020) and Buthelezi *et al.* (2024a).

Table 4.1. FROM – GLCS10 land cover classes (Buthelezi *et al.*, 2024a; Wei *et al.*, 2020).

Name	**Description**	**Code**
Cropland	Land under cultivation showing discernible patterns on satellite imagery.	1
Forest	Areas designated for commercial plantations, orchards, and native tree species.	2
Grassland	Areas that comprise open landscapes dominated by various species of grasses.	3
Shrubland	Land characterised by low-lying vegetation dominated by shrubs.	4
Wetland	Areas characterised by saturated or seasonally saturated soils	5
Water	Areas characterised by the presence of rivers, lakes, ponds, and reservoirs.	6
Tundra	Treeless landscapes in cold regions with vegetation adapted to harsh conditions, including mosses and lichens.	7
Impervious surface	Encompasses developed areas comprising both urban and rural residential zones as well as industrial sectors.	8
Bare land	Land devoid of vegetation cover.	9
Ice/Snow	Areas covered by frozen water, such as glaciers, ice caps, and ice shelves	10

However, it should be noted that the 2017 FROM - GLCS10 has an overall reported global accuracy of approximately 80%. This introduces potential error into the model, as inaccuracies in the training data are likely to propagate into the results. Thus, while the model achieved an accuracy rate of around 97%, this figure may primarily reflect its proficiency in emulating the training data itself, rather than representing the actual land cover with high precision. Additionally, the FROM-GLCS10 dataset served as the basis for accuracy assessment, providing a consistent reference standard aligned with the training data. While the dataset's known accuracy constraints mean that the results may reflect alignment with the training data rather than a precise measure of the eThekwini Municipality's actual land cover, it nonetheless offers a useful benchmark for evaluating the model's ability to replicate established land cover classifications. As such, the achieved accuracy should be understood within the context of the dataset's limitations, offering insights into the model's effectiveness with available data.

4.2.2.2 Landsat imagery

Landsat 7, Landsat 8, and Landsat 9 were used to map LULC change within the eThekwini Municipality. This enabled an extensive assessment of factors that contributed to spatial changes within the municipality over 20 years (2002 to 2022). Landsat 7 (ETM+) was sent into orbit on April 15, 1999, with a fixed ‘whisk-broom’ multispectral scanning radiometer with eight bands (Moradpour *et al.*, 2020). The ETM+ sensor can observe the Earth's surface over a span of 185 km in width and operates on a revisit cycle of 16 days (Cao *et al.*, 2022b). However, on May 31, 2003, the scan-line corrector (SLC) of the ETM+ sensor experienced a permanent malfunction, leading to a situation where ETM+ images only captured 78% of the intended scanned pixels (Wang *et al.*, 2021). Unscanned pixels in ETM+ images appear as a linear gap, measuring approximately 12 pixels in width. Therefore, these line gaps must be filled before Landsat 7 images can be used in any application.

Landsat 7 was followed by Landsat 8, which is equipped with the OLI and the Thermal Infrared Sensor (TIRS), providing a spatial resolution of 30 m and a 16-day revisit cycle (Gorelick *et al.*, 2017). OLI is a push-broom imager with nine spectral bands, and TIRS is also a push-broom imager with two bands (Vanhellemont, 2020). The OLI sensor exhibits enhanced calibration and signal-to-noise properties, narrower spectral bands, a superior 12-bit radiometric resolution, and more accurate geometry in comparison to the ETM+ sensor (Roy *et al.*, 2016). Landsat 8 was followed by Landsat 9, launched on the 27th of September 2021. Landsat 9 has two instruments on board, namely, the OLI-2 and the Thermal Infrared Sensor 2 (TIRS-2). These two instruments improve on similar instruments found onboard Landsat 8 (Showstack, 2022). The key distinction between OLI and OLI-2 lies in the data download process: OLI-2 downloads all 14 bits for each image pixel, whereas OLI only downloads 12 bits (Gross *et al.*, 2022).

Furthermore, Landsat 7, Landsat 8, and Landsat 9 images for the study years were acquired through the GEE platform, utilising the Landsat 7 Collection 2 Tier 1 calibrated top-of-atmosphere (TOA) reflectance, Landsat 8 Collection 2 Tier 1 TOA reflectance, and Landsat 9 Collection 2 Tier 1 calibrated TOA reflectance, respectively, as specified. The calculation of TOA reflectance values for the datasets employed in this research is found on the methodology established by Chander *et al.* (2009). These collections were filtered by the eThekwini Municipality boundary (as a shapefile imported to GEE) and cloud cover (<1%). The eThekwini Municipality boundary covered three Landsat scenes; thus, the filtering process was made uniform for all scenes, which were further clipped using the study area boundary. The clipped images were then mosaiced.

The choice to use TOA reflectance images rather than converting to bottom-of-atmosphere (BOA) or surface reflectance was guided by the study's focus on capturing large-scale land cover and land use changes. Numerous studies have shown that TOA reflectance is effective for applications where relative comparisons are more relevant than precise surface reflectance values (Grasboeck *et al.*, 2024; Sigopi *et al.*, 2024). Using TOA reflectance allowed for efficient data processing and clear insights into vegetation dynamics, meeting the objectives of this research effectively. However, for studies prioritising precise surface conditions, BOA data could provide additional detail and may be a useful consideration in future research (Nazeer *et al.*, 2021).

The initial dataset for classifications was composed of bands 1 to 7 from the mosaiced Landsat 7 images and bands 2 to 8 from the mosaiced Landsat 8 and Landsat 9 images. The reason for excluding other bands is that these bands do not have information about the surface; instead, they best characterise the atmosphere (Li *et al.*, 2020). Additionally, to improve the LULC classification, five spectral indices, namely, the Enhanced Vegetation Index (EVI), Normalised Difference Vegetation Index (NDVI), Normalised Difference Water Index (NDWI), Modified Difference Water Index (MNDWI) and the Normalised Difference Built-up Index (NDBI) were calculated in GEE for all Landsat images and added to the data for classification (Table 4.2).

However, for Landsat 7, before spectral indices were calculated in GEE for the 2007 and 2012 mosaiced images, they still needed to be processed further to fill the unscanned pixels. Hence, the Geo-statistical Neighbourhood Similar Pixel Interpolator (GNSPI) was employed to address the unscanned pixels, with a detailed explanation provided by Zhu *et al.* (2012). The GNSPI code, scripted in the Interactive Data Language, is accessible online. GNSPI utilises empirical or physical models and ordinary Kriging to predict the data lost due to SLC issues (Yin *et al.*, 2017). After the 2007 and 2012 images, unscanned pixels were filled, these images were ingested as assets back to GEE, and the five spectral indices used in this study were calculated (Table 4.2).

EVI and NDVI are useful indices for classifying vegetation; however, it should be noted that NDVI saturates when classifying densely vegetated areas (Buthelezi *et al.*, 2020a; Mutanga *et al.*, 2012). The shortcomings of NDVI are compensated by EVI, which performs better when classifying areas with high biomass and reduced atmospheric influence (Qiu *et al.*, 2018). NDWI and MNDWI are best suited for identifying water bodies (Raut *et al.*, 2020; Shahfahad *et al.*, 2022). NDBI has been revised multiple times and is critical for improving the built-up area classification (Santra *et al.*, 2021). It achieves this by separating built-up areas from barren land (He *et al.*, 2010).

Table 4.2. The spectral indices that were calculated for inclusion in the training data.

Index	Equation	Label	Reference
NDVI	$\frac{(NIR - RED)}{(NIR + RED)}$	1	Tucker and Sellers (1986)
EVI	$\frac{[(2.5\text{ X }(NIR - RED)]}{[(NIR + (6\text{ X }RED) - (7.5\ X\ BLUE) + 1]}$	2	Huete *et al.* (2002)
NDWI	$\frac{(NIR - SWIR)}{(NIR + SWIR)}$	3	Gao (1996)
MNDWI	$\frac{(GREEN - SWIR)}{(GREEN + SWIR)}$	4	Xu (2006)
NDBI	$\frac{(SWIR - NIR)}{(SWIR + NIR)}$	5	Zha *et al.* (2003)

Qu *et al.* (2021) proposed using different auxiliary features to improve the accuracy of LULC classification that utilises remote sensing images with medium resolution. Therefore, this study incorporated slope, calculated in ArcGIS Pro using 30 m resolution SRTM Digital Elevation Data.

4.2.3 Sample data composition

This study utilised single-date Landsat imagery to classify LULC classes in the eThekwini Municipality. The use of single-date imagery provides a clear snapshot of land cover for the selected year, enabling a straightforward analysis that captures the state of the landscape at a specific point in time. This approach is well-suited to monitoring stable LULC classes and ensures consistency in classification across the entire study area. While multi-date or composite imagery can capture seasonal variations, single-date imagery effectively reduces complexity and potential noise introduced by seasonal land cover fluctuations, allowing for a more focused analysis of long-term land use trends.

To compose the training dataset, the seven bands from the single-date 2017 Landsat 8 image, computed spectral indices, elevation data, and the 2017 FROM – GLCS10 image were stacked in GEE, resulting in a single multiband image. Stratified sampling was conducted, with a maximum of 10000 points per class from the 2017 FROM-GLCS10 dataset, applied to the multiband image used for classification. This sampling approach aimed to ensure robust representation across land cover types; however, it is acknowledged that generating this number of samples per class, particularly for smaller classes, may introduce spatial autocorrelation. For classes with limited spatial coverage, such as wetlands, multiple sample points could fall on the same or neighbouring pixels, which may lead to inflated accuracy metrics as similar spatial characteristics are sampled repeatedly, not necessarily improving the model's true performance on new data.

The sample data were exported to the R computing platform (*version 4.3.2*) through the RStudio IDE (*version 2022.07.2+576*) in a comma-separated values (CSV) file, and all computations were conducted within RStudio. Before training, the data were split into 70% training and 30% test sets and resampled using K-fold cross-validation (K = 5, repeated 10 times) in the *caret* package in RStudio to improve model generalisability. Although 10000 sample points per class were chosen for consistency, future studies could consider applying a minimum buffer distance between samples to reduce autocorrelation effects or adjusting sample intensity based on class area to further enhance model robustness.

4.2.4 Machine learning algorithms

4.2.4.1 Random forests

RF was adopted to conduct the LULC classification using Landsat 7, 8, and 9 images. RF is a group of regression trees that grow from the random selection of training data samples (Ali *et al.*, 2012), as outlined in Figure 4.2. Ma *et al.* (2017) and Masiliūnas *et al.* (2021) posited that RF, which improves from the CART algorithm, performs well when classifying remotely sensed imagery. RF can also solve classification and regression problems (Nghia *et al.*, 2021). Thus, it has become the most utilised machine learning algorithm in classifying remote sensing images (Luo, C. *et al.*, 2021).

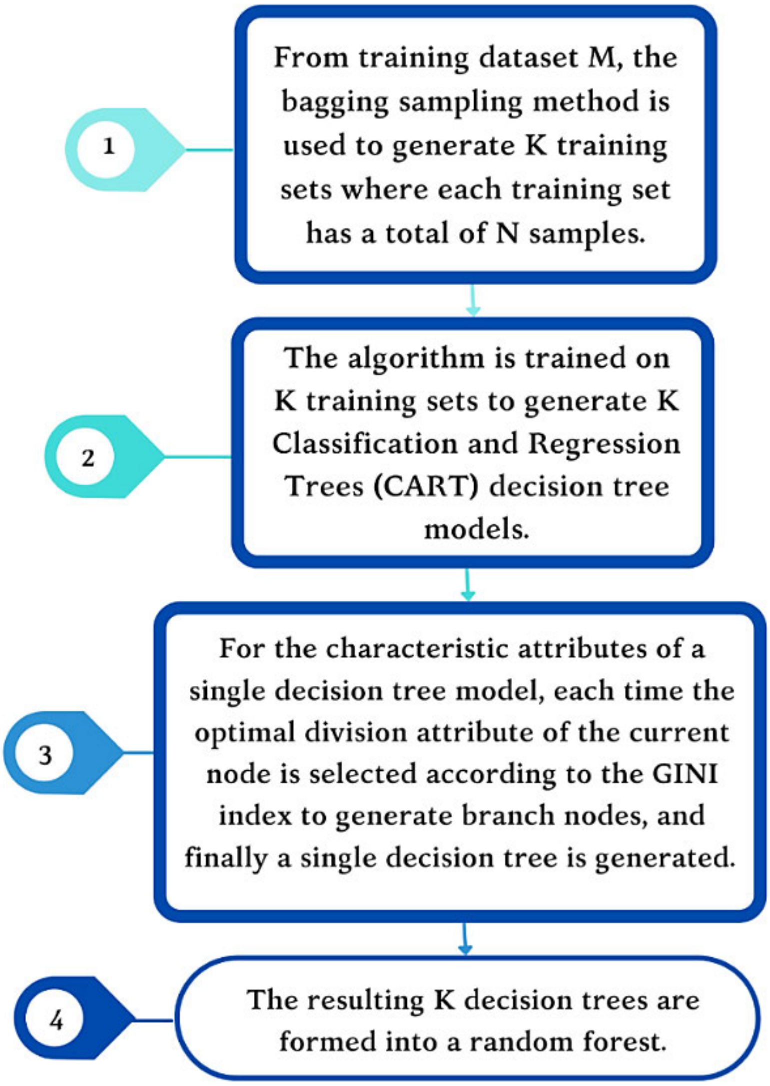

Figure 4.2. The formation of RF, as outlined in Chen *et al.* (2021).

4.2.4.2 Support vector machines

SVM is one of the most robust pattern recognition methods, which operates by determining an optimal separation line (hyperplane) that accurately separates two or more classes (Bennett-Lenane *et al.*, 2022). Determining the optimal hyperplane maximises the generalisation ability of the SVM model (Cervantes *et al.*, 2020). However, if the data is not linearly separable as in this study, the generalisation of the model is hindered. Thus, a kernel function is employed (Saygılı, 2022). This study selected the radial basis function (RBF) to perform the LULC classification because it is effective in handling non-linearly separable data, as was the case in this study (Anyanwu *et al.*, 2023).

4.2.4.3 *Extreme gradient boosting*

XGBoost is an extension of gradient boosting machines (GBMs), a widely employed technique in various remote sensing applications (Buthelezi *et al.*, 2020a). Its application has been limited to structural engineering, hence, its limited application in remote sensing (Nguyen *et al.*, 2021). XGBoost model employs additive learning to develop a “strong” learner through the integration of several “weak” learners (Fan *et al.*, 2021). The XGBoost algorithm was developed to achieve a low risk of overfitting and high accuracy (Nguyen *et al.*, 2021).

4.2.5 Parameter optimisation

RF in RStudio requires parameter optimisation, which significantly improves the algorithm's accuracy (Buthelezi *et al.*, 2020a). The performance of RF is primarily influenced by two main parameters: the number of features randomly selected for constructing each tree (*Mtry*) and the total number of trees to be generated (*Ntree*). However, it should be noted that only *Mtry* can be adjusted manually. Therefore, to obtain the optimal *Mtry*, the *expand.grid* function in RStudio was used. In the case of SVM, the optimised parameters were the cost (C) and gamma (γ), both of which are independent of each other. A lower value of C places emphasis on maximising the margin, whereas a higher value indicates a preference for minimising errors in the SVM algorithm. The γ relates to how much curvature is required in a decision boundary. When the γ parameter is low, it means the single training sample is far-reaching, whereas when it is high, the opposite is true. Optimised parameters for RF and SVM are presented in Table 4.3.

Table 4.3. Optimised parameters for both RF and SVM.

RF Parameter	**Value**	**SVM Parameter**	**Value**
Mtry	1	Cost (C)	1
Ntree	1	Gamma (γ)	0.083

XGBoost requires multiple parameters to be optimised, among them the number of trees, learning rate, and regularisation parameters (Nguyen *et al.*, 2021). The Bayesian optimisation method, outlined in Bergstra *et al.* (2011), was utilised to obtain optimal parameters for XGBoost, and the resulting parameter values are presented in Table 4.4.

Table 4.4. XGBoost optimal parameters that were obtained using the Bayesian optimisation method.

XGBoost Parameter	Value
Subsample Ratio (r_s)	1
Learning Rate (τ)	0.3
Maximum Tree Depth (D_{max})	6
Minimum Child Weight (ω_{mc})	1
Column subsample ratio (r_c)	0.9471

4.2.6 Variable importance

Variable importance for RF and XGBoost LULC classifications was determined using the *importance* and *varImp* functions in RStudio, respectively. RF's variable importance can be presented using the permutation-based metric and a node impurity metric. The node impurity metric (mean decrease in Gini coefficient) was used for this study. It is defined as the average of a variable's total decrease in node impurities after the splitting of the variable, averaged over all trees (Luo, C. *et al.*, 2021). For XGBoost, the relative importance (RI) score, which is also based on the Gini coefficient importance, was used (Kardani *et al.*, 2022). RI for this study was scaled from 0 to 100. Given that SVM used RBF to perform the LULC classification, it was impossible to determine variable importance for the algorithm. That is because, in kernels other than the linear kernel, the separating plane exists in another space because of the kernel transformation of the original space.

4.2.7 Accuracy assessment

The primary evaluation of LULC classifications involved assessing overall accuracy, user's accuracy, and producer's accuracy derived from the confusion matrix, along with calculating of the area under the curve (AUC). The accuracy measures were calculated in RStudio. The overall accuracy assesses the number of pixels correctly classified within the image and was employed as the primary metric in this study. The producer's accuracy measures the precision with which reference pixels are classified, while the user's accuracy assesses how accurately the classified map reflects the actual conditions on the ground (Patel and Kaushal, 2010). The AUC is a measure of sensitivity and specificity over all possible threshold values (Halimu *et al.*, 2019).

Furthermore, quantity and allocation disagreements were computed in RStudio and used to investigate the accuracy of the classifications further. Quantity disagreement measures the disparity in the quantity of a specific class of objects between the classified and reference maps, while allocation disagreement compares the spatial arrangement of pixels between the classified and reference maps (Fassnacht *et al.*, 2014; Lottering *et al.*, 2020; Pontius and Millones, 2011; Verma *et al.*, 2020). The allocation disagreement in this study uses the exchange and shift measures. Exchange occurs when a pair of pixels is classified as category A in the reference map and as category B in the classified map, and vice versa (Pontius and Santacruz, 2014). Whereas shift is a measure of allocation disagreement used when comparing maps with more than two categories, which identifies situations where the spatial distribution of classes differs between the maps. Still, these differences are not due to a simple exchange of categories (e.g., forest classified as water in the reference map and water classified as forest in the classified map) (Bontempo *et al.*, 2020).

4.2.8 Percentage area for each class

The LULC classification outputs were investigated in QGIS Desktop 3.26.1 for the quantity of the pixels belonging to each class using the raster layer unique values report tool. The values from the report were used to compute the percentages for the area occupied by each LULC class within the study area. The overall methodology is outlined in Figure 4.3.

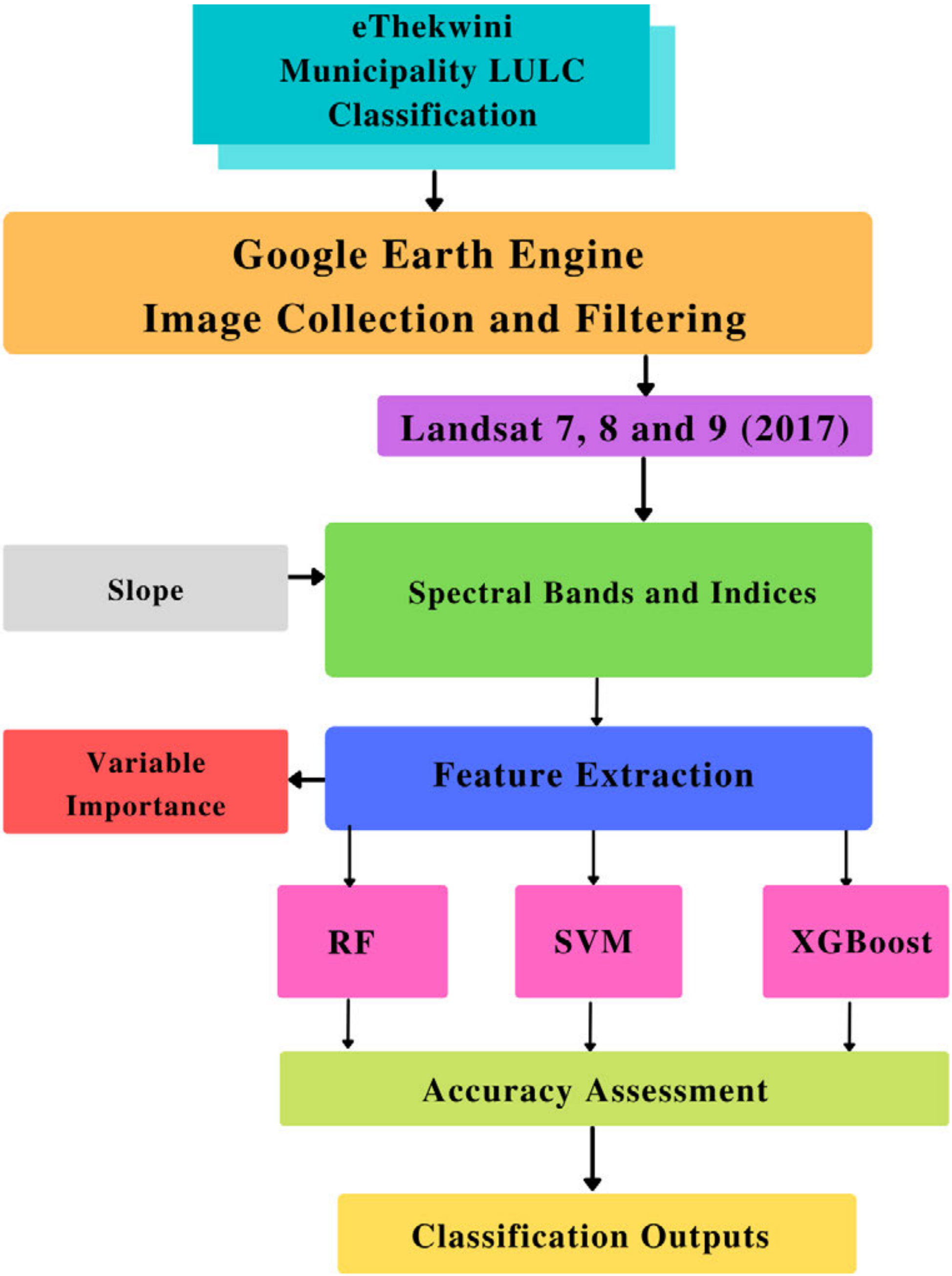

Figure 4.3**.** The overall framework used to perform RF, SVM, and XGBoost LULC classifications.

4.3 Results

4.3.1 Variable importance

Figure 4.4 shows the variable importance for RF LULC classifications based on the 2017 Landsat 8 image classification. The figure indicated that the red and blue bands were the most important variables, whereas slope had the least importance. When comparing the importance of spectral indices used in RF classifications, NDVI was the most important index.

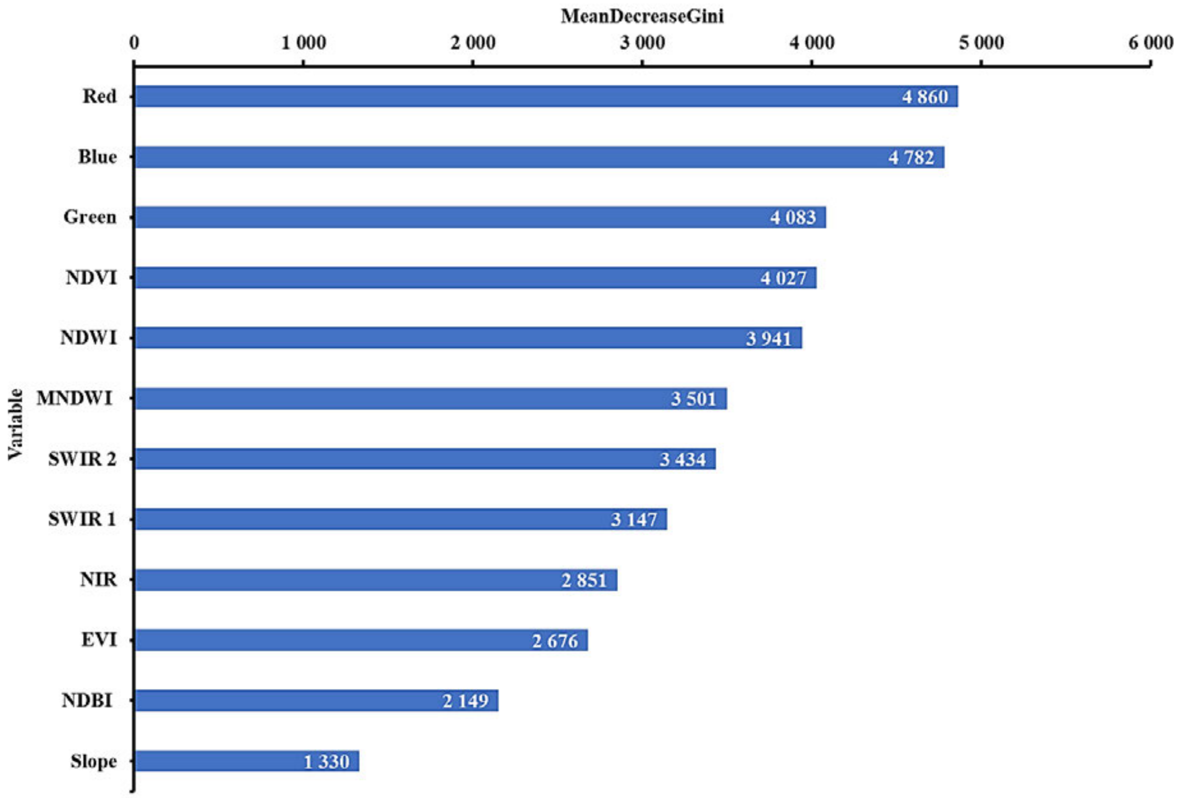

Figure 4.4. Variable importance based on the mean decrease in the Gini coefficient for RF LULC classification on the 2017 Landsat 8 image.

When XGBoost was used to perform LULC classification on the 2017 Landsat image, the red band had the highest importance, indicating it was the most influential variable in the classification (Figure 4.5). The MNDWI and NDVI follow, also playing significant roles in distinguishing different land cover types. The NDBI, NIR, and slope had the lowest importance, suggesting minimal to no impact on the classification in this context.

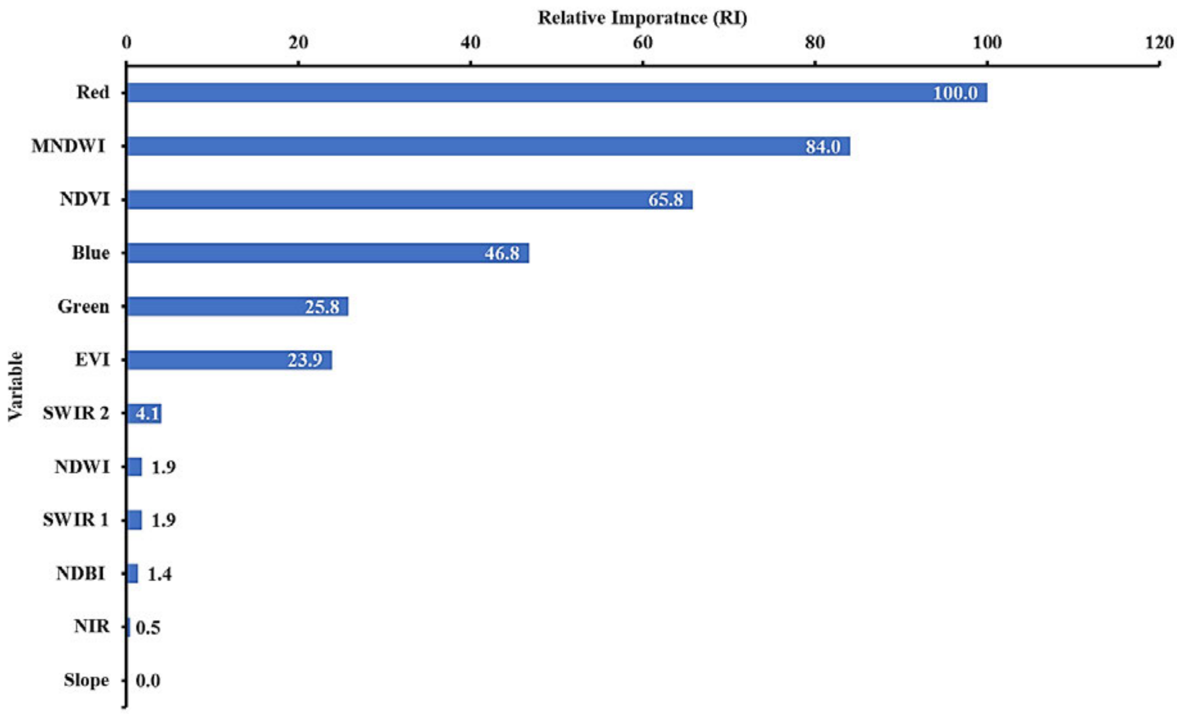

Figure 4.5. Variable importance based on the RI for XGBoost LULC classification on the 2017 Landsat 8 image.

4.3.2 Accuracy assessment

4.3.2.1 Confusion matrix

All three algorithms successfully classified the 2017 Landsat 8 image in RStudio. However, these classifications were executed at varying accuracies (Figure 4.6). Based on the overall accuracy for RF, SVM and XGBoost LULC classifications performed on Landsat images, it was observed that XGBoost classifications (80.57%) performed slightly better than RF (80.42%) and SVM (79.59%). Based on the user's accuracy, RF and XGBoost (97.16%) outperformed SVM (97.05%). However, RF (92.27%) did perform fractionally better than XGBoost (92.26%) and SVM (91.75%) based on the AUC measure. RF (79.77%) also performed better than XGBoost (79.74%) and SVM (78.49%) based on the producer's accuracy.

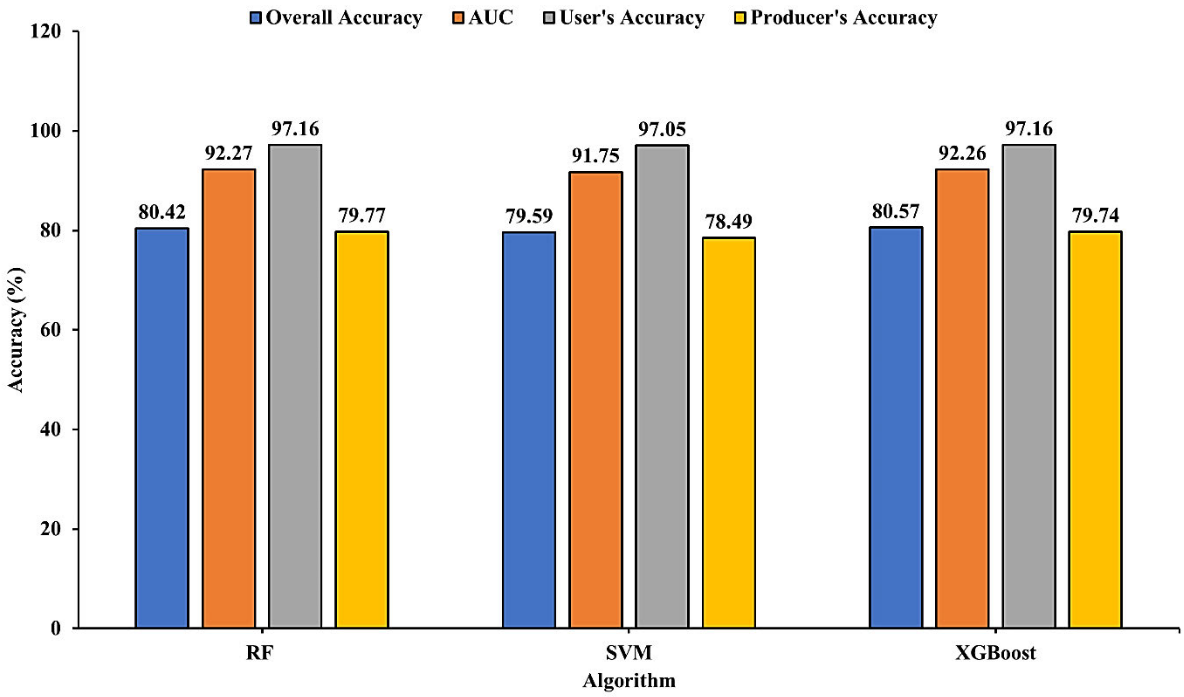

Figure 4.6. RF, SVM and XGBoost classification accuracies based on the overall accuracy, user's accuracy, producer's accuracy, and AUC measures from the 2017 Landsat 8 image.

4.3.2.2 Quantity and allocation disagreements

Figure 4.7 shows the results for disagreement metrics which represent the percentage of disagreement between LULC maps classified based on the 2017 Landsat 8 images and the reference map. The exchange and shift represent the percentage of allocation disagreement. RF LULC classification had a quantity disagreement of 15.72%, an exchange of 22.79% and a shift of 17.28% (Figure 4.7a). The quantity disagreement observed in the RF classification was significantly less than that observed in the SVM classification (Figure 4.7b), which was 70.66%. However, SVM performed better than RF when looking at the exchange and shift measures, which were 5.50% and 6.22%, respectively. Overall, XGBoost performed better than RF and SVM with a quantity disagreement of 11.92%, an exchange of 28.73% and a shift of 10.29% (Figure 4.7c)

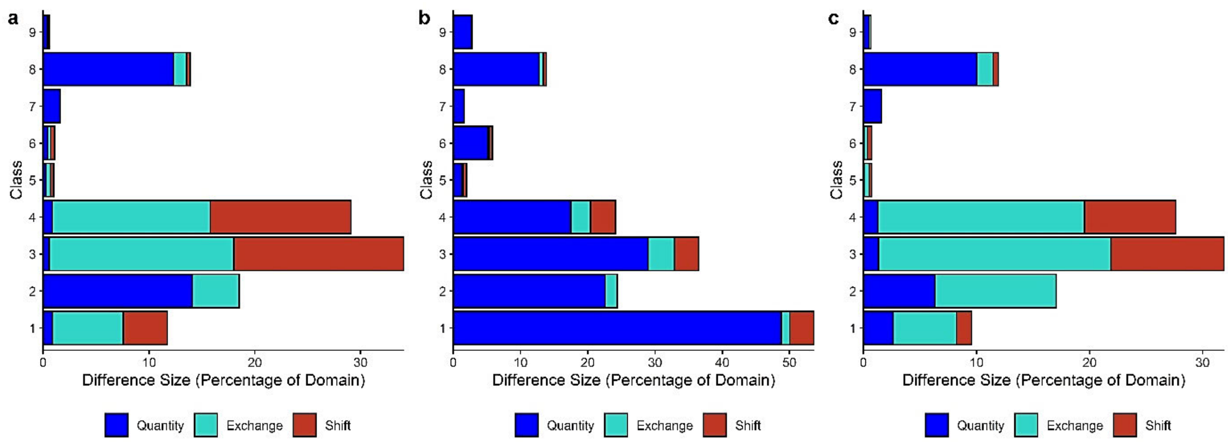

Figure 4.7. Disagreement metrics for the (a) RF, (b) SVM and (c) XGBoost LULC classification maps based on the 2017 Landsat 8 image.

Overall, XGBoost produced slightly more accurate classifications than RF and SVM. Hence, it was selected to map LULC change within the eThekwini Municipality.

4.3.3 Class area distribution

Figure 4.8 illustrates the changing landscape dynamics within the study area from 2002 to 2022. Over this period, notable trends include a consistent decline in cropland area from 31.5% in 2002 to 7.5% in 2017, followed by a slight increase to 11.8% in 2022, indicating potential shifts in agricultural practices or land use conversions. Forest cover remained relatively stable until 2017, experiencing a significant increase to 20.5% in 2022, possibly reflecting afforestation efforts or natural regeneration processes. Grassland areas fluctuated, peaking at 38.5% in 2012 before declining to 26.4% in 2022, suggesting changes in land management or ecological processes. Shrubland habitats remained consistent until 2017, with a slight expansion to 24.7% in 2022. Wetland and water areas showed minimal changes, indicating stable hydrological conditions. Impervious surface areas peaked in 2012 at 22.4% before declining to 13.8% in 2022, possibly reflecting urbanisation patterns. Bare land areas remained relatively stable, suggesting minimal changes in this class.

However, it was observed that when XGBoost classified Landsat 7 images, forest vegetation was underestimated compared to its classification of Landsat 8 and 9 images. Conversely, Landsat 8 and 9 classifications exhibited an underestimation of impervious surfaces compared to Landsat 7. Given the improved radiometric resolution in Landsat 9, the final 2022 classification was accepted and presented in Figure 4.9. Impervious surfaces are found in the eastern and northern parts of the eThekwini Municipality. Vegetated landscapes are found mainly in the western part of the municipality. It was also observed that forested areas are mostly fragmented. Fragmentation of forested areas was observed through the discontinuous distribution of forest patches, with numerous small and isolated patches scattered across the landscape.

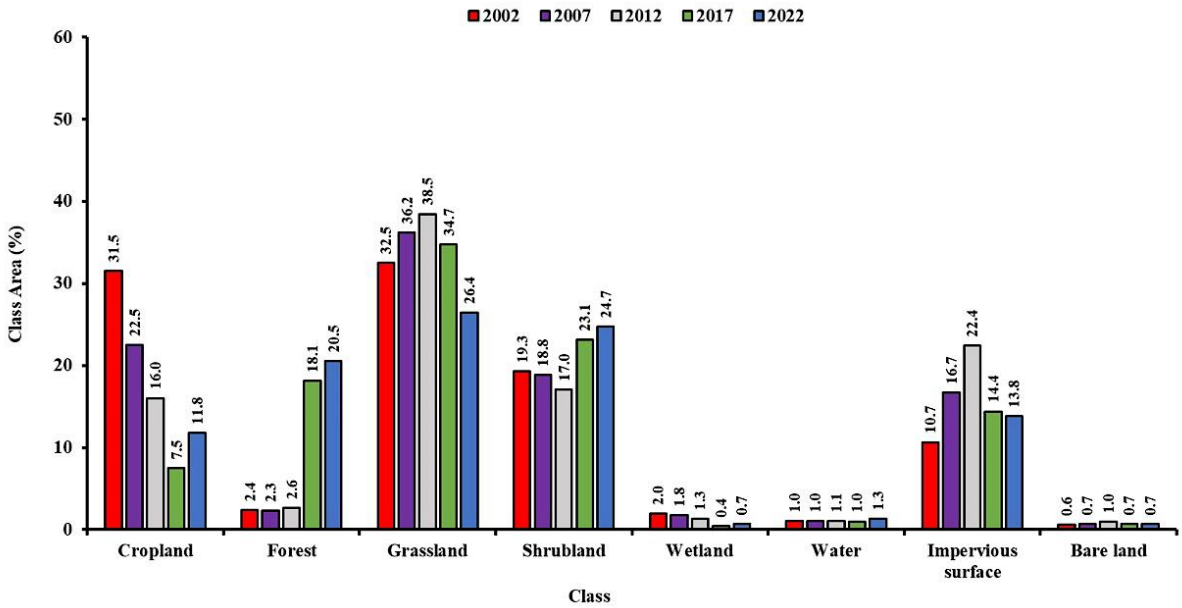

Figure 4.8. Comparison of the area covered by each class after classifying all the Landsat images using XGBoost.

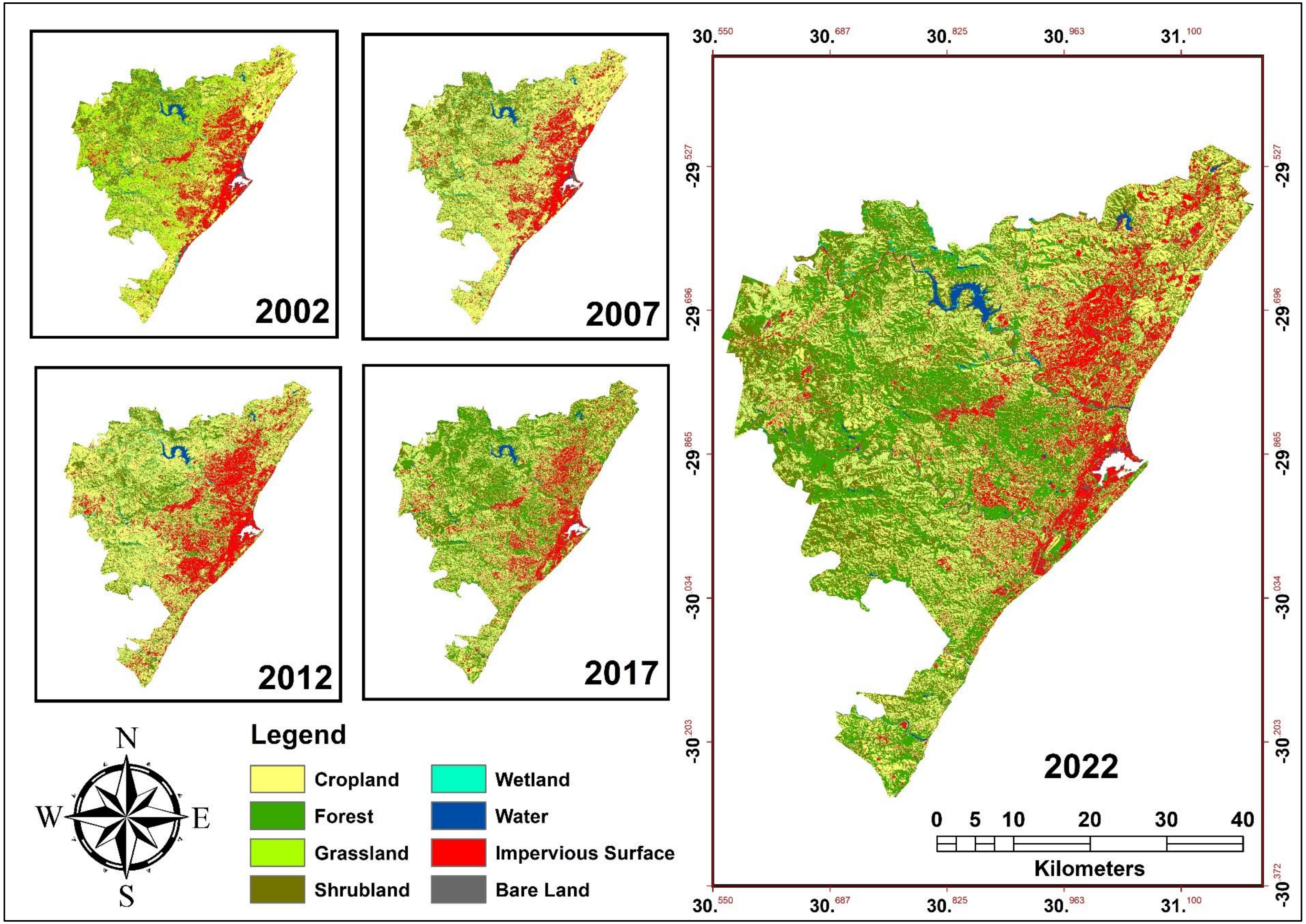

Figure 4.9. The spatial arrangement of LULC classes within the eThekwini Municipality from 2002 to 2022.

4.4 Discussion

Improved access to medium and high-resolution remote sensing data coupled with free cloud-based geospatial analysis platforms such as GEE has enabled large-scale LULC classifications to be conducted more efficiently (Tassi and Vizzari, 2020). Machine learning algorithms have also gained more interest in remote sensing studies because they have outperformed most conventional parametric techniques (Ngolo and Watanabe, 2022). Therefore, this study utilised Landsat data from GEE to map LULC change using RF, SVM and XGBoost from 2002 to 2022 for the eThekwini Municipality. The performance of these algorithms was compared using mainly the overall accuracy extracted from the confusion matrix and quantity and allocation disagreements where XGBoost produced the highest overall accuracy.

This is consistent with conclusions in recent research findings such as Pan (2018), who compared the performance of XGBoost in predicting the concentration of 2.5 µm aerosol particles (PM2.5) in the air with artificial neural networks (ANNs), RF, multiple linear regression (MLR) and SVM. XGBoost was found to have outperformed all the other algorithms based on the root-mean-square error (RMSE) (17.298) and R^2 (0.9520). Yu *et al.* (2021b) investigated the performance of XGBoost, RF and SVM in mapping the vertical forest structure, where it was observed that XGBoost (0.92) performed better than RF (0.90) and SVM (0.90) based on the F1 Score. In their study, Geng *et al.* (2021) applied RF, SVM, ANN, and XGBoost to predict seasonal maize biomass using field observation data and imagery from the Moderate-Resolution Imaging Spectroradiometer (MODIS). They found that XGBoost (0.77) and RF (0.77) performed better than ANN (0.72) and SVM (0.72) based on the R^2.

The advantage of XGBoost over other algorithms is based on its ability to reduce inaccuracies resulting from over- and underestimation and corrects the residual error, which results from the generation of a new tree based on the previous tree (Geng *et al.*, 2021; Li *et al.*, 2019). XGBoost can also accurately classify noisy data due to its loss function flexibility (Izadi *et al.*, 2021). However, it should be noted that the performances of both RF and SVM were not significantly lower than that of XGBoost. Furthermore, when the performance of the three algorithms was investigated using the AUC, RF performed better than both XGBoost and SVM. This meant all algorithms used in this study could perform LULC classifications on a regional scale.

However, the high accuracy achieved by the models indicate that they are highly effective at replicating the patterns found within the FROM-GLCS10 training data. However, because the

2017 FROM-GLCS10 dataset itself has an approximate global accuracy of only 80%, this accuracy rate must be interpreted with caution. The reliance on secondary data, particularly one without validation specific to the eThekwini Municipality, could mean that the model's accuracy does not fully reflect the true land cover conditions in the area. This limitation exemplifies the "garbage-in-garbage-out" principle, where inaccuracies in training data are likely to carry over into the model's results, thus impacting its reliability in accurately depicting real-world land cover.

Furthermore, using the FROM-GLCS10 data for accuracy assessment may have led to an inflated accuracy rate. When evaluating a model against training data with known limitations, accuracy metrics can be artificially high, suggesting that the model's precision may be overstated. This calls for caution in interpreting the findings, as the observed accuracy might only indicate consistency with the training data rather than a genuine reflection of land cover in the eThekwini Municipality. Future research could address this limitation by validating model outputs against high-resolution reference data specific to the study area, which would provide a more rigorous measure of model accuracy in capturing actual land cover characteristics.

This study also used single-date Landsat imagery which offers certain advantages, especially in providing a precise, time-specific representation of land cover that aligns with the study's focus on identifying clear changes over a defined period. Single-date imagery reduces the potential for misclassifications due to seasonal transitions, offering a stable reference point for comparing land cover types. Although seasonal crops like sugarcane or rotational forestry cycles may vary with different imaging dates, the use of single-date imagery simplifies the classification process, providing a reliable baseline that supports clear, year-to-year comparisons in LULC change dynamics. For future studies, incorporating multi-date imagery could offer additional insights into highly seasonal land cover types.

This study further evaluated the importance of variables used to classify LULC change. However, it should be noted that variable importance could not be extracted in RStudio for SVM, due to applying the RBF kernel. That is because, in a non-linear kernelised SVM, the separating plane exists in another space because of the kernel transformation of the original space. In RF classifications, the top four variables in terms of importance were the red band, blue band, green band and NDVI. The red and green bands provide critical information for detecting vegetation, given their sensitivity to a wider range of chlorophyll concentrations

(Odebiri *et al.*, 2022). Landsat's green band is positioned above the green edge, a range of wavelengths where vegetation's reflectance behaviour changes, similar to the red band and red edge, both of which shift towards longer wavelengths in areas with high chlorophyll concentration due to chlorophyll's absorption properties, serving as a crucial indicator of healthy and dense vegetation in remote sensing (Pastor-Guzman *et al.*, 2015). Pastor-Guzman *et al.* (2015) added that as chlorophyll concentration increases, the red spectral band would reach minimum reflectance, whereas the green band continues to be sensitive. The blue band is useful in differentiating deciduous from coniferous vegetation and overall vegetation from bare soil (Li *et al.*, 2019). NDVI is calculated using the red band and NIR and is a measure of vegetation greenness and health of vegetation in each pixel in a remotely sensed image (Kumar, B. P. *et al.*, 2022). This meant RF was more efficient at discriminating vegetation from other classes when performing LULC classifications.

The red band was also the most important variable in the XGBoost classification, followed by MNDWI, NDVI and the blue band. The MNDWI improves on the NDWI, which helps detect hydrological changes (Teng *et al.*, 2021). It was successfully employed by Pal and Pani (2016) to detect changes in the Ganga River water surface coverage in India. MNDWI uses green and SWIR bands to detect open water features and to discriminate them from impervious surface features as these are often correlated in other indices (Zhang and Liu, 2022). NDVI and the blue are critical for vegetation detection. This meant XGBoost was more efficient at discriminating vegetation and water bodies from other classes.

Given its better performance, the images classified using XGBoost were investigated for the area covered by each class within the study area boundary. The results showed that cropland, grassland, shrubland and impervious surfaces dominated the eThekwini Municipality landscape. Classifications also revealed that cropland, shrubland, and water exhibited a decreasing trend from 2002 to 2017, while grassland and impervious surface classes experienced an increase from 2002 to 2012. In 2022, cropland accounted for 11.8%, forest for 20.5%, grassland for 26.4%, shrubland for 24.7%, wetland for 0.7%, water for 1.3%, and impervious surface for 13.8% of the total land cover within the eThekwini Municipality. However, it should be noted that when XGBoost classified Landsat 7 images, it was observed that it underestimated forest vegetation compared to when it classified Landsat 8 and Landsat 9 images, which also underestimated the impervious surface compared to Landsat 7. This meant it was impossible to determine the extent of the increase in impervious surfaces after

2012. However, the improved radiometric resolution of Landsat 8 and Landsat 9 over Landsat 7 provided enhanced spatial and radiometric details (Mushore *et al.*, 2022). Therefore, it was concluded that outputs from classified Landsat 8 and Landsat 9 images were more representative of the spatial arrangement of the eThekwini Municipality.

The 2022 LULC map output showed that impervious surfaces were most prevalent along the coast, which was along the eastern side of the eThekwini Municipality. Cropland was prevalent in the northern part of the municipality, where Tongaat Hulett, a sugar and maize company is, a major landowner (Moffett and Freund, 2004). However, during the 1990s, Tongaat Hulett diversified its operations to include land management and property development, resulting in notable projects like gated townhouses, holiday complexes, shopping centres, and the establishment of the King Shaka International Airport in the region (Todes, 2014). Hence, impervious areas have been expanding towards the north.

It was also mentioned in this study that the eThekwini Municipality is susceptible to adverse environmental consequences due to accelerated spatial change resulting from attempts to rectify inequalities and socioeconomic distortions created by apartheid through infrastructure projects (Musvoto *et al.*, 2016; Sutherland *et al.*, 2014). These government infrastructure projects further contributed to the increase in impervious surfaces and the decrease in vegetated landscapes. These areas are surrounded mainly by croplands, forests, and shrubland. Furthermore, with the projected increase in population numbers within the eThekwini Municipality and infrastructural expansion, it is probable that impervious areas will expand further and, therefore, will reduce the area covered by vegetation (Otunga *et al.*, 2014).

The loss of vegetated landscapes means that natural ecosystem services that are vital for climate change mitigation, such as carbon storage, flood attenuation, and food production from these landscapes, are also lost (Tew, 2019). The 2022 LULC map revealed that forested areas exhibit a high degree of fragmentation. Fragmentation in forested areas was observed by identifying discontinuities or breaks in the forest cover across the landscape. This was evident through the presence of isolated patches of forest separated by non-forested areas. Forest fragmentation is often associated with species loss, bird nest parasitism, and increased edge effects, which also result in increased predator density (Slattery and Fenner, 2021). Increased predator density significantly impacts biodiversity through increased direct killing of prey and fear of predators, which changes some prey species' behavioural patterns, physiology and reproduction rate (Yousef *et al.*, 2021).

This study also underscores the significance of Landsat 9 in LULC classification, highlighting its utility and contribution to enhancing the accuracy of classification outcomes (Jombo and Adelabu, 2023; You *et al.*, 2022). By incorporating Landsat 9 imagery alongside Landsat 7 and Landsat 8, the study leveraged the improved radiometric resolution of Landsat 9 to refine the classification process, thereby providing more precise and detailed insights into LULC dynamics within the eThekwini Municipality. This aligns closely with findings by Shahfahad *et al.* (2023) and Ghasempour *et al.* (2023), who similarly compared the effectiveness of Landsat 8 and Landsat 9 for LULC mapping across a heterogeneous landscape. The successful integration of Landsat 9 underscores its potential as an asset in remote sensing applications, offering enhanced capabilities for monitoring and assessing environmental changes over time.

Therefore, by updating LULC maps for the eThekwini Municipality, this study aids decision-makers in mitigating the persisting challenges of climate change through appropriate environmental management policies and strategies. By applying applicable environmental policies, there will be fewer vegetated landscapes lost. This study also highlighted the applicability of remote sensing, machine learning and GEE data in LULC classifications. The utilisation of GEE in this study is very significant given the finding by Chaves *et al.* (2020) that big data processing is still challenging for analysts. GEE eliminates this challenge by allowing analysts to access, analyse and visualise geospatial big data in powerful ways without needing for specialised coding expertise or supercomputers (Tamiminia *et al.*, 2020). This study also employed Landsat 9, which was launched towards the end of 2021. Therefore, this study becomes one of the few studies that have used it for regional LULC classifications.

However, this study several limitations that may impact the generalisability and accuracy of the findings. First, the reliance on medium-resolution remote sensing data restricts the ability to capture finer-scale changes in LULC dynamics. This limitation could lead to an incomplete understanding of nuanced shifts in land degradation and forest rehabilitation. Higher-resolution imagery may have provided more detailed insights but was unavailable due to resource constraints. Additionally, the chapter employed specific machine learning algorithms like RF, SVM, and XGBoost, which, while robust, may not fully represent the efficacy of other potential algorithms.

4.5 Conclusion

This study successfully classified LULC change for the eThekwini Municipality using machine learning algorithms and Landsat data. The findings illustrated that XGBoost classifications using Landsat imagery could perform better classification than RF and SVM. Therefore, the eThekwini Municipality's LULC change was mapped using XGBoost and Landsat imagery. The produced maps will aid decision-makers in making socioeconomically sound plans that do not infringe on the environment. It is also recommended that the eThekwini Municipality update its LULC maps annually. Future studies can adopt the methodology used in this study to perform accurate LULC classifications. Also, studies that are not financially constrained can utilise high-resolution imagery to perform LULC classifications to improve accuracy.

4.6 Summary

This chapter aimed to predict LULC changes in the eThekwini Municipality using satellite imagery from the last three Landsat satellites and advanced machine learning techniques. The research spans from 2002 to 2022, employing the EVI, NDVI, NDWI, MNDWI, and NDBI to classify land cover types accurately. RF, SVM, and XGBoost were utilised for the classification, with XGBoost delivering the highest accuracy at 80.57%. The generated LULC maps indicated a significant reduction in cropland and an increase in impervious surfaces, reflecting ongoing urbanisation and land development trends. This comprehensive approach underscores the utility of Landsat 9's enhanced radiometric resolution in improving classification accuracy. The study also leveraged the GEE platform for efficient processing and analysis of large datasets used in this study, demonstrating its effectiveness in handling geospatial big data.

The findings provided crucial insights for sustainable environmental planning and development in eThekwini Municipality. By establishing a robust framework for continuous LULC monitoring, this chapter supports policymakers in updating the DMOSS and implementing informed environmental management strategies. The study also emphasised the importance of up-to-date LULC information in mitigating the impacts of global change, conserving natural resources, and enhancing resilience to climate-related hazards.

5. CHAPTER FIVE: ASSESSING THE EXTENT OF LAND DEGRADATION IN THE ETHEKWINI MUNICIPALITY USING LAND COVER CHANGE AND SOIL ORGANIC CARBON

This chapter is based on:

Buthelezi, M. N. M., Lottering, R., Peerbhay, K., & Mutanga, O. (2024). Assessing the extent of land degradation in the eThekwini municipality using land cover change and soil organic carbon. *International Journal of Remote Sensing*, 45(4), 1339–1367. https://doi.org/10.1080/01431161.2024.2307945

Abstract

More than 75% of the global land has already suffered degradation, leading to the recognition of land degradation as one of society's foremost challenges. This recognition stems from its profound adverse impacts on natural ecosystem functioning, biodiversity, soil productivity, and food availability. Consequently, understanding the spatial distribution of land degradation across all scales becomes imperative. This study employed land cover change and soil organic carbon (SOC) stock assessments to analyse land degradation within the eThekwini Municipality beyond the baseline period (2000 – 2015). Utilising remote sensing and machine learning techniques, this research examined land degradation within the eThekwini Municipality over the period spanning 2000 to 2022. Landsat 7 (Enhanced Thematic Mapper Plus - ETM+), Landsat 8 (Operational Land Imager - OLI), and Landsat 9 (Operational Land Imager 2 - OLI2) images were employed to extract variables for both land cover change and SOC stock prediction through XGBoost, LightGBM, random forest (RF), and support vector machine (SVM) models. Among these models, LightGBM demonstrates superior performance, achieving an overall accuracy of 80.646 in land cover predictions and 77.869 in SOC stock predictions. Analysis of land cover change within the eThekwini Municipality unveiled a shift from forests and shrubland landscapes to cropland and built-up areas. This shift results in the municipality encountering losses in SOC stock between 2015 and 2022. The model predicted that most SOC stock losses occur at the 20 – 50 cm depth (9.27%), in comparison to the 7.21% loss at the 0 - 20 cm depth. These findings underscore the pivotal role of remote sensing and machine learning in aiding policymakers to assess land degradation and implement pertinent measures to enhance the landscape.

Keywords: land cover change, degradation, soil organic carbon, machine learning, remote sensing

5.1 Introduction

Land degradation encompasses the ongoing and accelerated reduction of land productivity resulting from a combination of anthropogenic activities and natural causes (Reith *et al.*, 2021). Approximately more than 75% of the land globally has been degraded already (Prăvălie, 2021; Yu and Deng, 2022). In most regions, land degradation is induced by human activities such as urbanisation and agricultural intensification (Egidi *et al.*, 2021). These activities are a response to the rapid growth of the world population (Yu and Deng, 2022). Projected estimates suggest that by the year 2050, there will be a need to double agricultural production to meet the increasing demands of this growing global population (Skendžić *et al.*, 2021). Also by the year 2050, it is approximated that more than 60% of the world's population will be located in urban areas (Welford and Yarbrough, 2021). These estimates imply that degraded landscapes will expand further than the current estimates of 75%. Perović *et al.* (2021) reported that without any intervention, more than 90% of the land will be degraded globally by 2050.

Land degradation has significant negative implications on the natural ecosystem functioning, biodiversity, soil productivity and food availability (Perović *et al.*, 2021). It achieves these negative implications mostly through soil erosion and desertification (Eswaran *et al.*, 2019). Thus, land degradation is increasingly becoming one of the major challenges that society is currently facing. Therefore, the United Nations Convention to Combat Desertification (UNCCD) expressed the need to prevent further degradation and to restore degraded lands at the 2012 United Nations Conference on Sustainable Development (RIO + 20), where the target of zero net land degradation was set (Sutton *et al.*, 2016). Combating land degradation is also part of the Sustainable Development Goals (SDGs) as the third indicator of SDG 15 (Life on Land), which aims to protect, restore, and sustainably manage terrestrial ecosystems, forests, biodiversity, and combat desertification and land degradation (Keesstra *et al.*, 2021b). Under SDG 15 there are 12 targets, however, this study focuses on the third target (SDG 15.3) where UNCCD serves as the custodian agency (Xoxo *et al.*, 2022). SDG 15.3 states that "by 2030, combat desertification, restore degraded land and soil, including land affected by desertification, drought and floods, and strive to achieve a land degradation-neutral world."

Hence, UNCCD developed a Good Practice Guidance (GPG) document (Sims *et al.*, 2017), which provides recommendations for identifying the best approach to assess a country's land degradation conditions (Sims *et al.*, 2019). GPG also describes the three sub-indicators used to assess land degradation: land cover change, soil organic carbon (SOC) stocks, and land productivity (Sims *et al.*, 2020). Land cover change refers to the transformation of the structure and composition of the landscape as a result of anthropogenic activities and natural events (Sims *et al.*, 2017). Land productivity is the change in health and inherent biological productive capacity of the land to produce fuel, food and fibre and reflects changes in ecosystem functioning (Gonzalez-Roglich *et al.*, 2019). Whereas the SOC stock sub-indicator provides valuable information on soil properties that promote vegetation growth, such as soil fertility, nutrient availability, anion/cation exchange capacity and water holding capacity (Mirzaee *et al.*, 2016; Odebiri *et al.*, 2022; Wang, Bin *et al.*, 2018). The use of these three sub-indicators in land degradation monitoring follows the one-out-all-out statistical rule, which states that an area only needs to be determined to be degraded under one sub-indicator to be reported as degraded under SDG 15.3 (Xoxo *et al.*, 2022).

Therefore, this study used land cover change and SOC stock to assess land degradation in the eThekwini Municipality within and beyond the baseline period. The UNCCD stipulates that the baseline or reference period is set from 2000 to 2015 (Sims *et al.*, 2020). This period will serve as the benchmark against which the status of land degradation will be monitored until 2030 (Bär *et al.*, 2023). The utilisation of land cover change as an indicator of land degradation presents a valuable approach to monitoring the health and quality of land resources. However, it is crucial to exercise caution and ensure a thoughtful selection of class transitions that are considered indicators of land degradation. Whether a shift from one land cover class to another is perceived as an improvement, a neutral alteration, or degradation can fluctuate depending on the perspective and priorities of the particular country or region in question (Alamanos and Linnane, 2021). For the eThekwini Municipality and purposes of this study, the transition from natural vegetation (forests and grasslands) to cropland and built-up areas was considered land degradation. Furthermore, the transition from forests to grasslands was considered a neutral change. This perspective arises from the fact that while conversion from forest to grassland can sometimes result from land degradation, it is not universally classified as such because it can also be a natural or ecologically valuable process.

As aforementioned, a decline in SOC stock is one of the major indicators of land degradation (Lorenz *et al.*, 2019). However, there is no universally fixed percentage of SOC stock decline to indicate land degradation. A significant reduction in SOC, typically exceeding 10%, is often regarded as a substantial sign of land degradation in many assessments and scientific studies (Alamanos and Linnane, 2021; Sims *et al.*, 2019). Furthermore, SOC stock can undergo natural cycles of increase and decrease over time due to factors like vegetation shifts, climate change, land use practices, and soil management (Tsozué *et al.*, 2019). Therefore, it was essential for the study period to encompass these natural cycles to prevent them from being mistaken for actual changes in SOC stock. This is especially true for natural vegetation shifts and cycles, which contribute to the input and turnover of organic matter in the soil. Moreover, recent research highlights that prolonged vegetation data has a more pronounced influence on soil carbon monitoring compared to a yearly assessment (Zhang *et al.*, 2022). As such, this study is able to accommodate vegetation shifts and cycles by adopting a prolonged study period.

The interest in land degradation within the eThekwini Municipality is derived from the fact that there is an increased conversion, degradation, and loss of the vegetated landscapes within the municipality (Zungu *et al.*, 2020b). Hence, there have been multiple projects and studies such as Shih (2017), Mugwedi *et al.* (2018) and Hlatshwayo *et al.* (2019) that seek to map aboveground biomass and restore degraded landscapes in the municipality. However, very few studies have attempted to map land degradation within the municipality. Thus, the outcomes of this study will play a critical role in informing future land restoration projects and improving land degradation evaluations.

Remarkable progress has been made in monitoring sub-indicators of land degradation. Land cover change previously relied on in situ monitoring techniques (Buchhorn *et al.*, 2020a). However, the increased access and accuracy of remote sensing have seen more land cover studies and projects using it as a tool (Liping *et al.*, 2018). Remote sensing has also provided a reliable alternative to in situ and laboratory methods of estimating SOC stock as it provides adequate information for accurate and reliable digital soil mapping (DSM) (Odebiri *et al.*, 2022). Therefore, this study employed three remote sensing satellites to estimate and map land cover change and SOC stock within the eThekwini Municipality. These satellites were the Landsat 7 (Enhanced Thematic Mapper Plus - ETM+), Landsat 8 (Operational Land Imager - OLI) and the new Landsat 9 (Operational Land Imager 2 – OLI2). Landsat missions are vital remote sensing data sources with a 30 metre (m) spatial resolution and high radiometric precision and signal-to-noise ratio (Showstack, 2022). It should be noted that this study utilised a direct method of estimating SOC stock, which is based on reference SOC stock and the presence and absence of vegetation (Zhou *et al.*, 2008). This method is applicable due to the correlation between the carbon stored in the vegetation layer and the SOC stock in the topsoil layers (Ayala Izurieta *et al.*, 2022).

However, it should be taken into consideration that the use of remote sensing in determining land degradation sub-indicators relies on the selection of reliable machine learning approaches. This is especially true for the estimation of SOC stock using remote sensing, given their non-linear relationship (Abdoli *et al.*, 2023). These approaches can reveal complicated non-linear patterns contrary to typical linear regression models (Zhang, L. *et al.*, 2019). As a result, four machine learning algorithms, namely, extreme gradient boosting (XGBoost), light gradient boosting machine (LightGBM), random forests (RF), and support vector machines (SVM), were used to estimate land cover change and SOC stocks in the eThekwini Municipality.

Additionally, fewer studies have progressed from the use of the UNCCD default methodology and global datasets for land degradation assessments (Reith *et al.*, 2021). Therefore, this study becomes one of the few studies to utilise high-resolution datasets to assess land degradation at the sub-provincial level and beyond the baseline period.

5.2 Methods and Materials

5.2.1 Study area

This study focused on the eThekwini Municipality (Figure 5.1), which has an area of 2297 km² and a population of more than 3.5 million people (Zungu *et al.*, 2020b). The municipality has a sub-tropical climate which is characterised by mild and sunny winters and hot and humid summers (Zungu *et al.*, 2018). The spatial distribution of the eThekwini Municipality is primarily characterised by built-up areas comprising the city of Durban. These urban expanses are encompassed by peri-urban residential regions, alongside informal settlements and rural communities (Hellberg, 2014). The increasing population and rural-urban migration mean more residential spaces are required. Thus, the eThekwini Municipality established the Durban Metropolitan Open Space System (DMOSS), which is a network of areas reserved for the conservation of native fauna and flora (Khumalo and Sibanda, 2019; Zungu *et al.*, 2019). However, the role of DMOSS in limiting land degradation has not been thoroughly explored. The municipality's vegetation growing season starts in August for forests followed by vegetation falling with the Indian Ocean Coastal Belt in September and grassland in October (Wessels *et al.*, 2011).

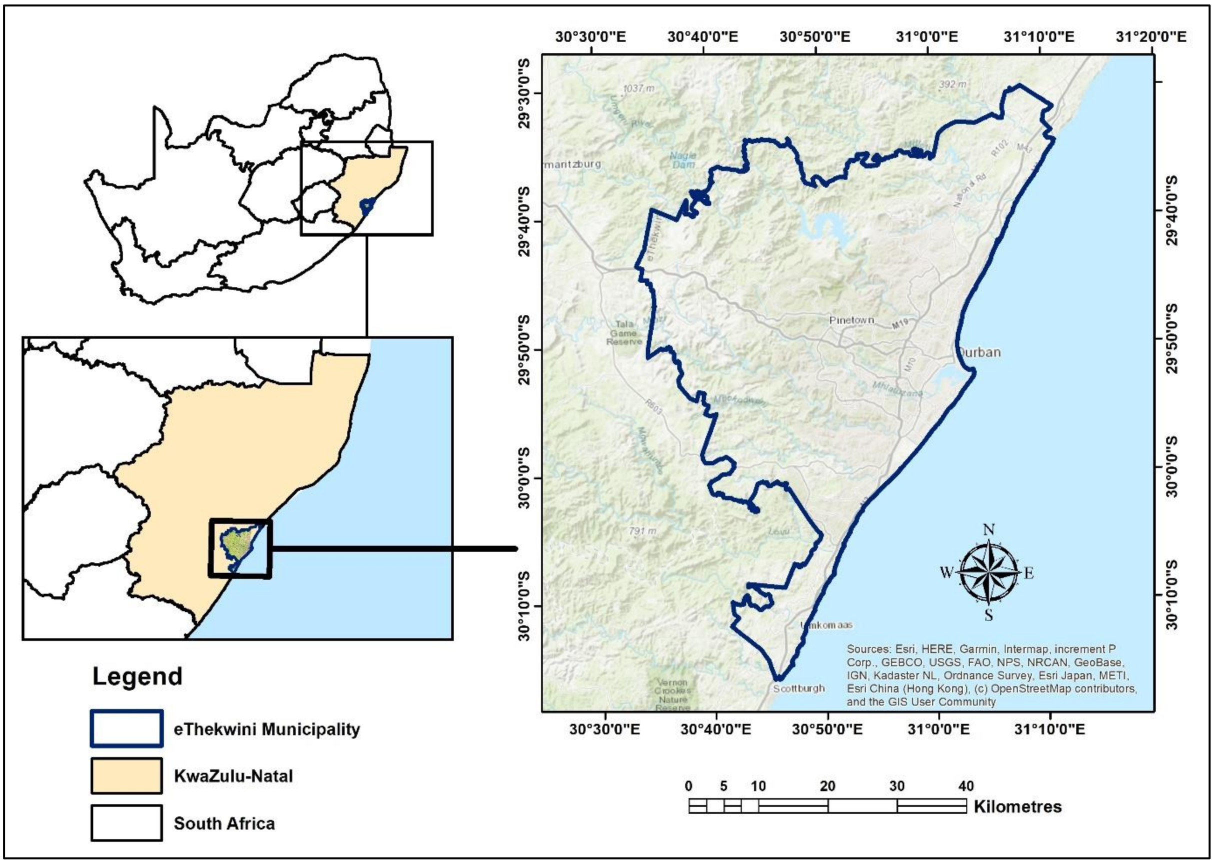

Figure 5.1. The location of the eThekwini Municipality within the province of KwaZulu-Natal (KZN) in South Africa.

5.2.2 Data

5.2.2.1 Image data description and acquisition

Landsat 7, Landsat 8, and Landsat 9 were used to estimate land degradation within the eThekwini Municipality. The bands in bold in Tables 5.1 and 5.2 were used in the analysis.

5.2.2.1.1 Landsat 7 (ETM+)

Landsat 7 was successfully launched on April 15, 1999, equipped with an ETM+ sensor capable of capturing Earth's surface with a 185 km swath width at a 16-day revisit cycle (Table 5.1) (Cao *et al.*, 2022a). However, starting in 2003, the Scan Line Corrector (SLC) for Landsat 7 malfunctioned, leading to spatial gaps in the imageries (Nhu *et al.*, 2020). In this study, Landsat 7 was employed to acquire an image from the year 2000, obviating the necessity for scan line error correction.

Table 5.1. Spectral bands and resolutions for Landsat 7 ETM+ sensor.

Band	Wavelength (µm)	Resolution (m)
Band 1 - Blue	**0.45 - 0.52**	**30**
Band 2 - Green	**0.52 - 0.60**	**30**
Band 3 - Red	**0.63 - 0.69**	**30**
Band 4 - Near-Infrared (NIR)	**0.77 - 0.90**	**30**
Band 5 – Shortwave-Infrared (SWIR)	**1.55 - 1.75**	**30**
Band 6 - Thermal Infrared (TIR)	10.40 - 12.50	60
Band 7 - Mid-Infrared	2.08 - 2.35	30
Band 8 - Panchromatic (PAN)	0.52 - 0.90	15

5.2.2.1.2 Landsat 8 (OLI)

The joint mission of the United States Geological Survey (USGS) and the National Aeronautics and Space Administration (NASA) resulted in the effective launch of the Landsat 8 satellite, which took place on February 11, 2013, (Roy *et al.*, 2014). This pivotal event marked a significant advancement in Earth observation technology and the ongoing commitment to monitor and understand our planet's dynamic landscapes from the vantage point of space. It has two push-broom sensors with a 30 m spatial resolution, viz., the OLI, which has nine data bands in the visible, near-infrared, shortwave-infrared wavelength ranges (0.433 to 2.290 µm) and the Thermal Infrared Sensor (TIRS), which has two data bands in the thermal infrared wavelength range (10.60 to 12.51 µm) (Table 5.2) (Mondal *et al.*, 2022; Vanhellemont, 2020). Landsat 8 follows a near-polar and sun-synchronous orbit, which provides a 16-day revisit cycle (Sofan *et al.*, 2020).

5.2.2.1.3 Landsat 9 (OLI 2)

The Landsat 9 satellite was launched on September 27, 2021, and carries two push-broom sensors with a 30 m spatial resolution, viz., the OLI 2 and Thermal Infrared Sensor 2 (TIRS 2) through the partnership of USGS and NASA (Table 5.2) (Guo *et al.*, 2022). Landsat 9 follows the same orbit, has the same revisit cycle, and has the same number of bands as Landsat 8.

Landsat 9's sensors improve on the sensors aboard the Landsat 8 satellite by providing data with a 14-bit radiometric resolution (Niroumand-Jadidi *et al.*, 2022). It should be noted that the bands in bold were used as variables in the execution of this study.

Table 5.2. Spectral bands and resolutions for Landsat 8 OLI/TIRS and Landsat 9 OLI 2/TIRS 2 sensors.

	Band	Wavelength (μm)	Resolution (m)
OLI and OLI 2	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	**0.450 - 0.51**	**30**
	Band 3 - Green	**0.53 - 0.59**	**30**
	Band 4 - Red	**0.64 - 0.67**	**30**
	Band 5 - Near-Infrared (NIR)	**0.85 - 0.88**	**30**
	Band 6 – Shortwave-Infrared (SWIR) 1	1.57 - 1.65	30
	Band 7 - SWIR 2	**2.11 - 2.29**	**30**
	Band 8 - Panchromatic (PAN)	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
TIRS and TIRS 2	Band 10 - TIRS 1	10.6 - 11.19	100
	Band 11 - TIRS 2	11.5 - 12.51	100

Given the wet and vegetation growing seasons in the eThekwini Municipality, the GEE date filter was set to August to December in each year of the study period. Increased vegetation growth during wetter months results in higher chlorophyll content and leaf area, thereby enhancing detectability and accuracy in vegetation monitoring through stronger signals in relevant spectral bands. As such, the Landsat 7 median image was acquired from images taken between August and December 2000. For Landsat 8, the median image was acquired from images taken between August and December 2015 and for Landsat 9, the median image was acquired from images taken between August and December 2022. The use of the median image contributes to outlier mitigation and the generation of consistent images, enhancing the accuracy and reliability of subsequent analyses.

5.2.2.2 Spectral indices

This study extracted eight spectral indices, which were all used for the retrieval of SOC stock and landcover change. Their description is presented in Table 5.3.

Table 5.3. Spectral indices that were calculated from Landsat 7, Landsat 8, and Landsat 9 imagery for inclusion in the training data.

Index	Formula	Equation	Description	Reference
Normalised Difference Vegetation Index (NDVI)	$\frac{(NIR - Red)}{(NIR + Red)}$	1	NDVI can discriminate vegetation types and detect vegetative stress.	Tucker and Sellers (1986)
Green Normalised Difference Vegetation Index (GNDVI)	$\frac{(NIR - Green)}{(NIR + Green)}$	2	GNDVI is sensitive to vegetation photosynthetic activities and, thus, can detect water and nitrogen uptake into the plant canopy.	Gitelson and Merzlyak (1998)
Enhanced Vegetation Index (EVI)	$\frac{[(2.5 \text{ X } (NIR - Red)]}{[(NIR + (6 \text{ X } Red) - (7.5 \; X \; BLUE) + 1]}$	3	EVI is sensitive to atmospheric influences and vegetation background signals and is less sensitive to background and atmospheric noise.	Huete *et al.* (2002)
Normalised Difference Water Index (NDWI)	$\frac{(Green - NIR)}{(Green + NIR)}$	4	NDWI is highly efficient at detecting slight changes in the water content of water bodies.	Gao (1996)
Modified Normalised Difference Water Index (MNDWI)	$\frac{(GREEN - SWIR)}{(GREEN + SWIR)}$	5	MNDWI improves the identification of open-water characteristics.	Xu (2006)
Soil Adjusted Vegetation Index (SAVI)	$(\frac{(NIR - RED)}{(NIR + RED + 0.5)}) \times (1 + 0.5)$	6	SAVI minimises soil brightness, which influences vegetation detection.	Huete (1988)
Modified Soil Adjusted Vegetation Index (MSAVI)	$\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR + 1)^2 - 8 \times (NIR - RED)}}{2}$	7	MSAVI minimises the effect of bare soil on SAVI.	Qi *et al.* (1994)
Normalised Difference Built-up Index (NDBI)	$\frac{(SWIR - NIR)}{(SWIR + NIR)}$	8	NDBI maximises the detection of built-up areas	Zha *et al.* (2003)

5.2.2.3 Sample data composition

5.2.2.3.1 Land cover change sample data

The training dataset for land cover change mapping was composed in GEE where the seven bands from the 2017 Landsat 8 image and the calculated spectral indices were combined with the 2017 Finer Resolution Observation and Monitoring-Global Land Cover-Segmentation at 10 m (FROM – GLCS10) image. The 2017 FROM – GLCS10 serves as reference data. It includes continuous field layers for all basic land cover classes (Table 5.4) and is aligned with the guidelines provided in the GPG document.

Table 5.4. The land cover classes found in the FROM – GLCS10 dataset (Gong *et al.*, 2019).

Name	**Description**
Cropland	Cultivated and non-cultivated land with patterns that can be viewed from a satellite.
Forest	Areas that are under commercial plantations, orchards, and indigenous trees.
Grassland	Areas that are under continuous cover of grass.
Shrubland	Land that is dominated by shrubs.
Wetland	Areas that are covered by water or areas where water is near the surface.
Water	Water bodies (rivers and reservoirs).
Impervious surface	Includes built-up areas (urban and rural residential areas and industrial areas).
Bare land	Barren land without any vegetation cover.

Stratified sampling with a maximum of 10000 points set for each 2017 FROM – GLCS10 class was then carried out on the Landsat image containing the information for the classification. The sample data (n = 80539) were exported to Microsoft Excel and then to Google Colaboratory in a comma-separated values (CSV) file. In Google Colaboratory, the data were divided into 70% training and 30% test data and then resampled using the K-fold cross-validation technique. K = 5 was used and repeated ten times, given the large size of the dataset.

5.2.2.3.2 SOC stock sample data

The training dataset for the retrieval of SOC stock was also composed in GEE, where the seven bands from the 2017 Landsat 8 image and the calculated spectral indices were combined with the 2017 Innovative Solutions for Decision Agriculture Ltd. (iSDA) SOC stock image. As such, the iSDA SOC stock data was utilised as reference data. The development of the iSDA dataset using two-scale ensemble machine learning is explained in Hengl *et al.* (2021). It presently delivers the most detailed soil property predictions for Africa, achieving a resolution of 30 meters (m) (Ewing *et al.*, 2023). The accuracy of the iSDA dataset was examined through a fivefold spatial cross-validation across all variables of interest. Notably, Soil Organic Carbon (SOC) exhibited a commendable R square value of 0.791, indicating a robust level of accuracy and making it a viable option for this study (Hengl *et al.*, 2021). It should be noted that iSDA SOC data can be obtained at two different depths, i.e., 0 – 20 centimetres (cm) and 20 – 50 cm. Hence, the SOC stock for the eThekwini Municipality was retrieved at both these two depths. Therefore, stratified sampling with a maximum of 12000 points was set for each cm and was then carried out on the Landsat image containing the information for training the algorithm. The sample data (n = 80539) for each depth were exported to Microsoft Excel and then to Google Colaboratory in comma-separated values (CSV) files. The data were divided into 70% training and 30% test data and then resampled using the K-fold cross-validation technique in Google Colaboratory. The K = 5 was also used and repeated ten times, given the large size of the dataset.

5.2.3 Analytic models

Four analytical models were evaluated for their ability to determine land cover change and retrieve SOC stock for the eThekwini Municipality.

5.2.3.1 Extreme gradient boosting

XGBoost is a highly efficient and sufficiently flexible model developed by Chen and Guestrin (2016b) under the Gradient Boosting framework (Zhang *et al.*, 2021). Therefore, it is described as an enhanced version of gradient boosting machines (GBM) (Chang *et al.*, 2018). XGBoost, as a tree ensemble method, employs boosting, which combines all the sets of weak learners and through additive training strategies, develops a strong learner (Buthelezi *et al.*, 2022; Fan *et al.*, 2018). XGBoost adopts a more regularised formalisation compared to GBM, which enables it to avoid over-fitting issues (Qiu *et al.*, 2022). This model can, therefore, be used for both regression and classification problems (Ahmedbahaaaldin *et al.*, 2021).

5.2.3.2 Light gradient boosting machine

LightGBM is a new and popular ensemble learning model developed by Microsoft (Ke *et al.*, 2017). The model is based on the gradient boosting framework, which is a powerful machine learning technique for building ensemble models by combining multiple weak learners predictors to get an improved predictive performance (Sun *et al.*, 2022). This enables LightGBM to avoid the low accuracy of a single learner (Buthelezi *et al.*, 2022). Additionally, the construction of LightGBM includes a Gradient-based one-side sampling (GOSS) method and the exclusive feature bundling (EFB) algorithm, which reduces the amount of data and features (Sun *et al.*, 2022). Furthermore, the histogram-based segmentation algorithm decreases the time it takes the algorithm to traverse the sample, and a leaf growth strategy with depth constraint provides the flexibility to control the growth of decision tree leaves (Dai, J. *et al.*, 2023).

5.2.3.3 Random forests

RF is a robust algorithm developed by Breiman (2001) as a nonparametric statistical method based on classification and regression trees (CART) and as a competitor to boosting methods (Cutler *et al.*, 2012; Zhang *et al.*, 2021). In RF, a bootstrap sample function, which is a variation of bootstrap aggregating, randomly splits the dataset into homogeneous subsets based on the target variable (Rasaei and Bogaert, 2019). From the resulting homogeneous subsets, a random subset of the samples is then used to grow and train each tree, and their results are aggregated (Holodinsky *et al.*, 2021). The bootstrap sample function takes samples with replacement in that some observations are repeated, and some are left out from the samples (Khan *et al.*, 2021). The observations that are left out and not used in growing trees are called the out-of-bag (OOB) observations and are used to estimate the model's accuracy (Odebiri *et al.*, 2022).

5.2.3.4 Support vector machines

SVM is a binary classifier which maps several classes in the training set with a surface that maximises the margin between them (Cervantes *et al.*, 2020). The margin is maximised through the determination of an optimal hyperplane and the model’s ability to minimise the upper bound of the generalisation error (Wang *et al.*, 2012). However, if the data are non-linearly separable, SVM’s generalisation ability is hindered (Cervantes *et al.*, 2020). Therefore, the data is mapped to a higher dimension feature space using a kernel function where a linear decision surface can be constructed for an optimal hyperplane to be generated (Griffel *et al.*, 2018). This study used the radial basis function (RBF) as the kernel, given its efficiency when classifying large datasets and its high flexibility (Buthelezi *et al.*, 2022).

5.2.4 Hyper-parameter optimisation

Almost all classification algorithms have hyper-parameters, which have a significant influence on the accuracy of these algorithms and require optimisation to get the best accuracy (Buthelezi *et al.*, 2020b). XGBoost and LightGBM have multiple hyper-parameters which need optimisation. These include subsample ratio (r_s), learning rate (τ), maximum tree depth (D_{max}), minimum child weight (ω_{mc}) and column subsample ratio (r_c) for XGBoost. The number of leaves (num_leaves), the learning rate (learning_rate), maximum learning depth (max_depth), the proportion of the selected feature to the total number of features (Feature_fraction) and the ratio of the selected data to the total data (Bagging_fraction) are only the parameters that have a significant influence on LightGBM performance (Tang *et al.*, 2020).

The Bayesian optimisation method was used to determine XGBoost and LightGBM optimal hyperparameters, given its robustness when dealing with many parameters (Georganos *et al.*, 2018; Tang *et al.*, 2020). The performance of RF is primarily influenced by two factors: the selection of features to be used for building each tree, known as *Mtry*, and the total number of trees generated, denoted as *Ntree*. It is worth noting that *Mtry* is the only parameter that can be manually optimised (Breiman, 2001).

However, these parameters are not directly applicable in Google Colaboratory, which is a Python programming language, as they are specific to the R programming language. Consequently, the optimised parameters in Google Colaboratory encompassed n_estimators, corresponding to the number of trees in the forest, akin to the *Ntree* parameter; and the max_features parameter, governing the number of features deliberated for node splitting, reminiscent of the concept of *Mtry*. The hyper-parameters optimised for SVM were cost (C) and gamma (γ), which are independent of each other, and the algorithm returns the pairing (C and γ) with the best accuracy. The final hyper-parameters for the four machine learning algorithms are presented in Table 5.5.

Table 5.5. Optimal hyper-parameters for the four machine learning algorithms used in this study.

Algorithm	Hyper-parameter	Land cover change	SOC stock
XGBoost	r_s	1	0.7
	τ	0.1	0.05
	D_{max}	5	5
	ω_{mc}	3	1
	r_c	0.5	0.7
LightGBM	num_leaves	86.72	86.72
	learning_rate	0.001	0.001
	max_depth	3	8.87
	feature_fraction	0.1	0.1
	bagging_fraction	0.9	0.9
RF	max_features	sqrt	sqrt
	n_estimators	100	100
SVM	C	1	1
	γ	scale	scale

5.2.5 Feature importance

Variable importance is a very crucial step in computational model applications (Wei *et al.*, 2015). It ranks the variables based on their influence on the model to make accurate predictions. This study used the Gini index to investigate the importance of the models used to map land cover change and retrieve soil organic carbon. That is because the Gini index offers an affordable means of acquiring multivariate feature importance scores and has proven effective in analysing high-dimensional datasets (Algehyne *et al.*, 2022). Features with higher Gini index are considered more influential in predicting the target variable as the index measures the extent to which a particular feature contributes to the overall predictive power of a model by calculating the total reduction in the Gini impurity achieved through splitting the data based on that feature (Liu *et al.*, 2022). Furthermore, it should be noted that feature importance for SVM is typically not directly provided by the algorithm itself, unlike XGBoost, LightGBM and RF.

5.2.6 Accuracy assessment

Three accuracy assessment metrics were used to evaluate the performance of the algorithms, namely, percentage overall accuracy (OA), together with the sensitivity, specificity, and quantity and allocation disagreements. The OA measures the number of pixels classified accurately within the image. The sensitivity indicates the chance of getting a positive test outcome in individuals with the desired condition, while specificity measures how effectively a test can differentiate individuals who do not have the target condition (van Stralen *et al.*, 2009).

Additionally, the performance of the models was assessed using the quantity and allocation disagreements and the F1 Score. Quantity disagreement is defined by Pontius and Millones (2011, p. 4409) as, "the amount of difference between the reference map and a predicted map that is due to the less-than-perfect match in the proportions of the categories". As such, the higher the quantity disagreement, the greater the discrepancy in the distribution of categories between the two maps. Whereas allocation disagreement refers to the difference between predicted and reference maps, resulting from a spatial mismatch in the pixel locations of each category (Siegel *et al.*, 2022). It should be noted that allocation disagreement is measured using two components, namely, exchange and shift. Shift represents a displacement of land-cover and SOC stock categories, whereas exchange reflects the swapping or interchange of these categories between the predicted and reference maps. A high allocation disagreement indicates that the model's predictions and the actual observations differ significantly in terms of where specific categories are assigned on the map. Ideally, both quantity and allocation disagreements should be as low as possible. The F1 Score is a weighted average of precision and recall (Islam *et al.*, 2020). It is worth noting that recall and sensitivity are synonymous and represent the same metric. It provides an unbiased view of a model's performance by taking into consideration both aspects (precision and recall), making it useful in scenarios where false positives and false negatives are equally important.

5.2.7 Overview

5.2.7.1 Sub-indicator 1: land cover change

To determine the land cover change in the eThekwini Municipality, all four analytic models were employed on Landsat 7, Landsat 8, and Landsat 9 data. The Landsat data were downloaded from GEE. The best-performing algorithm was selected to perform the final land cover change classification. The GPG document recommends the use of the change matrix to visualise the land cover class transitions. Therefore, the land degradation based on land cover change was analysed in Google Colaboratory, mapped in ArcGIS Pro Version 3.0.1, and visualised using the change matrix. The overall methodology for determining land cover change is outlined in Figure 5.2 (a).

5.2.7.2 Sub-indicator 3: SOC stock

The retrieval of SOC stock in the eThekwini Municipality also relied on the utilisation of four analytical algorithms where the best-performing algorithm was selected for the final retrieval of SOC stock. The Landsat 7, Landsat 8, and Landsat 9 images were downloaded from GEE. The changes in the predicted concentration of SOC stock were mapped from 2000 to 2022 in ArcGIS Pro. The overall methodology for determining SOC stock in the eThekwini Municipality is outlined in Figure 5.2 (b).

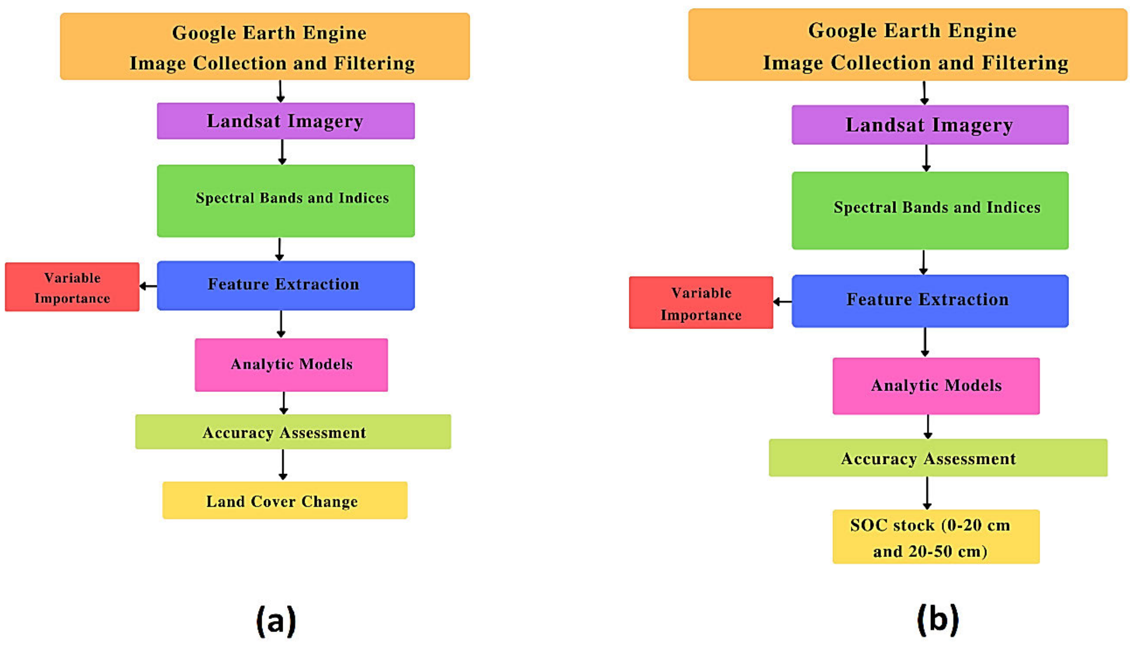

Figure 5.2. Schematic overview of assessing model performances and generation of (a) land cover change maps and (b) retrieval of SOC stock at different depths (0 – 20 cm and 20 – 50 cm) for the eThekwini Municipality.

5.3 Results

5.3.1 Variable importance

Figures 5.3, 5.4 and 5.5 show the feature importance of each feature in XGBoost, LightGBM and RF when predicting land cover classes, respectively. Figures 5.6, 5.7, and 5.8 show the feature importance of each feature in XGBoost, LightGBM and RF when predicting SOC stock, respectively. All predictions were conducted in Google Colaboratory.

5.3.1.1 Land cover change

For XGBoost, NDVI, B4 and NDBI were the top three most important features (Figure 5.3). NDWI had the lowest contribution to the performance of the model. Figure 5.4 illustrates that B2, NDBI and B4 were the most important features in the LightGBM prediction and GNDVI was the least important feature. For RF in Figure 5.5, NDVI, B3 and GNDVI were the most important features, and B5 had the least influence.

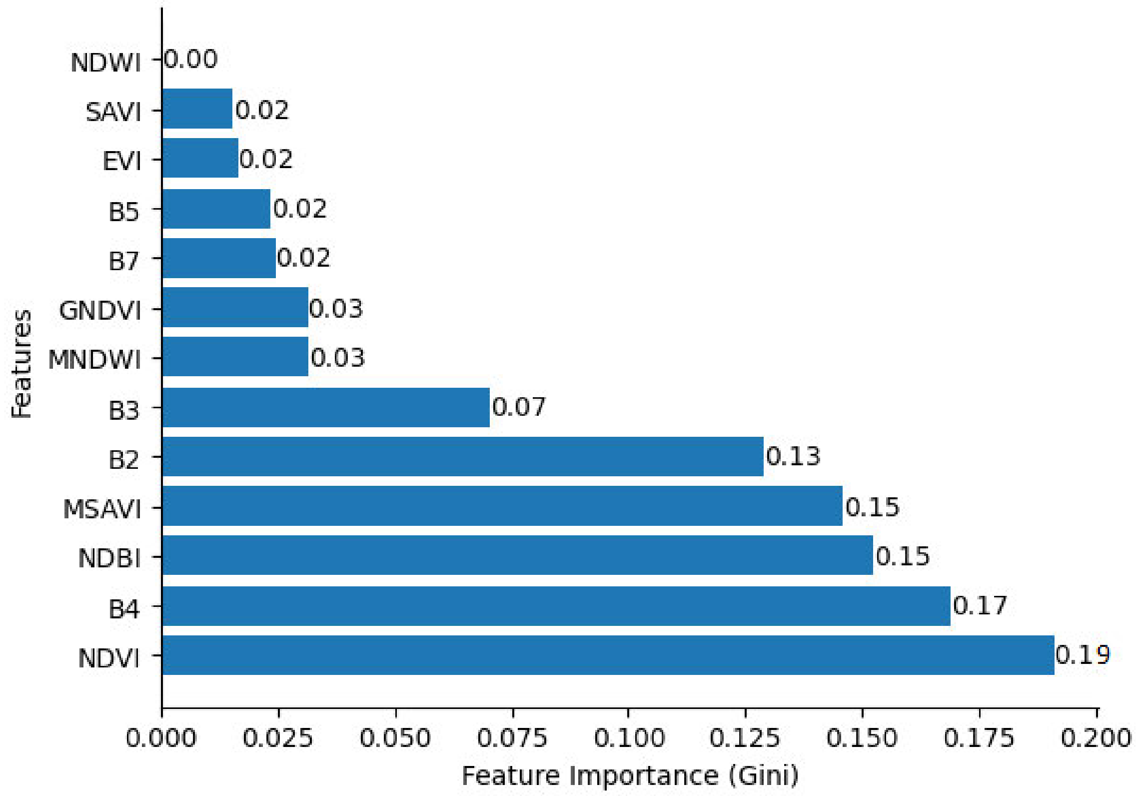

Figure 5.3. Visualising feature importance in XGBoost for mapping land cover change in the eThekwini Municipality.

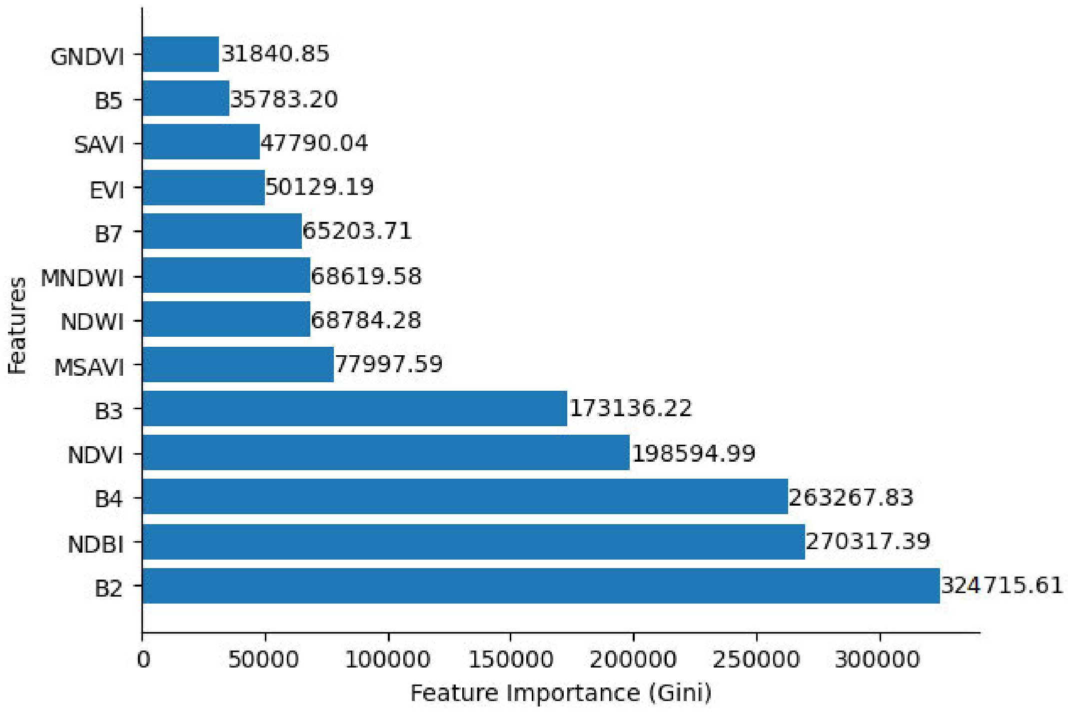

Figure 5.4. Illustrating feature importance in LightGBM for mapping land cover change in the eThekwini Municipality.

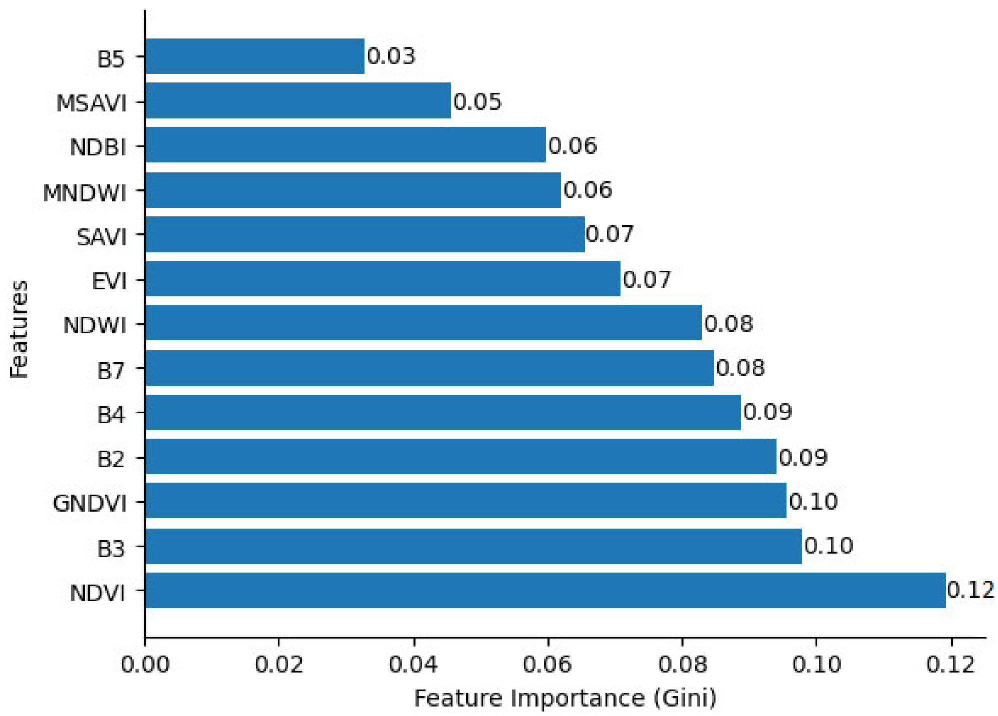

Figure 5.5. Visualising feature importance in RF for mapping land cover change in the eThekwini Municipality.

5.3.1.2 SOC stock

In Figure 5.6, among the 14 features used in XGBoost, B3, B7, and GNDVI were the three most important features. Conversely, NDVI was found to have the least impact on the model's performance. Figure 5.7 illustrates that B3, B7 and B2 were the most important features in the LightGBM prediction, while NDVI had the least impact. Among the spectral indices, GNDVI was the most important index. On the other hand, Figure 5.8 presents the feature importance for RF, indicating that B3, B2, and B4 were the most important features, while MSAVI had the least influence.

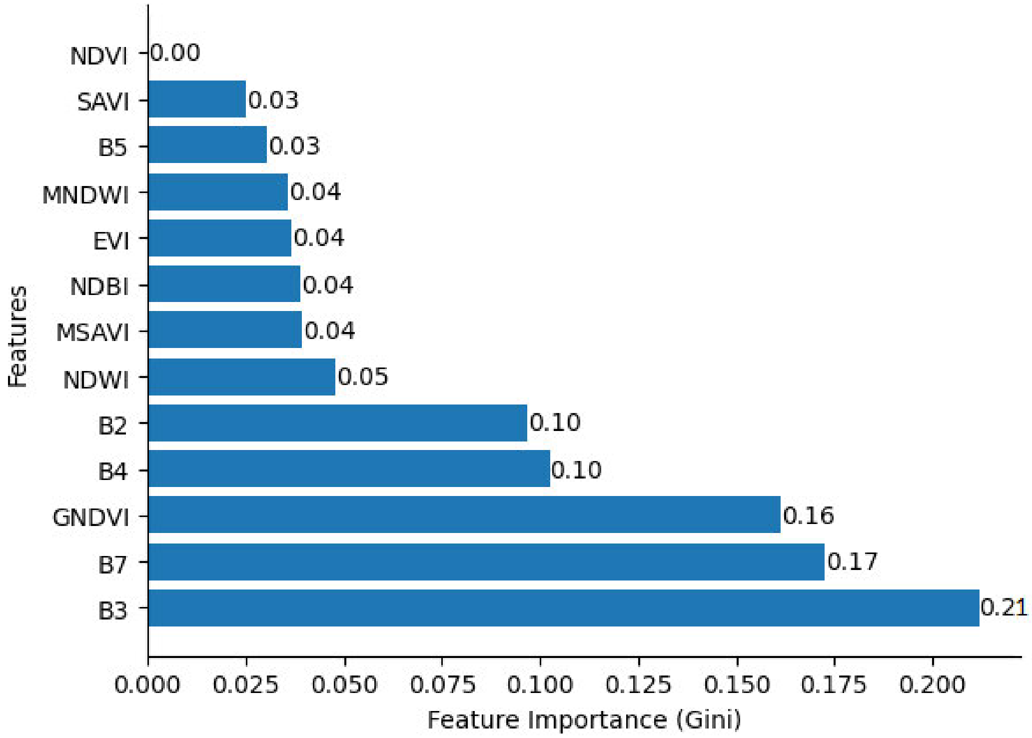

Figure 5.6. Visualising feature importance in XGBoost for retrieving SOC stock in the eThekwini Municipality.

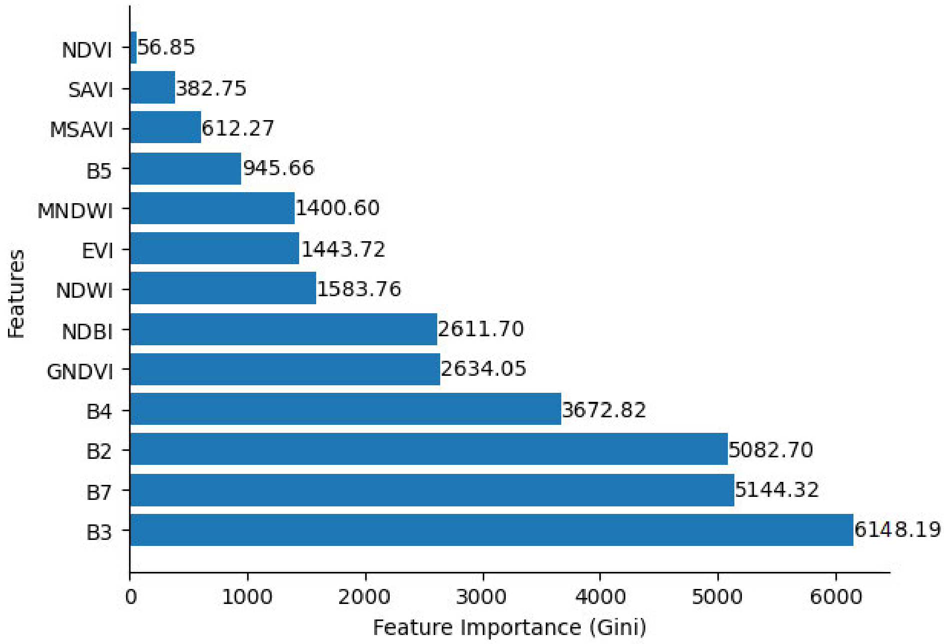

Figure 5.7. Visualising feature importance in LightGBM for retrieving SOC stock in the eThekwini Municipality.

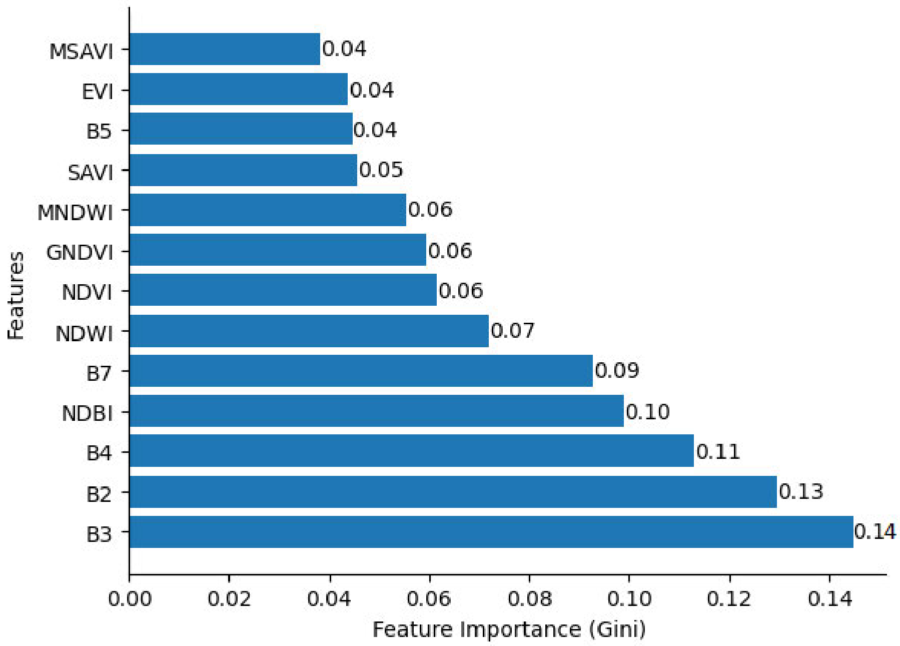

Figure 5.8. The feature importance of RF for predicting SOC stock in the eThekwini Municipality is depicted.

5.3.2 *Accuracy assessment*

The prediction accuracy results for land cover change mapping and SOC stock retrieval from the four analytic models showed varying performances.

5.3.2.1 Land cover change

Table 5.6 presents the accuracy obtained by each model when predicting land cover classes based on the 2017 Landsat 8 median image and the 2017 FROM – GLCS10 image. Based on the OA, LightGBM (80.646) and XGBoost (80.482) were the best performing models. When comparing the models using the F1 Score, LightGBM (0.804) was the best performing model.

Table 5.6. Accuracy metrics and comparative analysis for XGBoost, LightGBM, RF and SVM when predicting land cover classes.

	XGBoost	LightGBM	RF	SVM
Overall Accuracy	80.482	80.647	80.200	79.364
Specificity	91.742	92.697	91.406	90.204
Sensitivity	95.282	93.892	94.910	94.828
F1 Score	0.800	0.804	0.799	0.775

The disagreement metrics in Table 5.7 indicate that LightGBM had the best overall performance, given the lowest overall value of 24.8266. However, it should be noted that XGBoost had the lowest quantity disagreement value of 6.2602, which indicates that it performed best on this metric compared to the other models.

Table 5.7. Disagreement metrics and comparative analysis for XGBoost, LightGBM, RF and SVM when predicting land cover classes.

	Quantity	Exchange	Shift	Overall
XGBoost	6.2602	17.1003	1.5536	24.9141
LightGBM	6.3321	17.0221	1.4724	24.8266
RF	6.3931	16.8159	1.7581	24.9671
SVM	6.3311	17.1462	1.6260	25.1033

Therefore, given the results in Tables 5.6 and 5.7, LightGBM was used to map land cover classes for the eThekwini Municipality.

5.3.2.2 SOC stock

Table 8 shows the performance of the four models when retrieving SOC stock for the eThekwini Municipality. Just like the outcomes predicted for land cover classes in Table 5, LightGBM proved to be the most effective model. Based on the OA, RF (78.142) and LightGBM (77.869) were the best performing models. Furthermore, LightGBM achieved the highest F1 Score with a value of 0.784.

Table 5.8. Comprehensive results summary showcasing accuracy metrics and comparative analysis for XGBoost, LightGBM, RF and SVM when predicting SOC stock.

	XGBoost	LightGBM	RF	SVM
Overall Accuracy	73.770	77.869	78.142	60.383
Specificity	76.667	87.500	86.667	100.000
Sensitivity	88.800	92.593	90.400	72.388
F1 Score	0.691	0.784	0.743	0.595

Table 9 indicates that LightGBM had the best performance overall, with RF and XGBoost closely following. SVM, on the other hand, exhibited the highest overall disagreement.

Table 5.9. Disagreement metrics and comparative analysis for XGBoost, LightGBM, RF and SVM when predicting SOC stock.

	Quantity	Exchange	Shift	Overall
XGBoost	6.4337	17.5356	1.5942	25.5635
LightGBM	6.1886	6.1886	1.4510	24.3403
RF	6.3115	16.7026	1.7465	24.7606
SVM	6.7791	18.4564	1.7453	27.9808

Based on these metrics, LightGBM generally outperformed RF, XGBoost and SVM across multiple evaluation measures. Hence, it was selected to perform the final retrieval of SOC stock for the eThekwini Municipality.

5.3.3 Land cover maps

Figure 5.9 presents the 2000, 2015 and 2022 land cover maps for the eThekwini Municipality. The maps show a general increase in impervious surfaces towards the north coast of the municipality. However, from the maps, it is impossible to quantify land degradation. Hence, the use of the graph in Figure 5.10, the extent of degradation in Figure 5.11, and the transition matrices in Tables 5.10 and 5.11.

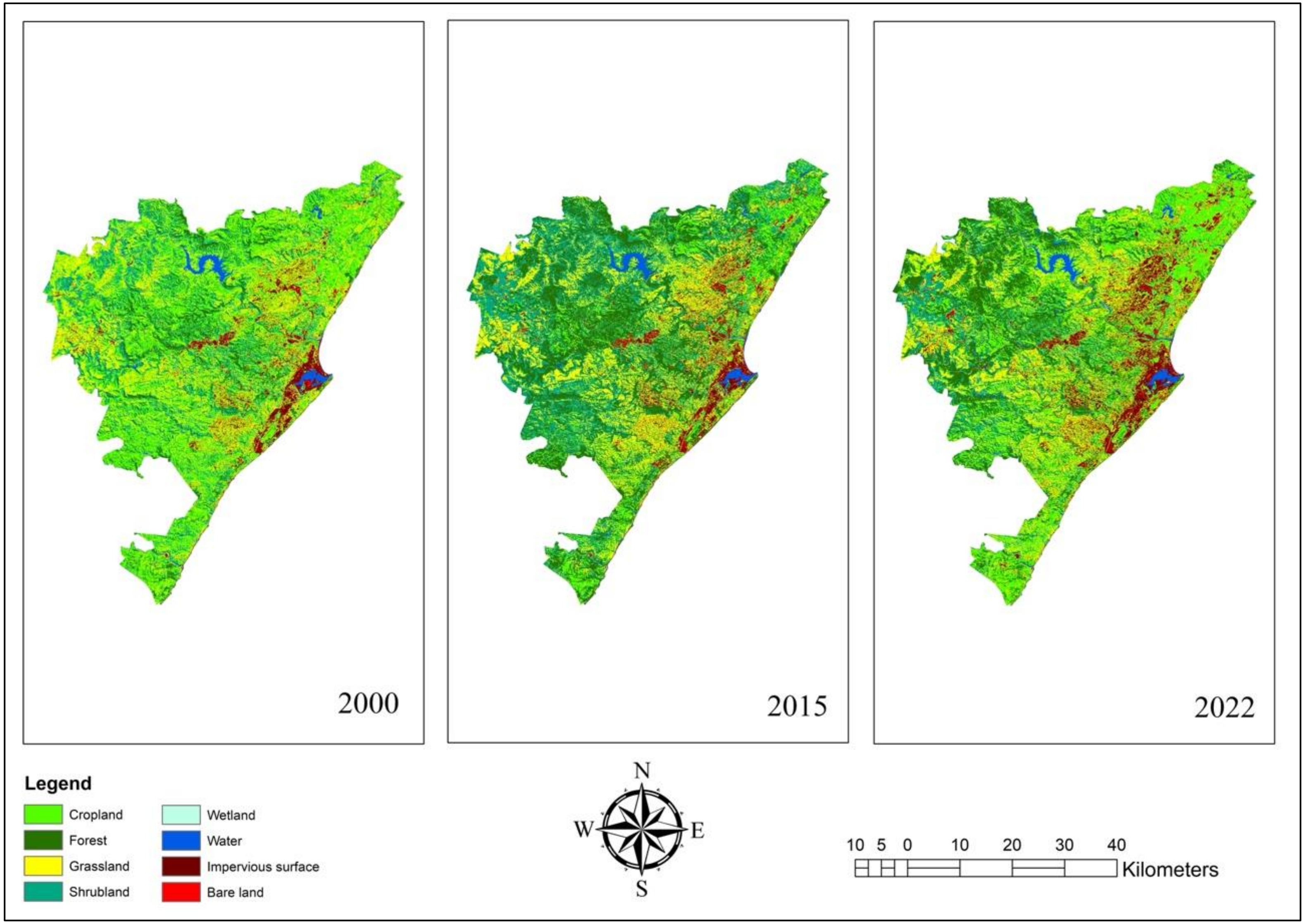

Figure 5.9. The spatial distribution of land cover classes with the eThekwini Municipality between 2015 and 2022.

Figure 5.9 presents the land cover class distribution in the eThekwini Municipality for the years during and beyond the baseline period (up to 2022) based on their respective area. Notably, cropland underwent significant changes, with an initial high of 878 km^2 in 2000, followed by a significant drop to 255 km^2 in 2015, and a subsequent resurgence to 638 km^2 in 2022. In contrast, forested areas increased from 223 km^2 in 2000 to 622 km^2 in 2015, before declining to 443 km^2 in 2022. Grassland remained relatively stable, with slight changes from 2000 to 2022. The area covered by shrubland decreased notably, from 482 km^2 in 2000 to 708 km^2 in 2015 and subsequently declining to 380 km^2 in 2022. Wetland areas and water bodies, albeit small, showed some growth, increasing from 6 km^2 in 2000 to 13 km^2 in 2022 and 31 km^2 in 2000 to 43 km^2 in 2022, respectively. Impervious surfaces, representing urban areas, saw consistent growth, from 127 km^2 in 2000 to 236 km^2 in 2022. Bare land areas remained relatively constant, with minor changes from 14 km^2 in 2000 to 18 km^2 in 2015 and 15 km2 in 2022.

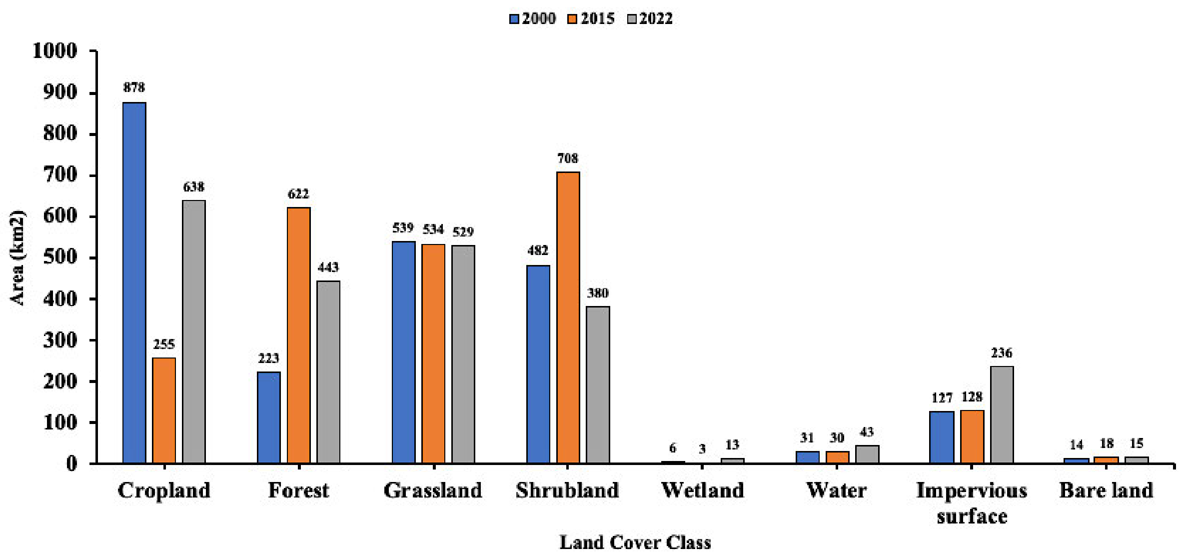

Figure 5.10. A comparison of land cover areas (in km^2) for the years 2015 and 2022 in the eThekwini Municipality.

It should be noted that land cover class transitions that are often considered indicators of land degradation include changes from natural or semi-natural land cover types (such as forests, grasslands, and wetlands) to more degraded land cover types (such as cropland, bare land, and impervious surfaces). As such, illustrated in Figure 5.10 is the extent of land degradation that occurred between 2000 and 2015 and 2015 and 2022. A trend of degradation can be observed across the entire municipality during both the periods under investigation. However, it is worth noting that between 2015 and 2022, land degradation intensified noticeably. Of particular concern is the northern region of the eThekwini Municipality, which was the area most affected by land degradation.

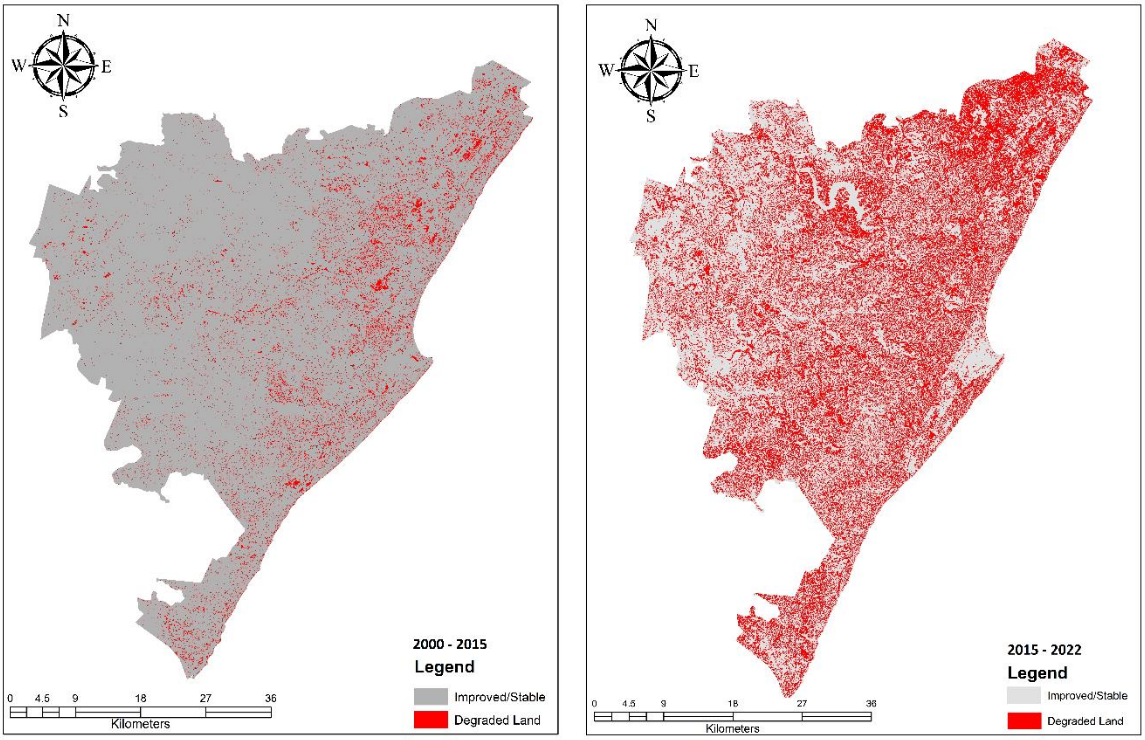

Figure 5.11. Maps showing degraded land within the eThekwini Municipality between 2000 and 2015 and between 2015 and 2022.

Tables 5.10 and 5.11 present the Land Cover Transition Matrix between 2000 and 2015 and 2015 and 2022, respectively. These matrices depict the conversions (km^2) between different land cover classes, providing significant insights into the dynamic changes in land use patterns. Between 2000 and 2015, most of the forest vegetated land was converted to shrubland and cropland. During the 2015 to 2022 period, the matrix highlights that the reduction in forest vegetation was primarily due to transitions to cropland, shrubland, grassland, and, to a lesser extent, impervious surfaces. Shrubland, on the other hand, is mainly converted to cropland, grassland, and impervious surfaces. While grasslands did not experience a substantial decrease, a considerable portion underwent conversions to cropland and impervious surfaces.

Table 5.10. A visual representation of land cover transitions between different classes from 2015 to 2022 in km^2.

		2015							
		Bare land	Cropland	Forest	Grassland	Impervious surface	Shrubland	Water	Wetland
2000	Bare land	3.98	2.46	0.20	2.91	6.84	0.72	0.43	0.11
	Cropland	0.21	172.41	7.57	53.37	3.80	17.31	0.49	0.32
	Forest	0.12	194.88	177.52	36.22	1.92	206.87	2.89	1.18
	Grassland	1.40	195.31	5.26	237.09	45.99	47.49	0.54	0.91
	Impervious surface	5.59	17.34	0.87	39.24	57.76	5.94	0.73	0.77
	Shrubland	0.30	294.75	30.60	168.77	8.57	202.88	1.19	1.11
	Water	1.94	0.21	0.61	0.49	1.28	0.60	24.14	0.86
	Wetland	0.13	0.29	0.07	0.45	0.55	0.36	0.55	0.39

Improved Degraded Stable Remained the same

Table 5.11. A visual representation of land cover transitions between different classes from 2015 to 2022 in km^2.

		2022							
		Cropland	Forest	Grassland	Shrubland	Wetland	Water	Impervious surface	Bare land
2015	Cropland	178.04	11.81	67.84	20.49	0.43	1.24	1.24	0.69
	Forest	171.37	370.10	37.12	107.25	8.10	12.54	11.75	0.37
	Grassland	131.58	7.02	313.86	56.05	0.99	1.24	104.91	1.71
	Shrubland	247.17	122.36	159.37	251.47	3.41	3.17	30.54	1.04
	Wetland	0.17	0.05	0.29	0.25	0.29	1.09	0.99	0.10
	Water	0.41	0.22	0.33	0.23	0.95	29.36	1.69	1.65
	Impervious surface	7.95	0.31	31.03	3.95	0.34	1.17	97.56	6.00
	Bare land	1.09	0.02	2.20	0.15	0.05	0.33	10.64	5.93

Improved Degraded Stable Remained the same

In summary, the observed land cover changes in the eThekwini Municipality pose adverse impacts on biodiversity, ecosystems, and overall environmental health. This highlights the need for urgent measures to address and mitigate the effects of land degradation.

5.3.4 SOC stock maps

Figures 5.12 and 5.13 provide a visual representation of the spatial distribution of predicted SOC stock at a depth of 0 to 20 cm for two distinct time periods: 2000 to 2015 and 2015 to 2022. The maps depict an increase in SOC stock between 2000 and 2015, followed by a decline between 2015 and 2022. By referring to the land cover classes presented in Figure 5.10, it becomes evident that SOC stock predominantly concentrates in vegetated areas. As a result, it can be inferred that the decrease in SOC stock correlates with a decline in vegetation cover. Moreover, it's worth noting that the model attributes high levels of SOC stock to water bodies. To summarise, the findings from Figure 5.12 point towards a concerning reduction in SOC stock and reflect a potential decline in vegetation cover between 2015 and 2022.

The observed spatial distribution of SOC stock at a depth of 20 to 50 cm, as depicted in Figure 5.13, further corroborates the trend of increasing SOC stock between 2000 and 2015 and decreasing SOC stock between 2015 and 2022 which was also observed at a depth of 0 – 20 cm (Figure 5.12). Notable, the model's predictions at the 20 to 50 cm depth also attribute high levels of SOC stock to water bodies.

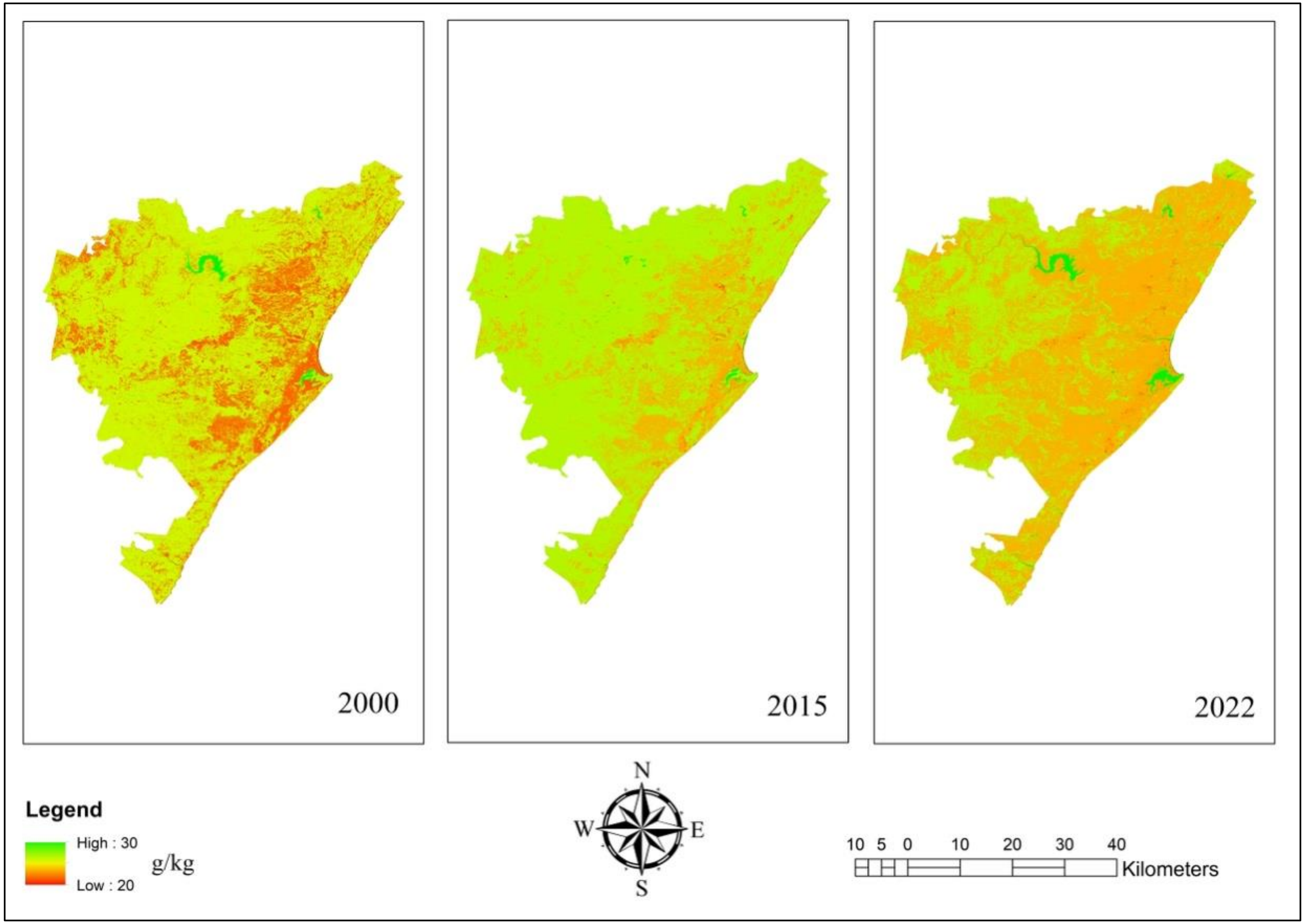

Figure 5.12. The predicted spatial distribution of SOC stock at 0 to 20 cm for the eThekwini Municipality.

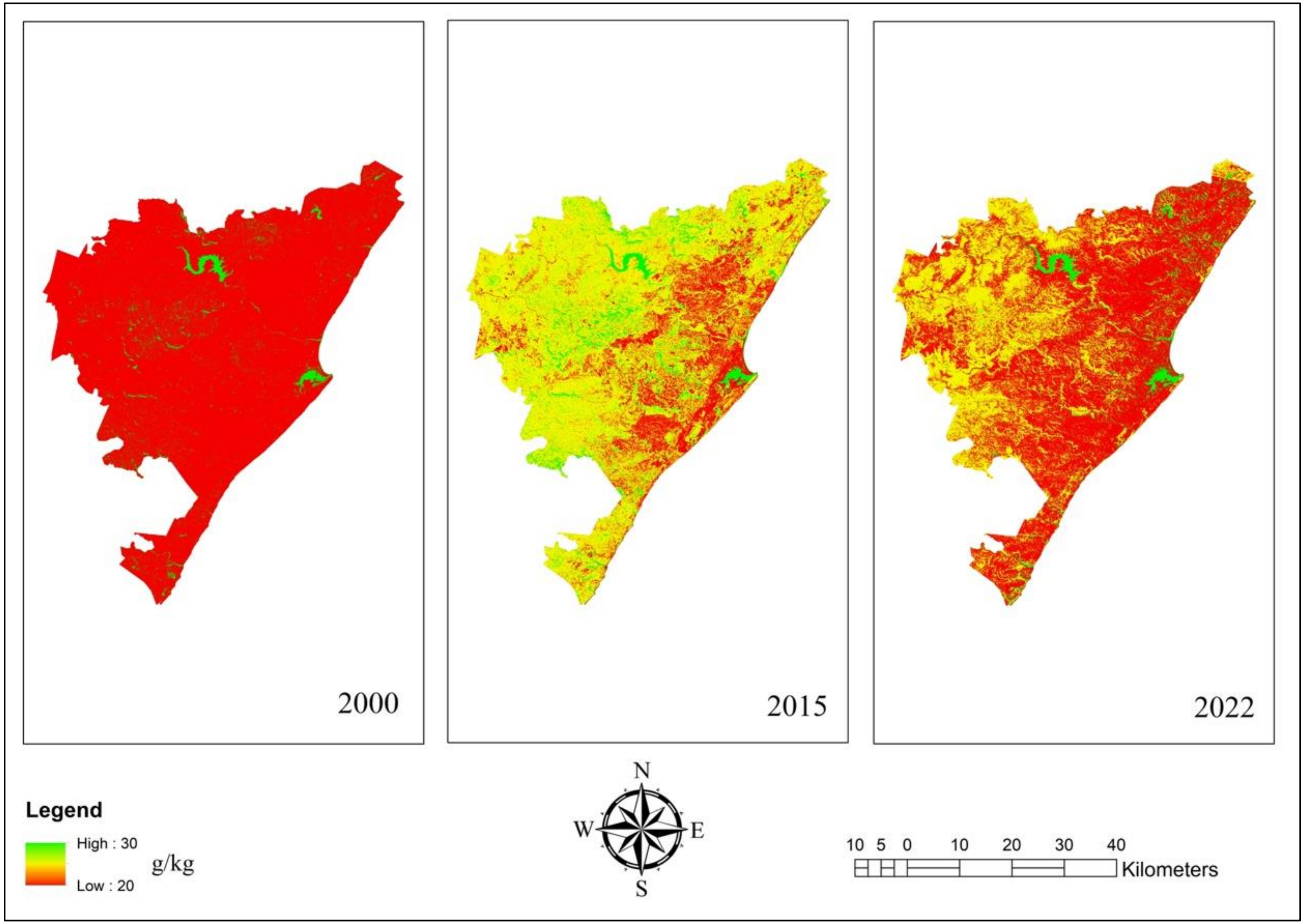

Figure 5.13. The predicted spatial distribution of SOC stock at 20 to 50 cm for the eThekwini Municipality.

Figure 5.14 illustrates the total SOC stock at the 0 – 20 cm and 20 – 50 cm depths in 2000, 2015, and 2022, revealing a significant concentration of SOC stock within the 0 – 20 cm depth range. The graph further strengthens the findings from the previous figure, supporting the observed increase in SOC stock decrease between 2000 and 2015 and a decline between 2015 and 2000. Comparing Figure 5.14 to the earlier maps in Figures 5.12 and 5.13, it becomes evident that there was not a substantial difference in SOC stocks between the years 2000 and 2015. Over this 15-year period, SOC stocks exhibited minimal changes, with an increase of just 0.11% for the 0 – 20 cm depth and 0.36% for the 20 – 50 cm depth. These findings suggest a relatively stable SOC profile over this specific timeframe. Notably, beyond the baseline period, at the 0 – 20 cm depth, there was a 7.21% decline in SOC stock, while at the 20 – 50 cm depth, the reduction was 9.27%. Consequently, it can be concluded that partial degradation occurred, as indicated by SOC stock reduction, primarily within the 20-50 cm depth range. This conclusion aligns with the established criterion for partial land degradation, where a 5% reduction in SOC stock serves as a key threshold.

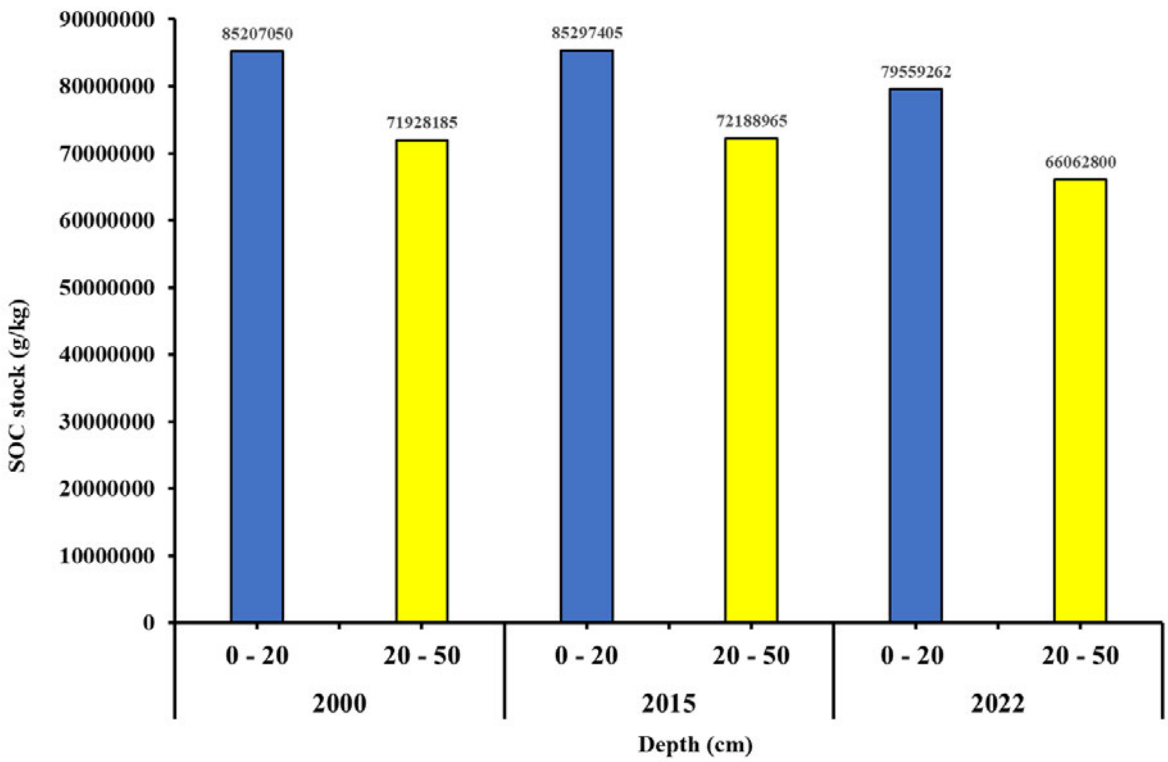

Figure 5.14. The distribution of SOC stock at the 0 – 20 cm and 20 – 50 cm depths in 2000, 2015, and 2022 for the eThekwini Municipality.

5.4 Discussion

The presented study is one of the few studies to have effectively evaluated land degradation at a municipal scale. Further, it distinguishes itself by extending its assessment of land degradation beyond the baseline period, setting it apart from a limited number of similar studies. As such, this study utilised remote sensing and machine learning to assess land degradation based on land cover change and SOC stock within the eThekwini Municipality. Remote sensing has significantly enhanced the ease of monitoring land cover change and SOC stock. In line with this, the present study harnessed the potential of Landsat 7, Landsat 8, and Landsat 9 data to derive variables crucial for predicting these parameters. Moreover, this study became one of the few studies to utilise the iSDA dataset as a reference for predicting SOC stock. Most African studies such as Odebiri *et al.* (2022) (International Soil Reference and Information Centre - ISRIC) and Reith *et al.* (2021) (SoilGrids) have relied on global datasets to obtain soil information. Hengl *et al.* (2021) argued that these datasets are at very generalised scales, and many countries are not mapped at all. As such, the introduction of the iSDA dataset provides an improved resolution and accuracy and mapping of all countries in Africa, which means the algorithms are likely to perform better when trained on this dataset. This follows the argument by Fu *et al.* (2023) who stated that the characteristics of the training samples significantly influence the classification accuracy of machine learning algorithms.

However, future research could enhance findings from this study by integrating locally verified SOC measurements as they become available This will improve model accuracy and provide a more robust validation of SOC estimates tailored to the specific conditions of the eThekwini Municipality.

Four machine learning algorithms, namely, XGBoost, LightGBM, RF and SVM were evaluated for their ability to predict land cover change and SOC stock. Out of the four algorithms employed, LightGBM emerged as the most effective in predicting both land cover classes and SOC stock, as indicated in Tables 5.6 to 5.9. This observation is consistent with the outcomes of Wang, B. *et al.* (2018), Bui *et al.* (2021) and Miao *et al.* (2022), who also noted the superior performance of LightGBM and XGBoost among various ensemble methods. Additionally, the studies conducted by Wang, B. *et al.* (2018) and Bui *et al.* (2021) underscored the superior performance of LightGBM over XGBoost in their comparative analyses. However, it should be noted that Miao *et al.* (2022) arrived at a different conclusion, reporting that

XGBoost exhibited better performance than LightGBM. Hence, it is advisable to consider employing both LightGBM and XGBoost in comparable research studies.

Given its superior performance, LightGBM was selected to predict land cover changes and SOC stock distribution within the eThekwini Municipality. When predicting land cover classes, the algorithm assigned priority to B2 among the raw spectral bands and the NDBI among the calculated spectral indices, as seen in Figure 5.4. B2, the blue band, is valuable for distinguishing vegetation from the soil, meaning the algorithm is effective in discriminating between vegetation and bare land. By prioritising NDBI, the algorithm also demonstrated efficiency in differentiating built-up areas and impervious surfaces from other land cover classes within the municipality.

LightGBM predicted a reduction in cropland, corresponding to an increase in forests and shrubland during the 2000 to 2015 period. Whereas during the 2015 to 2022 period, the algorithm predicted a decrease in forest vegetation and shrubland while cropland and impervious surfaces increased. This is consistent with the findings from Debebe *et al.* (2023) and Assede *et al.* (2023), who also observed that the decline in forest vegetation is often driven by agricultural expansion and population growth. In the context of the eThekwini Municipality, the reduction in forest vegetation and shrubland was further exacerbated by ongoing development in the northern regions. The transition matrices outlined in Tables 5.10 and 5.11 substantiate this trend, leading to the conclusion that the municipality is indeed undergoing a process of land degradation since 2015. Consequently, the imperative for restoration initiatives, such as reforestation and afforestation, becomes evident to counteract these adverse changes and foster sustainable land management.

However, it should be noted that in this study, a notable conversion of 122 km^2 from shrubland to forest was observed between 2015 and 2022 as reflected in Table 5.11. This change, however, encompasses both indigenous forest forests and commercial plantations., which are grouped together under a single forest class. The decision to use a broad forest class was influenced by the spectral similarities between commercial plantation species (such as *acacia* and *eucalyptus*) and indigenous forests, which can be difficult to differentiate using medium-resolution satellite imagery such as Landsat alone (Sibanda *et al.*, 2021). Additionally, the observed conversion from shrubland to forest could potentially be explained by natural succession processes and deliberate afforestation or reforestation efforts. Natural succession might occur when previously degraded shrublands gradually recover, with tree species establishing themselves over time under favorable environmental conditions (Poorter *et al.*, 2023). Targeted rehabilitation projects or policies aimed at increasing forest cover could also result in deliberate reforestation of shrublands.

Furthermore, while the classification approach used in this study allows for a general assessment of forest cover changes, it introduces limitations in interpreting land cover dynamics related to ecological restoration versus commercial forestry rotations. Specifically, commercial plantations follow harvesting and replanting cycles that can mimic patterns of deforestation and reforestation, potentially leading to an overestimation of indigenous forest recovery. Recognising this, future research would benefit from integrating high-resolution or multispectral data, which may allow for more accurate differentiation between commercial and indigenous forests. This refinement would provide a clearer picture of ecological rehabilitation and restoration efforts in contrast to commercial forestry expansion, thus enhancing the understanding of forest cover change drivers in the region.

LightGBM was also used to predict SOC stock and assigned priority to B3, as seen in Figure 5.7. B3, known as the red band in Landsat 8's spectral data, provides valuable insights into aspects such as vegetation health, density, and cover. These characteristics align with SOC stock patterns, as SOC tends to be concentrated in vegetated regions. Hence, it can be deduced that the model effectively achieved accurate predictions of SOC stock. LightGBM predicted minor improvement in SOC stock in both the 0 – 20 cm (0.11%) and 20 – 50 cm (0.36%) depths between 2000 and 2015. Furthermore, the algorithm accurately forecasted a 7.21% reduction in SOC stock at the 0 – 20 cm depth and a 9.27% decrease at the 20 – 50 cm depth between 2015 and 2022. The decline in SOC stock between 2015 and 2022 is in alignment with the predicted decline in forest vegetation and shrubland which are SOC hotspots. The decline in SOC stock also aligns with the increased cropland as Slessarev *et al.* (2023) found that cultivation leads to SOC loss. This observation gains further support from the increase in SOC stocks between 2000 and 2015, aligning with the decline in cropland and the simultaneous expansion of forests and shrubland.

The results from this study have confirmed that the eThekwini Municipality is experiencing land degradation, which will continue if no measures are put in place to restore the land. Zhao, L. *et al.* (2023) found that ecological programmes such as grazing prohibition, tillage prohibition and enclosure protection can be useful in improving degraded land. Moreover, the research by Wolka *et al.* (2023) revealed that landscape restoration initiatives, including the combination of area closure or resting, physical soil and water conservation efforts, and the planting of trees and shrubs, had a significant positive impact on enhancing the overall landscape. Therefore, this study also advocates for such activities within the eThekwini Municipality.

5.5 Conclusion

This study employed remote sensing and machine learning techniques to evaluate land degradation within the eThekwini Municipality spanning 2000 to 2022. Landsat 7, Landsat 8, and Landsat 9 images were used to extract variables for prediction by XGBoost, LightGBM, RF and SVM. LightGBM emerged as the best model and was therefore used to predict land cover change and SOC stock for the municipality. However, this is not to say that the other models, especially XGBoost, cannot be used to perform similar predictions. Land cover change for the eThekwini Municipality revealed that the municipality was losing forests and shrubland landscapes in favour of cropland and built-up areas, especially between 2015 and 2022. The decline in these land covers meant that the municipality also experienced SOC stock losses between 2015 and 2022. The model predicted that most SOC stock losses occurred at the 20 – 50 cm depth (9.27%) compared to the 7.21% loss at the 0 - 20 cm depth. These findings underscore the role of remote sensing and machine learning in aiding policymakers to assess land degradation and implement pertinent measures for landscape enhancement.

Moreover, in the context of SDG 15.3, which aims to combat desertification, stop land degradation, and preserve biodiversity, this study provides valuable insights and data-driven assessments to support informed decision-making toward achieving these sustainability objectives. Therefore, a crucial recommendation for decision-makers and policymakers is to implement targeted measures to mitigate the observed loss of forests and shrublands, especially in areas transitioning to cropland and built-up spaces. Furthermore, there is a need to develop and implement of policies that promote reforestation and sustainable land use practices to counteract the identified trends.

5.6 Summary

This chapter investigated land degradation in the eThekwini Municipality by examining changes in land cover and SOC stocks from 2000 to 2022. Landsat 7, Landsat 8, and Landsat 9 satellites were used to extract variables for land cover change and SOC stock prediction and employed XGBoost, LightGBM, RF, and SVM. LightGBM performed the best, with overall accuracies of 80.646% for land cover prediction and 77.869% for SOC stock prediction. Land degradation maps generated using LightGBM revealed a significant shift from forests and shrublands to cropland and built-up areas from 2000 to 2022, indicating increased urbanisation and agricultural expansion. There was also a notable decline in SOC stock between 2015 and 2022, especially at depths of 20 - 50 cm (9.27% loss) compared to 0 - 20 cm (7.21% loss), correlating with the reduction in vegetated areas. These changes contribute to reduced biodiversity and ecosystem health, emphasising the need for policies promoting reforestation and sustainable land management to combat land degradation and enhance SOC stocks. This chapter underscored the effectiveness of remote sensing and machine learning in monitoring land degradation and provided critical insights for policymakers to implement measures aimed at restoring degraded land.

6. CHAPTER SIX: OPTIMISING FOREST REHABILITATION AND RESTORATION THROUGH REMOTE SENSING AND MACHINE LEARNING: MAPPING NATURAL FORESTS IN THE ETHEKWINI MUNICIPALITY

This chapter is based on:

Buthelezi, M. N. M., Lottering, R., Peerbhay, K., & Mutanga, O. (2024). Optimising forest rehabilitation and restoration through remote sensing and machine learning: Mapping natural forests in the eThekwini Municipality. *Remote Sensing Applications: Society and Environment*, *36*, 101335. https://doi.org/10.1016/j.rsase.2024.101335

Abstract

Forests are crucial in delivering ecosystem services that underpin human well-being and biodiversity conservation. However, these vital ecosystems are threatened by forest degradation and rapid urbanisation. This study addresses this challenge by proposing a comprehensive framework for mapping natural forests at the municipal scale. The framework integrates remote sensing techniques with machine learning algorithms to provide valuable insights into the extent of natural forests within the eThekwini Municipality. The study utilised Landsat 7, Landsat 8, and Landsat 9 satellite imagery to analyse and map the historical and current distribution of natural forests. Five spectral indices, namely, Normalized Differential Vegetation Index (NDVI), Green Normalized Difference Vegetation Index (GNDVI), Chlorophyll Index Green (CIG), Enhanced Vegetation Index (EVI), and Enhanced Vegetation Index-2 (EVI-2), which were calculated from Landsat bands, were employed in the analysis. Light gradient boosting machine (LightGBM), categorical boosting (CatBoost), and extreme gradient boosting (XGBoost) machine learning algorithms were used to model forest distribution. Accuracy was assessed through confusion matrices, receiver operating characteristic (ROC) curves, area under the ROC curve (AUC), and the F1 scores. LightGBM achieved the highest overall accuracy (90.76%), followed by CatBoost (89.56%) and XGBoost (84.34%). LightGBM also obtained the best F1 score (90.76%). These findings highlight LightGBM's effectiveness in classifying natural forests, making it the preferred model for mapping the historical extent of natural forests in the eThekwini Municipality. However, classifications based on Landsat 7 significantly underestimated the extent of natural forests within the study area, whereas Landsat 8 and Landsat 9 data revealed an increase in natural forests from 2015 to 2023. These findings will guide effective and targeted forest rehabilitation and restoration efforts, ensuring the preservation and enhancement of forest ecosystem services.

Keywords: forest rehabilitation, natural forest, forest restoration, machine learning, remote sensing

6.1 Introduction

Forests provide vital ecosystem services extending far beyond their immediate boundaries (Castro *et al.*, 2023). Approximately 1.6 billion people depend on forest ecosystem services for their livelihoods (Thorn *et al.*, 2020). Aznar-Sánchez *et al.* (2018) define ecosystem services as encompassing the direct and indirect offerings that ecosystems provide for human well-being. These services primarily include provisioning, regulating, cultural, and supporting services. Forests also act as crucial carbon sinks, mitigating the impacts of climate change by absorbing and storing substantial amounts of carbon dioxide (Soto *et al.*, 2018). Furthermore, they regulate local and global climate patterns, influencing precipitation and temperature (Fujii *et al.*, 2017; Grammatikopoulou and Vačkářová, 2021). Beyond their environmental significance, forests serve as invaluable habitats for countless plant and animal species, fostering biodiversity and contributing to the delicate balance of ecological systems (Buchelt *et al.*, 2024).

However, these forests are being lost through degradation, which is defined as the loss of forests' biological complexity (Betts *et al.*, 2022) and reduction in the delivery of ecosystem services (Shapiro *et al.*, 2021). Forest degradation occurs due to human activities driven by various political, demographic, macroeconomic, institutional, and technological factors (Vásquez-Grandón *et al.*, 2018). Approximately 200 million hectares of global forests have been degraded (Stanturf *et al.*, 2014). Fa *et al.* (2020) added that intact forest landscapes comprised approximately 23% of global forests but have declined since 2000. Sustainability agendas overlook forest degradation in favour of halting deforestation (Thorn *et al.*, 2020). Additionally, Fa *et al.* (2020) argued that global climate and sustainability targets would not be achieved without conserving forest systems. Additionally, Tadesse *et al.* (2021) posited that the unsustainable utilisation and management of forest resources are exacerbated by the inability of policy-making institutions to incorporate and uphold diverse interests, particularly those related to the benefits of local communities residing in the forested areas.

Therefore, addressing the ongoing challenge of forest degradation necessitates a holistic and collaborative effort that goes beyond merely halting deforestation. Forest rehabilitation and restoration present such an effort and encompass a range of planned, financed, implemented, and monitored practices involving diverse actors such as governments, corporations, and non-governmental organisations (NGOs) (de Jong, 2010; Dharmawan and Pratiwi, 2023). Forest rehabilitation aims to establish a forest ecosystem that closely resembles the original natural habitat, often called the 'reference habitat,' in terms of plant diversity and composition (Mugwedi *et al.*, 2017). However, forest rehabilitation is a complex process, and the increase in tree cover and diversity is not guaranteed. Conversely, forest restoration exclusively targets the complete reinstatement of the original forest's structure, productivity, and species diversity (Brudvig, 2011). The ultimate objective is to align ecological processes and functions with those of the pristine, pre-degraded forest ecosystem. In the broader context of sustainable forest management, both rehabilitation and restoration approaches play vital roles in mitigating forest degradation and promoting biodiversity conservation, contributing to the long-term health and resilience of forest ecosystems.

However, the outcome of these approaches is determined by numerous influencing factors (Chokkalingam *et al.*, 2005; de Jong, 2010). These factors encompass site conditions such as the extent of forests, which are pivotal in assessing whether the chosen site requires management to support further recovery, accelerate recovery, or is poised to recover naturally over time without intervention. (Lewis *et al.*, 2019). Species selection plays a crucial role in determining the resilience and biodiversity of the rehabilitated forest, with the choice of tree species tailored to local ecological conditions (Fremout *et al.*, 2022). The selection of forest rehabilitation and restoration practices, which include natural regeneration, assisted natural regeneration and planting trees. If planting trees is considered a suitable rehabilitation and restoration practice, proper planting techniques, such as spacing and timing, are essential for ensuring the establishment and growth of planted trees (Ji *et al.*, 2023). Effective management practices, including weed control, irrigation, and pest management, are necessary to support tree survival and growth (Toro *et al.*, 2024). Community involvement fosters a sense of ownership and stewardship over restored forests, while supportive policies and regulations provide a framework for sustainable land management (Haji *et al.*, 2021). External threats such as wildfires, invasive species, and climate change pose challenges to rehabilitation and restoration efforts, necessitating proactive strategies for mitigation (Sample *et al.*, 2022; Simonson *et al.*, 2021). The presence of regular monitoring and adaptive management, which allow for adjustments to management practices based on monitoring data, ensures the long-term success of forest rehabilitation and restoration projects (Camarretta *et al.*, 2020). As such, Lewis *et al.* (2019) proposed a careful analysis of these factors before attempting any forest rehabilitation or restoration initiatives. They then suggested that site conditions be the first factor to be analysed, given that it will provide an understanding of the history and current state of the area's natural forests.

Therefore, this study provides a framework for monitoring natural forests at a municipal scale. The eThekwini Municipality was, thus, selected as a study area. The interest in this municipality stems from the persistent degradation of vegetated landscapes within its borders. Buthelezi *et al.* (2024a) found that the eThekwini Municipality has experienced intensifying land degradation since 2015. This was primarily driven by rapid and disjointed urbanisation (Carbonell *et al.*, 2023), which is caused by the shift away from apartheid spatial planning and the failure to provide employment and housing opportunities (Sutherland *et al.*, 2014; Williams *et al.*, 2019). This has led to the emergence of social inequalities and a spawn of multiple informal settlements (Jones, 2017). These settlements scattered around the eThekwini Municipality and rapid urbanisation are causing significant alterations in land use and land cover (LULC), impacting the functionality of various urban landscape elements, exerting significant stress on natural environments, and increasing the risk of disasters (Matarira *et al.*, 2023). These conditions are pushing many African cities to the limits of conservation (Chihambakwe and Moyo, 2023). That is because as urbanisation progresses, the complexity of interactions between humans and the environment intensifies due to the reduction of vegetated landscapes (Pillay *et al.*, 2023).

The challenge of urbanisation, particularly the expanding informal settlements towards forested land in the eThekwini Municipality, poses difficulties for environmental managers and policymakers in implementing forest rehabilitation and restoration projects. Lewis *et al.* (2019) proposed a framework that addresses this issue by providing a structured approach to rehabilitation and restoration, emphasising the importance of considering existing forest conditions, stakeholder engagement, and adaptive management. Therefore, this study offers a framework for environmental managers and policymakers to monitor the historical and current forest extent. This framework entails mapping the historical and current extent of natural forests using Landsat imagery between the years 2000 and 2023.

Lewis *et al.* (2016) identified remote sensing as a critical component in monitoring forests. As such, this study used Landsat 7 (Enhanced Thematic Mapper Plus - ETM+), Landsat 8 (Operational Land Imager – OLI) and Landsat 9 (Operational Land Imager 2 - OLI2) to map the historical and current extent of natural forests within the eThekwini Municipality. Landsat offers free dissemination, accurate spectral bands featuring a spatial resolution of 30 meters, regular and consistent revisits, and calibrated data (Alam *et al.*, 2020; Singh *et al.*, 2024). Additionally, the successful launch of Landsat 9 on September 27, 2021, ensured that Landsat continues the longest global environmental satellite record (Crawford *et al.*, 2023; Wulder *et al.*, 2022). Therefore, the continuous record of Landsat facilitated the utilisation of its multiple sensors in this study, starting with Landsat 7 for the years 2000 to 2013, Landsat 8 for the years 2014 to 2021, and Landsat 9 for 2022 and 2023.

However, remote sensing imagery requires machine learning and deep learning techniques to derive advanced semantic information, which can be used for precise classification and recognition practices (Han *et al.*, 2023). Consequently, non-parametric machine learning algorithms have emerged as the most effective algorithms and have been utilised to execute this task in various studies, including Buthelezi *et al.* (2022), Buthelezi *et al.* (2023), Mpakairi *et al.* (2023) and Vawda *et al.* (2024). These non-parametric algorithms operate without assuming normality in data distribution, demonstrating effectiveness and efficiency in terms of processing time and the capability to achieve higher accuracies compared to parametric algorithms (Fassnacht *et al.*, 2016; Gyamfi-Ampadu *et al.*, 2020). Additionally, employing multiple algorithms can lead to enhanced performance, improved generalisation, and a more robust and reliable analysis. This approach leverages the diverse strengths of different models, mitigates risks, and provides comprehensive insights into the data.

Hence, this study utilised three gradient boosting algorithms, namely, light gradient boosting machine (LightGBM), extreme gradient boosting (XGBoost) and categorical boosting (CatBoost) to extract information from Landsat imagery. These three algorithms are recent extensions to the family of gradient boosting algorithms, emphasising both speed and accuracy (Bentéjac *et al.*, 2021). Gradient boosting algorithms work by building an ensemble of weak learners, typically decision trees, in a sequential manner to create a robust predictive model (Aziz *et al.*, 2020). This study will utilise the best performing algorithm from these three algorithms based on the confusion matrix and the area under the receiver operating characteristic (ROC) curve (AUC). However, these algorithms require training using reference data, which provides a basis for the algorithm to learn and make accurate predictions, thereby enhancing the model's performance and generalisation capabilities (Chen *et al.*, 2023).

Given this background, this study aims to develop a comprehensive framework that integrates remote sensing and machine learning techniques for mapping natural forests within the eThekwini Municipality. Specifically, it evaluates the performance of three advanced machine learning algorithms, namely, LightGBM, CatBoost, and XGBoost, in accurately classifying and mapping the historical and current distribution of natural forests using Landsat satellite imagery. Additionally, the study assesses changes in natural forest cover within the municipality from 2000 to 2023, providing valuable insights to guide forest rehabilitation and restoration efforts. Finally, it identifies the most important spectral indices and Landsat bands crucial for accurate natural forest classification and mapping in the study area.

The novelty of this study lies in its emphasis on integrating remote sensing in monitoring existing natural forest conditions for forest rehabilitation and restoration. Moreover, it should be noted that this study is one of the very first studies to focus on forest rehabilitation and restoration of natural forests within the eThekwini Municipality. There have been projects centred on forests in the municipality, such as the Buffelsdraai Landfill Site Community Reforestation Project (Mugwedi *et al.*, 2017; Pillay *et al.*, 2023). However, these initiatives focus on replanting open or abandoned spaces (Moyo *et al.*, 2021). Additionally, this study emphasises the usefulness of remote sensing in forest rehabilitation and restoration studies, given its underutilisation in the existing literature on such initiatives.

6.2 Methods and Materials

6.2.1 Study area

The eThekwini Municipality is located within the province of KwaZulu-Natal, South Africa (Figure 1). Based on the Koppen classification, this area features a humid subtropical climate (Cwa) with distinct seasonal variations: hot and wet summers (November-April) and cool and dry winters (May-October) (Mushore *et al.*, 2023). The municipality covers 2297 km^2, which represents a modest 1.4% of KwaZulu-Natal's landmass and is South Africa's third-largest metropolis with the busiest port on the African continent (Zungu *et al.*, 2020b). Zungu *et al.* (2020b) added that the eThekwini Municipality's landscape was originally dominated by natural forests (65%). However, urbanisation has extensively altered the terrestrial habitat in the municipality, with additional major threats from invasive plant species, pollution, and climate change (Odindi *et al.*, 2015). As such, 53% of the initial vegetation has been converted for human activities such as agriculture, construction, roads, and settlements, and an additional 17% is classified as highly degraded (Zungu *et al.*, 2020b). This transition from a predominantly natural forested area to a highly urbanised environment underscores the critical need to assess the extent of natural forest loss. Therefore, developing an accurate framework for natural forest classification and mapping is essential, aligning with the core aims of this study.

Conservation efforts through controlled development, environmental servitudes, and land acquisition have preserved some portions of the green environment in near-pristine conditions in the municipality (Odindi *et al.*, 2015). One example is the Durban Metropolitan Open Space System (DMOSS), a network of designated areas aimed at preserving the native fauna and flora, which the municipality implemented (Buthelezi *et al.*, 2024a). However, these conservation efforts have continuously ignored natural forest rehabilitation and restoration. This has created a gap in natural forest rehabilitation and restoration within the municipality, highlighting the need for this study's focus on using advanced remote sensing and machine learning techniques to optimise these efforts.

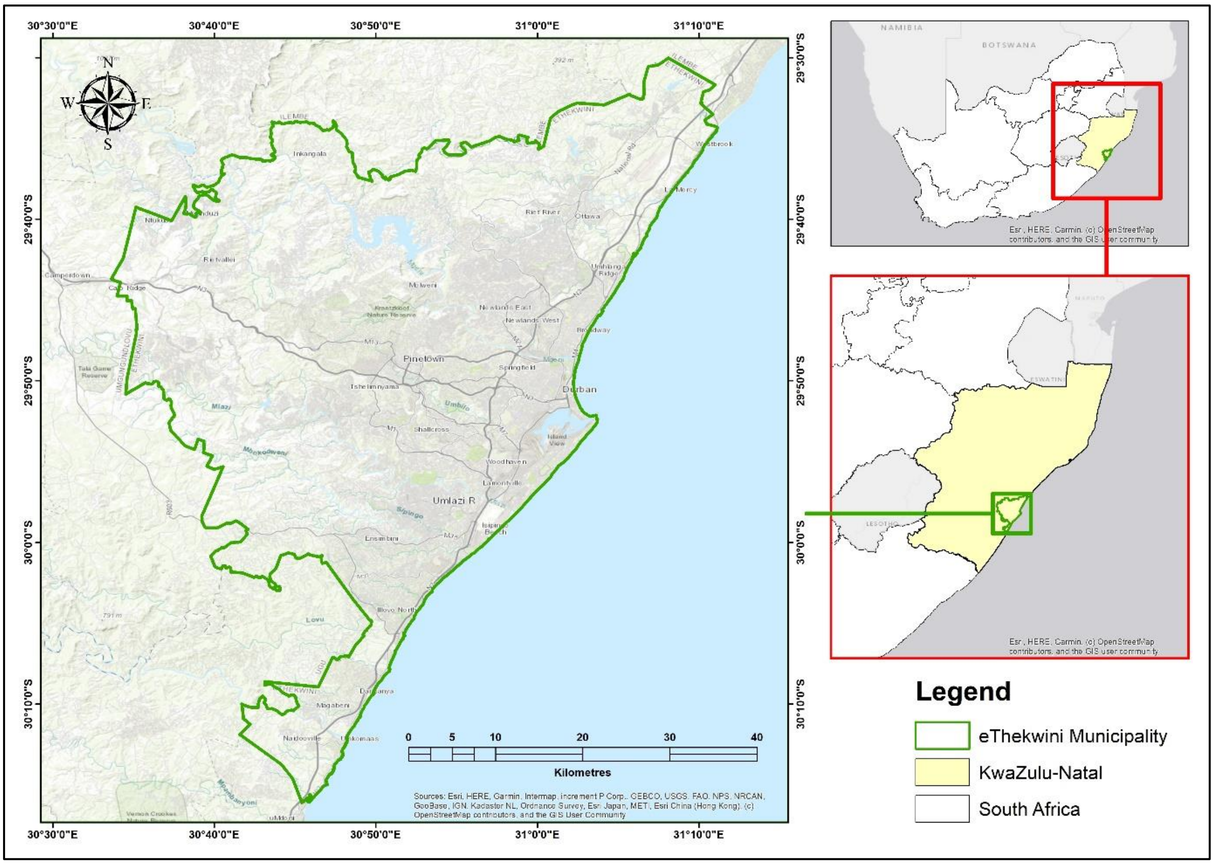

Figure 6.1. The location of the eThekwini Municipality in the province of KwaZulu-Natal, South Africa.

6.2.2 Data acquisition

6.2.2.1 Reference data

The reference data was extracted from the 2020 South African National Land Cover (SANLC) dataset. The dataset comprises 73 hierarchical classes that can be categorised into nine main classes, including water bodies, forest land, grassland, wetland, cultivated areas, shrubland, built-up areas, barren land, and mines and quarries (Ngcofe and Nkoana, 2023). As such, this study uses the contiguous (indigenous) forest, which is under the Natural Wooded Land class in the SANLC classification level 2 and forest land in level 1 (Figure 2). The Computer Automated Land-Cover (CALC) system, which was designed to autonomously generate land-cover datasets, conduct accuracy assessments, and detect changes between comparable land-cover datasets, was used to generate the 2020 SANLC dataset. The overall accuracy from the confusion matrix for the dataset is 85.47%, making this dataset reliable for use in training the algorithms. This means the SANLC dataset has a 14% classification error. As such, this should be factored into the interpretation of results.

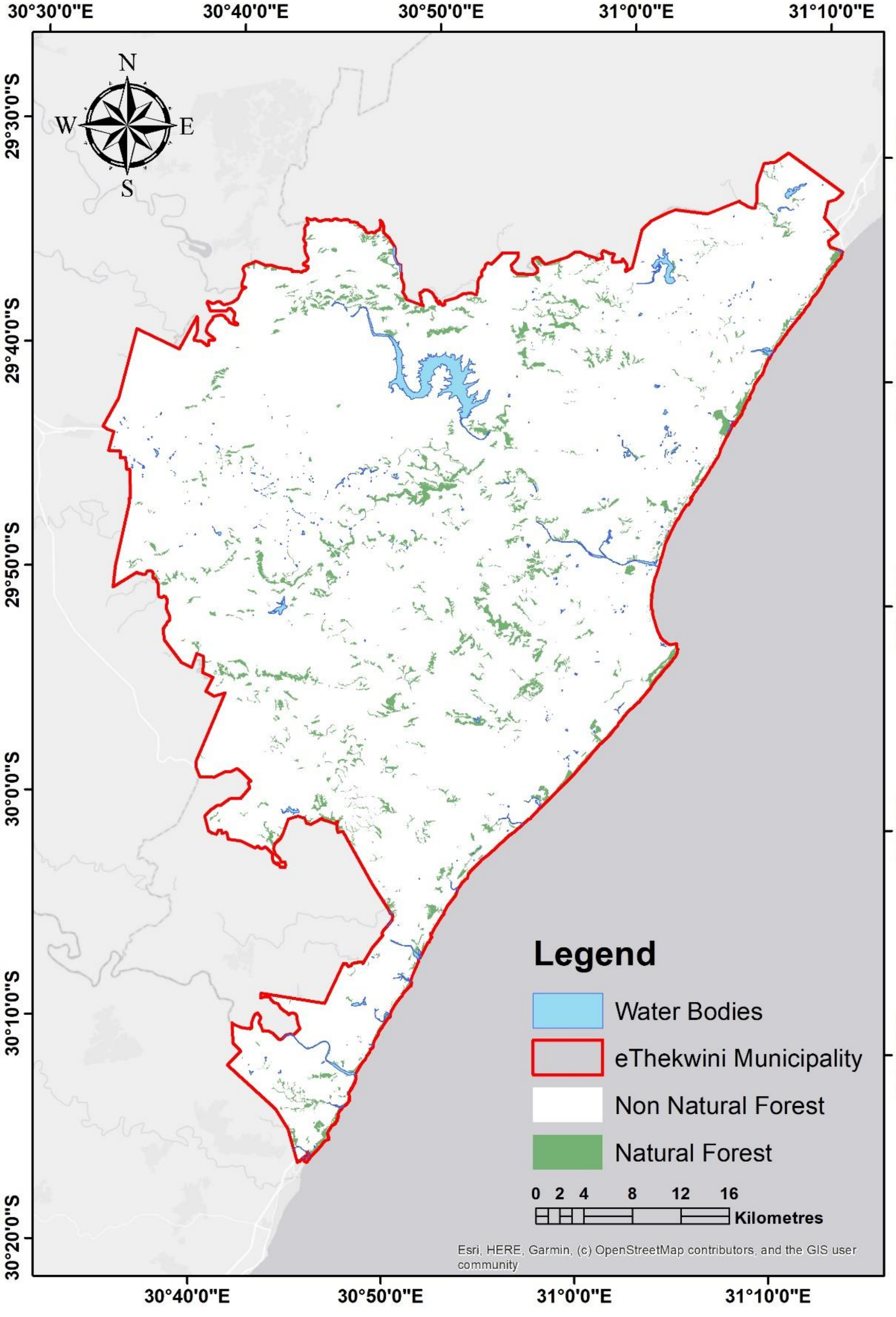

Figure 6.2. The 2020 distribution of natural forests within the eThekwini Municipality based on the SANLC.

6.2.3 Image data description, acquisition, and pre-processing

This study used Landsat 7, Landsat 8 and Landsat 9 to map the historical and current distribution of natural forests within the eThekwini Municipality. All Landsat satellites offer a revisit time of approximately 16 days (Wen *et al.*, 2024). Additionally, Landsat collections used in this study provide calibrated top-of-atmosphere (TOA) reflectance data. The calibration coefficients are derived from the image metadata. The calibration process is explained by Chander *et al.* (2009).

The decision to use TOA reflectance images in this study was driven by its emphasis on detecting broad forest cover changes. TOA reflectance has been shown in previous studies to be suitable for applications where relative comparisons are prioritized over exact surface reflectance values (Sigopi *et al.*, 2024). This approach allowed for streamlined data processing and clear analysis of forest dynamics. For studies that require precise details on surface conditions, bottom-of-atmosphere (BOA) data may offer additional insights and could be explored in future research (Nazeer *et al.*, 2021).

6.2.3.1 Landsat 7 (ETM+)

Launched on April 15, 1999, the Landsat 7 satellite, equipped with the ETM+ sensor, provided data until April 6, 2022 (Perez and Vitale, 2023). The ETM+ operates as a fixed whisk-broom multispectral scanning radiometer with eight bands, it detects spectrally-filtered radiation across the Visible and Near-Infrared (VNIR - 0.45–0.90 µm), Shortwave Infrared (SWIR - 1.55–2.35 µm), Longwave Infrared (LWIR - 10.4–12.5 µm), and panchromatic (0.52–0.9 µm) bands, offering spatial resolutions of 30 m, 60 m, and 15 m, respectively (Moradpour *et al.*, 2022). However, on May 31, 2003, the ETM+ experienced a scan line corrector (SLC) failure, causing data gaps in subsequent images; however, despite this issue, ETM+ maintains high-quality radiometry and geometry, contributing over 75% of the data for any given scene (Buthelezi *et al.*, 2022).

6.2.3.2 Landsat 8 (OLI)

Launched on February 11, 2013, the Landsat 8 satellite carries two instruments consisting of the OLI and the Thermal Infrared Sensor (TIRS) with over 500 image scenes per day ingested into the U.S. Landsat data archive at the USGS Earth Resource Observation and Science (EROS) Center (Roy *et al.*, 2014). In contrast to Landsat 7’s ETM+, Landsat 8’s OLI features narrower spectral bands, enhanced calibration and signal-to-noise characteristics, and increased 12-bit radiometric resolution (Vural *et al.*, 2021).

6.2.3.3 Landsat 9 (OLI2)

The Landsat 9 satellite is also equipped with two push-broom sensors, namely the OLI 2 and Thermal Infrared Sensor 2 (TIRS 2), was launched on September 27, 2021, as a collaborative effort between USGS and NASA, providing a spatial resolution of 30 meters (Eon *et al.*, 2023; Lulla *et al.*, 2021). Landsat 9 enhances the first operational land imager's (OLI1) radiation resolution from 12 bits in Landsat 8 to 14 bits, thereby increasing the sensor's sensitivity to detect finer distinctions, particularly in dense forests or water (You *et al.*, 2022).

Images from these satellites were acquired from Google Earth Engine (GEE). GEE is a cloud-based platform that streamlines geoprocessing tasks, providing users with a comprehensive set of tools and resources for efficient geospatial analyses and data processing in a scalable and accessible environment (Velastegui-Montoya *et al.*, 2023). The date filter in GEE was configured to select Landsat images acquired between August and December for each year of the study period. This takes advantage of the municipality’s wet season's increased chlorophyll and leaf area for stronger signal detection (Buthelezi *et al.*, 2024a). The median image was selected from the acquired images. Selecting the median offers robust noise suppression, effectively mitigating the influence of outliers (Maheswari and Radha, 2010). An additional filter in GEE included the selection of only images with less than 1% cloud cover. The Landsat 8 image from 2020 served as the training dataset for the algorithms.

6.2.4 Data processing and modelling

6.2.4.1 Spectral indices

This study employed five bands [Blue, Green, Red, Near-Infrared (NIR), and SWIR] with a spatial resolution of 30 meters. Additionally, five indices were calculated in GEE from Landsat bands, namely, Normalised Differential Vegetation Index (NDVI), Green Normalised Difference Vegetation Index (GNDVI), Chlorophyll Index Green (CIG), Enhanced Vegetation Index (EVI), and Enhanced Vegetation Index-2 (EVI-2) (Table 6.1). These indices can provide critical forest vegetation information (Matiza *et al.*, 2024).

Table 6.1. Landsat 9 spectral indices, along with their formulas, descriptions, and references.

Index	Formula	Reference	Description
NDVI	$\frac{(NIR - Red)}{(NIR + Red)}$	Tucker and Sellers (1986)	Quantifies the presence and health of vegetation.
GNDVI	$\frac{(NIR\ -\ Green)}{(NIR\ +\ Green)}$	Gitelson and Merzlyak (1998)	Provides insights into vegetation density.
CIG	$\frac{(NIR)}{(Green)} - 1$	Kumar *et al.* (2020)	Assesses chlorophyll content in plants.
EVI	$\frac{[(2.5\ \mathrm{X}\ (NIR - Red)]}{[(NIR + (6\ \mathrm{X}\ Red) - (7.5\ X\ BLUE) +}$	Huete *et al.* (2002)	It provides a more accurate representation of vegetation health by correcting for atmospheric influences and soil background effects.
EVI-2	$2.5\ \times \frac{NIR - Red}{NIR + (2.4\ \times Red) + 1}$	Jiang *et al.* (2008)	It is designed to further improve sensitivity (from EVI) in high biomass regions and reduce saturation effects.

Before extracting bands and calculating indices from Landsat 7 images acquired between 2003 and 2013, the missing data resulting from the SLC failure was filled in GEE. This study employed the *focal.mean()* technique, a morphological operation that serves as a simplified version of the broader *reduceNeighborhood()* function (Figure 6.3). Morphological operations refer to a collection of image processing techniques that modify individual pixels according to the values of neighbouring pixels (Jiang and Scott, 2020).

The bands selected for use in this study and the five calculated indices were stacked and exported as one image from GEE. The exported images from GEE and the reference image were superimposed in QGIS *version 3.32.1*, and random points were generated across the study area. The generated random points were used to extract data using the Point sampling tool (*n* = 828). The extracted data, including all bands, indices, and reference information, were then used to train LightGBM, CatBoost, and XGBoost. However, before training the algorithms for mapping the distribution of natural forests, the data were resampled to achieve class balance and then split into 70% training (*n* = 580) and 30% test sets (*n* = 248).

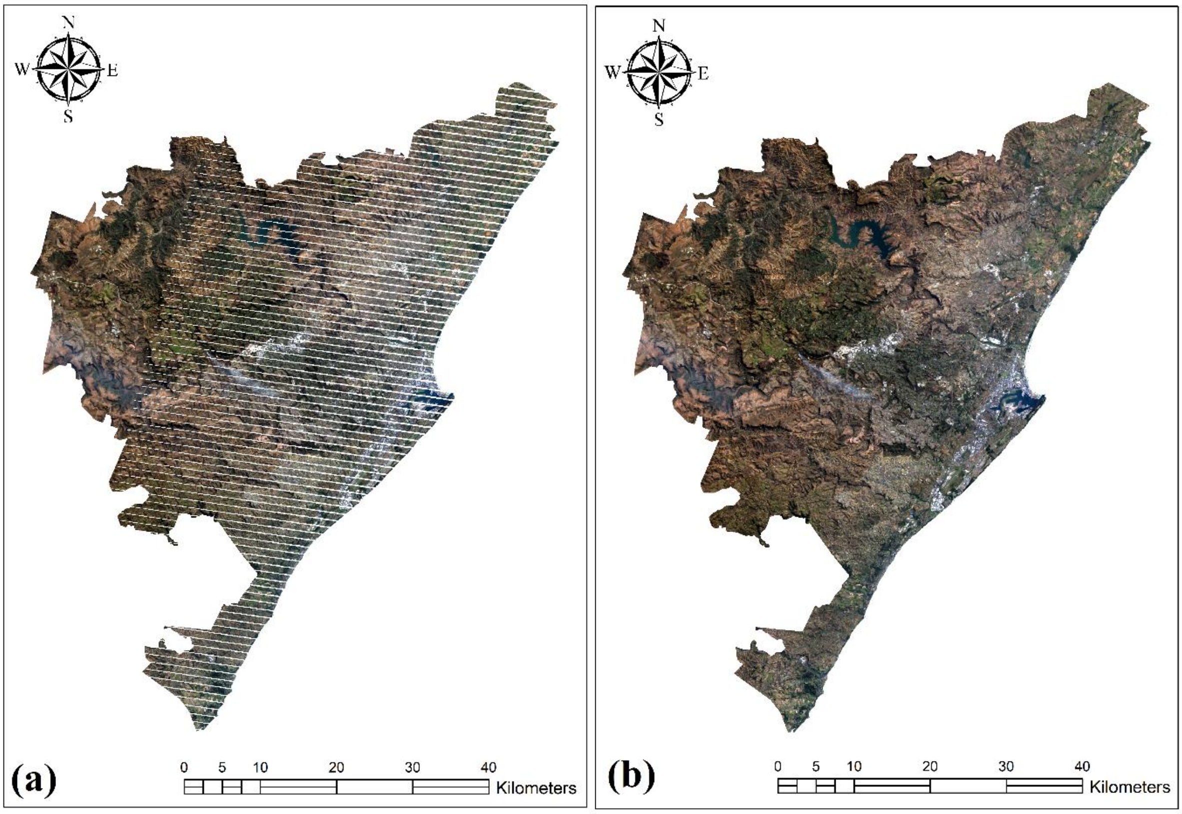

Figure 6.3. The Landsat 7 image from 2003 with missing data (a), which was subsequently filled using *focal.mean()* technique in GEE (b).

6.2.5 Machine learning algorithms

6.2.5.1 Light Gradient Boosting Machine

LightGBM was introduced by Microsoft DMKT in 2017 as a distributed boosting framework (Buthelezi *et al.*, 2024b; Ke *et al.*, 2017). The broad acceptance of this algorithm in regression, classification, and various machine learning tasks is attributed to its combination of excellent scalability, accuracy, flexibility, speed, and the ability to incorporate regulated model formulations for addressing overfitting (Alshboul *et al.*, 2024; Zhang *et al.*, 2020). LightGBM achieves this by accelerating the training process using multi-threaded parallel histograms, employing gradient-based one-side sampling and exclusive feature bundling for efficient data pre-processing (Li *et al.*, 2023).

6.2.5.2 Categorical Boosting

CatBoost is a powerful gradient boosting algorithm developed by Yandex that is excellent at handling categorical data and delivering high-performance results (Najm *et al.*, 2023; Zeng *et al.*, 2023). Unlike traditional gradient boosting algorithms, CatBoost employs an innovative technique that reduces overfitting and enhances model accuracy (Hancock and Khoshgoftaar, 2020). It achieves this by efficiently handling categorical variables and incorporating them directly into the decision trees without requiring extensive preprocessing. Furthermore, CatBoost demonstrates superior performance in terms of both speed and accuracy due to its advanced optimisation techniques and support for fast graphics processing unit (GPU) training (Joshi *et al.*, 2021). This makes it particularly suitable for large datasets and complex problems where traditional algorithms may struggle.

6.2.5.3 Extreme Gradient Boosting

XGBoost is a highly efficient and flexible gradient boosting algorithm that has become a staple in the machine learning applications due to its exceptional performance and scalability (Theodoridis and Tsadiras, 2022). It is designed to optimise both computational speed and model performance (Asselman *et al.*, 2023). XGBoost achieves this by adopting a tree-based structure where decision nodes make feature-based judgments, branches represent the outcomes, and leaf nodes give classification results (Yi *et al.*, 2024). It builds multiple decision trees sequentially, with each tree trained on the residuals of the previous one, and the combined results of all trees form the final prediction (Dong *et al.*, 2020). Therefore, XGBoost can handle sparse data, regularisation to reduce overfitting, and parallel processing to accelerate training (Chen and Guestrin, 2016a). Moreover, it supports various objective functions and custom loss functions, making it adaptable to a wide range of applications, from regression to classification tasks (Dhaliwal *et al.*, 2018).

While effective, LightGBM, CatBoost and XGBoost are limited by the intricate process of parameter selection (Li *et al.*, 2024). As such, Bayesian Optimisation was employed to optimise hyperparameters for these algorithms to counter this limitation.

6.2.6 Accuracy assessment

Accuracy assessment is a crucial step in model evaluation. For this study, an accuracy assessment was used to determine the best model for mapping current natural forest distribution using the SANLC. Therefore, the confusion matrix and the metrics based on it including, the receiver operating characteristic curve (ROC), the area under the ROC curve (AUC) and the F1 score were used to evaluate the accuracy of LightGBM, CatBoost and XGBoost. A ROC curve is a graphical representation that illustrates the performance of a binary classification model by plotting the trade-off between its true positive rate (sensitivity) and false positive rate (1-specificity) across various threshold values (Fawcett, 2006). The AUC metric is extensively employed to assess classification performance, especially in scenarios involving imbalanced data distributions (Han *et al.*, 2019). This metric quantifies the entire two-dimensional area beneath the complete ROC curve, akin to the concept of integral calculus, spanning from (0,0) to (1,1). The F1 score has been employed in broad applications across various domains of machine learning, including binary scenarios and multiclass situations (Chicco and Jurman, 2020). It employs a precision-recall framework and an averaging method that penalises extreme values (Buthelezi *et al.*, 2022; Fan *et al.*, 2018).

6.2.7 Variable importance

In extensive learning scenarios, especially when there are more variables than observations, not every variable is relevant for predicting the desired outcome (Gregorutti *et al.*, 2017). As such, variable importance is explored to recognise the contribution and impact of different variables in each context, aiding in the identification of key factors that significantly influence the outcome of interest. This study used the SHapley Additive exPlanation (SHAP) framework (Lundberg and Lee, 2017) to explore the most important variables in the best performing algorithm when mapping historical and current natural forest distribution within the eThekwini Municipality. The SHAP framework measures both the extent and direction (whether positive or negative) of the feature's impact on the prediction (Scavuzzo *et al.*, 2022). Additionally, the SHAP framework exhibits universality as it incorporates specialised functions for a wide range of machine learning algorithms (Miao *et al.*, 2024).

6.2.8 Overview

Figure 6.4 presents the schematic overview of the methodology used to map the current distribution of natural forests within the eThekwini Municipality.

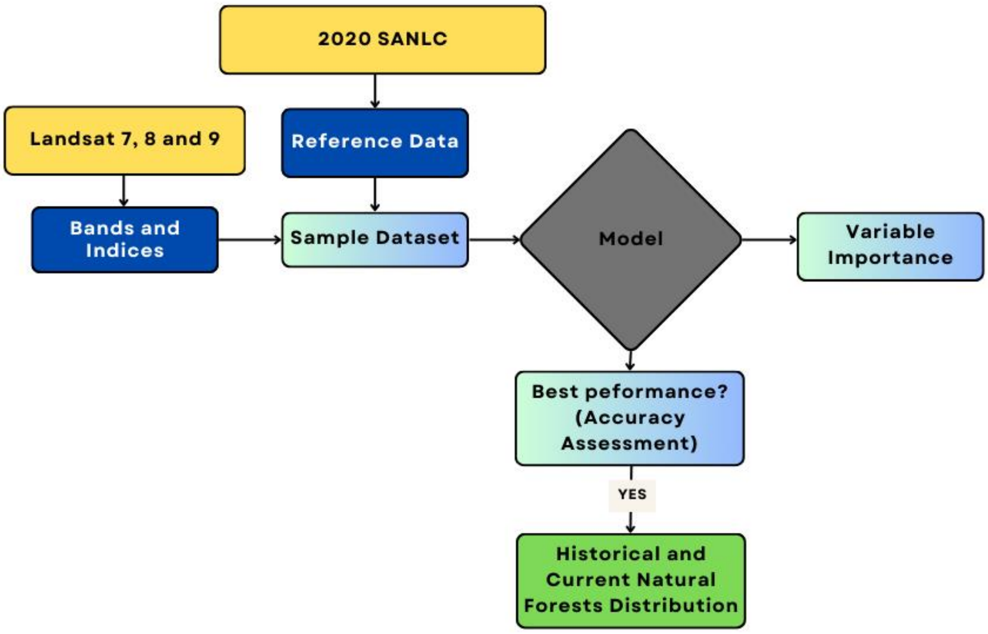

Figure 6.4. An illustrative summary of evaluating model performances and mapping the current distribution of natural forests in the eThekwini Municipality.

6.3 Results

6.3.1 Accuracy assessment

The performance of LightGBM, CatBoost, and XGBoost is presented in Figure 6.5. LightGBM achieved the highest overall accuracy at 90.76%, followed by CatBoost at 89.56% and XGBoost at 84.34%. In terms of the F1 score, which balances precision and recall, LightGBM again had the best performance with 90.76%, closely followed by CatBoost at 89.56%, while XGBoost had the lowest F1 Score at 85.39%.

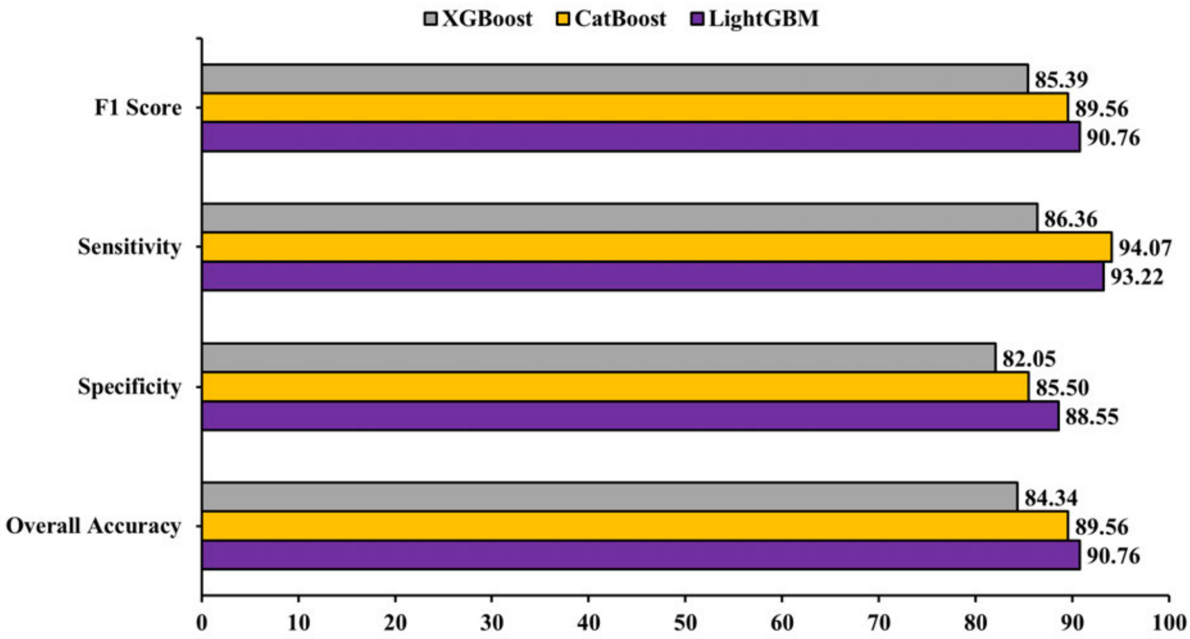

Figure 6.5. Performance comparison of LightGBM, CatBoost, and XGBoost for classifying natural forests based on the overall accuracy, specificity, sensitivity, and the F1 Score.

The performance of LightGBM, CatBoost, and XGBoost was further evaluated using ROC curves and AUC, as shown in Figure 6.6(a), Figure 6.6(b), and Figure 6.6(c), respectively. LightGBM exhibited the largest AUC of 0.91, indicating its superior ability to distinguish between positive and negative cases. CatBoost followed with an AUC of 0.90, reflecting strong but slightly lower performance compared to LightGBM. XGBoost had the lowest AUC at 0.84, suggesting it was the least effective in differentiating between positive and negative cases.

Overall, LightGBM demonstrated the best performance based on overall accuracy, AUC, and F1 score. CatBoost performed well but slightly lower than LightGBM, while XGBoost showed the least effectiveness across these metrics. As such, LightGBM was chosen to map the historical extent of natural forests within the eThekwini Municipality.

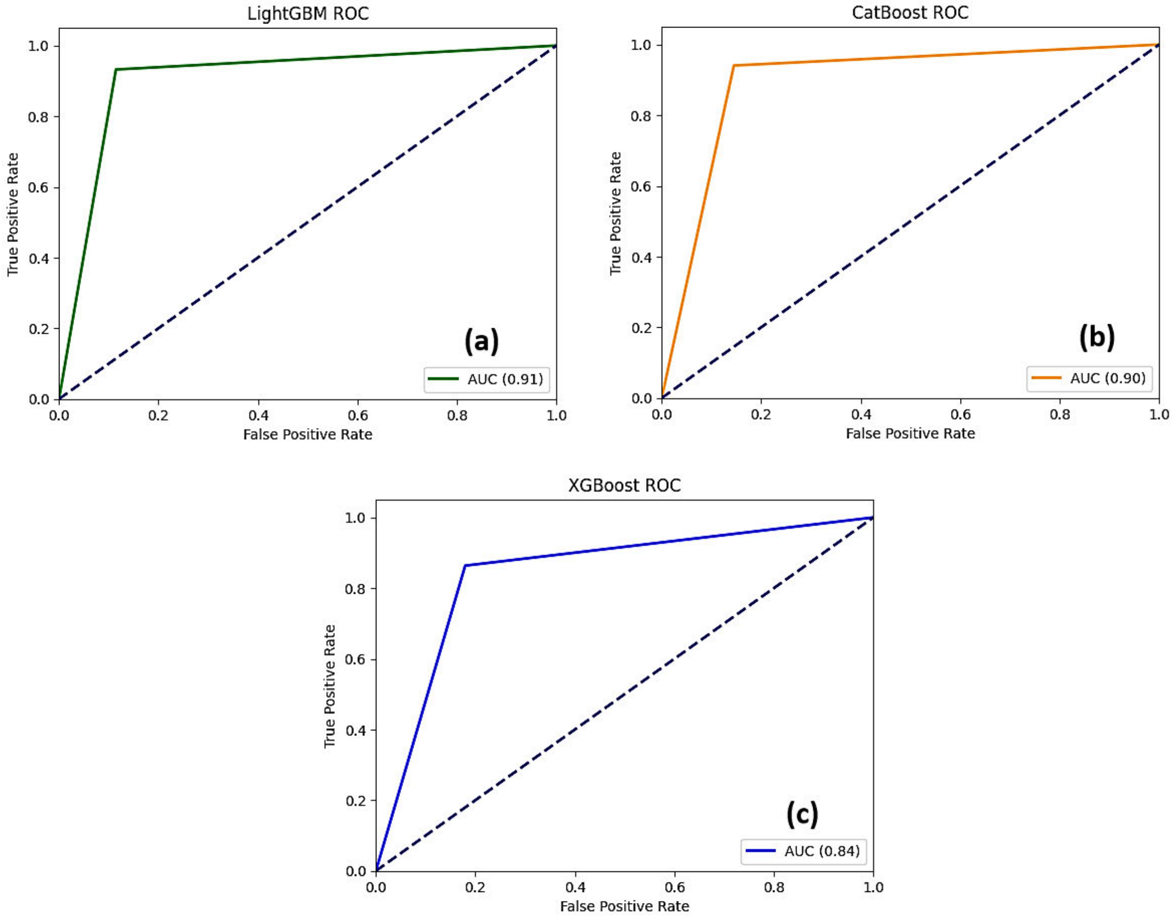

Figure 6.6. Performance comparison of LightGBM, CatBoost, and XGBoost for classifying natural forests based on the ROC and AUC.

6.3.2 Variable importance

The best performance was achieved with LightGBM, which meant it was used to map natural forests within the eThekwini Municipality, prompting an investigation into variable importance for this algorithm. The variable importance for the LightGBM algorithm is shown in Figure 6.7, highlighting that the red band (B4), NDVI, and GNDVI were the most important and influential variables. This indicates that these variables significantly contributed to the model's accuracy in mapping natural forests. The Red band, which captures red light reflected by vegetation, is crucial for differentiating between healthy and stressed vegetation. NDVI and GNDVI are vital for assessing vegetation health and density, enhancing the model's ability to accurately classify forested areas. Conversely, CIG was the least important variable, suggesting it had minimal impact on LightGBM performance. This could imply that CIG, while useful in other contexts, does not provide substantial additional information for natural forest mapping.

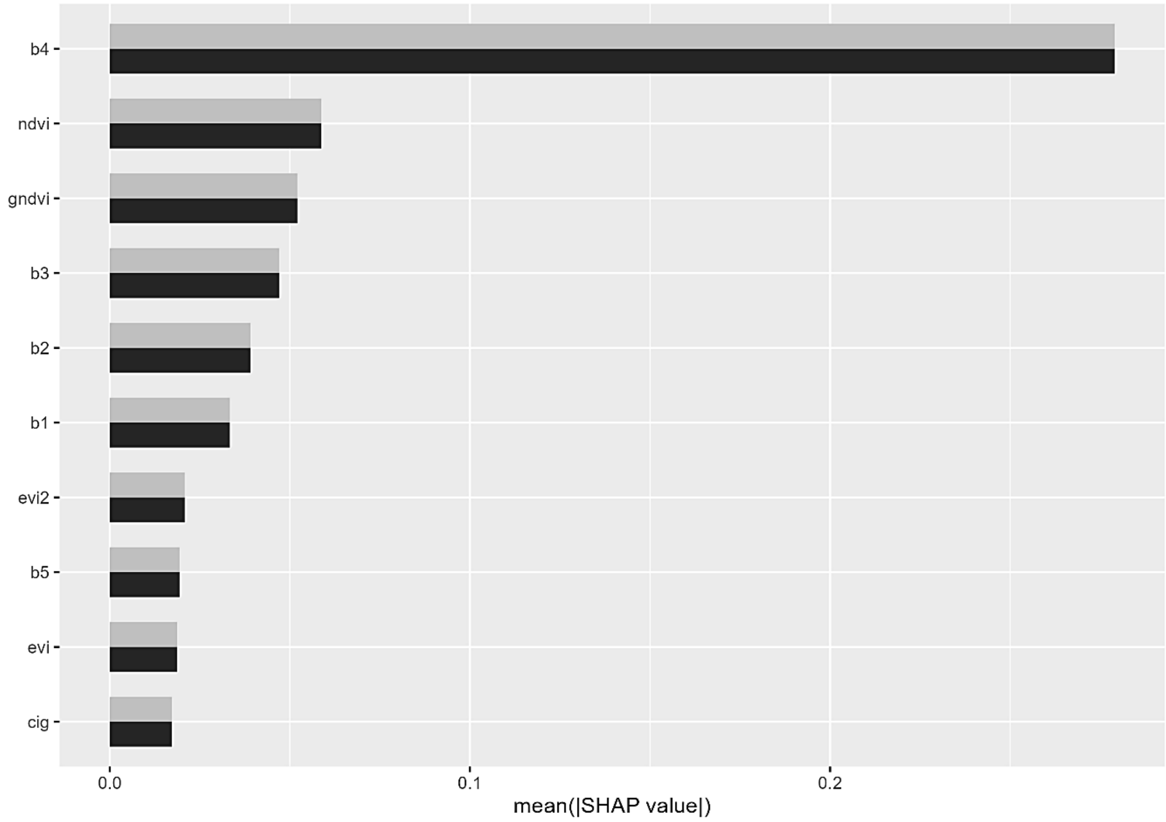

Figure 6.7. Variable importance ranking based on mean SHAP values for mapping natural forests using LightGBM.

6.3.3 Spatial distribution of natural forests

Figure 6.8 presents the distribution of natural forests within the eThekwini Municipality between 2000 and 2023. From the maps, it can be observed that LightGBM significantly underestimated the natural forested areas within the municipality when classifying based on Landsat 7 information (Figures 6.8a–c). Additionally, it was noted that LightGBM misclassified water bodies as natural forests when using Landsat 7 information. This misclassification likely stems from the limitations of the ETM+ sensor, which experienced a SLC failure in 2003, leading to data gaps and reduced image quality. The spectral similarities between water bodies and certain forested areas in specific bands may have also contributed to the model's confusion. This highlights the importance of using high-quality, gap-free imagery and refining classification algorithms to improve accuracy. Despite these early inaccuracies, the maps show a clear increase in natural forest areas between 2015 and 2023 (Figures 6.8d–

e). To provide further insight, the percentage area occupied by natural forests for each year depicted in Figure 6.8 is detailed in Figure 6.9.

Figure 6.9 shows a significant increase in forested areas over the study period. In 2000, natural forests occupied only 1.7% of the area, which decreased to 0.5% by 2005 and slightly increased to 0.7% in 2010. A substantial growth was observed starting in 2015, when the forested area jumped to 8.4%. This upward trend continued, with natural forests covering 18.8% of the area by 2020 and further increasing to 24.1% in 2023. This analysis suggests a marked recovery and expansion of natural forests within the municipality over the past two decades, highlighting successful conservation or natural regeneration efforts post-2010. The significant underestimation of forested areas in the early years (2000-2010) when using Landsat 7 data indicates potential limitations in Landsat 7 capabilities, which were improved upon in Landsat 8 and Landsat 9. These findings underscore the importance of utilising more advanced satellite data for accurate environmental monitoring and decision-making.

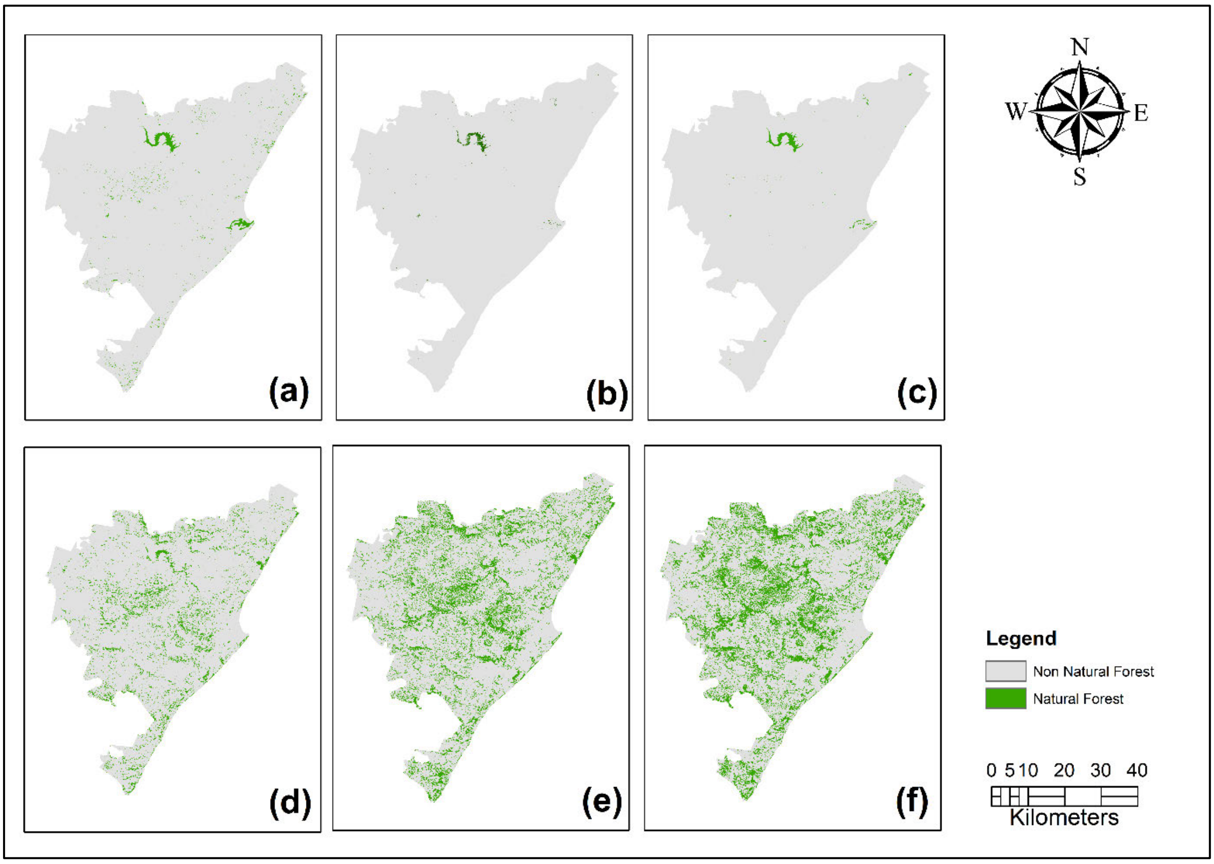

Figure 6.8. The spatial distribution of natural forests within the eThekwini Municipality as predicted by LightGBM, showing the distribution in (a) 2000, (b) 2005, (c) 2010, (d) 2015, (e) 2020, and (f) 2023.

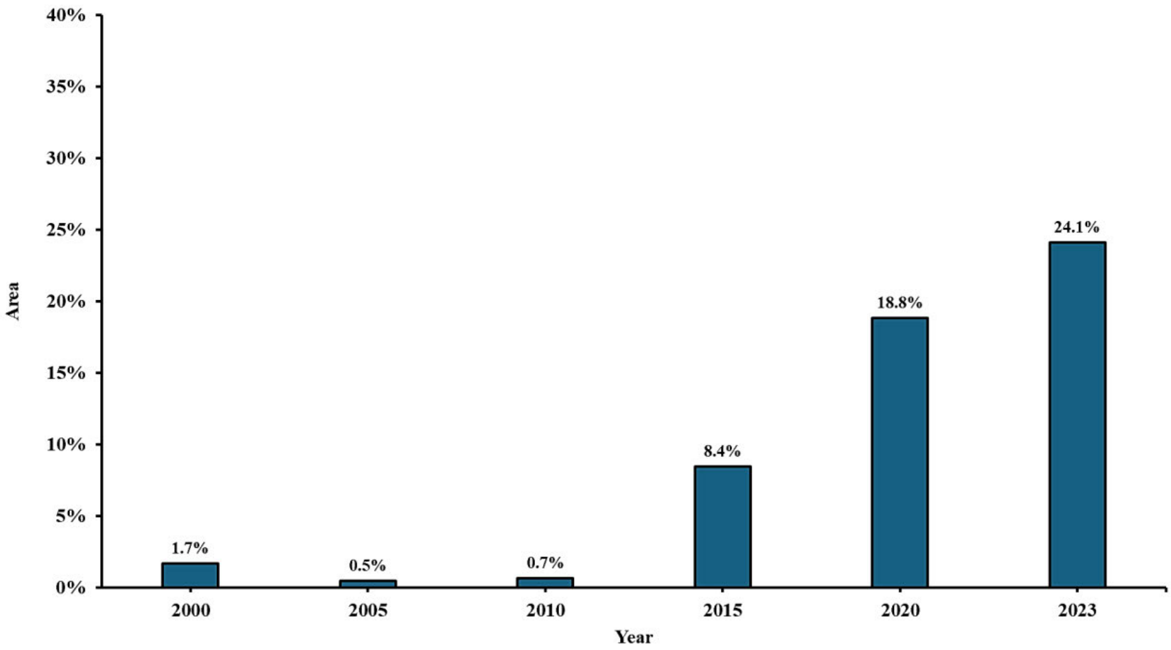

Figure 6.9. Percentage area of natural forests predicted by LightGBM within the eThekwini Municipality using Landsat information.

6.4 Discussion

This study employed LightGBM, CatBoost, and XGBoost machine learning algorithms to map the historical and current distribution of natural forests within the eThekwini Municipality. Landsat 7, Landsat 8, and Landsat 9 data were utilised to achieve this objective. Incorporating these advanced algorithms and Landsat imagery into the study, presented an opportunity for improving the accuracy, efficiency, and scalability of mapping natural forest distribution (Zhang, H. *et al.*, 2019). Additionally, this offers invaluable insights that are crucial for guiding forest rehabilitation and restoration efforts within the eThekwini Municipality. Similar studies, such as Pande *et al.* (2024) and Wang *et al.* (2024) have demonstrated the effectiveness of combining Landsat imagery with machine learning for accurately modelling land surface and vegetation changes. Therefore, in the context of this study, this combination not only enhances the understanding of forest dynamics but also provides a robust foundation for developing targeted conservation strategies, ensuring the long-term sustainability of natural forests in the eThekwini Municipality.

The SANLC dataset was selected as the reference dataset for natural forest classification due to its local production and validation, offering greater accuracy and regional relevance compared to datasets such as FROM-GLCS10 used in previous chapters. Although the SANLC product has an average classification error of 13%, conducting manual validation against historical Very High Resolution (VHR) imagery would enhance its reliability as a validation tool. Manual verification was not conducted in this study due to resource constraints, and this limitation is acknowledged. Future research is encouraged to incorporate such verification to improve data reliability. The 13% classification error should be factored into the interpretation of results, with its potential impact on analysis discussed to ensure balanced interpretation of findings.

LightGBM emerged as the most effective algorithm for natural forest mapping based on overall accuracy, the F1 score, and AUC. However, it should be noted that performance differences are small, especially between LightGBM and CatBoost. This is consistent with findings from Bentéjac *et al.* (2021). Kanber *et al.* (2024) also compared LightGBM with nine other algorithms, including XGBoost and CatBoost, and found that LightGBM achieved the highest accuracy. Moreover, Harumy *et al.* (2024) highlighted the faster computational time of LightGBM compared to CatBoost and XGBoost, which was also observed in this study. Faster computation time in machine learning applications is essential for accelerating model development, enabling real-time decision-making, handling large-scale data, and reducing costs (Taherdoost, 2024). These advantages make LightGBM a particularly valuable tool for large-scale tasks, where both accuracy and efficiency are crucial (Li *et al.*, 2024). As such, LightGBM's superior performance and faster computational time solidify its suitability as the preferred algorithm for natural forest mapping.

Moreover, the high accuracy and efficiency of LightGBM stem from the combination of gradient boosting, lightweight implementation, efficient tree growth strategies, histogram-based splitting, gradient-based sampling, and support for parallel and distributed computing (Seyyedattar *et al.*, 2024). However, the slight superiority of LightGBM in this study should not invalidate the strengths of CatBoost and XGBoost at performing classification tasks. This is because CatBoost and XGBoost have also demonstrated their ability to successfully perform such tasks, as evidenced by previous studies such as Zhang, H. *et al.* (2019), Yu *et al.* (2021a), Luo, M. *et al.* (2021), and Cao *et al.* (2023). As such, this study further affirms the efficacy of gradient boosting algorithms in mapping forest vegetation. Therefore, while LightGBM stands out for its exceptional performance in this context, the effectiveness of CatBoost and XGBoost should not be overlooked, as they also offer robust solutions for classification tasks. This study reinforces the versatility and reliability of gradient boosting algorithms, highlighting their valuable role in accurately mapping forest vegetation and contributing to more effective environmental management strategies.

This study further emphasises the importance of exercising caution when selecting the optimal algorithm for mapping natural forests, as the performance of each algorithm can vary significantly depending on the specific characteristics of the dataset and the application (Abbas *et al.*, 2023). As such, while LightGBM, CatBoost, and XGBoost have demonstrated impressive capabilities in predictive modelling tasks, their effectiveness can be influenced by factors such as the complexity of the terrain, the quality and resolution of the data, and the specific objectives of the task. A thorough evaluation of each algorithm's strengths and limitations in relation to the unique requirements of the task is essential to ensure the most suitable choice is made for achieving accurate and reliable results. Therefore, by carefully evaluating the strengths and limitations of each algorithm, researchers can make informed decisions that enhance the accuracy and reliability of natural forest mapping.

This study presents this example where the type of data used influences the model's output, as LightGBM significantly underestimated natural forest within the eThekwini Municipality when using information derived from Landsat 7 compared to when it used the other two Landsat sensors. This suggested potential shortcomings in Landsat 7's capabilities, possibly due to the SLC failure where almost 22% of the image data is lost (Wulder *et al.*, 2011). Consequently, the reliability of Landsat 7 data for accurate forest classification is compromised, particularly in this study, where the reference natural forests are highly fragmented. This emphasised the need for prioritising Landsat 8 and Landsat 9 for effective forest mapping and monitoring in similar cases. That is because Landsat 8 and Landsat 9 data yielded considerably more accurate results.

Additionally, Landsat 8 and Landsat 9 offer improved radiometric resolution compared to Landsat 7 (Padró *et al.*, 2018; Trevisiol *et al.*, 2024). Improved radiometric resolution offers several benefits for capturing subtle variations in forest vegetation. One key advantage is increased accuracy in image classification; with more levels to represent data per pixel, algorithms can better distinguish between subtle differences in land cover and vegetation health (Pasquarella *et al.*, 2018). This leads to more precise classifications of forest types and conditions. Finer radiometric detail allows for more accurate monitoring of changes over time, which is crucial for observing deforestation and forest degradation (Banskota *et al.*, 2014; Goetz *et al.*, 2015). Ose *et al.* (2016) further highlighted that radiometric resolution relates to the sensitivity of a sensor, specifically its capacity to measure and distinguish variations within the same spectral band of electromagnetic energy reflected by individual ground surfaces. As such, improved spectral analysis with higher radiometric resolution enables a more detailed examination of the electromagnetic spectrum reflected from vegetation (Houborg *et al.*, 2015). Therefore, employing high-quality data is essential, as the enhanced radiometric resolution of Landsat 8 and Landsat 9 results in more accurate forest mapping and monitoring.

Investigating variable importance for LightGBM offered valuable insights into the factors influencing the model's capability to map natural forests. The results reveal that three key variables were crucial for accurate mapping: the red band (b4), NDVI, and GNDVI. The red band captures red light reflected by vegetation, helping to differentiate between healthy and stressed or non-forested areas (Huete, 2004). NDVI, leveraging the difference between red and near-infrared bands, provides a robust measure of vegetation health and density, enhancing LightGBM's ability to classify forests accurately (Xue *et al.*, 2024). GNDVI, which uses the difference between green and near-infrared bands, focuses specifically on vegetation density, which allowed LightGBM to distinguish between forests and non-forested areas (Cardoso *et al.*, 2024). Interestingly, the study found that the CIG had minimal impact on LightGBM's performance for natural forest mapping. This suggests that while CIG is valuable for assessing chlorophyll content, it is less critical for this specific task compared to the other variables, as LightGBM can effectively identify natural forests based on overall vegetation health and density. As an example, Kumar *et al.* (2020) identified CIG as highly effective for classifying water-stressed vegetation. As such, future studies can build upon these insights to refine data selection and optimise model development for even more accurate natural forest mapping tasks.

The analysis from this study indicated a substantial increase in natural forest cover within the eThekwini Municipality between 2015 and 2023. This could be attributed to successful reforestation and forest conservation efforts or natural regeneration processes. These efforts include the Buffelsdraai Landfill Site Community Reforestation (Mugwedi *et al.*, 2017) and DMOSS (McPherson *et al.*, 2019). Nonetheless, the observed natural forest recovery warrants further investigation into the underlying social and economic factors that may have contributed to this positive change. Understanding these factors can inform forest rehabilitation and restoration. Ultimately, this study demonstrated the effectiveness of LightGBM in mapping natural forests using Landsat data, particularly Landsat 8 and Landsat 9. The observed increase in natural forest cover is encouraging; however, findings from this study provide a framework to continuously monitor the extent of natural forests and guide rehabilitation and restoration within the eThekwini Municipality.

6.5 Conclusion

This study successfully employed LightGBM, CatBoost, and XGBoost machine learning algorithms to map the historical and current distribution of natural forests within the eThekwini Municipality. By leveraging Landsat 7, Landsat 8, and Landsat 9 data, the study achieved high accuracy and efficiency, showcasing the potential of this approach for natural forest monitoring and mapping. While all three algorithms performed well, LightGBM emerged as the most effective for natural forest mapping in this specific context. Its efficiency makes it a valuable tool for large-scale studies. However, the study emphasises the importance of careful algorithm selection, as performance can vary depending on data characteristics and project objectives.

A significant finding of the study was the substantial increase in natural forest cover within the eThekwini Municipality between 2015 and 2023. This positive trend could be linked to successful conservation efforts or natural regeneration processes, warranting further investigation into the underlying social and economic factors. The study also highlighted the limitations of Landsat 7 data due to the SLC failure, impacting its effectiveness for natural forest mapping. Conversely, Landsat 8 and Landsat 9 data, with improved radiometric resolution, yielded superior results. This emphasises the value of advancements in satellite sensor technology for environmental monitoring tasks. Furthermore, the investigation into variable importance for LightGBM identified the red band (b4), NDVI, and GNDVI as the most critical factors influencing accurate mapping. These findings provide valuable insights into the spectral information most suitable for natural forest classification using machine learning models.

Ultimately, this study developed a framework that combined remote sensing with machine learning to map natural forests in the eThekwini Municipality and assessed the effectiveness of LightGBM, CatBoost, and XGBoost algorithms in classifying and mapping forest distribution using Landsat imagery. Moreover, it successfully examined changes in forest cover from 2000 to 2023, offering insights into forest rehabilitation and restoration. The study achieved these by demonstrating the effectiveness of LightGBM and advanced satellite imagery for natural forest mapping within the eThekwini Municipality.

The observed potential for natural forest recovery necessitates continued monitoring efforts and further research to guide forest rehabilitation and restoration. This approach can be a powerful tool for sustainable forest management and environmental protection in similar regions worldwide. However, future studies should consider integrating data from multiple remote sensing sources, such as Sentinel-2 or high-resolution commercial satellites, to complement Landsat data. This could improve the accuracy and detail of forest mapping, especially in highly fragmented or degraded areas. Additionally, expanding the use of machine learning algorithms to predict future trends in forest cover and identify areas at risk of degradation can guide proactive conservation strategies. This predictive capability could be instrumental in preventing further loss of forested areas and ensuring timely interventions.

6.6 Summary

This chapter employed advanced remote sensing techniques and machine learning algorithms to enhance forest rehabilitation and restoration efforts in the eThekwini Municipality. The research used imagery from the last three Landsat satellite imagery and five spectral indices (NDVI, GNDVI, CIG, EVI, and EVI-2) to accurately map the historical and current distribution of natural forests from 2000 to 2023. LightGBM, CatBoost, and XGBoost, were assessed for their performance in mapping natural forests. LightGBM achieved the highest overall accuracy (90.76%) and F1 score (90.76%), making it the preferred model. It was observed that Landsat 7 data underestimated forest extent, while Landsat 8 and Landsat 9 data revealed significant forest cover increases from 2015 to 2023.

The findings highlighted the effectiveness of LightGBM in mapping natural forests and underscored the importance of advanced satellite data for accurate environmental monitoring. This research provides a valuable framework for continuous forest monitoring, aiding policymakers and environmental managers in implementing effective conservation strategies within the eThekwini Municipality. This study's approach can serve as a model for other regions, promoting global efforts toward biodiversity conservation and ecosystem restoration.

7. CHAPTER SEVEN: A MACHINE LEARNING APPROACH TO MAPPING SUITABLE AREAS FOR FOREST VEGETATION IN THE ETHEKWINI MUNICIPALITY

This chapter is based on:

Buthelezi, M. N. M., Lottering, R. T., Peerbhay, K. Y., & Mutanga, O. (2024). A machine learning approach to mapping suitable areas for forest vegetation in the eThekwini municipality. *Remote Sensing Applications: Society and Environment*, *35*, 101208. https://doi.org/https://doi.org/10.1016/j.rsase.2024.101208

Abstract

Driven by climate change, global forests are undergoing significant growth, ecology, and distribution transformations, necessitating informed restoration and conservation strategies, particularly in the eThekwini Municipality where anthropogenic activities exacerbate these trends. Modelling current areas suitable for forest vegetation (2023) utilised bioclimatic variables from the WorldClim dataset, alongside elevation and slope from the Shuttle Radar Topography Mission (SRTM) dataset, with remote sensing data acquired from Landsat 9 and Sentinel-2A. Future forest suitability (2021 – 2040) was also projected using bioclimatic variables from two Global Climate Models (GCMs) under four WorldClim shared socioeconomic pathway (SSP)-based representative concentration pathway (RCP) scenarios. employing random forests (RF), light gradient boosting (LightGBM), and artificial neural networks (ANN), data processing was carried out using Google Earth Engine (GEE), QGIS and Python, with model accuracy primarily assessed using the receiver operating characteristic (ROC) curves and the area under the ROC curve (AUC). LightGBM demonstrated superior performance, achieving AUCs of 96.88% and 93.75% for current and future suitability mapping, respectively, with annual precipitation and vegetation changes identified as crucial variables. Currently, 30% of the municipality's land is deemed suitable, primarily concentrated in the central region. Future projections highlight the mountainous north-western region as most suitable, notably under the SSP370 scenario with a projected suitable area of 63%. Strategic recommendations include prioritising reforestation efforts, engaging private landowners, exploring urban reforestation opportunities, and implementing continuous monitoring for adaptive management, thereby enhancing carbon sequestration, biodiversity

conservation, and ecosystem resilience. Despite inherent uncertainties, this study provides valuable insights for informed decision-making in forest restoration and conservation.

Keywords: suitability, species distribution models, reforestation, climate change, ecosystems

7.1 Introduction

Climate change significantly impacts the growth, ecology, and distribution of trees worldwide (Ostad-Ali-Askari *et al.*, 2020; Shi *et al.*, 2021). This is due to several factors, including extended drying periods that increase drought risk and severity, as well as the acceleration of disturbances such as wildfires and insect outbreaks (Cook *et al.*, 2020). These changes can lead to the decline and even permanent alteration of forest ecosystems, often decreasing their socio-economic value (Mothes *et al.*, 2020). Seidl *et al.* (2017) stated that the permanent alteration of forests results from forest disturbances exceeding their ecological resilience. Droughts and forest disturbances have, thus, led to a large-scale decline in global forests (Bentz *et al.*, 2016). For example, Keenan *et al.* (2015) stated that the worldwide forest area declined by 3% from 1990 (4128 million hectares) to 2015 (3999 million hectares).

The challenges posed by global climate change are particularly intensified in Southern Africa, where the rate of warming outpaces the global average. This region is experiencing a more pronounced and accelerated climate change impact than many other parts of the world (Bauer and Scholz, 2010; Dalmaris *et al.*, 2015). As a result, Southern Africa is confronted with extended drying periods, leading to elevated vulnerabilities to droughts and disruptions within its forests. Furthermore, forest loss in this region is also accelerated by anthropogenic activities such as urban and agricultural expansion, timber extraction and fuelwood harvesting (Naidoo *et al.*, 2013). These human-induced activities are also evident in the eThekwini Municipality located in the province of KwaZulu-Natal, South Africa. Much like in Southern Africa, the municipality is grappling with frequent and prolonged dry spells, characterised by unpredictable rainfall patterns (Grab and Nash, 2023). These challenging conditions play a significant role in the degradation of vegetated landscapes within the region (Lutz, 2018).

The loss of forests and other vegetated landscapes within the eThekwini municipality is further accelerated by rapid change caused by the municipality's need to move away from apartheid spatial planning (Sutherland *et al.*, 2014). To meet this need, the municipality has attracted more people to the urban areas; however, it has failed to provide these people with employment and housing opportunities (Williams *et al.*, 2019). Consequently, these individuals seeking shelter establish informal settlements that exacerbate the deterioration of vegetated landscapes and expose themselves to the impacts of climate change (Ma *et al.*, 2021; Saharan *et al.*, 2019). Additionally, informal settlements in the eThekwini Municipality exhibit low socio-economic status and high population density (Mkhize and Sibanda, 2022). These conditions, coupled with dense building concentrations in compact areas, heighten vulnerability to climate-induced extreme weather events like floods and storms, posing risks of displacement, property loss, and livelihood disruptions (James, 2023). Forests offer potential mitigation against such events by moderating flood peak flow and delaying flood peak occurrences (Tamura, 2022).

Moreover, the focus on the degradation of forests and other vegetated landscapes mainly stems from the loss of these landscapes, resulting in the loss of vital ecosystem services (Mekuria *et al.*, 2018). The vitality of ecosystem services results from their ability to improve social, economic, and ecological structures (Orimoloye *et al.*, 2021). They improve these structures by providing food and primary energy, minimising threats from extreme natural disasters, and mitigating climate change (Ahammad *et al.*, 2021; Wisely *et al.*, 2018). Orimoloye *et al.* (2021) suggested that land regeneration and ecological conservation can be used to restore the lost ecosystem services in degraded landscapes. Therefore, this paper sought to identify and map areas suitable for forestation and afforestation as a form of land regeneration across the eThekwini Municipality. This will aid the restoration of ecosystem services for the municipality and could be adopted by other municipalities within and beyond the borders of South Africa. Mapping suitable areas is also key for implementing other effective ecological conservation strategies outside of reforestation and afforestation (Poirazidis *et al.*, 2019).

Given that forest suitability is primarily impacted by bioclimatic changes, this study prioritised the inclusion of bioclimatic variables (Carvalho *et al.*, 2017). These variables include single indicators such as annual mean temperature and precipitation, coldest and hottest monthly mean temperature, extremely low temperature and seasonal precipitation (Xie *et al.*, 2021). Forest distribution, as aforementioned, is also driven by changes in current land use and land cover (LULC) (Bortoleto *et al.*, 2016). Thus, an updated LULC map for the eThekwini Municipality was also used to map forest species suitability.

Ramalho *et al.* (2017) noted that the ineffective incorporation of projected climate change compromises most ecological restoration plans. Therefore, this study incorporated climate change data from two downscaled global climate models (GCM) outputs under the shared socioeconomic pathway - representative concentration pathway (SSP-RCP) scenarios from the recent Coupled Model Intercomparison Project (CMIP6). CMIP6 builds on CMIP5 by providing model outputs at higher resolution (0.25° x 0.25°) over a longer period (850 – 2100) and better representation of synoptic processes (Hurtt *et al.*, 2020; Su *et al.*, 2021). In addition to climate change data, LULC and environmental and geological variables, this study also included land ownership and remote sensing-derived variables. That is due to private land having higher vegetation productivity than public land and the feasibility of conservation and restoration being limited by private landowners not taking kindly to government restoration policies (Robinson *et al.*, 2019). This results because private landowners are often focused on maximising productivity for their own purposes, like grazing or timber production. This can lead to practices like planting more desirable species, fertilising the land, and controlling pests (Teague and Kreuter, 2020). However, it should be noted that there can be exceptions where some private lands may be neglected or poorly managed. Remote sensing-derived variables aid the derivation of spatially representative maps (Madundo *et al.*, 2023).

Climate change-induced alterations in global forests have been extensively documented (Ostad-Ali-Askari *et al.*, 2020; Shi *et al.*, 2021). However, the specific impact on the eThekwini Municipality and other similar regions remains relatively understudied. While existing literature acknowledges the broader implications of climate change on forests, few studies have delved into the distinctive challenges faced by regions such as the eThekwini Municipality, where the rate of warming surpasses the global average. The intensified impact of climate change in this municipality, coupled with anthropogenic activities, necessitates a focused investigation to inform targeted restoration and conservation strategies.

Therefore, to inform targeted reforestation and forest management in the eThekwini municipality, this study modelled the suitability of forest species within the municipality following the species distribution modelling (SDM)/environmental (or ecological) niche modelling (ENM) methodology. SDMs utilise environmental maps and field data to predict the geographic distribution of species (flora and fauna) and assess their response to environmental changes (Amiri *et al.*, 2020). They also possess the potential to identify the suitability of areas after particular ecological and climatic measures have been adopted (Poirazidis *et al.*, 2019).

However, over the last four decades, despite the introduction of numerous new models, researchers continue to encounter challenges in identifying suitable models tailored to their data and research objectives (Li and Wang, 2013). That is because past research indicates that there are variations in projected species distributions resulting from the utilisation of different datasets and models (Jones and Cheung, 2015). Thus, three algorithms were adopted as SDMs for this study, namely, random forests (RF), light gradient boosting (LightGBM), and artificial neural networks (ANN). Employing multiple algorithms allows for the representation of different machine learning paradigms, including ensemble learning (RF), gradient boosting (LightGBM), and neural networks (ANN). Utilising multiple algorithms also reduces the risk of relying on a single potentially suboptimal model. Moreover, each algorithm was chosen for its strengths in different aspects. LightGBM, for instance, is renowned for its speed and accuracy, making it suitable for handling large datasets efficiently (Ke *et al.*, 2017). On the other hand, ANN excel in capturing complex non-linear relationships, offering flexibility in modelling intricate ecological interactions (Miller *et al.*, 2023). RF, as part of the ensemble method, provides stability and robustness to the model predictions through its aggregation of multiple decision trees (Ndlovu *et al.*, 2022).

As such, in adopting these three algorithms, this study aims to explore the impact of different model structures on capturing the complex relationships between climate, topography, and forest suitability, thereby addressing a gap in the understanding of optimal forest suitability modelling approaches for the eThekwini Municipality and the chosen datasets.

7.2 Methods and Materials

7.2.1 Study area

The eThekwini Municipality shown in Figure 7.1, spans 2297 square kilometers (km^2) and is home to a population exceeding 3.5 million residents (Zungu *et al.*, 2020b). The municipality has a subtropical climate with mean annual precipitation (MAP) of approximately 1000 mm, which it receives during its warm summers (Maseko *et al.*, 2020). The mean annual temperature range for the eThekwini Municipality is between 16-20℃ (Mavimbela *et al.*, 2018). Situated in the centre of the Maputaland-Pondoland-Albany (MPA) Region, the municipality has a diverse climate, geology, soils, and a biogeographical location that sustains an extensive array of aquatic and terrestrial ecosystems (Boon *et al.*, 2016; Makhaya *et al.*, 2022).

However, the number of people within the municipality is estimated to grow by at least one percent per annum (Zungu *et al.*, 2019). The increase in the population is mainly driven by the job opportunities associated with the municipality being the main economic hub of KwaZulu-Natal (Zungu *et al.*, 2020a). The eThekwini Municipality is responsible for about 44% of total employment and contributes 57.1% to the gross domestic product (GDP) of the province

(Okem and Bracking, 2019). The increased population and the need for social transformation have resulted in rapid urban growth within the municipality (Sim *et al.*, 2016).

These expanding urban areas, the surrounding peri-urban residential areas, and informal and rural communities, have contributed to the significant loss and fragmentation of aquatic and terrestrial ecosystems (Hellberg, 2014). It is estimated that more than 53% of the eThekwini Municipality's vegetated landscapes have been converted for human benefit, while a further 17% is heavily degraded (Zungu *et al.*, 2020a). To limit this conversion of vegetated landscapes and conserve native lands, the municipality established the Durban Metropolitan Open Space System (D'MOSS) (Boon *et al.*, 2016). D'MOSS is formed by a network of human-managed green spaces and natural habitats (McPherson *et al.*, 2019). However, D'MOSS cannot be the only strategy to manage and restore forests and other vegetated landscapes within the eThekwini Municipality.

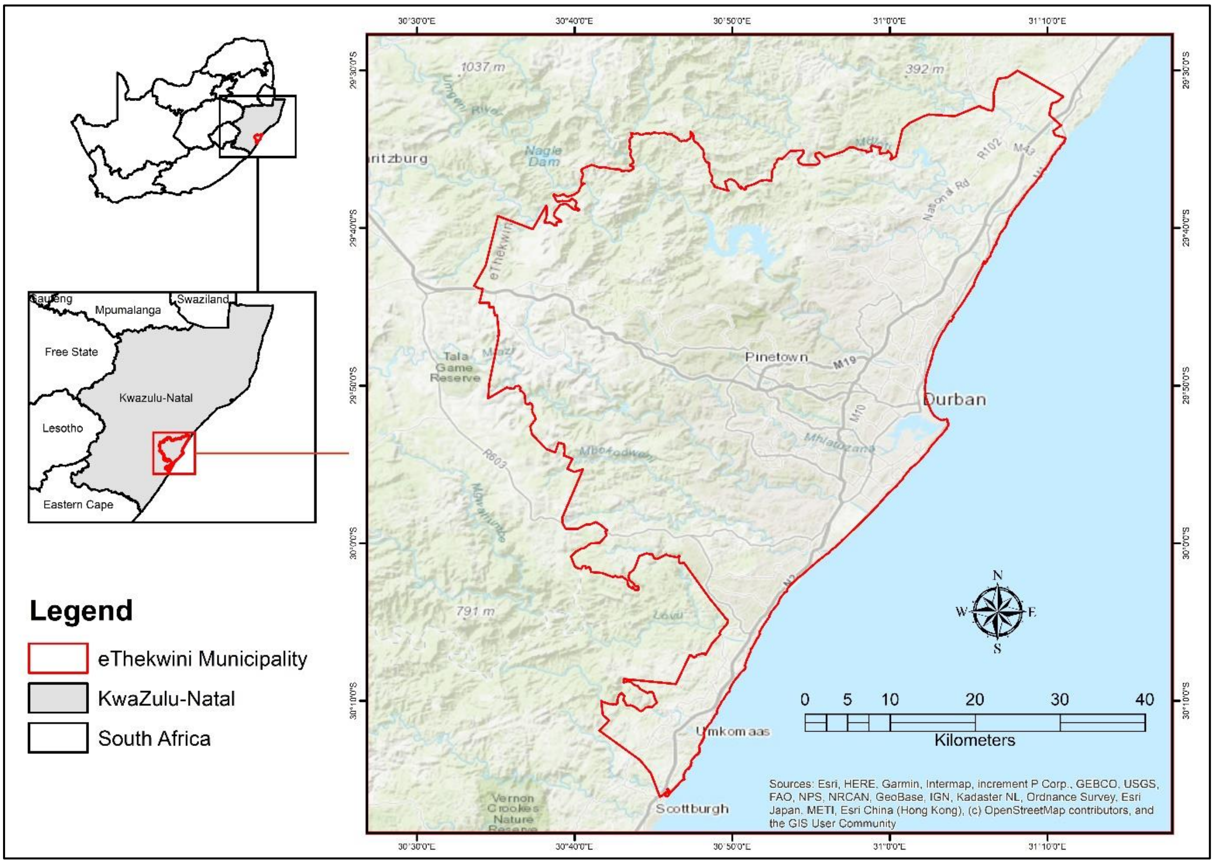

Figure 7.1. eThekwini Municipality's geographical location within the province of KwaZulu-Natal, South Africa.

7.2.2 Data

7.2.2.1 Current forest distribution

The current distribution of forests within the eThekwini Municipality was extracted from the Global map of forest cover 2020 - version 1 by the European Commission, Joint Research Centre (JRC) (Bourgoin *et al.*, 2023) (Figure 7.2). Further verification was conducted using Google Earth Pro. Although forests cover almost 30% of the municipality, they are heavily fragmented (Zungu *et al.*, 2020b). Forest fragmentation is said to be one of the major drivers of ecosystem degradation and the reduction of the forest's ability to provide important ecosystem services (Bryan-Brown *et al.*, 2020). Nonetheless, the areas where forests were located were used as presence data for the SDMs.

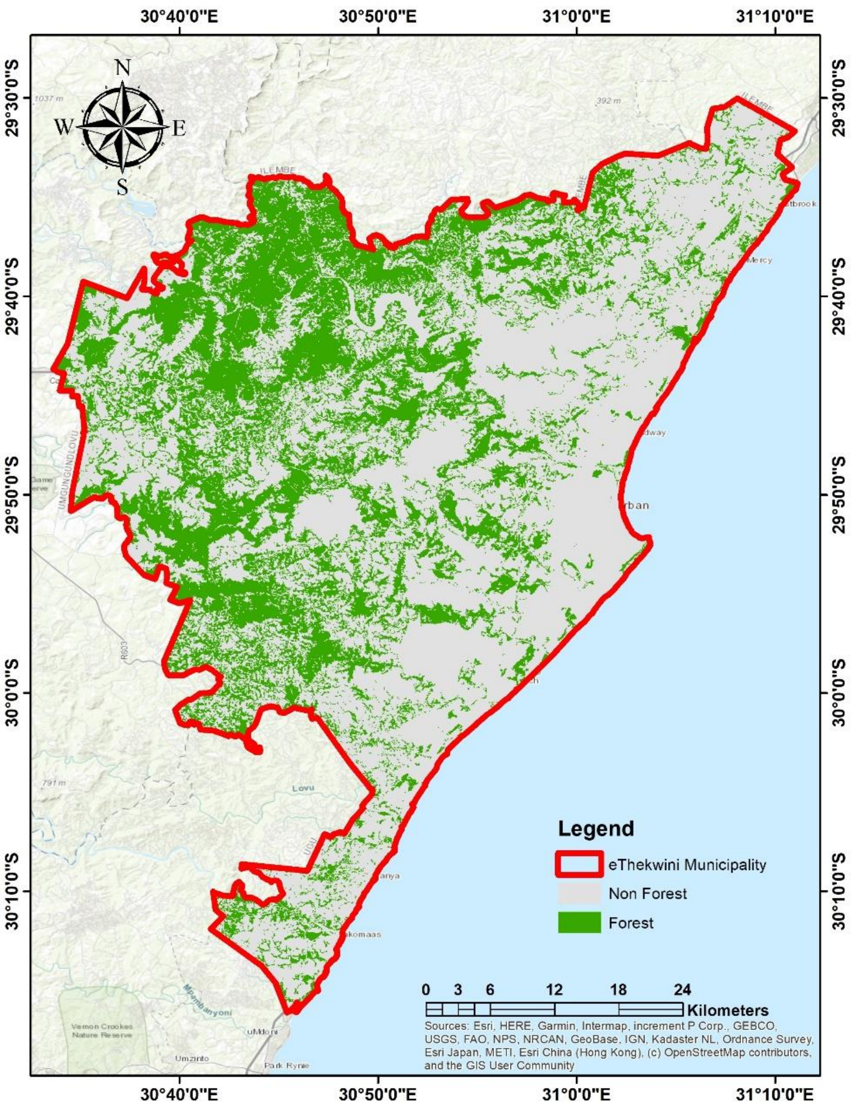

Figure 7.2. Presence of forest vegetation within the eThekwini Municipality.

7.2.3 Environmental variables for current forest suitability

A total of 19 bioclimatic variables were included as environmental variables. These variables are spatially interpolated and downloaded from the WorldClim (version 2) dataset at 30 arc-seconds resolution, approximately 1 km^2 (Fick and Hijmans, 2017). However, to avoid multicollinearity, which would result in the overfitting of the algorithms (Zhou *et al.*, 2021), a Pearson correlation analysis between the 19 bioclimatic variables was conducted in the RStudio Desktop version *2022.02.0+443* before the data was fit into the algorithms. In an occurrence where two bioclimatic variables had a correlation over 0.8, the variable with the least significance to forest distribution was removed (Dormann *et al.*, 2013). Thus, the nine variables selected in this study were bio1, bio3, bio4, bio6, bio7, bio10, bio11, bio12 and bio15 (Table 7.1). Additionally, elevation and slope were the two topographic variables included in the sample dataset. To obtain elevation information for the eThekwini Municipality, the Shuttle Radar Topography Mission (SRTM) 1 Arc-Second Global dataset was obtained from EarthExplorer (https://earthexplorer.usgs.gov/). The SRTM data was then clipped to the exact boundaries of the eThekwini Municipality using ArcGIS Pro version *3.2*. This clipped elevation dataset also served as the foundation for slope calculations within ArcGIS Pro. Additionally, it should be noted that the variables were kept at their original scale to maintain their distribution and relative importance in the dataset. That is because some normalisation and standardisation techniques can increase the complexity of normalised data compared to un-normalised data (Singh and Singh, 2020).

Table 7.1. Environmental variables used to train SDMs for current forest suitability.

Environmental Variables	**Description**	**Source**
bio1	Annual Mean Temperature	WorldClim
bio3	Isothermality (bio2/bio7)	WorldClim
bio4	Temperature seasonality	WorldClim
bio6	Min Temperature of Coldest Month	WorldClim
bio7	Annual Temperature Range	WorldClim
bio10	Mean Temperature of Warmest Quarter	WorldClim
bio11	Mean Temperature of Coldest Quarter	WorldClim
bio12	Annual Precipitation	WorldClim
bio15	Precipitation seasonality	WorldClim
elevation	Elevation	SRTM
slope	Slope	SRTM

7.2.4 Remote sensing variables

Remote sensing variables were obtained from two optical sensors: Landsat 9, equipped with the Operational Land Imager 2 (OLI-2) and the Thermal Infrared Sensor-2 (TIRS-2), and Sentinel-2A, which features the Multi-Spectral Instrument (MSI). The sensor that yielded the higher-quality SDMs was selected for the final output.

7.2.4.1 Landsat 9

The launch of the Landsat 9 satellite was a collaborative project between the National Aeronautics and Space Administration (NASA) and the United States Geological Survey (USGS). The satellite started collecting data on September 27, 2021, which became accessible to the public on February 10, 2022 (Gerardo and de Lima, 2023). It features an improved 14-bit radiometric resolution. Band information for Landsat 9 is presented in Table 7.2.

Table 7.2. Spectral bands and wavelength ranges for Landsat 9's OLI-2 and TIRS-2 sensors, along with their resolutions (Buthelezi *et al.*, 2024a).

	Band	**Wavelength (μm)**	**Resolution (m)**
OLI 2	Band 1 - Coastal aerosol	0.43 - 0.45	30
	Band 2 - Blue	0.450 - 0.51	30
	Band 3 - Green	0.53 - 0.59	30
	Band 4 - Red	0.64 - 0.67	30
	Band 5 - Near-Infrared (NIR)	0.85 - 0.88	30
	Band 6 – Shortwave-Infrared (SWIR) 1	1.57 - 1.65	30
	Band 7 - SWIR 2	2.11 - 2.29	30
	Band 8 - Panchromatic (PAN)	0.50 - 0.68	15
	Band 9 - Cirrus	1.36 - 1.38	30
TIRS 2	Band 10 - TIRS 1	10.6 - 11.19	100
	Band 11 - TIRS 2	11.5 - 12.51	100

7.2.4.2 *Sentinel-2A*

Sentinel-2A orbit has a close overpass time to that of Landsat 8, Landsat 9 and Satellite pour l'Observation de la Terre (SPOT) 5, thus, allowing the integration of Sentinel 2 data with existing and historical satellite missions (Barsi *et al.*, 2018). Image data from Sentinel-2A has 12 spectral bands and a 10-day revisit cycle (Gorelick *et al.*, 2017). Band information for Sentinel-2A is presented in Table 7.3.

Table 7.3. Spectral bands and wavelength ranges for Sentinel-2A's MS sensors, along with their resolutions.

Band	**Wavelength (µm)**	**Resolution (m)**
Band 1 - Violet	0.445	60
Band 2 - Blue	0.490	10
Band 3 - Green	0.560	10
Band 4 - Red	0.665	10
Band 5 - Red-edge 1	0.705	20
Band 6 - Red-edge 2	0.740	20
Band 7 - Red-edge 3	0.783	20
Band 8 - NIR	0.842	10
Band 8a - NIR narrow	0.865	20
Band 9 - NIR	0.945	60
Band 10 - NIR	1.375	60
Band 11 - SWIR1	1.610	20
Band 12 - SWIR2	2.190	20

7.2.5 Indices

Table 7.4 displays the indices extracted from Landsat 9 and Sentinel-2A data, which were integrated as variables into the dataset to model current forest suitability. The calculation and extraction were conducted in Google Earth Engine (GEE) with the cloud cover filter set to less than 5% and the dates filter set to 01 August 2023 to 31 December 2023. The choice of these dates is grounded in the occurrence of the wet and vegetation growing seasons in the eThekwini Municipality, which span from August to December. This results in elevated chlorophyll content and expanded leaf area, enhancing the visibility and accuracy of vegetation monitoring through stronger signals in relevant spectral bands (Buthelezi *et al.*, 2024a).

Table 7.4. Spectral indices with their formulas and references for forest suitability modelling (Buthelezi *et al.*, 2024a).

Index	Formula	Reference
Normalised Difference Vegetation Index (NDVI)	$\frac{(NIR - Red)}{(NIR + Red)}$	Tucker and Sellers (1986)
Green Normalised Difference Vegetation Index (GNDVI)	$\frac{(NIR\ -\ Green)}{(NIR\ +\ Green)}$	Gitelson and Merzlyak (1998)
Enhanced Vegetation Index (EVI)	$\frac{[(2.5\ \mathrm{X}\ (NIR - Red)]}{[(NIR + (6\ \mathrm{X}\ Red) - (7.5\ X\ BLUE) + 1]}$	Huete *et al.* (2002)
Normalised Difference Water Index (NDWI)	$\frac{(Green - NIR)}{(Green + NIR)}$	Gao (1996)
Modified Normalised Difference Water Index (MNDWI)	$\frac{(GREEN - SWIR)}{(GREEN + SWIR)}$	Xu (2006)
Soil Adjusted Vegetation Index (SAVI)	$(\frac{(NIR\ -\ RED)}{(NIR\ +\ RED\ +\ 0.5)}) \times (1\ +\ 0.5)$	Huete (1988)
Modified Soil Adjusted Vegetation Index (MSAVI)	$\frac{2 \times NIR + 1 - \sqrt{(2 \times NIR\ +\ 1)^2 - 8 \times (NIR - RED)}}{2}$	Qi *et al.* (1994)
Normalised Difference Built-up Index (NDBI)	$\frac{(SWIR - NIR)}{(SWIR + NIR)}$	Zha *et al.* (2003)

7.2.6 Environmental variables for future forest suitability

Future forest suitability (2021 – 2040) was determined using projected bioclimatic variables based on two GCMS under the four WorldClim SSP-based RCP scenarios (SSP126, SSP245, SSP370 and SSP585) from CMIP6 (Table 7.5). The data was downloaded at 30 seconds spatial resolution from WorldClim. The development of RCPs was aimed at providing consistent sets of projections of the components of radiative forcing. Whereas SSPs were developed to integrate socioeconomic development descriptions with climate change projections and be consistent with RCPs (Hewitt *et al.*, 2021). The SSP-based RCP scenarios in Table 5, starting from SSP126, represent low radiative forcing to high radiative forcing in SSP585.

Table 7.5. Four WorldClim SSPs and corresponding RCP scenarios that were used in this study (Gurney *et al.*, 2022).

Name	SSP	Description	RCP	Description
SSP126	1	Low challenges to mitigation and adaptation.	2.6	Radiative forcing will reach a level of 2.6 $W.m^{-2}$ in 2100.
SSP245	2	Medium challenges to mitigation and adaptation.	4.5	The total radiative forcing will be stabilised at 4.5 $W.m^{-2}$ before the year 2100.
SSP370	3	High challenges to mitigation and adaptation.	7.0	Radiative forcing will reach a level of 7.0 $W.m^{-2}$ in 2100.
SSP585	5	High challenges to mitigation, low challenges to adaptation.	8.5	Radiative forcing will rise to 8.5 $W.m^{-2}$ by the year 2100.

The two GCMs selected were the Hadley Centre Global Environment Model in the Global Coupled configuration 3.1 (HadGEM3-GC31-LL) and Meteorological Research Institute Earth System Model version 2.0 (MRI-ESM2-0). The selection of two GCMs stems from the fact that no GCM has been developed specifically for Africa; thus, multiple GCMs should be utilised. However, HadGEM3-GC31-LL has been suggested to be useful for African specific analysis (James *et al.*, 2018). Moreover, it should be noted that HadGEM3-GC31-LL in WorldClim does not have data for SSP370. This meant only MRI-ESM2-0 was used to estimate forest suitability under SSP370.

A Pearson correlation analysis between the 19 bioclimatic variables was performed using RStudio Desktop version 2022.02.0+443 to address multicollinearity in the current forest suitability analysis. In contrast, all bioclimatic variables were retained during algorithm training for future forest suitability. This was done to maintain consistency across all scenarios. The variables were also kept at their original scale when modelling future forest suitability. Moreover, topographic variables were omitted from the training dataset to prioritise the influence of bioclimatic variables on forest suitability under the four WorldClim SSP-based RCP scenarios.

7.2.7 LULC and land ownership

Updated LULC data with eight classes for eThekwini Municipality were used to overlay the final outputs for current suitability. This revealed areas practically available for planting (Zhou *et al.*, 2021). Areas deemed unsuitable for planting due to their properties were impervious surfaces, water bodies, and wetlands. Further, as mentioned previously, land ownership strongly influences management actions and the feasibility of conservation (Robinson *et al.*, 2019). Therefore, this study also marked suitable areas that were within private land.

In essence, the most optimal areas for reforestation will be situated beyond the confines of private land, offering opportunities for restoration and aligned with areas characterised by land degradation.

7.2.8 Species distribution models description

7.2.8.1 Random forests

The RF algorithm was developed by (Breiman, 2001) based on bootstrap aggregation where each tree in the ensemble is created from a bootstrap sample extracted with replacement from the training data (Kuter, 2021). The average of the created trees produces a bagged estimate in regression, whereas, in classification the most voted trees produce the bagged estimate (Fernández-González *et al.*, 2019). RF has become one of the most utilised supervised learning algorithms, given its ability to produce good results from both large and small subsamples (Peng *et al.*, 2022). The RF algorithm has been successfully employed as an SDM in studies by Shabani *et al.* (2018), Piri Sahragard *et al.* (2018) and Liu *et al.* (2019).

7.2.8.2 Light Gradient Boosting

The LightGBM algorithm developed by Microsoft is based on the Gradient Boosting Decision Trees (GBDT), which is one of the most popular machine learning algorithms. GBDT combines multiple weak learners to improve accuracy (Friedman, 2001). However, the conventional GBDT exhibits limited diagnostic accuracy when dealing with high-dimensional data (Lao *et al.*, 2023). As such, implementations such as LightGBM, extreme gradient boosting (XGBoost) and categorical boosting (CatBoost) have been proposed to improve the performance of GBDT (Ke *et al.*, 2017). Given its parallel processing and graphics processing unit (GPU) capabilities, Al Daoud (2019) found LightGBM to be faster and more accurate than both XGBoost and CatBoost. LightGBM utilises a histogram-based algorithm, a leaf-wise tree growth strategy and provides robust support for handling categorical features (Wang *et al.*, 2022).

7.2.8.3 Artificial Neural Networks

Like RF, ANN has been employed successfully as an SDM (Pecchi *et al.*, 2019). ANN's development was based on simulating the function and structure of the biological neural network (Sairamya *et al.*, 2019). ANN is formed by computational nodes (neurons) arranged in interconnected computational layers (Misra and Li, 2020). These layers store experimental knowledge, which they then generalise and organise (Arboleda *et al.*, 2018). ANNs perform best through better-connected neurons in a network (Choudhury *et al.*, 2018). It has also been argued that the number of hidden layers can influence the performance of ANN. However, Kuter *et al.* (2018) argued that increasing the number of hidden layers only increases the specificity of the algorithm, which results in longer training times. The structure of the ANN used for this study to map current forest suitability is presented in Figure 7.3. Future forest suitability is mapped using the same structure; however, it is without remote sensing variables and topographic variables.

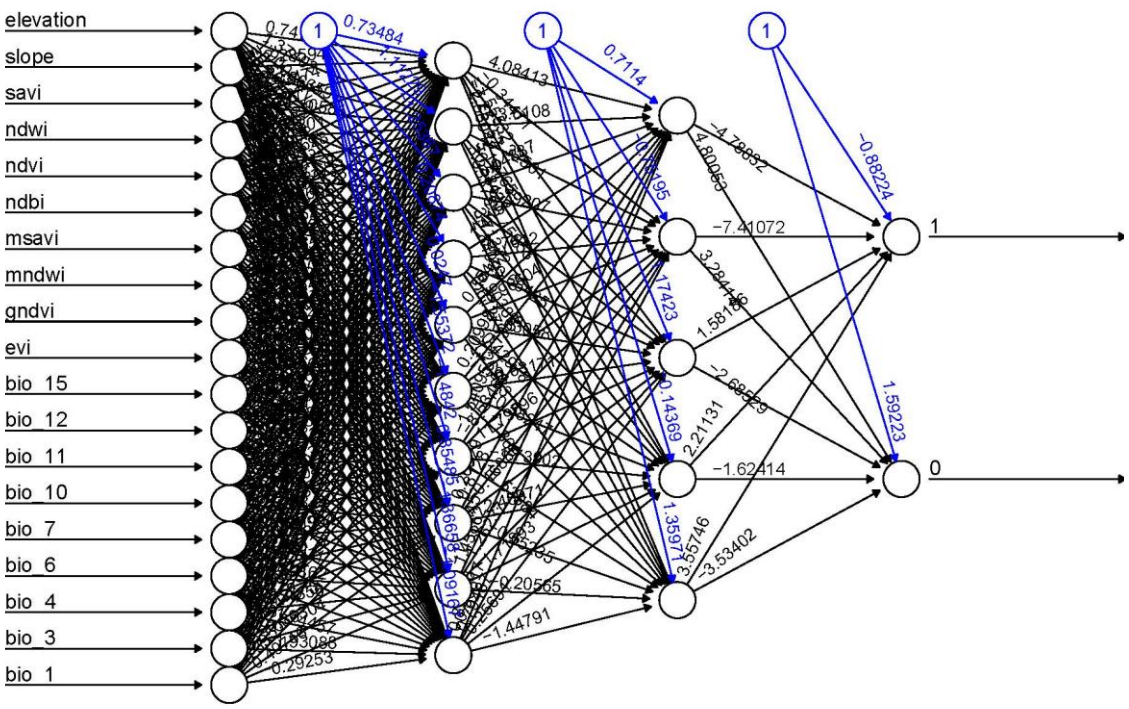

Figure 7.3. The structure of ANN which has two hidden layers, with ten neurons in the first hidden layer and five neurons in the second hidden layer.

7.2.9 Data processing for modelling

Bioclimatic variables for current forest suitability were overlaid in QGIS version 3.32, where pixel values were extracted across the study area using the Raster pixels to points tool. Using the Point sampling tool, the points generated from bioclimatic variables were used to extract pixel values from the remote sensing and topographic variables and current forest distribution. Pixel values for current forest distribution were then used as reference data and represented presence and pseudo absence (n = 3065). This was repeated using only bioclimatic variables for future forest suitability modelling. RF, LightGBM and ANN were built and trained using Python. Before model training for both current and future forest suitability, data were resampled to balance the classes and divided into 70% training (n = 2146) and 30% test sets (n = 919). To improve accuracy, LightGBM and ANN hyperparameters were optimised using Bayesian Optimisation, while RF's key parameters were optimised through an exhaustive grid search. The whole process was repeated using environmental variables to determine future forest suitability.

7.2.10 Species distribution model accuracy assessment

SDM output accuracy is crucial, given its implication on management plans and resources. If the SDM overestimates suitable areas, surveyors and managers will spend resources in unsuitable areas and if it underestimates, suitable areas will be left unexplored (Rosner-Katz *et al.*, 2020). Therefore, the receiver operating characteristic curve (ROC) and the area under the ROC curve (AUC) were used to evaluate the accuracy of RF, LightGBM and ANN forest suitability estimations alongside the confusion matrix. The optimal configurations for current and future suitability maps were carefully selected to ensure the most accurate results. The best-performing combination of algorithm and satellite data was chosen for the current suitability mapping, while the best-performing algorithm was selected for the future suitability mapping.

Additionally, to determine whether there was a significant statistical difference between the overall classification accuracy of the models, McNemar’s test was conducted in RStudio using the *mcnemar.test* function. This was done for both current and future suitability model performances. The hypotheses tested were as follows: the null hypothesis (Ho) stated that there was no significant difference between the overall classification accuracy of the models ($p > 0.05$), while the alternate hypothesis (Ha) posited that there was a significant difference between the overall classification accuracy of the models ($p < 0.05$). McNemar's test is frequently employed to compare the sensitivities and specificities of two models (Kim and Lee, 2014). As such, in this study, McNemar's test will help determine whether there is a significant difference in the overall classification accuracy between the models, allowing for a robust assessment of their performance.

7.2.11 Variable importance

Variable or feature selection is a crucial step in machine and deep learning that involves selecting the most relevant features from a dataset to minimise dimensionality and boost model performance (Bouke *et al.*, 2023). This study used the SHapley Additive exPlanation (SHAP) framework (Lundberg and Lee, 2017) to investigate variable importance for assessing both land degradation sub-indicators. SHAP determines variable importance through a game theory which assigns a specific average importance value (SHAP value) to each variable (Antwarg *et al.*, 2021). Compared to the popular Gini Coefficient, the SHAP framework is more universal because it has a special function for most machine learning algorithms (Odebiri *et al.*, 2022).

7.2.12 Overview

Figure 7.4 provides a schematic overview of the methodology employed to map the present forest suitability for the eThekwini Municipality. In the case of future forest suitability, the identical process was followed, as depicted in Figure 7.4. However, only bioclimatic variables were included in the algorithm training. Moreover, all suitability maps were generated at a greater than 50% confidence.

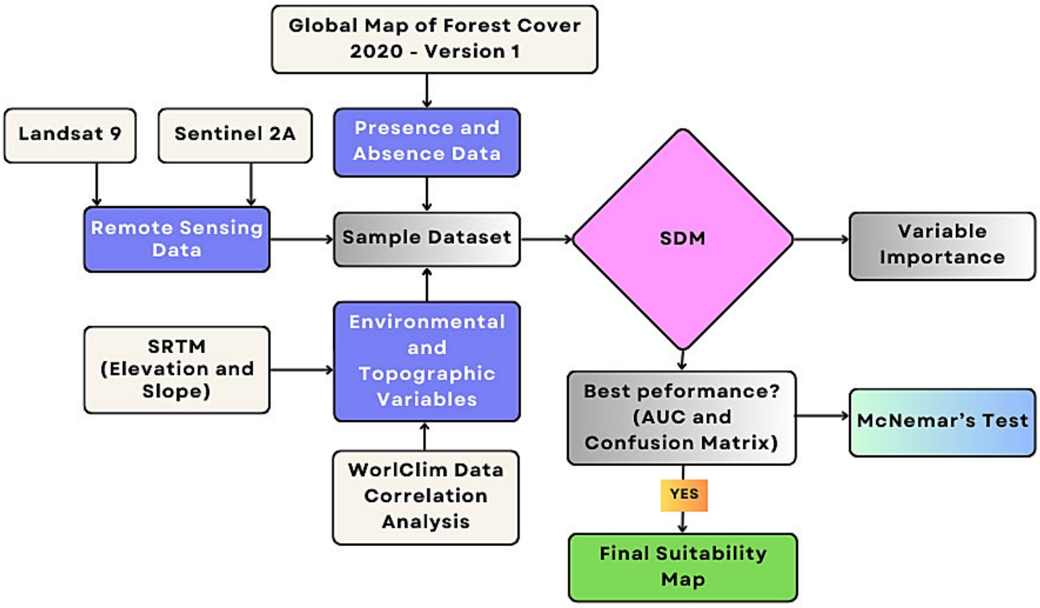

Figure 7.4. Schematic overview of assessing model performances and mapping current forest suitability in the eThekwini Municipality.

7.3 Results

7.3.1 Accuracy assessment

7.3.1.1 Current forest suitability

Figure 7.5 illustrates the accuracy results of the models in mapping current forest suitability within the eThekwini Municipality using Landsat 9 data. LightGBM displayed the highest AUC performance at 96.88%, followed by RF with 95.31% and ANN with 92.19%. When assessing overall accuracy, LightGBM maintained the lead with an accuracy rate of 97.62%, followed by Random Forest at 96.43% and ANN at 94.05%. These metrics indicate the consistent superiority of LightGBM over other models in the context of the dataset employed in this study.

Subsequently, the models were employed to map the current suitability of forest vegetation in the eThekwini Municipality using Sentinel-2A data (Figure 7.6). RF exhibited an AUC of 95.31% and an overall accuracy of 96.43%. LightGBM exhibited a slightly better performance than RF, achieving a marginally higher AUC of 95.91% while maintaining a comparable overall accuracy of 96.43%. Additionally, the ANN model demonstrated commendable performance with an AUC of 94.35% and an overall accuracy of 95.24%.

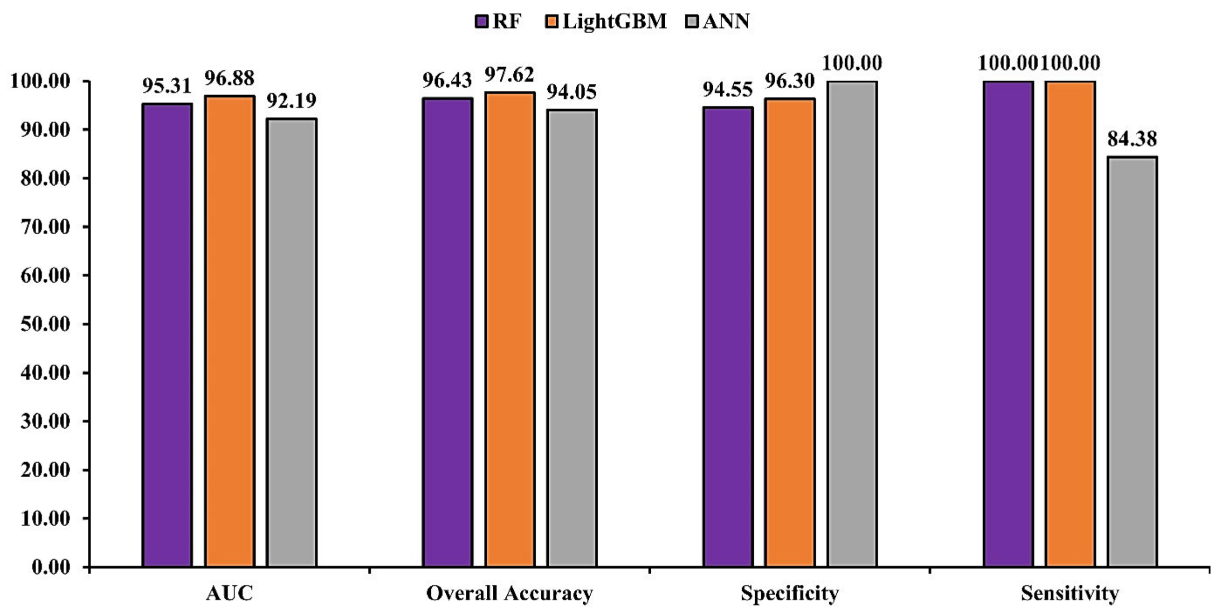

Figure 7.5. Accuracy comparison of RF, LightGBM, and ANN for forest suitability mapping using Landsat 9 data.

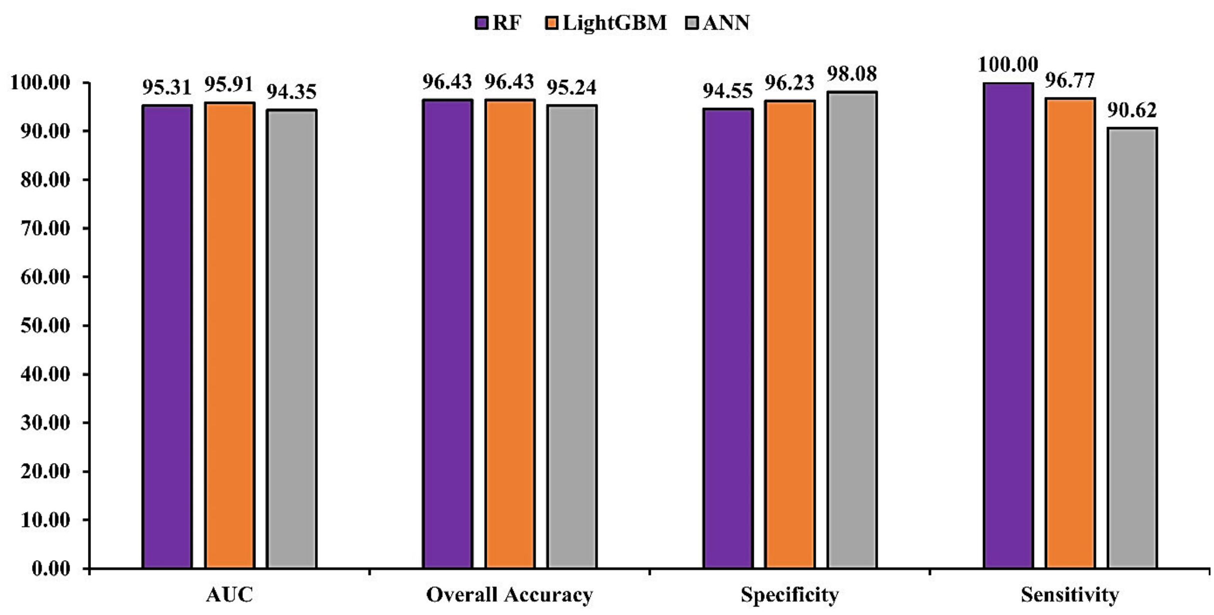

Figure 7.6. Accuracy comparison of RF, LightGBM, and ANN for forest suitability mapping using Sentinel-2A data.

A consistent trend emerges when comparing the outcomes presented in Figure 7.5, where models utilised Landsat 9 data for mapping forest suitability, with their performance illustrated in Figure 7.6 using Sentinel-2A data. LightGBM slightly outperforms both RF and ANN models in both scenarios, showcasing the highest AUC of 96.88% and an overall accuracy of

97.62% when Landsat 9 data are employed. These findings underscore the robust performance of all three models, indicating their utility in mapping forest suitability. Furthermore, the importance of both Landsat 9 and Sentinel-2A datasets in suitability modelling is emphasised.

The findings from McNemar's test offer valuable insights into the comparative performance of the models (Table 7.6). Specifically, for the Landsat 9 dataset, all model comparisons exhibited statistically significant differences ($p < 0.01$) in classification accuracy. This indicates that there are meaningful distinctions in the performance of the models on the Landsat 9 dataset, suggesting that no single model consistently outperformed the others across all comparisons. In contrast, analysis of the models' overall accuracies when using the Sentinel-2A dataset revealed no significant difference between RF and LightGBM ($p = 0.84$). However, both RF and LightGBM demonstrated significantly higher accuracy compared to ANN ($p = 0.01$ for both comparisons). These results suggest that, for the Sentinel-2A dataset, RF and LightGBM performed comparably well, while ANN exhibited lower classification accuracy.

Table 7.6. McNemar's test p-values for RF, LightGBM, and ANN comparison when mapping current forest suitability for the eThekwini Municipality.

Model Comparison	**McNemar's Test p-value**
	Landsat 9
RF vs LightGBM	0.01
RF vs ANN	0.01
LightGBM vs ANN	0.01
	Sentinel-2A
RF vs LightGBM	0.84
RF vs ANN	0.01
LightGBM vs ANN	0.01

Given that all model comparisons exhibited statistically significant differences when using Landsat 9 data and that the best performance was achieved with the LightGBM and Landsat 9 configuration, the final current forest suitability map was generated from this configuration.

7.3.1.2 Future forest suitability

The comparative analysis of RF, LightGBM, and ANN in Figure 7.7 reveals distinctive performance characteristics. LightGBM exhibited an AUC of 93.75%, surpassing RF's

92.59%, while ANN lagged significantly with a lower AUC of 50.0%. RF and LightGBM showcased remarkable overall accuracy, achieving 94.29% and 95.24%, respectively, whereas ANN demonstrated comparatively lower accuracy at 61.90%. Conversely, ANN showed a sensitivity of 0.00%, indicating a failure to identify positive instances. In summary, RF and LightGBM emerged as robust performers, while ANN showed limitations that warranted further investigation and refinement.

The McNemar's test results for future forest suitability revealed significant differences in classification accuracy between the models, as indicated by *p*-values of 0.01 across all model comparisons (Table 7.7). This underscores the importance of considering various models rather than relying solely on one, as none consistently outperformed the others across all comparisons.

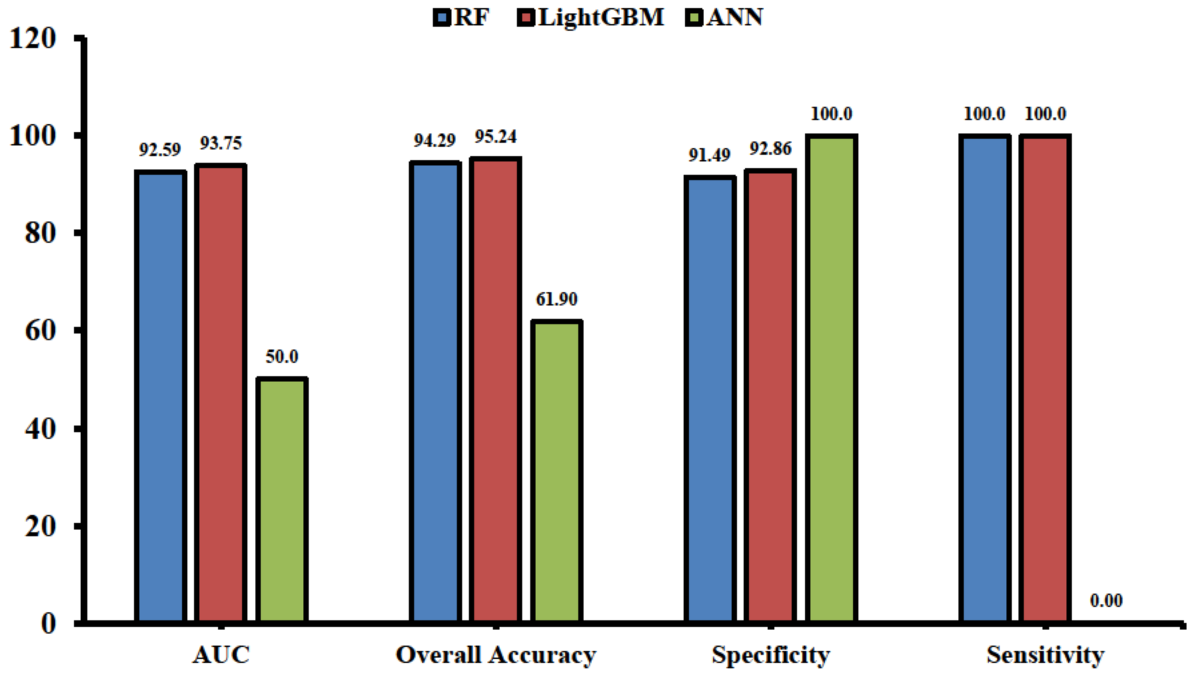

Figure 7.7. Accuracy comparison of RF, LightGBM, and ANN for future forest suitability mapping.

Table 7.7. McNemar's test p-values for RF, LightGBM, and ANN comparison when mapping future forest suitability for the eThekwini Municipality.

Model Comparison	McNemar's Test *p*-value
RF vs LightGBM	0.01
RF vs ANN	0.01
LightGBM vs ANN	0.01

Given the accuracy assessment and McNemar's test results, the final future suitability maps were mapped using the LightGBM.

7.3.2 Variable importance.

7.3.2.1 Current forest suitability

The best performance was achieved with the LightGBM and Landsat 9 configuration, as such, variable importance was investigated for this configuration. It should be noted that only the 15 most important variables were considered for this analysis (Figure 7.8). The higher the mean absolute SHAP value for a variable, the more important that variable is to the model's predictions. In the LightGBM performance using Landsat 9 data, bio12, which is annual precipitation and NDVI, emerged as the most important variables. This meant the model was highly sensitive to precipitation changes and vegetation changes. This is further supported by EVI being the second most important remote sensing derived variable.

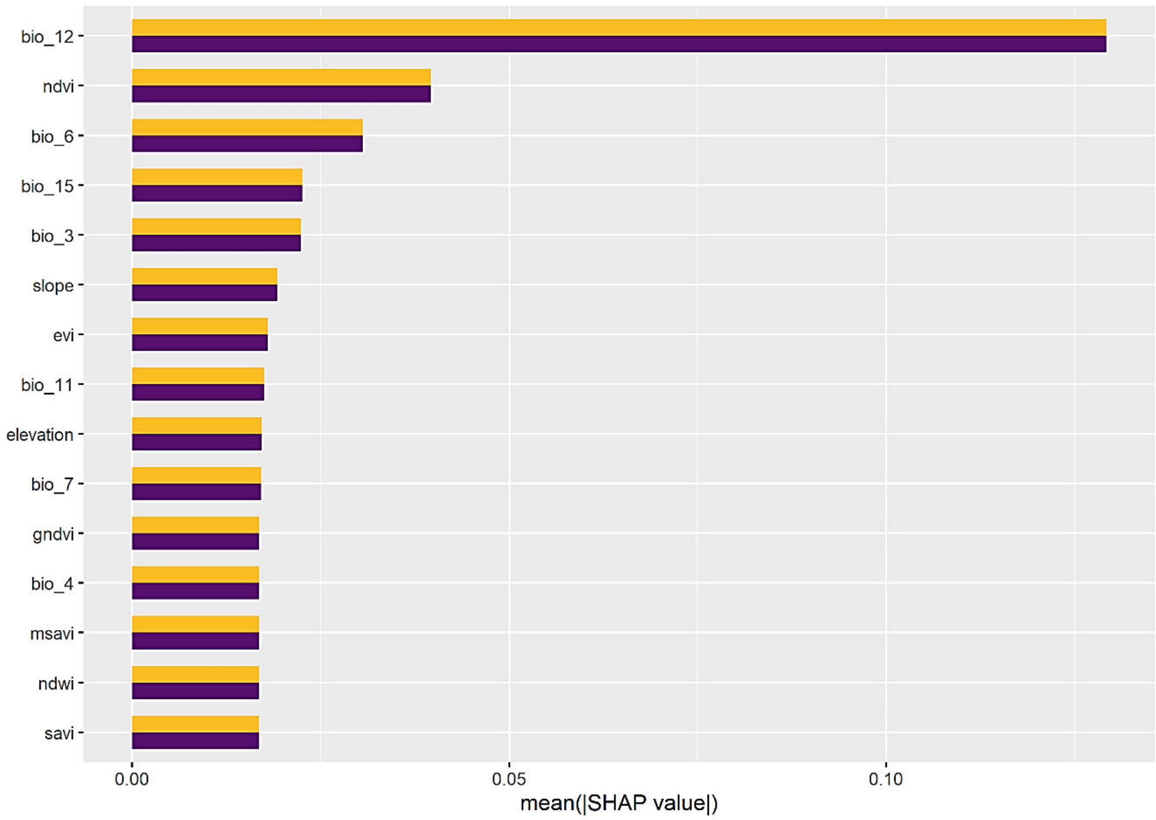

Figure 7.8. Importance ranking of variables based on the mean SHAP values to map forest suitability by LightGBM using Landsat 9 data.

7.3.2.2 Future forest suitability

Similarly to the current forest suitability mapping, LightGBM demonstrated the best performance. Notably, the variable bio_12 emerged with the highest mean absolute SHAP value, followed by bio_19, bio_17, and bio_15 (Figure 7.9). This indicates that these variables are crucial in explaining the model's output, signifying their significance in influencing forest suitability. Specifically, the results suggest that changes in precipitation, as reflected by the highest ranking of bio_12, will considerably impact forest suitability within the eThekwini Municipality. These findings underscore the importance of understanding and monitoring these key climatic variables for effective forest management and conservation strategies.

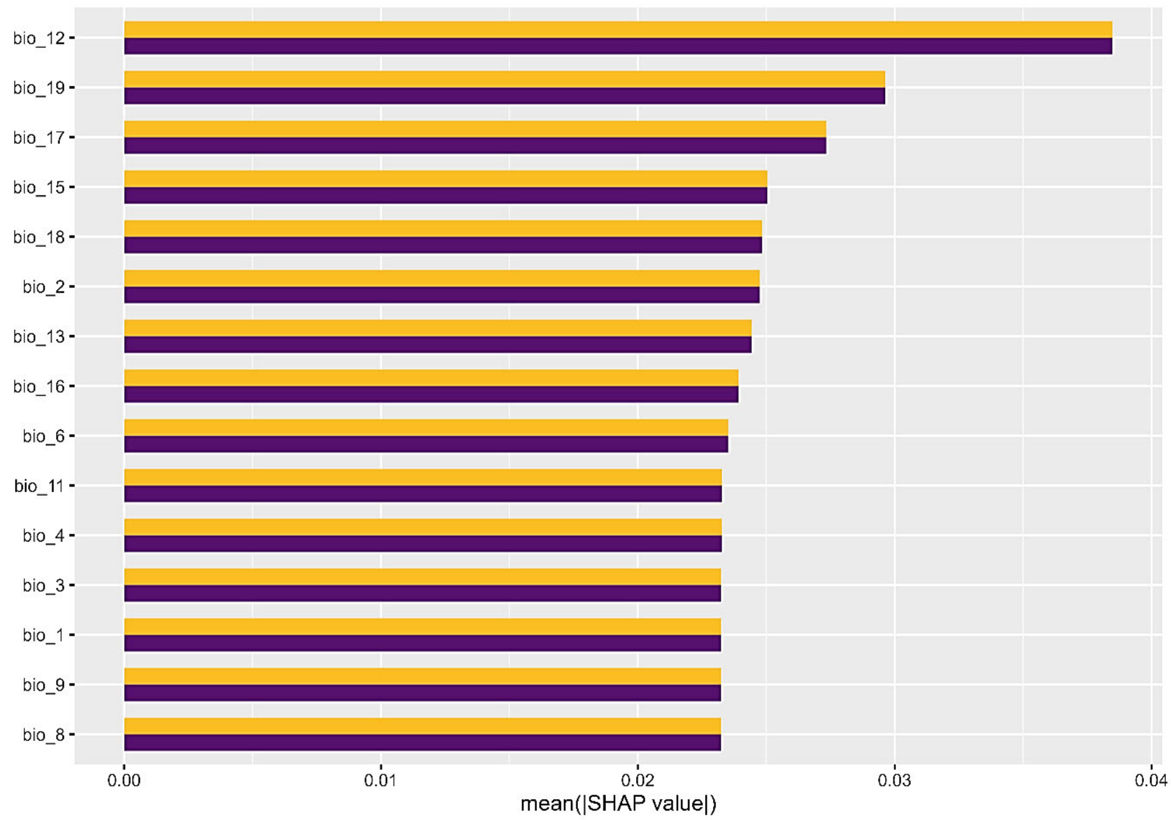

Figure 7.9. Importance ranking of variables based on the mean SHAP values used to map future forest suitability by LightGBM.

7.3.3 Spatial distribution of suitable areas

7.3.3.1 Current forest suitability

Figure 7.10 shows the map of current forest suitability within the eThekwini Municipality, generated by LightGBM using Landsat 9. Most suitable areas lie in the municipality's central region, extending largely towards the coast. On average, the model predicts that 30% of the eThekwini Municipality's land is suitable for forest vegetation.

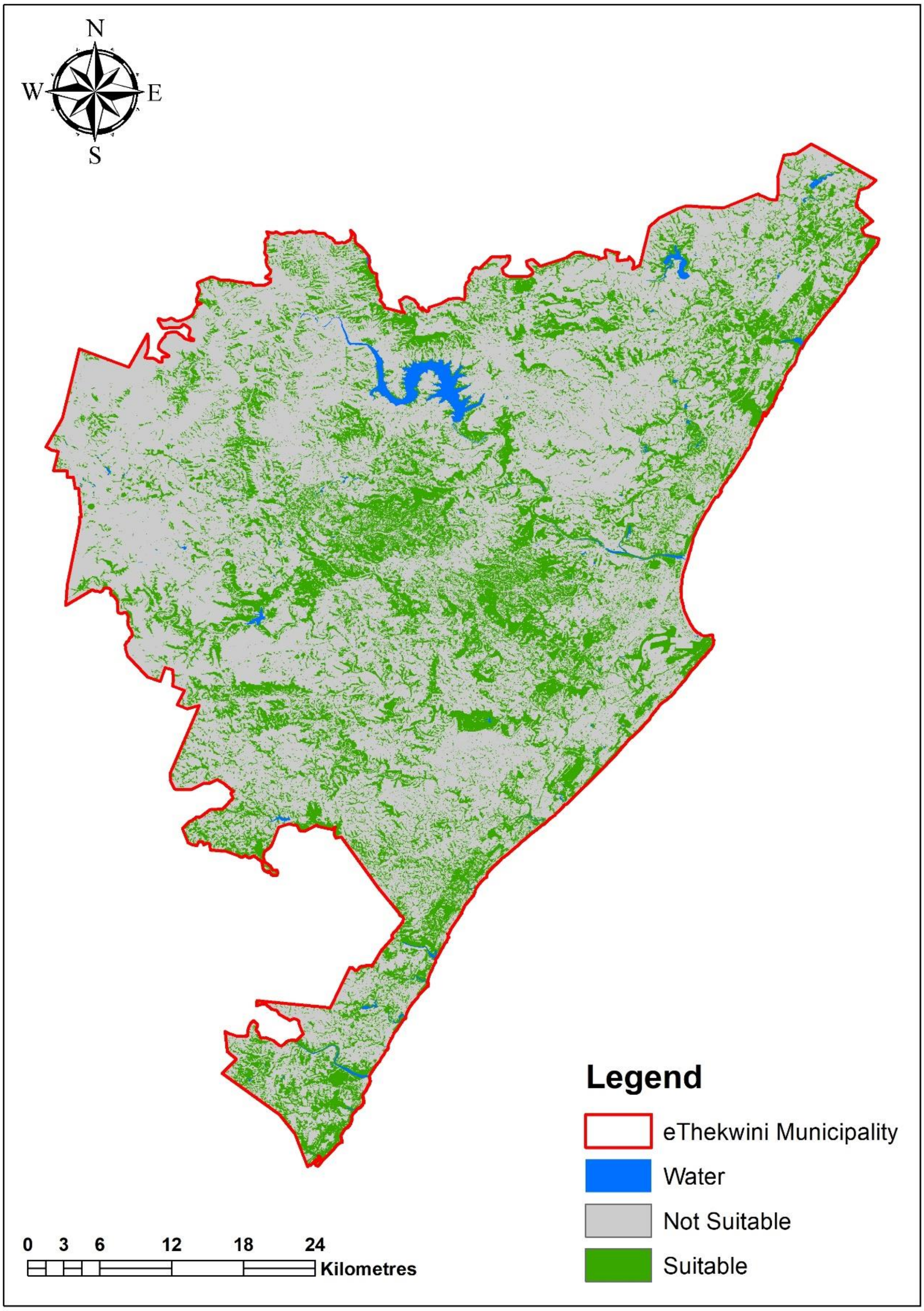

Figure 7.10. The spatial distribution of regions deemed suitable for forest vegetation, as predicted by LightGBM utilising Landsat 9 data.

7.3.3.1.1 *LULC and land ownership*

Figure 7.11(a) reveals areas suitable for forest vegetation and within privately owned land. Meanwhile, Figure 7.11(b) delineates areas unsuitable or unavailable for planting, incorporating impervious surfaces, water bodies, and wetlands, as per the latest eThekwini Municipality's LULC map. Most of the private land is located on the western side of the municipality, which means that the municipality owns the central and coastal regions. However, while the most suitable land is within the municipal area, mainly concentrated in the central region and towards the coast, Figure 7.11(b) shows that coastal areas are largely unavailable for planting due to development occurring in that region.

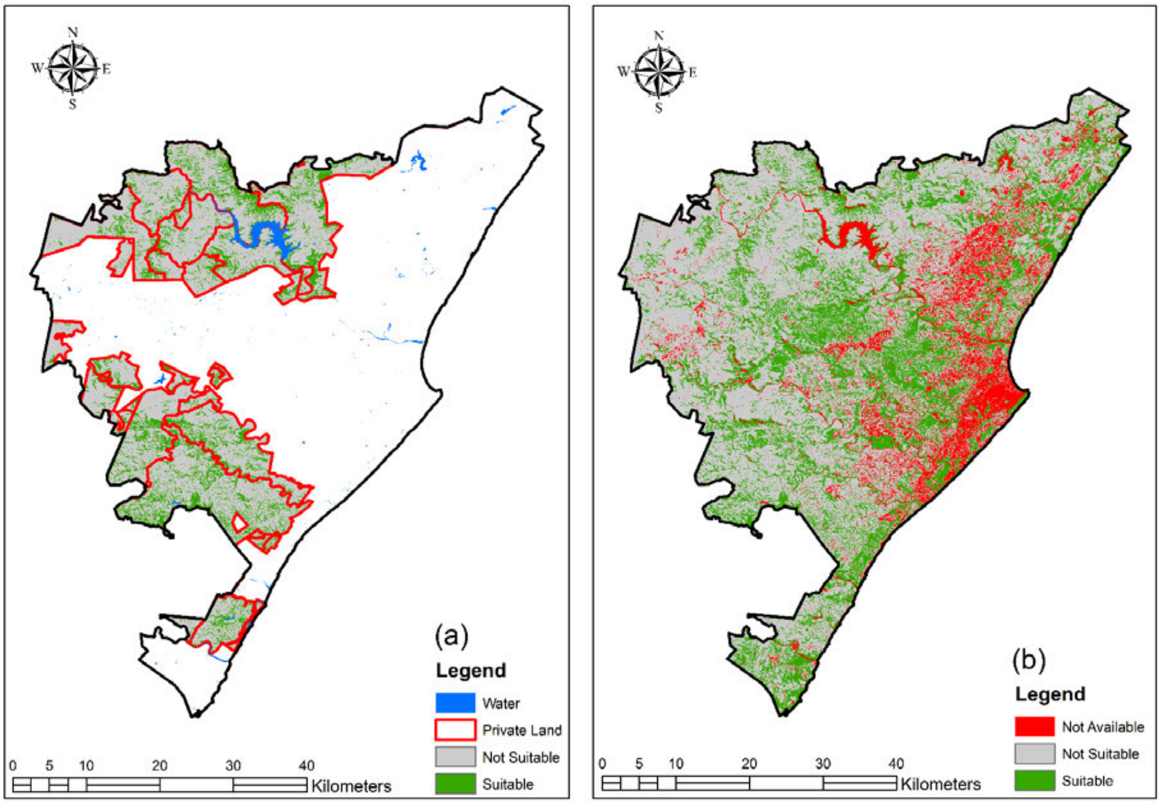

Figure 7.11. The delineation of privately owned land (a) and regions unsuitable for planting, as indicated by the eThekwini Municipality's latest LULC map (b).

7.3.4 Future forest suitability

Figure 7.12 and Table 7.8 present the future forest suitability maps generated by LightGBM based on HadGEM3-GC31-LL and MRI-ESM2-0 data. The maps indicate that the mountainous north-western part of the municipality will be the most suitable region.

Comparing the two GCMs, MRI-ESM2-0 predicts a larger area to be more suitable than HadGEM3-GC31-LL. SSP370 had the largest area suitable for forest vegetation in the four scenarios, covering 62.61% of the eThekwini Municipality area. This suggests potentially greater reforestation opportunities under the more challenging scenario of SSP370, where there will be high challenges to mitigation and adaptation. However, under SSP126 and SSP585, there will be limited opportunities for reforestation given that the area predicted to be suitable for forest vegetation is more reduced compared to the other scenarios.

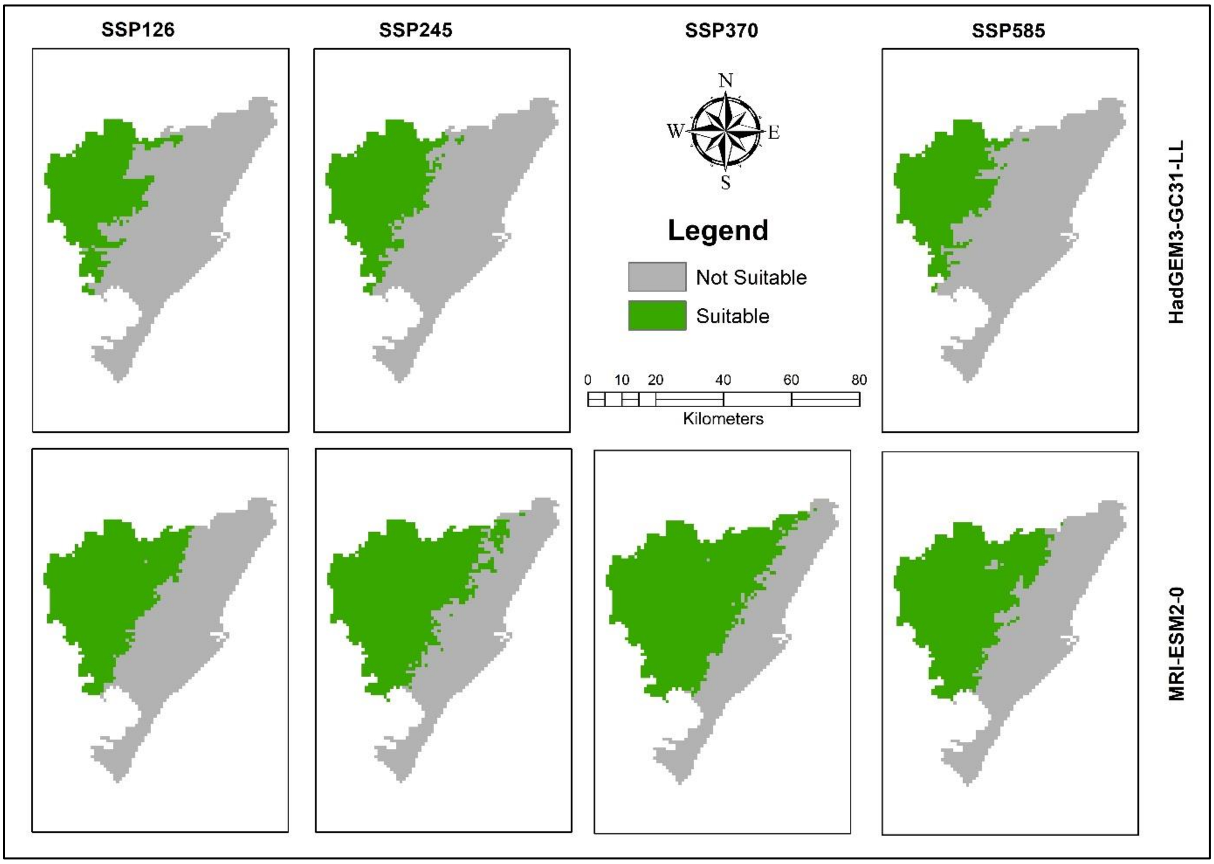

Figure 7.12. The spatial distribution of areas projected to be suitable for forest vegetation between 2021 and 2040, as predicted by LightGBM using HadGEM3-GC31-LL and MRI-ESM2-0 data under four RCP scenarios.

Table 7.8. The percentage areas of areas determined to be suitable for forest vegetation by LightGBM using HadGEM3-GC31-LL and MRI-ESM2-0 data under four RCP scenarios.

	SSP126		SSP245		SSP370		SSP585	
	Not Suitable	Suitable	Not Suitable	Suitable	Not Suitable	Suitable	Not Suitable	Suitable
HadGEM3-GC31-LL	68.16%	31.84%	65.35%	34.65%			68.94%	31.06%
MRI-ESM2-0	55.30%	44.70%	44.40%	55.60%	37.39%	62.61%	49.49%	50.51%

Overall, this study demonstrated the enhanced accuracy achieved in mapping forest suitability through machine learning algorithms driven by remote sensing data. By addressing algorithmic challenges and leveraging the synergy of these technologies, the findings emphasise the strategic implications for adaptive forest management and data-driven decision-making.

7.4 Discussion

Forests play a pivotal role in providing essential goods and services (Susaeta *et al.*, 2024), and their degradation can lead to a loss of these benefits. Reforestation and afforestation emerge as viable solutions to counteract the decline in forested areas and the associated ecosystem services (Ménard *et al.*, 2023). This study contributes a methodology for assessing areas currently suitable for forest vegetation, which will be suitable in the future, using the eThekwini Municipality as a case study.

7.4.1 Current forest suitability

This study utilised remote sensing, topographic, and bioclimatic data to map current forest suitability in the eThekwini Municipality. A comparative analysis was conducted between two remote sensing sensors, Landsat 9 and Sentinel-2A. Additionally, three algorithms, namely, RF, LightGBM, and ANN, were assessed to determine their performance with Landsat 9 and Sentinel-2A data. The findings revealed that LightGBM consistently outperforms RF and ANN, achieving the highest AUC (96.88%) and overall accuracy (97.62%) when applied to Landsat 9 data (Figure 5). When models were applied to Sentinel-2A data (Figure 7.5), LightGBM maintained its superiority with a slightly higher AUC (95.91%) and comparable overall accuracy (96.43%) compared to RF. This is consistent with the findings of Huang and Chen (2021), who found LightGBM to perform better than ANN in a large set of random data. Moreover, Guo *et al.* (2023) also found that LightGBM performs better than RF and XGBoost.

However, Wang, Z. *et al.* (2023) noted that RF can perform better than LightGBM given the best conditions.

Additionally, the results of McNemar's test highlight significant differences in model performance when mapping current forest suitability, particularly notable in Landsat 9 data, where all model comparisons showed statistically significant distinctions ($p < 0.01$). This implies varied effectiveness among models on Landsat 9, with no single model consistently outperforming others. Conversely, with the Sentinel-2A dataset, RF and LightGBM demonstrated similar performance, both significantly outperforming ANN ($p = 0.01$ for both comparisons), indicating their superiority over ANN in classification accuracy. These results indicate the robust performance of all models, emphasising their suitability for forest mapping, particularly when employed on Landsat 9 data. As such, the LightGBM with Landsat 9 data configuration was used to generate the final current forest suitability map.

Moreover, variable importance plays a critical role in explaining the algorithm's performance. Additionally, it provides insights into the factors that have the greatest impact on the model's accuracy and variables that should be prioritised for further analysis or intervention. This study used the SHAP technique to investigate variable importance for LightGBM. The SHAP values indicated that bio12 (representing annual precipitation) and NDVI were identified as the most significant factors. This signifies that the model exhibited high sensitivity to alterations in precipitation and vegetation. However, Martinez and Labib (2023) findings revealed non-linear trends in the relationships between NDVI and individual vegetation types, with canopy and shrub coverage exerting a more significant impact on mean NDVI exposure values than grass coverage at 300 and 500 m, indicating sensitivity to specific types and quantities of vegetation. The algorithm compensates for this by having EVI as the second most important remote sensing derived variable. Building on NDVI, EVI refines vegetation greenness measurements by boosting sensitivity in high biomass areas such as dense grasslands and factoring in atmospheric and background noise (Bari *et al.*, 2021; Huete *et al.*, 1997; Matsushita *et al.*, 2007).

The final current forest suitability map showed that highly suitable areas stretch towards the coastline in the central region. This central zone aligns with established protected areas like the Durban Metropolitan Open Space System (D'MOSS), highlighting the ecological significance of these regions. On average, the LightGBM predicted that 30% of eThekwini Municipality holds the potential to support thriving forests. This percentage presents both exciting possibilities and significant challenges. The vast extent of suitable land underscores the immense potential for reforestation and afforestation initiatives, contributing to biodiversity conservation, carbon sequestration, and improved environmental resilience. However, the substantial area also necessitates careful planning and resource allocation to ensure sustainable and effective forest restoration and afforestation efforts. Moreover, factors like human-induced disturbances, invasive species encroachment, and the impacts of climate change can significantly influence forest suitability over time (Peñuelas and Sardans, 2021). Therefore, ongoing monitoring and data updates are essential to maintain the map's accuracy and inform adaptive forest management strategies.

Beyond identifying suitable areas, overlaying those locations with private land boundaries was critical in informing the feasibility of reforestation and afforestation in the eThekwini Municipality. This is because the decisions of private landowners, ranging from logging practices to active conservation efforts or even neglect, can significantly influence the success of reforestation initiatives (Ruseva *et al.*, 2015). Furthermore, identifying landowners enables direct engagement and negotiation of agreements for planting, managing, and protecting trees on their property. This can involve formal leases, conservation easements, or collaborative partnerships. Engaging and building relationships with landowners fosters a sense of ownership and responsibility for the reforestation project, increasing the likelihood of its long-term success and sustainability. Furthermore, certain areas identified as suitable for forest vegetation may be unavailable for afforestation due to specific land uses, including water bodies, impervious land, and wetlands, as considered in this study.

Moreover, some areas were determined to be suitable within urban areas. This is of significance due to the United Nations Framework Convention on Climate Change (UNFCCC) through the Reduction of Emissions from Deforestation and Degradation in developing countries (REDD+) recognising urban reforestation and afforestation as dependable and sustainable approaches for long-term carbon sequestration and climate change mitigation (Matiza *et al.*, 2024; Teo *et al.*, 2021). Therefore, it is recommended that land managers in the eThekwini Municipality explore urban reforestation and afforestation initiatives.

However, the JRC’s Global Map of Forest Cover dataset was selected as the primary dataset for model training and validation in assessing current and future forest suitability. This dataset offers comprehensive global coverage and accessibility, aligning with the study’s regional-scale focus on the eThekwini Municipality (Bourgoin *et al.*, 2024). Despite these advantages, the dataset presents certain limitations. Notably, it lacks a quantitative and qualitative accuracy assessment. Additionally, the dataset does not distinguish between commercial forestry plantations and indigenous forest areas, which can impact suitability analysis accuracy, as commercial species such as Pinus and Eucalyptus are known to thrive in areas that may not be ecologically suitable for native forests.

While these limitations are acknowledged, the JRC's Global Map of Forest Cover dataset was chosen because it provides a standardised and accessible baseline that enables consistent application of machine learning models across large areas. Given the study's focus on evaluating modelling techniques for suitability analysis, the dataset was appropriate for initial suitability modelling. However, this limitation is discussed here to emphasise that, in areas where ecological specificity is critical, datasets that differentiate between commercial and indigenous forests would improve alignment with conservation goals. Future studies are encouraged to utilise or incorporate locally validated data with higher specificity to indigenous forest types, wherever possible, to enhance the ecological relevance and accuracy of forest suitability assessments.

7.4.2 Future forest suitability

As aforementioned, factors like human-induced disturbances, invasive species encroachment, and the impacts of climate change can significantly influence forest suitability over time. Therefore, using bioclimatic variables and the three algorithms, namely, LightGBM, RF and ANN, future forest suitability in the eThekwini Municipality was assessed. LightGBM outperformed the other two algorithms with an AUC of 93.75%, surpassing RF's 92.59%, while ANN lagged significantly with a lower AUC of 50.0%. Both RF and LightGBM demonstrated remarkable overall accuracy at 94.29% and 95.24%, respectively, whereas ANN exhibited comparatively lower accuracy at 61.90%. Conversely, ANN displayed a sensitivity of 0.00%, signifying a failure to identify positive instances. Additionally, McNemar's test results for future forest suitability revealed significant differences in classification accuracy between the models, as indicated by p-values of 0.01 across all model comparisons.

The performance differences among LightGBM, RF, and ANN in assessing future forest suitability in the eThekwini Municipality can be attributed to variations in model structures, data handling capacities, and algorithmic efficiencies. LightGBM and RF, both well-suited for ecological modelling, excel due to their robust handling of large datasets, complex variable interactions, and stable classifications qualities that enable effective modelling of bioclimatic variables in forest suitability assessments ((Breiman, 2001; Ke *et al.*, 2017)). LightGBM's gradient-boosting approach and RF's ensemble of decision trees allow each model to capture nuanced relationships within environmental data, ensuring strong predictive capabilities. ANN, on the other hand, tends to require larger datasets and extensive training to capture non-linear relationships effectively, making it prone to overfitting in smaller or imbalanced datasets often found in environmental research (Ahmed *et al.*, 2023). The ANN model's sensitivity challenges indicate its limitations in identifying positive instances within the dataset, which contrasts sharply with the effectiveness of LightGBM and RF in such contexts. Significant differences indicated by McNemar's test ($p = 0.01$) underscore ANN's relative unsuitability for forest suitability assessment compared to LightGBM and RF, highlighting the importance of choosing adaptive and reliable models that can handle complex environmental interactions in ecological forecasting.

Therefore, LightGBM was used to generate the maps for future suitability based on data from HadGEM3-GC31-LL and MRI-ESM2-0. The selection of these two GCMs stems from the fact that no GCM has been developed specifically for Africa; thus, multiple GCMs should be utilised. Likewise, studies by Alaminie *et al.* (2021), Annor *et al.* (2023), and Mmame and Ngongondo (2023) have demonstrated the usability of HadGEM3-GC31-LL and MRI-ESM2-0. Additionally, the maps were generated under four RCP scenarios.

When LightGBM was used to generate maps for future forest suitability, the most important variables were bio_12, with the highest mean absolute SHAP value, followed by bio_19, bio_17, and bio_15. This is consistent with Zhang *et al.* (2021), who found bio_12 among the highest-ranking variables in forest vegetation suitability modelling. This convergence of results reinforces the critical role of precipitation patterns, particularly annual and seasonal variations, in determining the future viability of forests in different regions.

In forecasting future forest suitability in the eThekwini Municipality, the analysis points to the mountainous north-western region as the most likely suitable area, attributed to factors like increased rainfall and lower temperature occurring in this region in the future. Notably, the climate models, specifically MRI-ESM2-0, predicted a larger area to be suitable for forest vegetation than the HadGEM3-GC31-LL model, suggesting a potentially more favourable climate for forest growth in this scenario. Surprisingly, the SSP370 scenario, characterised by the highest challenges for mitigation and adaptation, presents the largest suitable area for forest vegetation. This outcome could be explained by the adaptability of trees to more extreme conditions, potentially leading to increased forest cover. Conversely, in the SSP126 scenario with the least challenges, LightGBM predicted the smallest area to be suitable for forests, likely due to its more moderate climate conditions favouring other vegetation types like grasslands and crops. Additionally, SSP585 predicts a smaller area suitable for forest vegetation, particularly under the HadGEM3-GC31-LL model. In their study, Yao *et al.* (2022) found the SSP585 scenario suitable for grassland and irrigated farming, hence, the limited suitability of forest vegetation.

Crucially, the future suitability analysis suggests that by 2040, many areas currently covered by forests may no longer be suitable for this vegetation type. This finding emphasises the need to consider the ecological feasibility of these projections and their practical implications for conservation and forest management. Moreover, it points to potentially significant shifts in forest suitability that could impact biodiversity, soil stability, and carbon sequestration in the region. Climate variables, including drier conditions and temperature increases, are major contributing factors to the anticipated shifts in forest suitability. These changes may alter habitat suitability for indigenous forests by reducing growth rates and resilience in native forest species, particularly in areas already at the edge of their climatic tolerance thresholds (Girona *et al.*, 2023). As such, adaptive conservation strategies will be essential to mitigate these impacts.

Furthermore, conservation planning might address these shifts by identifying and prioritising forest areas most resilient to climate change. Possible measures include restoring buffer zones, introducing drought-resistant species, and preserving existing habitats in microclimates that could provide refuge for forest species under changing conditions.

Overall, based on the findings from this study, to enhance future forest growth, land managers should prioritise reforestation and afforestation efforts in the identified suitable areas, particularly the mountainous north-western region, which is projected to have the most favorable conditions under various climate scenarios. Establishing partnerships with private landowners in these areas will also be crucial for successful large-scale initiatives. Additionally, exploring urban reforestation and afforestation opportunities is crucial, as this aligns with global initiatives like REDD+ for carbon sequestration and climate change mitigation. Moreover, continuous monitoring of forest suitability, incorporating updated data and considering evolving factors like climate change and human disturbances, is essential for accurate suitability maps and adaptive forest management.

Additionally, it should be noted that this study is contingent on climate models and future projections, introducing inherent uncertainties. Actual climate change impacts may deviate from the predictions used in this study. Improved accuracy in future predictions may result from additional data and refined models. Acknowledging these limitations and implementing the recommended actions will empower policymakers and land managers to make informed decisions, fostering the long-term sustainability of the eThekwini Municipality's valuable forest ecosystems.

7.5 Conclusion

This study has successfully devised a comprehensive methodology for evaluating current and future forest suitability in the eThekwini Municipality, leveraging remote sensing, machine learning, topographic, and bioclimatic data. The LightGBM algorithm emerged as the most effective tool for mapping suitability, emphasising the significance of precipitation patterns and other bioclimatic variables in determining forest viability. However, it should be noted that this study also underscores the importance of considering various models rather than relying solely on one, as all models showed their robustness in mapping forest suitability, particularly when employed on Landsat 9 data.

Regarding current suitability, approximately 30% of the municipality is suitable for forest vegetation, concentrating in the central region and aligning with existing protected areas. The engagement of private landowners in these identified areas is deemed essential for the success of reforestation initiatives. Looking ahead to future suitability, the mountainous north-western region is predicted to be the most suitable under various climate scenarios, benefiting from increased rainfall and lower temperatures. Notably, the most challenging mitigation scenario (SSP370) revealed the largest suitable area, suggesting a potential adaptation of trees to extreme conditions.

Recommendations stemming from these findings include a strategic focus on reforestation and afforestation efforts in suitable areas, particularly in the north-western region. Collaboration with private landowners, exploration of urban reforestation opportunities, and continuous monitoring of forest suitability are proposed to adapt management strategies effectively. However, it is imperative to acknowledge certain limitations. The reliance on climate models introduces uncertainties about future impacts, and model performance could be enhanced with additional data and refined models. Despite these limitations, the study offers valuable insights and practical recommendations for policymakers and land managers, enabling informed decisions about forest restoration and conservation efforts in the eThekwini Municipality. This ensures the long-term sustainability of its crucial forest ecosystems.

7.6 Summary

Using bioclimatic data from the WorldClim dataset, elevation and slope from the SRTM dataset, and remote sensing data from Landsat 9 and Sentinel-2A, this chapter predicted current (2023) and future (2021-2040) forest suitability. Employing RF, LightGBM, and ANN, the models, particularly LightGBM, demonstrated high accuracy. It was found that currently, 30% of the municipality is suitable for forest vegetation, with future projections highlighting that the mountainous north-western region will increasingly be more suitable under the SSP370 scenario. These findings suggest prioritising reforestation efforts, engaging private landowners, exploring urban reforestation, and implementing continuous monitoring for adaptive management to enhance carbon sequestration, biodiversity conservation, and ecosystem resilience.

8. CHAPTER EIGHT: A REMOTE SENSING AND MACHINE LEARNING APPROACH TO STREAMLINE FOREST REHABILITATION AND RESTORATION IN THE ETHEKWINI MUNICIPALITY: A SYNTHESIS

8.1 Introduction

This chapter provides a significantly expanded evaluation of the research findings, critically assessing the results in relation to the stated aims and objectives. It includes a detailed analysis of limitations in the methodology, data sources, and analytical approaches presented across chapters, and offers recommendations for future research to address these gaps. This chapter also discusses the broader implications of the findings, synthesising insights into forest management, restoration, and ecological conservation in the eThekwini Municipality.

Forests are crucial for maintaining ecological balance, supporting biodiversity, and providing essential ecosystem services. However, the persistent challenges of forest degradation and deforestation, intensified by global climate change, present obstacles that call for focused forest rehabilitation and restoration efforts. Projections indicate continued adverse effects on forest ecosystems (Kumar, R. *et al.*, 2022). Extended drying periods, increased drought severity, and the acceleration of disturbances such as wildfires and insect outbreaks are expected to exacerbate forest loss (Lloret and Batllori, 2021). Southern Africa, including regions like the eThekwini Municipality, faces heightened vulnerability due to warming rates surpassing the global average (Anekwe *et al.*, 2023). Anthropogenic activities such as urban expansion, agricultural development, and resource extraction further compound these challenges. The socio-economic implications are significant, as forest degradation diminishes ecosystem services crucial for food security, climate regulation, and disaster mitigation (Leal Filho *et al.*, 2021).

Initiatives like Reducing Emissions from Deforestation and Forest Degradation (REDD) aim to incentivise forest conservation through regulatory frameworks and financial incentives (Shah and Race, 2024). These programmes are designed to provide economic benefits to communities and landowners who engage in sustainable forest management practices (Manda and Mukanda, 2023). By offering financial rewards for maintaining forest cover and implementing conservation strategies, REDD seeks to align economic incentives with environmental goals (Cezarino *et al.*, 2023). However, their effectiveness remains debated, and forest restoration and rehabilitation advancements are essential to complement these efforts. Forest rehabilitation and restoration offer significant advantages in halting forest loss and mitigating the adverse effects of deforestation and degradation (Khan *et al.*, 2021; Pecchi *et al.*, 2019; Picchio *et al.*, 2021). By re-establishing native vegetation, these efforts enhance biodiversity, improve soil quality, and restore essential ecosystem services. Restored forests can also act as natural barriers against extreme weather events, reducing the risk of floods and landslides (Rey *et al.*, 2024). Additionally, they play a crucial role in climate change mitigation by absorbing carbon dioxide from the atmosphere. Socio-economically, these efforts support sustainable livelihoods through activities like agroforestry and ecotourism (Rasul and Gurung, 2024). Overall, forest rehabilitation and restoration not only combat forest loss but also build resilient ecosystems capable of adapting to future environmental changes, ensuring the sustainability of natural resources. Future projections suggest that forest ecosystems will struggle to adapt without targeted restoration and rehabilitation, leading to substantial biodiversity loss and compromised ecosystem resilience (Wardell-Johnson *et al.*, 2015).

Therefore, this study focused on enhancing these processes by integrating remote sensing and machine learning techniques. This approach aims to enhance natural forest monitoring and regional forest suitability modelling, thereby streamlining forest restoration and rehabilitation efforts. By employing advanced technologies, this method offers several benefits: more accurate and timely data collection, improved decision-making for conservation strategies, and optimised resource allocation (Mulatu *et al.*, 2017; Nagendra *et al.*, 2013). Additionally, by predicting the most suitable areas for reforestation, these methods can significantly increase the success rates of restoration projects, ultimately contributing to healthier, more resilient forest ecosystems (Hu *et al.*, 2020). The objectives that support this aim were outlined in chapter one, subsection 1.3.

8.2 Regional disparities in forest management research

Chapters two and three revealed significant regional disparities in forest management research. Asia and South America were leading in research output. North America also demonstrated considerable research activity. In contrast, Africa lags behind these continents, highlighting the need for more focused research efforts in this region. This disparity highlights a critical gap in global forest management research, suggesting that African forests might not be receiving the attention and resources necessary for their preservation and sustainable management. Kumar and Mutanga (2018) indicated that the lack of publications from developing countries can be attributed to several factors, including limited data accessibility, fewer research opportunities, and a lack of technological and technical skills necessary to process the data required for implementing reforestation projects. These challenges stand in contrast to the more favourable conditions in developed countries. Matiza *et al.* (2023) reached a similar conclusion in their review of remote sensing and machine learning approaches for accurate carbon storage estimation in natural forests, noting that Africa produced only 10% of the studied publications. This finding underscores the urgency for increased investment in scientific research and capacity-building initiatives in Africa to effectively address the pressing challenges of forest management and conservation (Schweizer *et al.*, 2021).

Bamwesigye *et al.* (2020) emphasised that forest management initiatives face significant challenges in Africa, particularly in East Africa, where wood biomass serves as the primary household fuel. These include conflicting land-use policies, corruption, and occasional information gaps, all of which contribute to substantial forest degradation and deforestation. As a result, there is a strong focus on marketing and selling non-timber forest products (NTFPs) to boost income for impoverished communities while promoting forest conservation (Zhu and Lo, 2021). This focus has led to increased research outputs, as exemplified by the review conducted by Derebe *et al.* (2023), where they found a relatively higher number of publications from African countries compared to other continents. They attributed this to the critical role NTFPs play in rural communities' livelihood stability and economic sustenance, prompting extensive research in this area.

Therefore, addressing the disparities in forest management research by increasing investment and capacity-building initiatives in Africa is imperative. This will enhance the preservation and sustainable management of African forests and ensure that underrepresented regions receive the necessary attention and resources. By overcoming challenges such as limited data accessibility, fewer research opportunities, and a lack of technological and technical skills, African countries can better implement effective forest management and conservation strategies. Moreover, promoting the marketing and sale of NTFPs will provide a sustainable income source for impoverished communities and contribute to forest conservation efforts.

8.3 Land use and land cover change and land degradation in the eThekwini Municipality

This study identified a significant gap in comprehensive knowledge regarding the rate of LULC change and land degradation within the eThekwini Municipality, as well as their impacts on forest ecosystems and ecosystem services. Chapter four utilised Landsat imagery to map LULC changes using machine learning algorithms from 2002 to 2022 for the eThekwini Municipality. The findings underscored the significant utility of remote sensing in LULC change mapping, demonstrating its effectiveness in capturing and analysing spatial and temporal dynamics over large areas with high accuracy (Wang, S. *et al.*, 2023). The integration of advanced machine learning algorithms, such as extreme gradient boosting (XGBoost), random forest (RF), and support vector machines (SVM), further enhanced the precision and reliability of LULC classifications (Shao *et al.*, 2024; Zafar *et al.*, 2024). By leveraging the capabilities of Landsat imagery and cloud-based platforms like Google Earth Engine (GEE), chapter four provided detailed insights into the patterns and trends of land cover changes over two decades. This approach facilitated the identification of critical changes, such as the decline in cropland and fluctuations in forest and grassland areas, along with the continuous expansion of impervious areas towards the north of the municipality. This expansion, driven by infrastructure projects aimed at rectifying socioeconomic inequalities from the apartheid era (Sutherland *et al.*, 2014), has led to a decrease in vegetated landscapes. Ultimately, this chapter has proven invaluable for informing sustainable land management and policymaking in the eThekwini Municipality.

The decline in vegetated lands correlated with findings in chapter five, where increasing land degradation was observed in the eThekwini Municipality. This chapter employed four machine learning algorithms on Landsat 7, Landsat 8, and Landsat 9 satellite data to estimate land degradation based on land cover change and soil organic carbon (SOC) stock from 2000 to 2022. Moreover, remote sensing combined with advanced machine learning algorithms also proved highly effective in assessing land degradation, offering a scalable and accurate alternative to traditional methods (Angerer *et al.*, 2023). The main drivers of land degradation identified were urban expansion, deforestation, and unsustainable agricultural practices. Pinpointing specific areas that experienced significant degradation aids in identifying hotspots for targeted intervention (Yan *et al.*, 2024). Consequently, policymakers and land managers can utilise these insights to prioritise areas for restoration efforts and implement strategies to mitigate further degradation.

8.4 Mapping the natural forests of eThekwini Municipality

Establishing a framework for monitoring natural forests in the eThekwini Municipality using remote sensing is crucial for streamlining and enhancing forest rehabilitation and restoration efforts (Appanah *et al.*, 2016). This framework will enable the continuous assessment of forest conditions, allowing for timely and informed decision-making to effectively address and mitigate degradation. Therefore, chapter six employed Landsat 7, Landsat 8, and Landsat 9 satellite imagery and utilised three gradient boosting machine learning algorithms, namely, light gradient boosting machine (LightGBM), categorical boosting (CatBoost), and XGBoost, to map and analyse the historical and current distribution of natural forests within the eThekwini Municipality. The findings demonstrated a significant underestimation of natural forested areas when utilising Landsat 7 data. However, maps from Landsat 8 and Landsat 9 showed a clear increase in natural forest areas between 2015 and 2023. These findings underscored the importance of advanced satellite data for accurate environmental monitoring and decision-making. As such, by leveraging the capabilities of advanced machine learning algorithms and satellite imagery, this chapter provided detailed insights into the patterns and trends of natural forest changes, guiding effective and targeted forest rehabilitation and restoration efforts in the eThekwini Municipality.

However, it is essential to address the discrepancies in findings on forest cover trends, particularly the differences observed between chapters regarding the reported increase in forest cover in 2022. These variations stem from the use of different modelling approaches and datasets across analyses. Such differences in methodology and data sources highlight how model selection and dataset characteristics can significantly influence forest cover assessment outcomes, underscoring the importance of consistency and transparency in model usage to enable accurate comparisons across studies.

8.5 Areas suitable for forest vegetation in the eThekwini Municipality

This study also identified the use of suitability models as a critical component of streamlining forest rehabilitation and restoration. By accurately predicting areas most conducive to forest growth, these models enable more efficient allocation of resources and strategic planning (John *et al.*, 2020). This targeted approach not only enhances the success rates of rehabilitation and reforestation initiatives but also ensures that interventions are both cost-effective and environmentally sustainable.

Therefore, chapter seven focused on assessing current and future forest suitability in the eThekwini Municipality using machine learning models. The data used to model forest suitability included bioclimatic variables, elevation, and slope. Three machine learning algorithms were used, namely: RF, LightGBM, and artificial neural networks (ANN). Current forest suitability maps indicate that approximately 30% of the eThekwini Municipality is suitable for forest vegetation, primarily in the central region and coastal areas. While future projections identified the north-western mountainous regions of the municipality as most suitable. Additionally, future suitability analysis indicates that by 2040, many areas currently forested may become unsuitable for sustaining native forest vegetation, driven primarily by climate variables such as drier conditions and rising temperatures. This projected shift underscores the importance of assessing the ecological feasibility and practical implications of these changes for conservation and forest management. With potential impacts on biodiversity, soil stability, and carbon sequestration, these shifts could significantly influence the region's ecological health. In particular, areas near the climatic tolerance limits of native forest species may experience reduced growth rates and resilience, highlighting the need for adaptive conservation strategies to mitigate these effects.

In response, conservation planning should consider prioritising forest areas with higher resilience to climate change. Potential strategies include restoring buffer zones, introducing drought-resistant species, and preserving habitats within microclimates that may serve as refuges for forest species under evolving environmental conditions. These adaptive measures could help maintain critical forest functions and biodiversity in the face of anticipated climatic changes.

Ultimately, these findings support the use of machine learning algorithms in ecological conservation, providing a robust framework for adaptive forest management. The algorithms enable precise targeting of reforestation efforts, ensuring resource efficiency and sustainability. Furthermore, the study's methodology can be applied to other regions, offering a scalable approach to forest suitability mapping that integrates remote sensing data and advanced machine learning algorithms.

8.6 Limitations of the study

When interpreting the results of this project, several limitations are important to consider. Chapters two and three provided thorough systematic literature reviews. However, the potential bias introduced by excluding non-open-access papers, particularly those from developing countries, was a limitation. This constraint likely skewed the geographical distribution and thematic focus of findings, favouring studies from developed countries. Additionally, the observed increase in publications over the last five years may reflect an overall increase in publication accessibility rather than a genuine rise in interest in the selected keywords. Although a normalisation of data was beyond the study's scope due to budget constraints, this limitation is explicitly acknowledged, recognising that accessibility limitations may have affected trends interpretation.

Chapter four utilised the 2017 Finer Resolution Observation and Monitoring-Global Land Cover-Segmentation at 10 m (FROM – GLCS10) dataset, a globally recognised dataset with approximately 80% accuracy, as a foundation for model training and accuracy assessment. While this dataset provides broad, consistent coverage compatible with the study's scope, it was not specifically validated for the eThekwini Municipality. Consequently, some limitations are acknowledged in capturing precise LULC information. Nonetheless, the model achieved a high accuracy rate (97%), indicating a strong internal alignment with the dataset used. Future studies may benefit from incorporating high-resolution, locally validated data to further enhance accuracy and ensure even more reliable results specific to the eThekwini Municipality.

The stratified sampling approach in chapter four, which generated 10000 sample points per class without spatial buffers, successfully ensured a comprehensive representation across all classes. However, for smaller classes like wetlands, the potential for sample overlap on adjacent pixels may have led to spatial autocorrelation, possibly influencing accuracy metrics. This study recognises the potential benefit of employing a buffer-based sampling strategy in future research, which could help to further minimise spatial autocorrelation and enhance the precision of class representation.

Moreover, the classification scheme in chapter four grouped commercial plantations and orchards within the broader forest class. This approach provided a practical, streamlined categorisation that facilitated the analysis of general forest cover trends in the eThekwini Municipality. However, given the prevalence of commercial forestry in the area, there remains a potential for forestry rotations to be classified similarly to deforestation or reforestation of indigenous forests. Future research could build on this foundation by incorporating datasets that distinguish between indigenous and commercial forests, thereby enabling more nuanced ecological interpretations and enhancing insights into specific forest dynamics.

Chapter five's modelling of SOC utilised the 2017 iSDA SOC stock image, a well-regarded dataset offering comprehensive regional coverage that enabled a broad-scale SOC analysis across the eThekwini Municipality. This dataset provided a consistent basis for model training and validation. However, it was not specifically verified at a local scale. Future studies could enhance the robustness of SOC predictions by incorporating independently validated, site-specific SOC measurements, which would support even greater accuracy in assessing SOC distribution and its ecological implications.

Chapter seven's suitability analysis employed the Joint Research Centre (JRC)'s Global Map of Forest Cover, a dataset with extensive global coverage, which was well-suited for assessing forest suitability on a regional scale. While this dataset does not include a quantitative accuracy assessment and does not distinguish between commercial and indigenous forests, it effectively supported broad suitability analysis. For greater precision in habitat assessments, future studies could benefit from datasets that differentiate between forest types, allowing for an even more detailed understanding of habitat suitability for native forests. Additionally, the current suitability analysis utilised remote sensing data to capture recent deforestation and degradation patterns, providing valuable insights into present-day land cover dynamics. For future projections, however, the model focused exclusively on climatic factors to avoid potential biases from recent land-use changes, offering a clear contrast between current and projected conditions. Integrating both remote sensing and long-term climatic data in future analyses could provide a balanced perspective, supporting both immediate rehabilitation and strategic forest planning.

Overall, the study relied on medium-resolution remote sensing data, which may not capture finer-scale changes in forest cover and land degradation. In contrast, higher-resolution imagery could provide more detailed insights. Additionally, the study focused on specific machine learning algorithms, potentially overlooking other models that could offer better performance or insights for certain tasks. The geographic focus on the eThekwini Municipality may limit the generalisability of the findings to other regions with different ecological, climatic, and socio-economic contexts. Furthermore, the study did not extensively analyse the impact of local policies, management practices, and socio-economic factors on forest restoration and rehabilitation efforts.

8.7 Recommendations and avenues for future research

Building on the limitations identified in this study, several recommendations are proposed to strengthen future research in forest monitoring, restoration, rehabilitation, and conservation. To address spatial autocorrelation effects and enhance the reliability of accuracy assessments, future studies should employ buffer-based sampling strategies for model validation. This approach is particularly beneficial for small, heterogeneous land cover classes, where applying spatial constraints between sample points can minimise overlap and prevent inflated accuracy metrics. In addition, utilising datasets like the South African National Land Cover (SANLC) dataset used in chapter six, which differentiates between forest types such as indigenous and commercial forests, would enable more ecologically nuanced analyses. This level of detail supports a clearer understanding of forest dynamics and enhances the precision of conservation strategies tailored to the specific ecological and management needs of each forest type.

Future studies should integrate high-resolution satellite imagery to capture fine-scale changes in LULC. This approach would address limitations from medium-resolution datasets like FROM-GLCS10, providing a more detailed and accurate assessment of land degradation, forest cover dynamics, and small-scale ecological changes. Validate findings with high-resolution, locally verified datasets specific to the study area would reduce potential misinterpretations and enhance the robustness of results. Establish continuous monitoring systems with near-real-time remote sensing data will enable researchers to track rapid changes in forest cover, LULC dynamics, and environmental degradation with greater temporal precision. This real-time approach would improve responsiveness to deforestation events, land use shifts, and environmental disturbances, providing decision-makers with timely data for effective interventions.

Additionally, exploring and comparing a wider range of machine learning and deep learning algorithms is crucial for the identification of the most effective models for specific tasks such as forest suitability mapping and land degradation assessment. Performing comparative analyses across regions with distinct ecological, climatic, and socio-economic contexts can be very crucial as they would help validate the generalisability of the study’s findings and methodologies. Expanding this research to different geographic areas can reveal region-specific patterns in LULC change, land degradation, and forest restoration needs, fostering insights that may guide localised conservation policies.

Finally, future studies should evaluate the effectiveness of existing policies and management practices on forest restoration and degradation and recommending policy adjustments based on empirical evidence is essential. Furthermore, incorporating participatory approaches that involve local communities and stakeholders in the research process will ensure sustainable and inclusive forest rehabilitation and restoration practices.

8.8 Conclusion

This study aimed to develop and implement a remote sensing and machine learning-based approach for streamlining forest restoration and rehabilitation in the eThekwini Municipality, focusing on regional forest suitability modelling and natural forest monitoring. The findings have underscored the critical role of advanced technologies in enhancing forest management practices. The integration of remote sensing and machine learning techniques has proven instrumental in improving natural forest monitoring and regional forest suitability modelling. Using medium-resolution satellite imagery and sophisticated algorithms, this study achieved accurate and timely data collection, which facilitates informed decision-making and optimised resource allocation for forest restoration efforts.

The research objectives were successfully addressed, highlighting the global trends in forest rehabilitation, the effectiveness of remote sensing in LULC change mapping, and the identification of suitable areas for forest vegetation within the eThekwini Municipality. The study also provided a robust framework for monitoring natural forests at a municipal scale, essential for streamlining forest rehabilitation and restoration initiatives. Therefore, based on the findings from these research objectives, the main conclusions of this study are as follows:

i. Based on a systematic review of 117 publications, there is an urgent need for comprehensive and sustainable forest management practices, emphasising forest rehabilitation and restoration as crucial strategies. The review further revealed an increasing research interest in these areas, particularly from 2019 to 2023, with notable contributions from Asian and South American countries. Key policy recommendations from the literature highlight the importance of community participation, government support, and the utilisation of context-specific practices to enhance the effectiveness of forest rehabilitation and restoration efforts globally.
ii. Suitability models and remote sensing are increasingly used to map forest suitability, with significant growth in research since 2020, primarily using Landsat and the

Maximum Entropy (MaxEnt) model. Additionally, there is a research gap in developing countries, emphasising the need for more studies and advanced sensor technologies in these regions to support effective forest rehabilitation and restoration.

iii. The mapping of LULC change within the eThekwini Municipality from 2002 to 2022 revealed that XGBoost can outperform RF and SVM. Additionally, XGBoost is more efficient at discriminating vegetation and water bodies from other classes compared to RF and SVM, making it the most effective algorithm for mapping LULC changes within the eThekwini Municipality. The study identified significant class transitions in LULC cover from 2002 to 2022. Cropland and shrubland decreased, while grassland and impervious surface areas increased.

iv. Using remote sensing and machine learning techniques to assess land degradation in the eThekwini Municipality from 2000 to 2022, LightGBM was identified as the best model for predicting land cover change and SOC stock, which are key indicators of land degradation. LightGBM revealed a significant loss of forests and shrubland to cropland and built-up areas, particularly between 2015 and 2022. The findings also showed a notable decline in SOC stock, especially at the 20-50 cm depth, underscoring that the eThekwini Municipality is experiencing significant land degradation. These results highlight the critical role of remote sensing and machine learning techniques in informing policymakers and promoting sustainable land use practices to mitigate land degradation and support biodiversity conservation.

v. Using remote sensing and machine learning techniques to map the distribution of natural forests in the eThekwini Municipality, LightGBM emerged as the most effective algorithm, revealing a substantial increase in natural forest cover from 2015 to 2023. The superior performance of Landsat 8 and Landsat 9 data over Landsat 7, attributed to their improved radiometric resolution was highlighted. Additionally, the analysis identified the red band (B4), Normalised Difference Vegetation Index (NDVI), and Green Normalised Difference Vegetation Index (GNDVI) as critical factors for accurate natural forest mapping.

vi. Developing a method to evaluate current and future forest suitability in eThekwini Municipality using various data sources, LightGBM was the most effective model, highlighting the importance of rainfall patterns. Currently, 30% of the area is suitable for forests, concentrated in the central region of the municipality. Future suitability is predicted to be highest in the mountainous north-western region due to increased rainfall and lower temperatures. Even under the most challenging climate scenario, this area is predicted to be highly suitable.

Ultimately, this study has demonstrated the significant potential of remote sensing and machine learning in advancing forest rehabilitation and restoration efforts. By implementing the recommended strategies, future research can further enhance the sustainability and resilience of forest ecosystems, ultimately contributing to the preservation and management of vital natural resources in the face of ongoing environmental challenges.

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