Using Machine Learning Algorithms to Develop a Remotely-Sensed Framework for Drought Monitoring in Different Climate Regions in South Africa

by

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A thesis submitted to the Faculty of Natural Science, University of the Western Cape, in academic fulfilment of the requirements for the degree

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ABSTRACT

Droughts pose a significant threat to rainfed smallholder farming systems, particularly in regions with varying climatic conditions. This study aimed to develop a spatial modelling framework for assessing the occurrence and frequency of droughts across different climatic zones, with a focus on rainfed smallholder farms. Specifically, this study sought to develop a spatial modelling framework for assessing the occurrence and frequency of droughts on rainfed smallholder farms across different climatic zones in South Africa i.e. the Limpopo, North West, Mpumalanga and Gauteng Provinces. By integrating satellite-derived vegetation indices, specifically the Normalised Difference Vegetation Index (NDVI) and the Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), with state-of-the-art machine learning algorithms, the accuracy of drought mapping in rainfed smallholder farms was significantly enhanced. The study employed the Gradient Boosting Decision Tree (GBDT), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF) and Transformer models to capture complex spatial and temporal patterns of drought dynamics. The results showed that the Transformer model was effective in detecting rainfed smallholder farms (with an Overall Accuracy of 0.85 and a mean Intersection over Union (IoU) of 0.86). The study further evaluated the agricultural and meteorological drought conditions from 2004 to 2023. The Vegetation Condition Index (VCI) from SPOT VEGETATION 1 and PROBA-V data and the Standardised Precipitation Index (SPI) from CHIRPS data were computed. The results showed that the Limpopo Province experienced the most frequent and severe droughts, with 15 years of severe drought recorded over the 19-year study period. Overall, these results underscored the vulnerability of the study area to recurring droughts and highlighted the need for frequent assessment, monitoring and forecasting. The accurate forecasting of drought events is essential for the formulation of effective climate adaptation and mitigation strategies, particularly in vulnerable regions. This study further evaluated the application of the Maximum Entropy (MaxEnt) model to predict the Multivariate Standardised Precipitation Index (MSPI) for the years 2034, 2044, 2054, 2064 and 2074 under the Representative Concentration Pathways (RCP) 4.5 and 8.5 scenarios. The findings revealed significant spatial and temporal variations in drought occurrence probabilities, with an increase from 0.68 in 2034 to 0.82 in 2074 under RCP 4.5. This indicates an intensification of the drought conditions over time. This study enhances drought monitoring using remote sensing and machine learning, offering insights for climate resilience and support for vulnerable communities.

PREFACE 1

This research study was conducted in the Department of Earth Sciences, in the Faculty of Natural Sciences, at the University of the Western Cape in South Africa, from February 2022 to July 2025, under the supervision of Professor Timothy Dube.

Full Name: Trisha Deevia Bhaga **Signature:** ……………….

Date: 17 July 2025

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

Full Name: Prof Timothy Dube **Signature**: ……………..

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Date: ……………….

DECLARATION

I declare that this thesis, entitled **"Using Machine Learning Algorithms to Develop a Remotely-Sensed Framework for Drought Monitoring in Different Climate Regions in South Africa"** is my own work, that it has not been submitted before, for any degree or examination, at any other university, and that all the sources that I have used, or quoted, have been indicated and acknowledged by means of complete references.

Full name: Trisha Deevia Bhaga

Signed: **Date**: 17 July 2025

PUBLICATIONS AND MANUSCRIPTS

The following manuscripts have been submitted and published in international, peer-reviewed journals, or presented at a local and international conference. The co-authors played a role in reviewing and improving the manuscripts, with my contribution being the largest:

1. **Bhaga, TD,** Dube, T, Shekede, MD and Shoko, C (2024). A review on the methods of drought monitoring using remote sensing and its impacts on rural farmers across sub-Saharan Africa. *Remote Sensing Applications: Society and Environment*. [Under review - RSASE-D-24-00589]

2. **Bhaga, TD,** Dube, T, Shekede, MD and Shoko, C (2024). Leveraging the Google Earth Engine platform to delineate smallholder farms in the different semi-arid climate regions of South Africa. *International Journal of Applied Earth Observation and Geoinformation*. [Under review - JAG-D-24-04323]
3. **Bhaga, TD,** Shekede, MD, Shoko, C and Dube, T (2024). Assessing drought frequency and probability across different regions in South Africa using satellite-derived metrics: a nineteen-year analysis. *Geomatics Natural Hazards and Risks*. [Under review -258955065]
4. **Bhaga, TD,** Shekede, MD, Shoko, C and Dube, T (2025). Modelling the occurrence of droughts in South Africa using the Maximum Entropy model. *Journal of Arid Environments.* [Under review - JAE25-113]

The research was presented at the following conferences:

1. **Bhaga, TD**, Dube, T, Shekede, MD and Shoko, C (27-29 June 2023). *A review of the methods and impacts of droughts on predominantly rainfed rural farmers across different climatic regions in sub-Saharan Africa.* University of Novi Sad, Serbia, International Conference on Hydro-Climate Extremes and Society [Online].

2. **Bhaga, TD**, Dube, T, Shekede, MD and Shoko, C (6 October 2023). *Assessing the performance of remotely-sensed data and machine learning algorithms in the Google Earth Engine to delineate rainfed smallholder farms in different climate regions of South Africa.* University of Cape Town, Cape Town, GISSA.

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DEDICATION

This thesis is dedicated to:

Sharmela Bhaga (my Mother),
Arvin Bhaga (my Father),
Meenal and Rekha Bhaga,
and
Prinal Moodley

Your support and encouragement have been invaluable.

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ABBREVIATIONS

ANOVA	Analysis of Variance
AVHRR	Advanced Very High-Resolution Radiometer
CNN	Convolutional Neural Network
DEM	Digital Elevation Model
ET	Evapotranspiration
EVI	Enhanced Vegetation Index
GBDT	Gradient Boosting Decision Tree
GEE	Google Earth Engine
MaxEnt	Maximum Entropy
MNDWI	Modified Normalised Difference Water Index
MODIS	Moderate Resolution Imaging Spectrometer
MSAVI2	Modified Soil-Adjusted Vegetation Index 2
MSI	Multi-spectral Imager
MSPI	Multivariate Standardised Precipitation Index
NDVI	Normalised Difference Vegetation Index
NDWI	Normalised Difference Water Index
NIR	Near Infrared
OA	Overall Accuracy
OLI	Operational Land Imager
PA	Producers' Accuracy
RF	Random Forest
RMSE	Root Mean Square Error
SDGs	Sustainable Development Goals
SPI	Standardised Precipitation Index
SPOT	Satellite Pour l'Observation de la Terre
SVM	Support Vector Machine
UA	User's Accuracy
USGS	United States Geological Survey
VCI	Vegetation Condition Index

CHAPTER ONE

GENERAL INTRODUCTION

1.1 Background and Problem Statement

Africa has a large population of rainfed smallholder farmers, and its economy is highly-dependent on agriculture (FAO, 2021), which is a vital sector in sub-Saharan Africa for employment and food production (Dubovyk et al., 2015; Idris, 2020; Enongene, 2024). The World Bank estimates that 60% of sub-Saharan Africans who live in rural regions rely on rainfed agriculture for their household income (Raji et al., 2024). However, due to high rainfall variability related to climate change, smallholder farming systems are exposed to recurrent droughts, which negatively affect crop and livestock production.

Climate change is expected to increase the frequency and duration of droughts across a number of regions, including Africa (West et al., 2019; Ruwanza et al., 2022; Raji et al., 2024). Droughts will affect 75% of the world's population by 2050 (United Nations Convention to Combat Desertification (UNCCD), 2022). The smallholder agricultural sector is usually affected by recurrent droughts, which results in significant crop and livestock losses, thereby threatening livelihoods (Ebobenow & Arreyndip, 2021; Zobeidi et al., 2021; Maziya et al., 2024). Furthermore, drought-related environmental deterioration and soil erosion can lower the fertility and production of the land, which worsens the effects on farmers. Consequently, research on the effects of droughts on rural farmers is necessary to provide critical knowledge for enhancing farming methods, for making informed decisions, as well as for reducing the adverse impacts of drought on their livelihood sources.

Mapping smallholder rainfed farms has been a major challenge in a number of agricultural settings across the globe, due to a number of challenges, such as the field size, satellite resolution and landscape heterogeneity (Govender et al., 2022; Cloete et al., 2024; Heiss et al., 2025). Smallholder farms are smaller than commercial farms, which makes it difficult to detect individual smallholder farms by using moderate resolution (10 m to 30 m) satellite imagery (Feng et al., 2019; Raihan, 2024). Spectral mixing is also a challenge when mapping and detecting smallholder farms, since a single pixel may contain a number of different land cover types (Tufaner & Ozbeyaz, 2020; Valadao et al., 2021; Heiss et al., 2025). High resolution satellite data (<5 m) can overcome these challenges; however, these data are expensive and have limited temporal resolutions, which limits their applicability for continuous monitoring and assessment (Huang et al., 2018; Raihan 2024; Heiss et al., 2025).

Moreover, the diverse cropping methods that are commonly practised in smallholder farming, such as intercropping, add to the complexity, because distinguishing between different crop types becomes challenging due to their similar spectral signatures (Mpakairi et al., 2022; Heiss et al., 2025). Further complexities occur when smallholder farms in the same region have different planting and harvesting times, because vegetation indices change unpredictably over time (Mpakairi et al., 2023; Maziya et al., 2024). The presence of natural vegetation, settlements and infrastructure within these landscapes makes it difficult to differentiate croplands from the surrounding land cover types (Mpakairi et al., 2023). Traditional drought-monitoring methods, such as ground-based observations and rainfall station data, are often sparse and inconsistent and they lack the geographic coverage that is required to identify localised drought conditions in smallholder farming systems (Brown & McCarty, 2017; Mpakairi et al., 2023; Maziya et al., 2024). The lack of a drought monitoring framework results in early warning systems being inaccurate and underdeveloped, which then delays and affects possible interventions, such as targeted drought relief and irrigation support (Enongene, 2024). In addition, previous studies have focused mostly on mapping croplands with a large spatial scale, such as commercial farms, due to their homogeneity, which makes commercial farms easier to map (Brown & McCarthy, 2017; Moomen et al., 2024). There is less focus on the mapping of smallholder farms, despite their contribution to food security (Moomen et al., 2024). Commercial farms have large, uniform fields and are easily detected by using moderate-resolution satellite data, whereas smallholder farms are often more diverse and smaller in size (Moomen et al., 2024). The lack of knowledge about smallholder farms can cause inaccuracies in national and regional agricultural assessments, and it can lead to misinformed policy decisions and resource allocations (Brown & McCarthy, 2017; Raihan, 2024; Heiss et al., 2025).

Technological advancements have led to an improvement in remote sensing techniques (Huang et al., 2018), which can therefore be used for various reasons, such as observing climate changes, drought monitoring, land cover changes and land use, monitoring surface water bodies, crop productivity, computing evapotranspiration and identifying crop conditions (Huang et al., 2018). Remote sensing technology is an alternative to traditional, physically-based monitoring and provides effective, low-cost and repeatable observations in a timely manner. In addition, remotely-sensed data can be used in areas that are difficult to access and overcome the issue of inconsistency in data collection, due to vandalism or the poor maintenance of equipment (Valadao et al., 2021; Bhaga et al., 2020).

The use of machine learning algorithms has been on the rise of late, as they can be used to monitor various conditions in a more advanced manner. In addition, these machine learning algorithms allow for the better extraction of environmental information from remotely-sensed data (Tufaner & Ozbeyaz, 2020). Machine learning methods require less inputs, are less complicated than dynamic and physical methods and achieve more accurate results (Mokhtar et al., 2021; Liu et al., 2020). Combining machine learning, artificial intelligence and high-resolution satellite imagery can improve the classification of smallholder farms (Raihan, 2024). The integration of radar data, such as Sentinel-1, improves mapping accuracy by offering cloud-penetrating capabilities, which is a critical feature for monitoring areas with regular cloud cover (Huang et al., 2018; Liu et al., 2020). Besides this, these technologies can transform early warning systems for drought monitoring (Huang et al., 2018; Bhaga et al., 2020). In the light of South Africa's high climate variability and the increasing frequency of severe droughts, particularly in rainfed smallholder farming regions, there is a critical need for efficient and reliable drought-monitoring frameworks. This study aims to develop a spatial modelling framework to assess the occurrence and frequency of droughts across different climatic zones, with a focus on rainfed smallholder farms. By integrating satellite-based remote sensing with advanced modelling techniques, this research seeks to enhance early drought detection and to improve agricultural resilience. The findings will contribute to national and global efforts in climate adaptation and food security, and they will align with the Sustainable Development Goals (SDGs), which include SDG 1 (No Poverty), SDG 2 (Zero Hunger), SDG 3 (Good Health and Well-being), SDG 10 (Reduced Inequality), SDG 13 (Climate Action) and SDG 15 (Life on Land), as well as the African Union's Agenda 2063. Ultimately, this study will provide a scientifically-robust, policy-relevant and spatially-explicit framework for drought monitoring, and it will offer valuable insights for smallholder farmers, policymakers and researchers who are working towards climate resilience and agricultural sustainability.

1.2 Research Question

To what extent can multisource remote-sensing data, coupled with climate data and drought and water indices, enhance the understanding of rainfed smallholder farms under drought conditions?

1.3 Aims and Objectives

1.3.1 Aim

The study aims to develop a spatial modelling framework to assess the occurrence and frequency of droughts across different climatic zones, with a focus on rainfed smallholder farms.

1.3.2 Objectives

The objectives of this study are:

- To review methods used to delineate rainfed smallholder farms and drought monitoring and impacts of droughts on predominantly rainfed farmers across different climatic regions;
- To assess the performance of multisource, remotely-sensed data and machine learning algorithms in delineating small-scale rainfed agricultural regions in different climatic regions of rural South Africa;
- To assess the frequency of drought occurrence at multiple temporal scales over a nineteen-year period across different ecological regions in South Africa, using satellite-derived metrics; and
- To model the occurrence of droughts in different climatic regions in South Africa by using the Maximum Entropy (MaxEnt) model for the period between 2034 and 2074.

1.4 Description of the Study Area

The study was conducted across three South African provinces, namely North West, Limpopo and Mpumalanga (Figure 1.1). These three provinces are distinguished by their own soil, topographical and climatic characteristics, which influence their agricultural output and processes. These provinces were selected, based on the presence of subsistence farmers and rural communities, as well as their climate, aridity and the frequency and probability of drought events. The variations in climate between the different provinces will be used to evaluate the use of remote sensing in different climatic zones. Provinces, like the North West and Limpopo, are prone to droughts, which have an adverse effect on rainfed rural farms in these regions (South African Weather Service, 2021). The North West Province experiences an average annual temperature of 28°C and is categorised as having a hot semi-arid climate (BSh) (Weather and Climate, 2024). The North West receives 540 mm of rain annually (South African Weather Service, 2021). Mpumalanga has a highland tropical climate with dry winters

(Cwb), summer rains (September to March) and an average annual precipitation of 69.93 mm (Weather and Climate, 2024). The average annual temperature is 21.78ºC, which is 0.56% warmer than the average temperature for the rest of South Africa (South African Weather Service, 2021). Limpopo's climate is classified as hot and semi-arid (BSh), with the majority of its rainfall occurring from November to February (Weather and Climate, 2024). Limpopo's average daily maximum temperature is 30°C, and the region gets about 55.48 mm of rain every year (South African Weather Service, 2021).

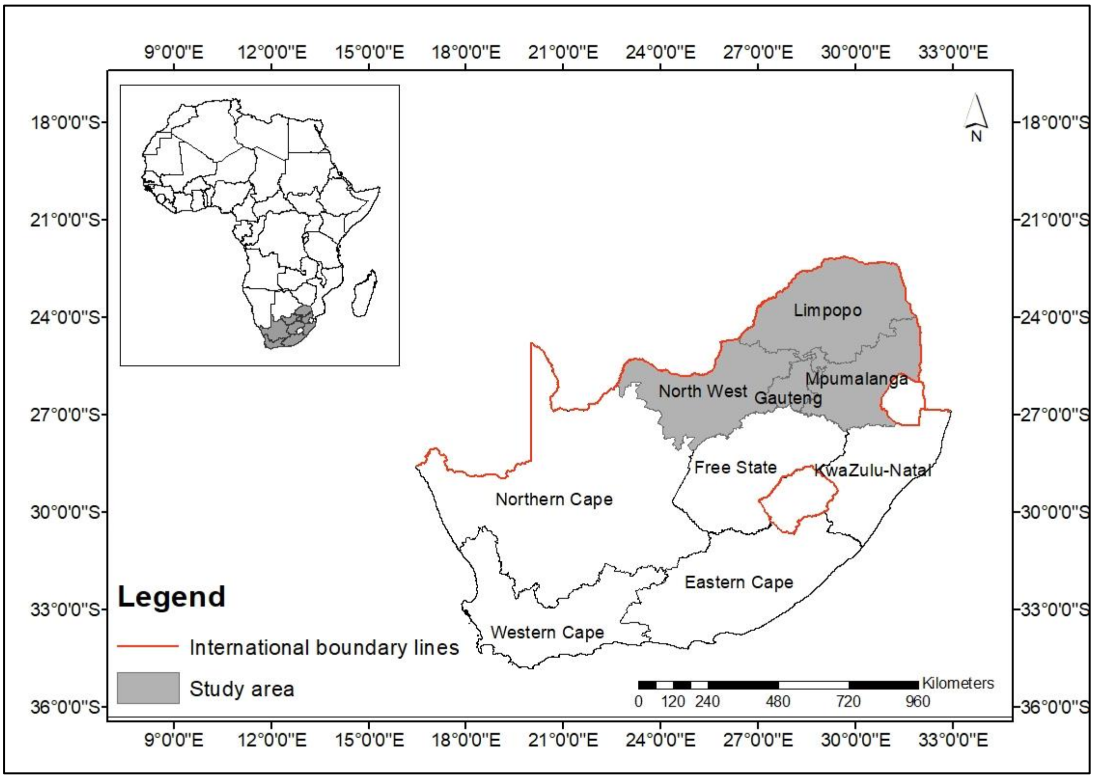

Figure 1.1 Study area map

1.5 Thesis Structure

The following chapters, Chapters Two to Five, form the core of the thesis and address the research objectives. Chapter Six presents the primary findings and their ramifications. This study consists of four papers that are under review in international peer-reviewed journals. Every chapter consists of its own independent Introduction, Materials and Methods, Results and Discussion sections. There may be repetition and overlap in certain sections of this thesis, despite efforts to adhere to a general style. The structure is as follows:

Chapter One introduces the general background and study gaps, and it highlights the importance of mapping and delineating rainfed rural farms and understanding the impact of droughts on these areas. This is followed by the research questions, aim and objectives.

Chapter Two reviews the current remote sensing methods, as well as the applications and challenges in delineating rainfed smallholder farms in sub-Saharan Africa.

Chapter Three explores the use of remote sensing and advanced machine learning techniques to delineate and map rainfed smallholder farms in the Limpopo, Mpumalanga, North West and Gauteng Provinces of South Africa. A framework for delineating and mapping rainfed smallholder farms is developed and tested in these provinces. Although this serves as a provincial demonstrator, the framework should be transferrable to regions with the same climate in other countries of sub-Saharan Africa.

Chapter Four assesses the geographical extent, the probability of occurrence and the magnitude of drought conditions over rainfed smallholder farms across the Limpopo, Mpumalanga, North West Provinces of South Africa. Gauteng was not included in this chapter, due to the low presence of rainfed smallholder farms. This study is an assessment of remote sensing applications to detect droughts in these regions over 19 years.

Chapter Five uses machine learning methods to model and predict the occurrence of droughts by using the Maximum Entropy (MaxEnt) method. Modelling the occurrence of droughts improves the development of early warning systems, which is essential for mitigating the impacts of drought. Drought models can assist with developing water management policies and improve agricultural practices.

Chapter Six synthesises the key findings of Chapters Two to Five, situating them within the broader context of mapping and delineating rainfed smallholder farms and the impacts of droughts on these farms. It concludes with future research directions and recommendations.

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CHAPTER TWO

LITERATURE REVIEW

Abstract

The occurrence and frequency of droughts have a dire impact, especially on rural farmers in arid and semi-arid regions, who depend on rainfed agriculture. The agricultural sector in sub-Saharan Africa is a vital part of the economy and is severely impacted by drought. With studies indicating that droughts are set to become more frequent due to climate variability, semi-arid environments, like sub-Saharan Africa, need to develop drought prediction and warning systems timeously, in order to minimise their impacts, such as the loss of vegetation and livestock, food insecurity and famine. Hence, there is an urgent need to delineate rural farms by using remote sensing methods, to evaluate the impacts of drought on rural farmers and to review the remote sensing methods used for drought monitoring and their applicability in sub-Saharan Africa. Therefore, this paper provides a detailed review on the progress of the various remote sensing methods used to delineate rural farms and for drought monitoring in sub-Saharan Africa, and it highlights the impacts of drought on rural farmers. The research gaps in drought monitoring are also highlighted to provide insights for future studies and to assist in understanding droughts and preparing for them. This will help rural farmers with drought adaptation strategies and water resource managers with proactive decision-making, in order to alleviate the impacts of drought and to achieve the African Union Agenda 2063 goals.

Keywords: Drought impacts, drought vulnerability, GIS, remote sensing, rural farmers.

This chapter is based on the following manuscript:

Bhaga, TD, Dube, T, Shekede, MD and Shoko, C. (2024). A review on methods of drought monitoring using remote sensing and its impacts on rural farmers across sub-Saharan Africa. *Remote Sensing Applications: Society and Environment*. [Under review - RSASE-D-24-00589]

2.1 Introduction

Drought is an extreme hydro-climatological phenomenon that occurs frequently around the world and has an impact on several industries, including agriculture (West et al., 2019). For instance, according to the Intergovernmental Panel on Climate Change (IPCC) 2012 Report, there were several catastrophic droughts in North America, South America, Europe, Africa, Asia and Australia during the 1950s. From 2012 to 2018, there was a severe drought in North-East Brazil (NEB) in South America (Marengo et al., 2021) and, since 95% of the region's agriculture is rain-fed, the six-year drought that followed worsened the poverty and food insecurity, forcing 96% of the NEB region into a state of emergency (Marengo et al., 2021). India, which depends mostly on rainfall for its cultivated land, suffered from three significant droughts in 2002, 2009 and 2012, which had a negative effect on the country's agricultural sector (Udmale et al., 2014). Due to the 2012 West African drought, subsistence farmers had to migrate, sell their animals and alter their agricultural practices (Adaawen, 2021).

Climate change is expected to cause droughts to occur more frequently and for longer periods of time (West et al., 2019). According to future projections, they will affect 75% of the world's population by 2050 (United Nations Convention to Combat Desertification (UNCCD), 2022). The IPCC 2012 Report expects the occurrence of droughts to increase in Africa, due to climate change (Ruwanza et al., 2022); the agricultural sector is usually affected by their occurrence, as water shortages cause the loss of crops and cattle, therefore threatening their assets and income (Zobeidi et al., 2021).

In many developing nations, agriculture is a major contributor to the Gross Domestic Product the (GDP) (Ebobenow & Arreyndip, 2021). According to the UN Department of Economic and Social Affairs, approximately 3.4 billion people (45% of the global population) live in rural areas and work in agriculture (United Nations Department of Economic and Social Affairs Social Inclusion, 2021; Adeyemi et al., 2023). Smallholder farmers, also referred to as rural farmers, work on little land-parcels and frequently use family labour. Roughly 80% of the food in developing nations and one-third of the food worldwide are thought to be produced by rural farmers (Food and Agriculture Organisation of the United Nations, 2021). India has a sizeable rural farming population and a large agricultural sector (Pattnaik & Lahiri-Dutt, 2022). Many people rely on agriculture as their primary source of income, and in the Indian state of Gujarat, 86% of women stated that this was their primary occupation (Pattnaik & Lahiri-Dutt, 2022). Despite the country's growing urbanisation, China still has a large rural farming population that relies heavily on agriculture and it ranks among the top producers of a wide range of agricultural goods, including rice, wheat, corn, cotton, vegetables, soybeans and tea (Hu et al., 2022). Brazil is well-known for exporting poultry, cattle, veal, coffee, soybeans and sugarcane (de Silva e Souza & Gomes, 2023) and, according to the 2017 agricultural census, Brazil has 5 073 324 rural farms that employ over 15 million people (IBGE, 2019). There are many rural farmers in Africa, and the continent's economy depends heavily on agriculture (Food and Agriculture Organisation of the United Nations, 2021). Agriculture is a vital sector for employment and food production in sub-Saharan Africa (Dubovyk et al., 2015). The World Bank estimates that 60% of sub-Saharan Africans who live in rural regions rely on agriculture for their household income. Nigeria has a significant agricultural sector that employs a large portion of the population, which boosts the economy and accounted for 21.2% of the nation's GDP in 2017 (Owoicho et al., 2023). In Ethiopia, smallholder farmers account for 90% of agricultural production and they use 95% of the country's farmland (Haile et al., 2022). Rural farmers in Kenya employ 70% of the rural population and 40% of the total population and the agricultural sector contributes 33% of Kenya's GDP (USAID, 2023). The FAO estimates that approximately 17% of Zimbabwe's GDP comes from the agricultural sector, which employs roughly 60-70% of the country's workforce. In contrast, 35%-38% of the GDP comes from cattle farming. In South Africa, agriculture makes up 14% of the country's indirect GDP and contributes 3% of the country's GDP directly (Meza et al., 2021). Approximately 14% of people either directly, or indirectly, depend on the agricultural sector for their work and income (Meza et al., 2021). In South Africa, there are approximately four million subsistence farmers who cultivate between 75 and 80% of the food consumed by home-owners on 13% of the country's agricultural area, which contributes to its food security (Ruwanza et al., 2022; Hawkins et al., 2022). Given that the world's population is expected to exceed 9.7 billion by 2021, a 60% increase in food production is necessary to meet the increased demand for food (FAO, 2021). As a result, sustainable and effective rural agricultural practices are essential.

When faced with drought conditions, rural farmers frequently encounter major obstacles (Ebobenow & Arreyndip, 2021) and severe consequences, such as crop failure from low precipitation, pests and diseases brought on by the dry weather, decreased crop yields and the reduced productivity of the livestock, which directly affect their means of income. Drought-related environmental deterioration and soil erosion can lower the fertility and production of the land, which worsens the effects on farmers. Consequently, research is necessary on the effects of drought on rural farmers, in order to provide them with the knowledge they need to modify their farming methods, to make educated decisions and to reduce the adverse impacts of drought on their livelihood sources.

Remote sensing offers a unique opportunity for providing information about drought detection and for identifying rural farms, where other monitoring techniques are not available (Varghese et al., 2021; Alahacoon & Edirisinghe, 2022; Ndayiragije & Li, 2022). There are a number of published research articles on the identification of rural farms and the mapping of drought occurrence using remotely-sensed data in different climatic zones (Persello et al., 2019; Mashaba-Munghemezule et al., 2021; Mei et al., 2022; Orimoloye et al., 2022; Zhou et al., 2022). For example, Persello et al. (2019) conducted a study in Nigeria and Mali by using deep learning to delineate smallholder farms. They used WorldView-2/3 images and the Fully Convolutional Networks (FCN) for pixel-wise classification. The FCN method achieved F score accuracies higher than 0.7 and 0.6 and they outperformed traditional methods. It used cutting-edge methods to delineate fields in rural agricultural areas; however, it used data that were very expensive, which hindered its applicability. A study by Mashaba-Munghemezule et al. (2021) utilised Sentinel-1 and Sentinel-2 data to map rural maize farms in the Makhuduthamaga District in Limpopo, South Africa. The study used Random Forest (RF), Support Vector (SVM) and model stacking (ST). The Sentinel-1 results performed the worst and achieved Overall Accuracies (OA) that varied between 67.9% to 84.5%, while RF achieved the lowest accuracy. On the other hand, Sentinel-1 and Sentinel-2 integrated data achieved the highest accuracies in mapping rural maize farms, with an OA and F score of 0.99 and with SVM performing the best. This study did not compute red-edge indices, which is known to detect vegetation accurately. A study by Mei et al. (2022) tested the applicability of mask region-based Convolutional Neural Network (Mask R-CNN) in Bihar and Uttar Pradesh in India to map rural farm boundaries using WorldView-3 data. The Mask R-CNN achieved F1 Scores of more than 0.72 and AP values of more than 0.66 for the detection and delineation of rural farms. However, the Mask R-CNN performed poorly in areas where farm boundaries were not visible in the image, or where they were obstructed by trees or shadows and in areas where fields were irregularly shaped, despite using high-resolution data that are not freely available. A study by Orimoloye et al. (2012) that was conducted in the Free State Province in South Africa, used regression-based models by using MODIS and the Vegetation Condition Index (VCI) to identify drought conditions. Google Earth Engine (GEE) was also used to perform a land-use classification during 2001, 2015 and 2020, using Landsat-7 and Landsat-8 data. The Multiple Regression (MR), Principal Component Regression (PCR), Partial Least

Square Regression (PLSR), Random Forest Regression (RFR), Support Vector Regression (SVR) and Multivariate Adaptive Regression Splines (MARS) were computed for this study. The VCI was able to detect drought conditions in the area. The study achieved an OA of 0.86, 0.95 and 0.93 for 2001, 2015 and 2020, respectively. The land-use classification map indicated that grasslands and barren surfaces had the highest land cover and that cultivated lands decreased drastically in size, due to the occurrence of droughts. The RMSE results indicated that the best model for VCI prediction in the study area is the PLSR. Zhou et al. (2022) conducted a study in the Shandong Province, which is situated in China. It aimed to assess the performance of three machine learning algorithms, namely, the Bias-corrected Random Forest (BRF), eXtreme Gradient Boosting (XGBoost) and Support Vector Machine (SVM) to estimate the Standardised Precipitation Evapotranspiration Index (SPEI). The algorithm with the most accurate performance was used to map the spatial distribution of the Standard Precipitation Evapotranspiration Index (SPEI) in drought years, in order to simulate drought conditions in the study area from 2002 to 2020. The BRF SPEI-3 performed the best and achieved a R^2 value of 0.96 and an RMSE value of 0.19; however, the SVM and XGBoost performed similarly and achieved R^2 values of 0.72 and 0.74, respectively, and an RMSE of 0.51 and 0.49, respectively. The results of the study were able to identify droughts that occurred in 2002-2003, 2006-2007 and 2010-2011, and the methods were able to identify low-intensity droughts that occurred between 2012 and 2019, which coincided with the in-situ data. This study showed the ability of BRF to detect droughts; however, the BRF occasionally underestimated the drought severity during extreme drought conditions.

Very little research has been conducted in sub-Saharan Africa on the use of machine learning algorithms for drought monitoring and rural farm detection. Food security and water security problems will worsen, agricultural systems will fail, and rural farmers will suffer, if efficient frameworks for drought monitoring or early warning systems are not put in place. Using the previously-mentioned data, this research aims to present a thorough analysis of the advancements made in remote sensing for the identification of rural farms and the detection of droughts in sub-Saharan Africa. This will subsequently provide water resource managers and rural farmers with proactive decision-making techniques for drought adaptation, in order to lessen the effects of a drought. This paper first highlights the literature used for this research. This is followed by the remote sensing methods that were used to delineate rural farms and the impacts of drought on rural farmers across different climatic regions across the globe. Thereafter, the available approaches for delineating rural farms and drought monitoring, using remote sensing and GIS, will be discussed. This project is a step toward coming up with smart technologies that yield critical information for scientists to make recommendations and for resource managers to draw up in-field decisions. Therefore, it will contribute to achieving Sustainable Development Goals (SDGs) 1 (no poverty), 2 (zero hunger), 3 (good health and well-being), 10 (reduced inequality), 13 (climate Action) and 15 (life on land), as well as the African Union Agenda 2063 Goal 1, which is to ensure a high standard of living, quality of life and well-being for all citizens, as well as Goal 3, namely, to ensure healthy and well-nourished citizens.

2.2 Methods and Materials

Literature search

This study applied a systematic review methodology to identify the literature related to the impacts of drought on rural farmers in sub-Saharan Africa across different climatic regions. Research papers were searched by using the Web of Science, Scopus and Science Direct, which are data bases linked to Google Scholar. The search criteria consisted of journal articles that were published between 2000 and 2023. The search term combinations that were used were as follows: (i) “drought monitoring AND remote Sensing OR GIS,” (ii) “Drought modelling AND Remote Sensing OR GIS,” (iii) “Drought management AND Remote Sensing OR GIS,” (iv) “Drought monitoring framework AND Remote Sensing OR GIS,” (v) “Drought impacts in arid and semi-arid regions,” (vi) “Drought impacts on rural farmers,” and (vii) “Drought AND rural farmers”. A total of 312 references from the Web of Science, 4 968 from Scopus and 2 080 from Science Direct were retrieved (n = 7 360) (Figure 2.1). These publications were exported to Endnote for further screening. Duplicates were then excluded, which amounted to 2 384 articles (n = 4 976). These articles were then analysed to ensure that the studies applied GIS or remote sensing for drought monitoring and that they evaluated the impacts of droughts on rural farmers, and a total of 1 422 suitable articles were retrieved.

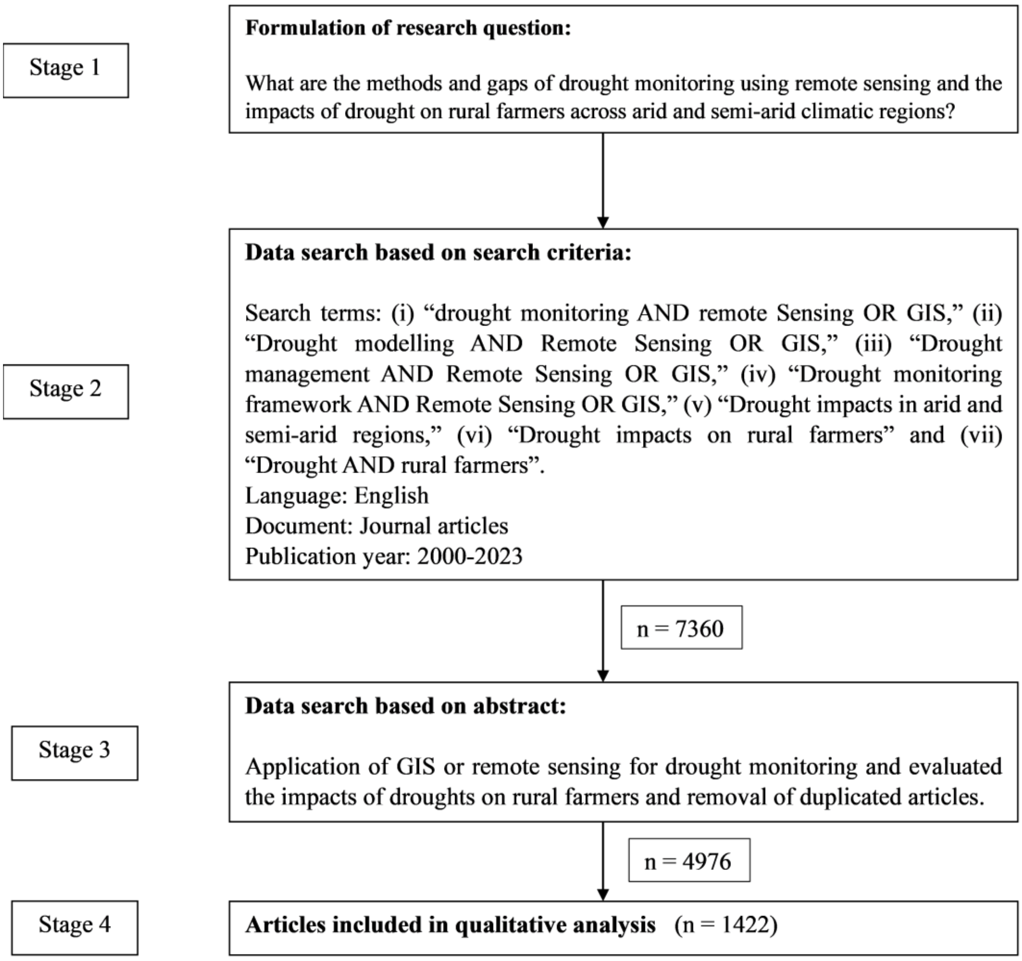

Figure 2.1 Flow diagram for the articles considered in this review

2.2.1 Remote sensing application in delineating rural farms

Satellite imagery is a commonly-used satellite data source that is used to delineate rural farms. These photos are processed to extract useful data regarding changes in the landcover and use, as well as other aspects, including farm boundaries, crop health and agricultural land use. Delineating farm boundaries and keeping an eye on farm conditions are two uses for the valuable information that multispectral and hyperspectral sensors, such as MODIS, Landsat-8 and Sentinel-2, may provide regarding agricultural land usage, crop health and vegetation indices (Munghemezulu et al., 2021). Because GPS enables precise object tracking and placement, it is a frequently-utilised technique in mapping and surveying. By recording the coordinates of particular locations, or by following the perimeter of a farm, GPS receivers can be used to draw boundaries around rural farms (Kondo et al., 2014). GIS combines attribute data with geographical data, in order to generate maps and analyse spatial relationships (USGS, 2023). By combining data from satellite photography, aerial surveys and ground-based measurements, GIS analytic tools can be used to define rural farms and to produce precise maps that show their boundaries, farming practices, as well as other information (Munghemezulu et al., 2021).

In order to determine farm boundaries and evaluate surface features, LiDAR sensors collect precise elevation data and produce high-resolution Digital Elevation Models (DEMs) (Fujihara et al., 2020; Magidi et al., 2021; Orimoloye et al., 2022). Ground-based sensors can give crucial information about the farm boundaries, soil conditions, moisture levels, temperature and other climatic factors that affect agricultural productivity (GeoPard Agriculture, 2023). Examples of these sensors include electronic, optical, mechanical and location sensors. The particular objectives and specifications of the farm delineation project determine which sensors should be used. To get precise results, a mix of sensors and data-integration methods is frequently used. Satellite imagery for agricultural uses is available from several satellite missions, including their data acquisition characteristics and associated costs, which are included in Table 2.1. The most common satellite imagery that is used includes the Landsat programme, Sentinel-2, Moderate Resolution Imaging Spectroradiometer (MODIS), Planet, DigitalGlobe, PlanetScope and RapidEye (Table 2.1).

Table 2.1 Satellite missions used in previous studies to delineate rural farms

Satellite name	**Operator**	**Pixel size (m)**	**Spatial resolution**	**Temporal resolution (days)**	**Data availability**
Airbus SPOT	Airbus Defence and Space	1.5, 6, 10, 20	High	26	Expensive
Landsat TM	USGS	30	Medium	16	Freely available
Landsat ETM+	USGS	30	Medium	16	Freely available
Landsat MSS	USGS	80	Low	180	Freely available
Landsat OLI	USGS	30	Medium	16	Freely available

MODIS	National Aeronautics and Space Administration (NASA)	500, 1000	Low	1	Freely available
PlanetScope	Planet	3	High	1	Expensive
RapidEye	BlackBridge (now known as Planet Labs)	5	High	5.5	Expensive
Sentinel-1	European Space Agency (ESA)	5	High	12	Freely available
Sentinel-2	ESA	10, 20, 60	High	5	Freely available
SPOT	Airbus Defence and Space	10, 20	High	26	Expensive
WorldView-1; 2; 3; 4	DigitalGlobe	0.50; <1; 1.4; 1.24	High	1.7; 1.1	Expensive

2.3 Results

2.3.1 Impacts of drought on rural farmers across sub-Saharan Africa

The impacts of drought vary in space, over time and, therefore, effective drought prediction, coping and adaptation strategies need to be developed. However, the impacts of a drought are severe in arid and semi-arid regions and these regions are often the most ecologically, socially and politically marginalised (Quandt, 2021). Droughts can have a catastrophic impact on a region's environmental, social and economic conditions (Maybank et al., 1995).

2.3.1.1 Environmental and socioeconomic impacts of drought

Ecosystem processes are impacted by droughts (Mishra & Singh, 2010) and result in the loss of flora, water and grazing land (Ruwanza et al., 2022). According to Vetter et al. (2020), droughts can also lead to water contamination and a decrease in water quality. Table 2.2 shows the statistics of rural farming in sub-Saharan African countries. Zimbabwe is classified as having as having a hot semi-arid climate (BSh), with 67% of its population living in rural areas and 70% being involved in rural farming. South Africa has an Oceanic climate (Cfb), with 32% of its population living in rural areas and 17.2% being involved in rural farming. The socioeconomic effects of a drought include the poor effects on the peoples' physical and mental health, the financial ramifications and food insecurity, which is particularly problematic for rural farmers (Table 2.2) (Botai et al., 2016). According to studies by Fanadzo et al. (2021), Quandt (2021), Archer et al. (2022), Hawkins et al. (2022), Ntali and Lyimo (2022), Mungandani et al. (2022) and Adeyemi et al. (2023), droughts negatively affect the mental health of farmers and farm workers in Nigeria, South Africa, Ethiopia, the Cameroon and Zimbabwe. The Sahel and southern Africa regions have experienced more than 382 droughts since the 1960s (Shiferawa et al., 2014; Ruwanza et al., 2022). In the 1980s and in 2010, droughts in the Sudano-Sahelian zone of Cameroon had a significantly negative influence on the livelihoods and sustainability of the system (Ntali & Lyimo, 2022), while food production and the livelihoods of rural farmers in Uganda have also been impacted by drought (Table 2.2). Due to the drought in Zimbabwe, almost 3.5 million people lack access to food (Sharara et al., 2022), and rural farmers have financial challenges because agriculture is a major source of income for them (Table 2.2). From the 1970s to the 2020s, South Africa has experienced seven significant droughts that have had an impact on different regions (Sousa et al., 2018; Ruwanza et al., 2022). Droughts have a severely negative effect on the environment and on society; they affect the rural farmers' livelihoods and homes, as well as governmental policies (Mishra & Singh, 2010; Bahta & Myeki, 2022). Additional negative effects include a reduced income, migration, poor animal health, the loss of crops and animals, unemployment, the rising food costs and declining livestock and land values (Maybank et al., 1995; Shiferawa et al., 2014; Ruwanza et al., 2022). A study on the effects of drought was carried out in Yobe, Nigeria, by Hassan et al. in 2019. The environmental effects included lower water levels in lakes and other surface water bodies, the failure of crops and livestock losses. Food insecurity, resource-related conflicts and migration are just a few of the socioeconomic effects and the drought in Nigeria also resulted in famine and environmental refugees. Agriculture contributed to 18.4% of the GDP prior to the droughts, but to just 7.3% after the 1970 droughts, which resulted in extreme poverty and hunger. According to the study, farmers in drought-affected areas reported greater rates of mental health issues than farmers in non-drought-affected areas. The farmers' livestock and crops, as well as their livelihoods, were all impacted by the drought. Quandt (2021) examined the effects of drought on smallholder farmers in Kenya. The area saw negative effects on the ecosystem, such as a reduction in the river-flow, a decline in the number of cattle and agricultural activity, and an outbreak of human illness. The socioeconomic impacts experienced in the area included human hunger, death, conflict and the death of livestock. In an attempt to find adaptation strategies, many smallholder farmers found side-jobs outside of the agricultural field. Many farmers also depended on relief aid and food, changing their agricultural practices to casual labour and charcoal burning (Ruwanza et al., 2022). South Africa has also been greatly impacted by droughts. For instance, farming areas in the Province of the Eastern Cape, where water resources like dams and boreholes were over-abstracted, suffered grave consequences (Archer et al., 2022). Similarly, during the 2003 drought in the KwaZulu-Natal (KZN) Province, the water that was brought in by tankers only reached households along the major roads, and the tributaries, springs and boreholes near the Tugela River dried up (Vetter et al., 2020). In Mpumalanga, the average temperature increased by 0.5°C between 2000 and 2014, resulting in drought conditions and a shortage of fodder (Ebhuoma et al., 2020). In the Sekhukhune District of Limpopo, the drought caused low yields, a reduction in the amount of water available for domestic use, as well as a loss of vegetation (Mpandeli et al., 2015). Furthermore, because the majority of smallholder farmers in the Free State and North West Provinces rely on rainfall for their agricultural operations, both provinces experienced drought conditions in 2015-2016 (Botai et al., 2016). A additional 10 000 farms were impacted by the drought in the Northern Cape region, as their boreholes dried up and they lost crops and cattle (Bahta & Myeki, 2022). Fanadzo et al. (2021) conducted a significant study in the Western Cape that examined the effects of droughts on smallholder farmers. The results of this study showed that cattle theft and a lack of water led to confrontations along the West Coast. In addition to the occurrence of depression among smallholder farmers, this study also included reports of suicides. In the Western Cape region, a large number of farmers also moved, and according to farmers in the Eastern Cape (Nieu Bethesda, Graff Reinet, Cradock, Pearston and Murraysburg) the health of their livestock declined (Archer et al., 2022). According to farmers surveyed by Archer et al. (2022), there was little to no milk production, which resulted in a high lamb mortality rate and livestock losses.

In addition, rural farmers began using mixed cropping systems and adjusted their planting dates to match the weather changes. Poor stock, lower prices for livestock sales, as well as the need to purchase fodder for the animals to keep them in good health, all resulted in a loss of revenue.

The price of mohair fell by 30% for sheep farmers in Graaff Reinet, in the eastern Cape Province of South Africa, and the price of feedlot lambs decreased from R40/kg to R27/kg (Archer et al., 2022). Due to the loss of grass resources brought on by the 2015 drought in the uMzinyathi and uThukela districts, situated in KwaZulu-Natal, 28% of goats and 42% of cattle perished, which resulted in food insecurity throughout the province (Vetter et al., 2020). Ebhuoma et al. (2020) interviewed a large number of farmers in Mpakeni to investigate their vulnerability to the drought in rural Mpumalanga. The findings showed that a large number of farmers killed and sold their goats and cows in 2015 and 2017 because they were unable to keep them alive during the food scarcity, and because they had to buy pastures. The findings of research carried out by Maponya & Mpandeli in 2012 in the Province of Limpopo showed that the drought had an influence on food production and access to food, and that it also worsened the rural poverty in the region. The survey showed that the drought forced farmers in the Capricorn District to sell their cattle, which resulted in food insecurity. Drought conditions in 2014 affected mining operations, as well as livestock and grain production, in the Sekhukhune District of the Province of Limpopo (Mpandeli et al., 2015). According to a study by Maponya et al. (2021) in Gauteng, 75% of households reported food shortages, and many of them said they were unaware of the region's ongoing drought. In a different study, Botai et al. (2016) reported that farmers in the North West and Free State Provinces of South Africa lost cattle and crops because of the drought conditions, resulting in increased unemployment and food insecurity in these areas. In the Northern Cape of South Africa, a research study by Bahta and Myeki (2022) sought to determine the impact of drought on rural livestock farmers. The findings showed that the region's farmers experienced lung infections as a result of the dusty surroundings, and that animals in the area were more vulnerable to immune deficiencies, as they were not getting enough nutrients. The drought of 2019 resulted in roughly a 21% drop in the livestock prices. The most significant finding of these research was that smallholder farmers in sub-Saharan Africa are not drought resilient, because they lack ownership, financing and government assistance during dry spells.

The findings of these studies highlight the significance of understanding the progress and research gaps related to the impact of droughts on rural farmers in sub-Saharan Africa. These effects may be reduced by employing remote sensing technology, which will expedite future research and drought preparedness. Using remote sensing techniques will aid future studies and drought preparedness in a time-efficient and cost-efficient manner, which can help to alleviate the impacts of drought on rural farmers.

Table 2.2 Statistics of sub-Saharan African countries. Note: Djibouti is not included in sub-Saharan Africa, as it is handled administratively as part of the Middle East and North Africa. Population (in millions) based on UN statistics in October 2022

Country	**Köppen climate types**	**Land areas (km^2)**	**Population (in millions)**	**% Population living in rural area**	**% Population involved in rural farming**	**% contribution of rural farming to GDP**
Angola	Cwb (Sub-tropical highland oceanic climate)	1 246 700	34.504	33	85	9.5
Benin	Aw (Tropical savanna climate)	112 760	12.997	51	70	25
Botswana	BSh (Hot semi-arid climates)	581,730	2.481	28	28	2
Burkina Faso	BSh (Hot semi-arid climates)	273 600	22.101	69	80	25
Burundi	Aw (Tropical savanna climate)	25 680	12.551	86	90	35
Cameroon	Aw (Tropical savanna climate)	475 442	27.2	42	60	20
Cape Verde	BWh (Hot desert climate)	4 033	0.6	35	34.8	8
Central African Republic	Aw (Tropical savanna climate)	622 980	5.457	57	80	53

Chad	Aw and BWh (Tropical savanna climate and Hot desert climate)	1 259 200	17.180	76	80.5	25
Comoros	Am (Tropical monsoon climate)	1 861	0.822	70	60	30
Congo (Democratic Republic)	Aw (Tropical savanna climate)	2 267 050	95.894	54	70	20
Côte d'Ivoire	Aw (Tropical savanna climate)	322 462	27.48	49	60	25
Equatorial Guinea	Am (Tropical monsoon climate)	28 051	1.63	26	60	6.9
Eritrea	BSh and BWh (Hot semi-arid climates and Hot desert climates)	121 041	3.620	58	80	24
Eswatini (formerly known as Swaziland)	Cfa and Cfb (Humid subtropical climate and Oceanic climate)	17 364	1.16	77	70	9
Ethiopia	Cfb (Oceanic climate)	1 128 571	120.283	78	80	40
Gabon	Aw (Tropical savanna climate)	267 667	2.34	10	50	5
Gambia	Aw (Tropical savanna climate)	10 120	2.640	37	75	18

Ghana	Aw (Tropical savanna climate)	238 533	32.83	42	55	19.71
Guinea	Aw (Tropical savanna climate)	245 720	13.532	63	70	18
Guinea-Bissau	Aw (Tropical savanna climate)	28 120	2.061	55	80	35
Kenya	Aw (Tropical savanna climate)	582 646	55.1	71	70	33
Lesotho	Cfb (Oceanic climate)	30 360	2.281	71	80	6
Liberia	Am (Tropical monsoon climate)	96 320	5.193	47	70	31
Madagascar	Aw (Tropical savanna climate)	581 800	28.916	61	80	26
Malawi	Aw (Tropical savanna climate)	94 280	19.890	82	80	30
Mali	Aw and BSh (Tropical savanna climate and Hot semi-arid climates)	1 220 190	21.905	55	80	35
Mauritania	BWh (Hot desert climate)	1 030 700	4.615	44	50	16
Mauritius	Am (Tropical monsoon climate)	2 040	1.27	59	23	3.3

Mozambique	Aw (Tropical savanna climate)	786 380	32.077	62	80	25
Namibia	BSh and BWh (Hot semi-arid climate and Hot desert climates)	825 615	2.604	47	40	5.1
Niger	BWh (Hot desert climate)	1 266 700	25.253	83	80	40
Nigeria	Aw (Tropical savanna climate)	923 768	223.8	47	70	25
Rwanda	Aw (Tropical savanna climate)	24 670	13.462	82	75	33
Sao Tome and Principe	Aw (Tropical savanna climate)	960	0.223	25	70	15
Senegal	BSh (Hot semi-arid climate)	192 530	16.877	51	70	16
Seychelles	Af (Tropical rainforest climate)	455	0.1	42	22	2.14
Sierra Leone	Am (Tropical monsoon climate)	72 180	8.421	57	60	20
Somalia	BSh (Hot semi-arid climate)	627 340	17.066	53	70	75

South Africa (Democratic Republic)	Cfb (Oceanic climate)	1 221 037	60.6	32	17.2	2.14
Sudan	BWh (Hot desert climate)	1 868 000	45.657	64	80	40
Tanzania	Aw (Tropical savanna climate)	885 800	63.588	64	70	28
Togo	Aw (Tropical savanna climate)	54 390	8.645	57	60	40
Uganda	Aw (Tropical savanna climate)	200 520	45.854	74	70	25
Zambia	Cwa (Humid subtropical climate)	743 390	19.473	55	75	19
Zimbabwe	BSh (Hot semi-arid climate)	390 745	15.505	67	70	17

2.3.2 Initiatives that are aimed at aiding rural farmers affected by drought in sub-Saharan Africa

Several programmes and initiatives have been created to assist sub-Saharan African rural farmers who are impacted by droughts. These programmes, which are supported by a number of organisations like the World Bank, African Union, government ministries and the UN, range in their scope, from national to regional, and from continental to global. The goal of the World Bank's Sahel Irrigation Initiative is to build small-scale irrigation systems in the drought-prone Sahel area, which includes Burkina Faso, Chad, Mali, Mauritania, Niger and Senegal. The goal of this programme is to expand the Sahel's irrigated area, and that each participating nation will get a grant of US$25 million (The World Bank, 2023). The African Drought Risk and Development Network (ADDN) aims to improve the drought resilience of farmers in sub-Saharan Africa by promoting sustainable land management, water resource management and climate information services (Economic Commission for Africa, 2008). The African Drought Risk and Development Network (ADDN) seeks to increase the farmers' resilience to drought in sub-Saharan Africa (Economic Commission for Africa, 2008). The International Strategy for Disaster Reduction (ISDR) and the Dryland Development Center of the United Nations Development Programme (UNDP) provide funding for the ADDN. In order to help African governments strengthen their catastrophe risk management plans, the African Union established the insurance business African Risk Capacity (ARC) in 2014 (African Risk Capacity, 2023). When natural disasters strike, the ARC quickly supplies vulnerable populations with financial support. Launched in 2013, the Drylands Development Programme (DRYDEV) is supported by the Netherlands Ministry of Foreign Affairs (MoFA) and the World Vision Australia (WVA). DRYDEV sought to support over 227 000 smallholder farmers and to enhance food security, water management and rural economic development (SNV, 2023). With a US $50 000 000 budget, the six-year project supported Kenya, Ethiopia, Mali, Niger and Burkina Faso. In Ethiopia, Uganda, Chad, Kenya, Mali, Senegal, Niger, Sudan, South Sudan, Mauritania, Burkina Faso, Nepal and Myanmar, the Building Resilience and Adaptation to Climate Extremes and Disasters (BRACED) initiative aims to mitigate or completely eradicate poverty, insecurity, natural disasters and climate extremes (BRACED, 2018). The UK Department for International Development (DFID) provides funding for BRACED, which aims to enhance local, national and international policies and practices.

The Comprehensive Africa Agriculture Development Programme (CAADP), an initiative of the African Union, supports food security and agricultural growth in Africa, as part of Agenda

2063. Through the CAADP, African countries are committed to devoting at least 10% of their national budget to rural and agricultural development (African Union, 2021). The CAADP assists nations to strengthen their resilience to climate variability and with disaster preparedness, by developing efficient policies, strategies and early warning systems for disaster preparedness. Certain CAADP activities, such as improving access to water resources, encouraging climate-smart agriculture methods, as well as assisting farmer cooperatives, are specifically designed for areas that are vulnerable to drought. The Food and Agriculture Organisation (FAO) has developed its Farmer Field Schools (FFS) in South-East Asia. The FFS initiative is implemented in schools to provide training on drought-tolerant crops, water-saving techniques, soil conservation and sustainable land management practices to enhance the farmers' knowledge and skills (FAO, 2023). According to the FAO, there are more than 1 700 members across 130 countries. Regular meetings and non-formal adult education methods are the foundation of an FFS group, which promotes knowledge- and experience-sharing in a risk-free setting. The southern African Drought Resilience Initiative (SADRI) was launched by The World Bank and the Cooperation in International Waters in Africa (CIWA), and its aim was to provide tools to improve the implementation of drought resilience strategies from September 2020 until October 2022 (Zwane, 2021). In 2016, the government of Zimbabwe introduced command agriculture. A portion of the harvest from the following harvest season is used to repay farmers who participate in the government- and private sector-sponsored Command Agriculture programme for loans with which to buy seeds, fertilizers, herbicides, pesticides, fuel and equipment (Matunhu et al., 2022). These programmes have a major influence on the lives of rural farmers in sub-Saharan Africa and help them to manage the impacts of droughts.

2.3.3 Available approaches for delineating rural farms by using machine learning algorithms

There are many benefits to using machine learning algorithms to identify rural farms, particularly in areas of sub-Saharan Africa where data are scarce. According to Persello et al. (2019), machine learning algorithms can process vast volumes of data quickly and with high accuracy. They reduce human error, yield impartial, reliable data, and they offer monitoring that is almost in real-time. The most widely-utilised techniques include Object-Based Image Analysis (OBIA), Random Forest (RF), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Semantic Segmentation Models and Ensamble Methods, which include stacking, boosting and combining other machine learning algorithms (Table 2.3). By using remotely-sensed data, RF is a supervised learning method that is frequently used to identify rural farms (Persello et al., 2019). These common machine learning methods are highlighted in Table 2.3 and have been applied to the mapping of rural farms in sub-Saharan Africa. In order to produce precise classifications using information from satellite photography, unmanned aerial vehicles, or aerial pictures with a ground reality, RF integrates many decision trees. Farm landscapes can also be distinguished by using remote sensing variables, including spectral bands, vegetation indices and texture measurements (Vogels et al., 2017; Zhou et al., 2022). SVM uses labelled training data, where farms are labelled as positive or negative (non-farm), along with spectral, spatial and contextual features that are extracted from remotely-sensed data to find an optimal hyperplane in a high-dimensional feature space. This allows SVM to accurately separate the data into different classes (Mashaba-Munghemezule et al., 2021). The input features are transformed into a higher-dimensional space by using kernel functions, which allows non-linearly-separable data to be separated. In SVM-based farm delineation, the Radial Basis Function (RBF) and Polynomial Kernals are often-utilised kernal functions because they help to capture intricate correlations between the input features and the farm class. Each pixel's chosen attributes are evaluated by the algorithm, which then generates a probability or confidence score that indicates how likely it is to belong to the farm class. Areas with high probabilities can be classified as agriculture areas, based on a predetermined threshold. Because CNN can instantly learn complex spatial and spectral properties from the data, they are useful for evaluating images (Table 2.3). The majority of training data is made up of patches or images that are taken from remotely-sensed data, labelled accordingly and classified as either agricultural or non-farm areas.

A significant number of studies have been conducted around the globe using these algorithms; however, the number of studies conducted in sub-Saharan Africa is significantly lower. Using Landsat and Sentinel data, the RF was utilised in a study by Magidi et al. (2021) to categorise irrigated regions in the South African Province of Mpumalanga. The goal of the study was to create a model that would help decision-makers in government to make well-informed choices about different aspects of agriculture each year. The Google Earth Engine (GEE) was used to calculate the Normalised Difference Vegetation Index (NDVI), by using Landsat-8 and Sentinel-2 data collected during July and August of 2020. With a Kappa Coefficient of 80% and an overall accuracy of 88%, the study shows the potential GEE has in mapping irrigated regions. In order to classify agricultural crops in Zimbabwe's Masvingo area, Chen et al. (2020) investigated the Gray Level Co-occurrence Matrices (GLCM) texture characteristics using dual-polarised Sentinel-1 and Landsat-8 data by computing the Support Vector Machine

(SVM). When Landsat-8 data was layered with Sentinel-1 and speckle filtered, it produced an OA of 96.02% and a Kappa Coefficient of 0.95. Sentinel-2, on the other hand, achieved an OA of 62.11% and a Kappa Coefficient of 0.59. These findings demonstrate that SVM makes it possible to integrate Landsat-8 and Sentinel-1 data for crop discrimination and farm delineation. A study conducted in Nigeria by Abubakar et al. (2021) was based on Sentinel-2 data; it evaluated the efficacy of RF and SVM with various kernal functions for distinguishing between various agricultural land covers, throughout the 2016 growing season for maize and field data. The GLCM was employed for texture analysis, and the RF and SVM were used for picture classification. The Radial Basis Kernel Function (SVM-RBF), Linear Kernel Function (SVM-L), Polynomial Kernel Function (SVM-P) and Sigmoid Kernel Function (SVM-S) are the four distinct SVM kernel functions that were computed. This study showed that textural features are very good at identifying built-up areas, water and maize fields. It also showed that the SVM outperforms the RF in classifying and demarcating rural farm areas. Using deep learning and Sentinel-2 data, Waldner and Diakogiannis (2020) employed CNN to map rural farms in various nations, including South Africa, for a national to global farm boundary extraction. Delineating rural farms and tight boundaries might be facilitated by the Regional Convolutional Neural Network (R-CNN), and the Mask R-CNN functioned similarly to a UNet. Abioye et al.'s (2022) analysis of the use of CNN in numerous studies demonstrated the potency of the algorithm and the necessity for additional research, particularly in sub-Saharan Africa, before it can be used to identify rural farms. A summary of the strengths and weaknesses of these machine learning algorithms is presented in Table 2.3.

Table 2.3 The most common machine learning algorithms for mapping farms using remote sensing in sub-Saharan Africa

Algorithm	Strengths	Weaknesses	References
RF	Achieves highly-accurate results. Non-parametric and able to manage large volumes of data, measures degrees of variable importance and is computationally efficient.	Accuracy depends on the quality and representativeness of the training data and the selection of appropriate features, poor performance with high-dimensional data.	Persello et al. (2019); Vogels et al. (2017); Magidi et al. (2021); Zhou et al. (2022).
SVM	Able to handle complex datasets and generalise unseen data, effective for high-dimensional data, less prone to overfitting, able to handle linear and non-linear classification tasks, able to work with limited data and easy to interpret.	Accuracy relies on the quality and representativeness of the training data and the selection of appropriate features and kernel function, can be computationally intensive, sensitive to noise and can perform poorly with imbalanced datasets.	Chen et al. (2020); Abubakar et al. (2021); Mashaba-Munghemezule et al. (2021).
CNN	Able to capture intricate spatial and spectral patterns in remote sensing data, accurate and detailed farm delineation, hierarchical representation allows for the recognisation of objects at different levels of detail, parameter sharing leads to efficiently	Requires large amounts of labelled training data and computational resources for training, overfitting in scenarios with small training datasets, can be computationally expensive	Waldner and Diakogiannis (2020); Abioye et al. (2022).

	processing large images and high-dimensional data, can be trained for specific tasks with limited data, highly flexible and able to be adapted for various applications.	especially for large datasets, understanding CNN results can be difficult, augmentations can lead to poor generalisation.	

2.3.4 The use of indices for drought monitoring

For the purpose of monitoring droughts, remote sensing technology has many benefits, particularly in hard-to-reach locations (Sharara et al., 2022). Between 2000 and 2022, there were 203 420 papers on the topic of drought monitoring with remote sensing or GIS, but only 443 of these studies were carried out in sub-Saharan Africa. Satellite data are used to compute drought indices, as part of the remote sensing approach to monitoring droughts. Using one or more climatic variables, such as rainfall, temperature, evapotranspiration, flow, groundwater level, reservoir levels, soil moisture and snowfall, drought indices are used to determine the length and severity of a drought. There are already more than 150 drought indices available; however, it is still necessary to choose the suitable drought indices for drought monitoring in certain nations or regions (Alahacoon & Edirisinghe, 2022). Remotely-sensed drought indices can be classified as optical indices, thermal indices, microwave indices and integrated indices.

The 20 most widely-used drought indices, as shown in Table 2.4, will be examined in the sections that follow. Tefera et al. (2019) calculated the Standardised Precipitation Index (SPI) and the Standardised Precipitation Evapotranspiration Index (SPEI) as drought assessment tools in the Tigray Region of Ethiopia between 1901 and 2016. Cohen's Kappa statistics revealed a positive linear correlation ($r > 0.7$, $p < 0.001$) across all time-scales and a fair degree of agreement between the two indices. The indices agreed at the various time scales, and this was also demonstrated by the Bland-Altman approach. The study demonstrated that the Tigray Region's drought may be evaluated by using SPI and SPEI. Bekuma et al. (2022) conducted a study in the Oromia National Regional State's Zones, which was comprised of 17 rural areas and 289 rural farmers in Western Ethiopia, between 1981 and 2017. The study employed various drought indices to analyse the pattern and temporal variability of droughts. The Rainfall Anomaly Index (RAI), the Palmer Drought Severity Index (PDSI) and the Deciles Index (DI) were computed by using climatic data using the Drought Indices Calculator (DrinC). It was possible to identify drought years in 1984, 1991, 1999–2005, 2011 and 2012 by using PDSI and RAI. The findings demonstrated the significance of drought indices in drought monitoring, mitigation and adaptation strategies. All three indices concurred that the frequency of droughts was increasing. The multi-index method demonstrated the decrease in rainfall and an increase in the frequency of droughts with accuracy. In a different study, Asfaw et al. (2018) employed PDSI to determine the severity of the droughts from 1901 to 2013 in the Woleka sub-basin of Ethiopia. The results demonstrated that the frequency of droughts has been rising over time, since the 2000s. From 1951 to 1980, there were two drought years, and from 1981 to 2013, there were twelve. In Xulu et al.'s (2018) investigation, which was carried out in KwaMbonambi plantation forests in KwaZulu-Natal, PDSI and MODIS-derived NDVI (500 m resolution) were computed by using GEE across a 15-year period, from 2002 to 2016. A strong association ($r = 0.34$) was found between PDSI and NDVI, and NDVI may identify tree stress that is brought on by dryness.

Kibret et al. (2020) improved Ethiopia's planning techniques for food security and climate change adaption by utilising MODIS-EVI at a 250 m resolution. The EVI was computed for maize, haricot beans, wheat and barley by using data gathered between 2003 and 2018. With an overall accuracy of 76-94%, the EVI obtained from MODIS is able to monitor land-use patterns, it can aid with drought risk assessments and it can give real-time information. The goal of a study by Kourouma et al. (2021) was to characterise a drought and to learn more about how it affects on Ethiopia's crop productivity. Using MODIS data, the NDVI and VCI were computed from 2003 to 2017. The NDVI achieved a coefficient of determination (R^2) 0.45 for teff and 0.43 for maize, whereas VCI achieved R^2 values of 0.65 and 0.64 for teff and maize, respectively. The findings of the study support the use of NDVI and VCI in drought risk management strategies by helping to understand the patterns of drought. In 2014, Jovanovic et al. used SPOT data to examine the suitability of NDWI in the Western Cape. The results demonstrated that NDWI, which was developed by using SPOT-Vegetation photos, may identify patterns in the prevalence of drought. Research by Moisa et al. (2022) evaluated the agricultural drought in the Gilgel Gibe sub-basin by using Ethiopia's Land Surface Temperature (LST) index. The LST was computed by using the thermal bands. The study employed Landsat TM 1990, ETM+2000 and Landsat OLI/TIRS 2020 data to analyse agricultural droughts that occurred in 1990, 2000 and 2020. The results show that the LST in the research area increased by a mean of 27.1°C, 30.6°C and 33.6°C in 1990, 2000 and 2020, respectively.

Legesse and Suryabhagavan (2014) used many rainfall datasets in Tanzania, including ARC2, CHIRPS and TAMSAT, to characterise the effects of drought by using the Water Requirement Satisfaction Index (WRSI). The findings showed that CHIRPS (R^2=0.52-0.61) best described the beginning and length of the period of rainfall. The maximum accuracy was attained by TAMSAT and CHIRPS, with R^2 values of 0.44-0.58 and 0.46-0.55, respectively. The outcomes of the study demonstrated that WRSI can be applied to drought early warning systems in an efficient and effective manner. Using the WRSI, Tarnavsky et al. (2018) evaluated the patterns and severity of drought in Ethiopia's East Shewa Zone. This study employed data from the

Rainfall Estimate (RFE) and AVHRR, which were gathered during the rainy season (June to September) between 1996 and 2008. The findings showed that between 2000 and 2002 the area had a very bad drought. The WRSI demonstrated a 76% deviation in grain yield variability, which indicated its accuracy as an agricultural drought indicator. With appropriate identification, planning and mitigation techniques, drought risk mapping can assist decision-makers and lower the likelihood of a drought, as demonstrated by the results obtained by these 20 indicators.

Table 2.4 Meteorological drought indices

Index	Developer	Data required	Strengths	Weaknesses
Standardised Precipitation Index (SPI)	McKee et al. (1993)	Precipitation	Able to detect droughts and the impact of low precipitation rates. Able to detect the evolution of a drought. Able to detect different types of drought using different SPI scales.	Historical precipitation needed. SPI-6 was unable to detect moderate droughts, only severe droughts. Existing long-term precipitation data is needed.
Normalised Difference Vegetation Index (NDVI)	Tucker (1979)	Remotely-sensed satellite data	Results are visually easy to read and vegetation activity can be determined. The impact of a drought on vegetation clearly visible and able to differentiate between drought periods and recovery periods.	Cloud cover led to noise interference. Cloud cover affected data coverage, especially during wet seasons. Satellite images suffered from cloud contamination and therefore required more procressing.

			Able to detect decrease in tree activity due to drought conditions.	
Deciles Index (DI)	Gibbs and Maher (1967)	Precipitation	Can be used to compare different areas and requires less data, compared to other indices. It is easy to calculate and the results are clear and easy to read and understand.	Requires rainfall record of more than 30 years.
Palmer Drought Severity Index (PDSI)	Palmer (1965)	Precipitation, temperature and soil moisture	Able to provide detailed the spatio-temporal effects of drought. Able to provide information on drought severity experienced by wheat.	Does not consider the spatial changes of soil, vegetation and hydrological processes. Rainfall and temperature, as well as soil characteristics are needed at each location. Monthly information on temperature, rainfall and water-holding capacity of soil is needed.

Normalise Difference Water Index (NDWI)	Gao (1996)	Satellite imagery	Able to determine trends in changes in wetness. Able to detect changes in vegetation, drought severity and impacts on agriculture. Able to detect changes in water body size.	Cannot measure soil water content. Needs to be used in conjunction with the soil type, location and climate conditions, to determine drought conditions. Cloud contamination affected accuracy.
Standardised Precipitation Evapotranspiration Index (SPEI)	Vicente-Serrano et al. (2010)	Precipitation and potential evapotranspiration	Drought intensity can be determined. SPEI-6 effective for below normal rainfall rates. SPEI-12 able to show long-term rainfall patterns. Able to determine drought intensity and severity. Able to provide information on drought length, occurrence and intensity.	SPEI-3 only indicates short-term and medium-term moisture conditions. Need at least 20 to 30 years of climate data. Historical climate data needed, such as temperature (maxium, minimum and/or median), evapotranspiration and rainfall. Gaps in data records were problematic.

Aridity Index (AI)	Thornthwaite (1931)	Precipitation, actual evapotranspiration and potential evapotranspiration	Efficient in relation to climate classification.	Climate data required and needs to be used in conjunction with other drought indices.
Enhanced Vegetation Index (EVI)	Liu and Huete (1995)	Satellite imagery	Effectively responds to rainfall in a timely manner and indicates the impacts of a drought on vegetation. Able to indicate vegetation productivity. Able to determine the spatial impacts and frequency of drought on vegetation.	Historical climate data is needed and gaps in the data are problematic. Crop rotation by farmers affects EVI and therefore accurate comparisons between different years are compromised. Cloud cover impacted data derived from satellite imagery.
Soil Adjusted Vegetation Index (SAVI)	Huete (1988)	Satellite imagery	Achieved highly-accurate results in predicting aboveground biomass in dryland areas.	Does not determine soil evaporation and the effects of stress, due to limited water
Land Surface Water Index (LSWI)	Gao (1996)	Satellite imagery	Easy to calculate. Detects drought conditions and able to	Overestimates the size of waterbodies due to cloud

			detect early warnings of drought.	contamination, aerosols and water vapour.
Temperature Condition Index (TCI)	Kogan (1995)	Maximum and minimum temperature	Able to detect drought conditions and the severity of droughts.	Background brightness affected results.
Vegetation Condition Index (VCI)	Kogan (1995)	Satellite imagery	Able to identify drought conditions and vegetation health. Able to detect the impacts of drought on vegetation health. Able to determine the spatial pattern of drought conditions.	High volumes of climate data were needed. Significant standard deviation for VCI, therefore results are uncertain and requires further studies. Cloud contamination affected accuracy.
Vegetation Health Index (VHI)	Kogan (1995)	Satellite imagery and temperature	Highly correlated to precipitation and soil moisture and highly suitable for detecting drought conditions.	Poor performance in areas with dense vegetation.

Streamflow Drought Index (SDI)	Nalbantis and Tsakiris (2009)	Discharge	Gaps in data are not problematic and it is easy to use. Can be calculated at various timescales.	Periods with no flow affects the results. Requires long streamflow data history to achieve high accuracies.
Surface Water Supply Index (SWSI)	Shafer and Dezman (1982)	Snow, recharge, discharge, reservoir water storage	Provides hydrological health of study area, as it considers all water resources in the study area.	Unable to compare different basins due to differences in calculations. If new data or new data sources are added, it needs to be recalculated to account for these changes.
Effective Drought Index (EDI)	Byun and Wilhite (1999)	Precipitation	Standardised index and therefore results for different study areas can be compared. Able to detect the beginning, end and duration of droughts.	Temperature not directly integrated, as it only considers rainfall data. Daily data needed and therefore may be difficult to calculate EDI in areas without daily rainfall data.
Rainfall Anomaly Index (RAI)	Van Rooy (1965)	Precipitation	Easy to compute and can be calculated at a monthly, seasonal and annual timescale.	Needs datasets without any gaps or gaps that can be filled.

Infrared Percentage Vegetation Index (IPVI)	Crippen (1990)	Satellite imagery	Effective for the fast processing of large datasets.	Cannot determine soil salinity.
Land Surface Temperature (LST)	Wan et al. (2004)	Temperature	High capability to estimate the spatial pattern of temperatures for larger areas.	Different vegetation covers affects LST results.
Water Requirement Satisfaction Index (WRSI)	Food and Agriculture Organisation		High resolution and good spatial coverage over all terrains.	Stress factors, apart from available water, can affect the results. Errors in satellite-derived rainfall data affects the results.

2.4 Discussion

2.4.1 Strengths and limitations of the remote sensing of the occurrence and impacts of droughts on rural farmers

Remotely-sensed techniques can reliably identify and detect the onset of a drought in a timely and economical manner, as well as its effects on vegetation, and therefore on rural farmers. Using various satellite data and drought indices, remote sensing has been demonstrated to be a valuable tool for detecting and analysing drought situations (Bhaga et al., 2020). Furthermore, satellite data can be utilised to create early warning systems for droughts and to improve the knowledge about, and readiness for, them (Botai et al., 2016; Orimoloye et al., 2021; Varghese et al., 2021). Rural farmers will benefit from the creation of early drought warning systems and an increased awareness and preparedness for the phenomenon, as they will be better-equipped to modify cropping patterns ahead of time and mitigate the worst effects of the drought. Water resource management greatly benefits from the use of remotely-sensed satellite data to identify drought conditions (Masocha et al., 2018; Theron et al., 2021; Gxokwe et al., 2022). In addition, remote-sensing techniques have greatly improved as a result of technological breakthroughs and the urgent requirement for prompt and precise drought detection and prediction (Ruwanza et al., 2022). There is no consensus on which is the best index or indices, despite their abundance, as each of them has its own pros and downsides. According to a review of the literature, the SPI and NDVI indices were most frequently employed in research undertaken worldwide. The capacity to identify various drought types, their progression, the effects of low precipitation rates, as well as their universal applicability across all climate zones, are among the benefits of SPI. The NDVI has several advantages, such as its capacity to identify a decline in the vegetative activity brought on by a drought, it has visually appealing results and it gives a clear indication of how a drought affects vegetation.

According to Govender et al. (2022), the limitations of satellite data include the revisit times of satellite sensors and the presence of clouds. These limitations can inhibit the feasibility of using remotely-sensed data for drought monitoring, prediction and detection, as well as its impacts. Coarse spatial resolution imagery is problematic for the monitoring of smallholder farming regions, as the pixel sizes exceed the size of the area (Govender et al., 2022). Satellite images need to have an extremely high resolution, in order to detect field boundaries. The features of sub-Saharan African rural farms, such as their small plot sizes, irregularly-shaped areas with hazy boundaries, strong seasonal variations in surface reflectance due to cloud cover, as well as the presence of rain-fed agriculture that occurs during high cloud cover, make mapping these farms difficult (Persello et al., 2019). A further constraint identified in the reviewed literature was the amount of climate data that is needed to compute these drought indices. Sub-Saharan Africa frequently has gaps in its in-situ climatic data records, which makes it difficult to calculate indices and, therefore, necessitates filling these gaps. As a result, climate data are frequently gathered from multiple sources with various spatial scales, which presents challenges for data collection. The correctness of the input data that are used determines the outcome. Limitations in data availability are particularly troublesome, since changes over time, like shifts in the cropping pattern, cannot be identified. The limitations of this study include the fact that few studies were carried out in South Africa and that certain journal articles were not available in their entirety. This had a detrimental effect on the quantification of the research on the frequency of droughts and their effects on South African rural farmers. Sensor forms and data sample size were not taken into account in this investigation.

2.4.2 Research gaps and future research opportunities

Most studies have primarily been conducted in West and East Africa, which suggests that there is a research gap in the rest of sub-Saharan Africa, especially in South Africa, where the frequency of droughts is growing. The effects of drought on rural farmers and appropriate mitigation techniques are still disregarded, despite the fact that the majority of rural farmers, especially those in sub-Saharan Africa, depend on rainfed agriculture. Delineating rural farms is also challenging, due to the small areas that require highly-spatial datasets, as pixel mixing causes misclassification, especially during the wet season. Future research needs to prioritise overcoming seasonality issues and enhancing big data analysis. In order to increase the accuracy of spatial datasets, future research must concentrate on combining remote sensing data with in-situ observations. This will be followed by the processing of these datasets using machine learning techniques. Hydrology, remote sensing and agriculture all require interdisciplinary research. Future research can use these data to build thorough frameworks for evaluating the effects of drought and to design measures for mitigation that will work for sub-Saharan African rural farmers. Involving local communities and carrying out citizen science research can improve data gathering, encourage information sharing, and help to integrate the remote sensing results with in-situ realities.

Since droughts are complicated natural phenomena, it is not possible to anticipate or monitor their frequency and intensity purely from in-situ or remotely-sensed data. The majority of rainfed agricultural areas frequently have poor in-situ data. For regions where in-situ data are scarce, the availability of a variety of free satellite datasets, with varying geographical, spectral and temporal properties, offers an alternative technique of data gathering. This makes it possible to quickly implement monitoring and prediction in locations that were previously unreachable because of degraded or non-existent in-situ data. Remote-sensing methods and other satellite data can be used to close this knowledge gap. Thanks to advancements in sophisticated computer processing techniques for drought detection and monitoring, there are new options and techniques for drought management.

In order to reduce drought vulnerability and to assist with drought preparedness, sub-Saharan Africa needs to test the effectiveness of big data analysis and machine learning algorithms by using Artificial Intelligence (AI), the Google Earth Engine (GEE) and various satellite data, in conjunction with climate data. This testing should take place, in order to develop adaptation strategies for rural farmers and to develop a drought early warning system. According to published research, cloud computing and machine learning algorithms enable data integration that enhances drought monitoring, prediction and mitigation. However, even if a small number of studies have been conducted to examine their relevance in drought monitoring and prediction and other related fields, future research is required to examine these strategies, in order to improve drought monitoring in places with limited data.

In order for decision-makers and rural farmers to collaborate on improving the livelihoods, coping mechanisms and adaptation strategies of rural farmers, as well as providing them with the necessary knowledge and skills, more support organisations need to be created for rural farmers and introduced to them. Numerous studies have shown how droughts affect smallholder farmers, especially those in sub-Saharan Africa. Nevertheless, these effects are still unclear, and there are currently no support structures in place to help these farmers cope with droughts, in the long run. Research examining the cultural setting, gender, ethnicity and economic level of farmers is necessary to ascertain how droughts affect them in various regions. To evaluate the effectiveness of remote sensing technology, more research is required that distinguishes between rural and commercial farms. In order to gain a deeper understanding of these problems and the effects of drought and climate change on their farming methods and livelihoods, researchers ought to think about incorporating citizen science. Rural farmers should be empowered by providing them with information on the occurrence of droughts to help them create coping and adaptation mechanisms. Effective measures must be implemented as soon as possible, in order to increase their resistance to drought.

2.5 Conclusion

The purpose of the review of the literature in this study was to evaluate the state of remote-sensing methods for mapping rural farms, for detecting droughts and for analysing their impact on rural farmers. This study has identified areas for further research, as well as research gaps. Many studies indicate that droughts will occur more frequently, thus it is important to make predictions and to develop adaptation plans as soon as possible, especially for rural farmers. The literature search revealed advancements in the use of multispectral indices for drought monitoring, drought prediction, the use of machine learning algorithms to identify rural farms, and the use of satellite data, but more studies are required for developing nations, particularly in sub-Saharan Africa. Despite there being an increase in published studies, spectral and spatial resolution continues to provide difficulties in drought prediction and monitoring, when utilising remote sensing techniques. Among these issues are inaccurate drought detection results, which have been linked to inadequate spatial resolution. For rural farmers who rely on rainfed agriculture, the use of machine learning algorithms to identify farms must be combined with climate data. These data need to be explored further in developing nations, to determine their applicability in predicting the occurrence of droughts, which will help them with their management practices and means of subsistence. Consequently, new avenues for enhancing rural farm delineation and drought monitoring are made possible by the utilisation of the Google Earth Engine and Petascale. More studies need to investigate these methods in sub-Saharan Africa, in order to improve food security and peoples' livelihoods and to achieve the SDGs and Union Agenda 2063 goals.

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CHAPTER THREE

ASSESSING THE PERFORMANCE OF REMOTELY-SENSED DATA AND MACHINE LEARNING ALGORITHMS TO DELINEATE RAINFED SMALLHOLDER FARMS IN DIFFERENT CLIMATE REGIONS OF SOUTH AFRICA

Abstract

This work explores the use of remote sensing and advanced machine learning techniques to delineate and map rainfed smallholder farms in the semi-arid regions of the Limpopo, Mpumalanga, North West and Gauteng Provinces of South Africa. Sentinel-2-derived spectral indices, specifically the Normalised Difference Vegetation Index (NDVI) and Modified Soil-Adjusted Vegetation Index 2 (MSAVI2), were integrated with the Gradient Boosting Decision Tree (GBDT), Support Vector Machine (SVM), Convolutional Neural Network (CNN), Random Forest (RF) and Transformer models to enhance classification accuracy. The results demonstrated that MSAVI2 consistently outperformed NDVI across all four study areas. The results showed that the Transformer model outperformed other models, achieving the highest overall accuracy of 0.85 and a mean Intersection over Union of 0.86 across all study regions. In addition, combing NDVI with MSAVI2 significantly improved the models' ability to delineate rainfed smallholder farms, as the results of detecting rainfed smallholder farms were more accurate. The study underscores the effectiveness of integrating vegetation indices with machine learning algorithms for the precise mapping of smallholder farms. This approach is crucial for efficient resource allocation and improved crop management. Furthermore, these findings contribute to alleviating the impacts of drought, thereby achieving the African Union's Agenda 2063 goals and Sustainable Development Goals.

Keywords: Rainfed smallholder farms; Vegetation indices; Transformer model; Machine learning; South Africa

This chapter is based on the following manuscript:

Bhaga, TD, Dube, T, Shekede, MD and Shoko, C. (2024). Leveraging the Google Earth Engine platform to delineate smallholder farms in different semi-arid climate regions of South Africa. *International Journal of Applied Earth Observation and Geoinformation*. [Under review - JAG-D-24-04323]

3.1 Introduction

Smallholder farms are small-scale farming enterprises that are often run, owned and managed by single, or small, families and are largely dependent on rainfed crops (Jin et al., 2019; Bey et al., 2020; Bahta & Myeki, 2022). The definition of smallholder farms varies; however, for this study, a smallholder farm refers to a small-scale farming operation that is operated by an individual or family members and that grows maize, vegetables and fruits, and rears livestock (Carelsen et al., 2021). Conversely, large-scale farming denotes a system that involves the growth of crops and livestock on a large piece of land and it often involves the use of machinery, pesticides and many farm workers (Lowder et al., 2016; Tittonell et al., 2020). Rainfed crops rely on rainfall for crop cultivation, whereas irrigated crops rely on water from other sources, such as rivers, lakes, reservoirs, dams or groundwater (Makombe et al., 2007). Vegetables, fruits, maize, cattle, sheep and goats are among the crops and animals that rural farmers frequently grow and rear (Zobeidi et al., 2021; RegenZ, 2024). The farms are characterised by limited resources, such as land, capital and equipment, and they usually encompass very small sections of land. South Africa's smallholder farming sector is vital for the country's food supply and for rural livelihoods. There are 500 million smallholder farms across the globe and there are approximately 2 million in South Africa alone (in contrast to 35 000 commercial farms) (South African Government, 2024; RegenZ, 2024). However, these farmers face multiple challenges, such as droughts, climate change, financial constraints and limited supportive policy frameworks. Droughts affect food security and rural development, as well as the generation of jobs and income for smallholder farmers, therefore mapping these smallholder farms will offer valuable insights into the spatial patterns of rural development and agricultural landscapes (Edwards et al., 2015; Bahta & Myeki, 2022; Ebhuoma et al., 2020).

Numerous attempts have been made in mapping smallholder farms using remotely sensed methods with openly-available data (Jin et al., 2019; Bey et al., 2020; Mpakairi et al., 2023) (Table 3.1). Combined, these projects improve the mapping and knowledge of smallholder farms, which advances worldwide efforts to improve agricultural practices and ensure food security.

Table 3.1 Summary of studies using remote sensing techniques to map smallholder farms

Study/programme	Satellite data	Methods	Scale
Jin et al. (2019)	Sentinel-1 and 2	RF	Kenya & Tanzania
Bey et al. (2020)	Landsat	Various algorithms	Mozambique
Walder and Diakogiannis (2020)	Sentinel-2	CNN	South Africa
Mashaba-Munghemezulu et al. (2021)	Sentinel-1 and 2	RF and SVM	South Africa
Mpakairi et al. (2023)	Sentinel-2	NDVI using RF, DNN, SVM	South Africa
GEOGLAM (Whitcraft et al., 2015)	Landsat and Sentinel	Various algorithms	Underdeveloped countries
USDA's Cropscape (Han et al., 2012)	Landsat	Various algorithms	USA
GFSAD (Yadav & Congalton, 2019)	Landsat and MODIS	NDVI	Global
GLAD (Potapov et al., 2020)	Landsat	Various algorithms	USA
Sen2Agri (Valero et al., 2021)	SAR, Sentinel-1 and 2	Various algorithms	Global
ARDC (Picoli et al., 2020)	Landsat and Sentinel	Various algorithms	Africa
EBD (Estevez et al., 2022)	Multi-source data	Various algorithms	Global

Mapping smallholder farms in South Africa supports several Sustainable Development Goals (SDGs); it increases agricultural production, improves resource allocation and promotes sustainable practices (Mpakairi et al., 2023). In particular, it supports SDG 1 (No poverty), by providing smallholder farmers with economic empowerment, and SDG 2 (Zero hunger), by enabling effective crop planning. In addition, by promoting climate-smart agricultural practices, mapping smallholder farms supports the climate resilience targets of SDG 13. Overall, by boosting the agricultural output and resource efficiency, mapping smallholder farms helps the continent to become more economically independent and to develop sustainably. It promotes the growth of a resilient, stable and prosperous Africa and is consistent with the objectives of the African Union (AU) Agenda 2026. Previous studies have utilised various machine learning and remote sensing techniques to map agricultural land in South

Africa. Mpakairi et al. (2023) used the Normalised Vegetation Index (NDVI) with Random Forest (RF), Deep Learning Neural Network (DNN) and SVM in the Google Earth Engine (GEE) to distinguish between irrigated and rainfed farms, and has achieved accuracies of 0.77 (RF) and 0.71 (DNN). Mashaba-Munghemezulu et al. (2021) combined Sentinel-1 and Sentinel-2 data to map smallholder farms in Limpopo, achieving an overall accuracy of 0.99 by using RF and SVM. Waldner and Diakogiannis (2020) applied Convolutional Neural Networks (CNNs) to delineate smallholder maize farm boundaries from Sentinel-2 images, achieving an accuracy of 92%. Recent advances in deep learning, such as the Transformer method, have introduced innovative ways to enhance classification in remote sensing (Lin et al., 2022; Ramathilagam et al., 2023). The Transformer method is well-suited to process large-scale, high-dimensional datasets, and although its application in remote sensing is still in its early stages, it has the potential to improve agricultural mapping, especially when dealing with time-series data (Lin et al., 2022; Yan et al., 2023). Lin et al. (2022) aimed to develop a Transformer-based segmentation network to accurately map farm areas in complex regions with small-scale features, such as roads and water bodies. Compared to the conventional machine learning methods, the Transformer method has the potential to map rainfed smallholder farms, because the Transformer method is able to detect patterns in the vegetation dynamics, crop development cycles and rainfall dependencies (Li et al., 2020; Koutilya & Bandaru, 2023; Yan et al., 2023). This method provides improved accuracy in identifying rainfed agricultural regions by concentrating on critical time periods, such as the start of the rainfall and the peak growing season or harvest (Li et al., 2020; Lin et al., 2022; Yan et al., 2023). In addition, the integration of the Transformer model with other advanced machine learning models, such as CNN, has proved its potential in crop classification. Studies by Li et al. (2020) and and Yan et al. (2023) used a hybrid Transformer and CNN hybrid; the results indicated that the hybrid approach outperformed the traditional approach with an overall accuracy of 95.4%.

Previous studies have focused on mapping at a national level, a quaternary catchment level and a regional level; however, few studies have focused on mapping at a local level. Therefore, a spatial framework needs to be developed for mapping rainfed smallholder agricultural regions in South Africa. The novelty of this study lies in that it provides accurate data by leveraging cutting-edge geospatial techniques and technologies on the GEE platform. It addresses the difficulties that are faced by smallholder farms, namely a lack of data and scarce resources, in contrast to previous research, which focused on large-scale commercial farming. This study aims to close a significant information gap by producing scaleable, high-resolution maps across South Africa, to evaluate the accuracy, reliability and suitability of different vegetation indices, specifically the Normalised Difference Vegetation Index (NDVI), the Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) and the NDVI combined with MSAVI2, in conjunction with advanced machine learning models, such as the Gradient Boosting Decision Tree (GBDT), Random Forest (RF), Convolutional Neural Network (CNN), Support Vector Machine (SVM) and the Transformer model, for mapping rainfed smallholder farms in South Africa. The results can aid resource management, legislation and smallholder farmer support systems.

3.2 Methods and Materials

3.2.1 Study area

The study was conducted across rainfed, smallholder-dominated agricultural regions in four different provinces in South Africa that fall within different climate zones, namely, the North West (104 882 km^2), Mpumalanga (76 495 km^2), Limpopo (125 755 km^2) and Gauteng (18 178 km^2) Provinces, to test if climatological factors affect the performance of these methods (Figure 3.1). The North West and Limpopo Provinces are prone to drought, which negatively impacts rainfed rural farms (Cole et al., 2021). The North West is classified as a hot semi-arid climate (BSh) and has an average annual temperature of 28°C (Cole et al., 2021), with an annual rainfall of 540 mm. The climate of Mpumalanga is highland tropical with dry winters (Cwb), it experiences summer rainfall (September to March) and receives approximately 69.93 mm of rainfall annually (Weather and Climate, 2024). The annual temperature is 21.78ºC, which is 0.56% higher than the rest of South Africa's average temperatures (Weather and Climate, 2024). Limpopo has a hot semi-arid climate (BSh) and receives most of its rainfall between November and February (South African Weather Service, 2021). Its daily maximum temperature is 30°C, on average, and it receives approximately 55.48 mm of rain annually (Weather and Climate, 2024). Gauteng is classified as a warm temperate climate (Cwa) region in the north and a sub-tropical highland climate (Cwb) in the south. It receives most of its rainfall in the summer months (October to March), has an average annual temperature of 28ºC (South African Weather Service, 2021) and receives an annual precipitation of 713 mm (Weather and Climate, 2024).

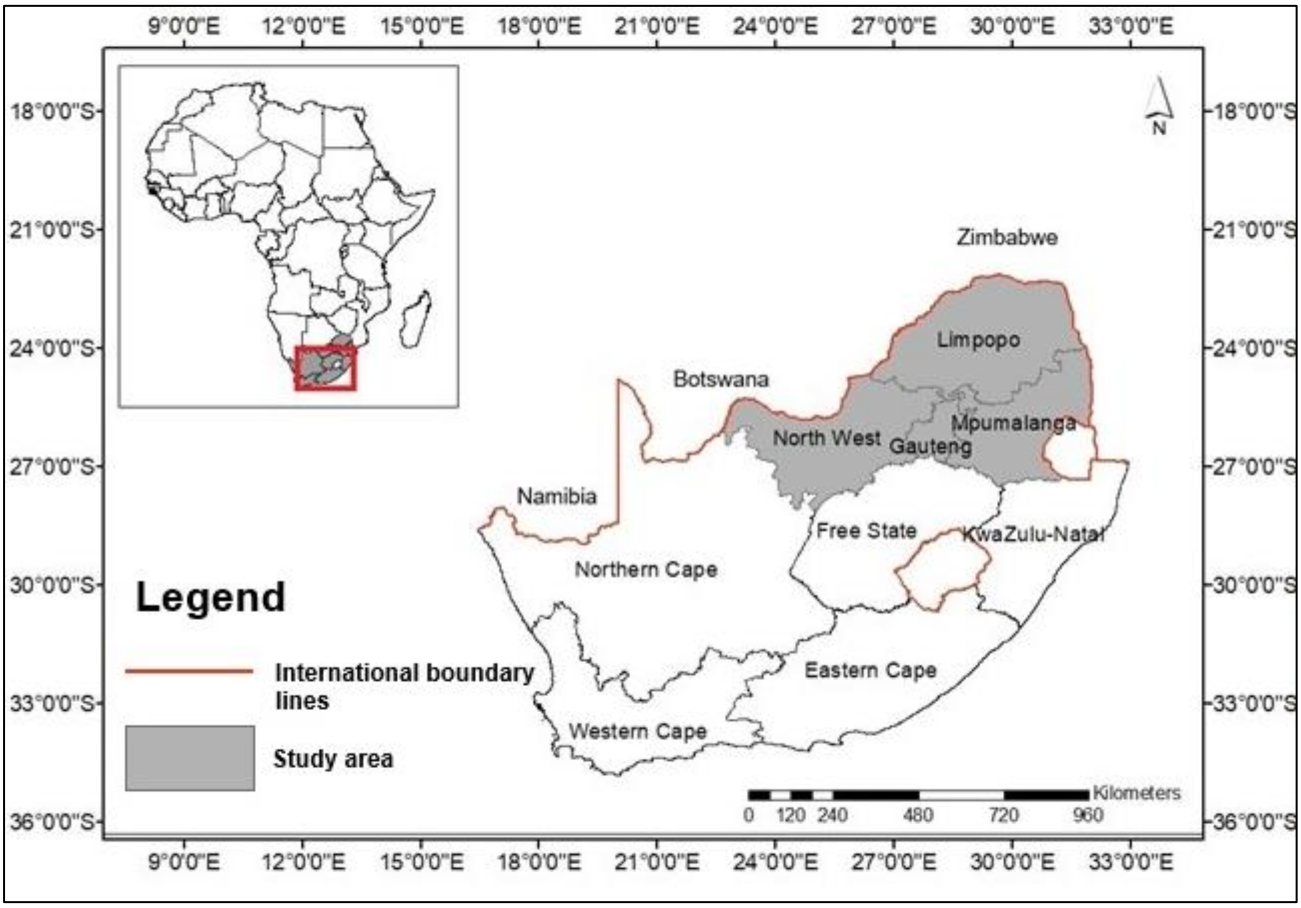

Figure 3.1 The location of the provinces within South Africa used for this study

3.2.2 The collection of training data

For classifying images, training data (n = 19,900) were gathered from a variety of sources, including in-situ data, aerial photograph data and secondary data. The ground-based training points (n = 900) were taken at random throughout the regions of study between 2021 and 2022. The plot size was calculated by using the resolution of the Sentinel-2 MSI data used in this study and, in order to classify the images, the primary land cover in each of the 400 m^2 plots was randomly selected for ground data. Ground survey sites were crucial for validating the land cover classification, especially for accurately identifying the rainfed smallholder farms in the study area. The ground-truthing data included points of the dominant land cover type during the wet and dry seasons. In addition to the ground survey points, high-resolution imagery from Google Earth complemented the validation process through photo-interpretation, which allowed for the further comparison of land cover classification against visually-interpreted data. Data obtained from secondary sources were cross-validated by using high-resolution imagery to ensure their accuracy. In order to avoid bias and to improve the accuracy of the models, the stratified random sampling method was used to ensure a representative sample of irrigated and rainfed croplands across different land cover types, which helps to mitigate the potential impact of uneven sample distribution (Mashaba-Munghemezulu et al., 2021; Mpakairi et al., 2023).

Sentinel-2 MSI cloud-free data were collected between January 2022 and December 2023. Due to the large geographic extent of the research area, gathering field data and acquiring all of the images of the area at the same time was not feasible. The image classifiers were trained by using the in-situ collected training points, as well as aerial photographs and secondary data. The 500 km^2 grids were used as a guide to methodically scan the high-resolution images in Google Earth (https://www.googleearth.com) for photo-interpreted points. The observed land cover class in the image was used to determine the land cover for each training point, and it was classified into one of six groups, namely, forest, grassland, water, built-up areas, bare land or cultivated land. Cultivated land was then grouped into rainfed land and irrigated land. Each training point was super-imposed on high-resolution images in Google Earth to confirm the land cover of the secondary data-derived points. The points that matched the land cover were kept, while those that did not, were removed. This procedure made it possible to visually confirm the land cover classification of the training location, which was crucial for assuring the accuracy, as well as the quality, of the data that were employed.

3.2.2.1 Collection and processing of satellite data

This study used Sentinel-2 data that were retrieved through GEE (https://code.earthengine.google.com) to identify various kinds of land cover and rainfed croplands. Sentinel-2 provides high-resolution (10 m) optical imagery, which is crucial for detailed crop mapping. The photos (n = 34 251) covered the years 2022 to 2023 and had a 0% cloud cover (Figure 3.2). Because each region in the study area has a different cropping season, due to the prevailing environment, surface reflectance photographs taken by satellites and drones at several times of the year were utilised to guarantee that all land cover types were identified. For instance, in certain areas of the research area, crops are cultivated in the winter and the summer. As a result, photos of those locations were taken in the subsequent months to show the fluctuations in the land cover types. This method makes it possible to comprehend the land cover and land use in the studied area with more accuracy and comprehensiveness (Jin et al., 2019; Wang et al., 2022; Mpakairi et al., 2023). Although the surface reflectance pictures from the GEE have already been corrected for atmospheric and radiometric inaccuracies, this study followed Gxokwe et al. (2022) and Mpakairi et al. (2023) by masking out the regions with smoke and cirrus clouds by using the quality assessment band (QA60), to ensure that the data were clean, of a high quality, to enhance the model's performance. To ensure consistency across the satellite images, normalisation was applied to standardise the spectral values of the bands and to eliminate the bias caused by differences in the reflectance values. These images were then used to calculate the Normalised Difference Vegetation Index (NDVI) and Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) using Equations 3.1 and 3.2, respectively, within the GEE environment (Figure 3.2). The NDVI and MSAVI-2 vegetation indices were computed to differentiate rainfed smallholder farms from irrigated farms (Bey et al., 2020; Waldner & Diakogiannis 2020; Magidi et al., 2021a; Onyango et al., 2021; Mpakairi et al., 2023). Plant health is indicated by the NDVI and MSAVI2 was selected, in order to address the weaknesses of the NDVI (Magidi et al., 2021a; Mashaba-Munghemezulu et al., 2021; Gxokwe et al., 2022). The NDVI measures the health of the vegetation and is able to detect rainfed smallholder farms effectively, due to the distinct seasonal greening patterns that these areas display, when compared to non-cultivated areas. The NDVI is able to differentiate between rainfed smallholder farms and non-cultivated areas due to its sensitivity to plant biomass and photosynthetic activity (Cho & Ramoelo, 2019; Kourouma et al., 2021). The NDVI and MSAVI2 were calculated as follows:

$$\text{NDVI} = (\text{NIR} - \text{Red}) / (\text{NIR} + \text{Red}) \qquad \text{Equation 3.1}$$

$$\text{MSAVI2} = \frac{2\times NIR+1-\sqrt{(2\times NIR+1)2-8\times(NIR-Red)}}{2} \qquad \text{Equation 3.2}$$

The Gradient Boosting Decision Tree (GBDT), Convolutional Neural Network (CNN), Support Vector Machine (SVM), Random Forest (RF) and Transformer models were then trained to enhance the classification and detection of rainfed smallholder farms by using Sentinel-2 images. The training data made up 70% of the total, and the validation data made up 30%. The training data were split in R-studio and then converted into GIS files, which was followed by importing the images to GEE for model training and validation (Magidi et al., 2021; Magidi et al., 2021a; Gxokwe et al., 2022). The GBDT model is efficient for complicated datasets because it builds an ensemble of decision trees iteratively, with each new tree resolving errors from the preceding trees (Mashaba-Munghemezulu et al., 2021; Onyango et al., 2021). The RF model ensures robustness and highly-accurate classification by building numerous decision trees during training and producing the mode of the classes as the final prediction

(Magidi et al., 2021; Mpakairi et al., 2023). Multiple convolutional layers of the CNN model are intended to handle spectral and spatial characteristics, and to automatically extract hierarchical features from the input data (Jin et al., 2019; Waldner & Diakogiannis, 2020; Bey et al., 2020). The advantage of the CNN is that it can identify textures and spatial patterns. In order to train the CNN model, a U-Net model was trained with the training data across the study areas to recognise forest, grassland, water, built-up areas, bare land and cultivated land. Cultivated land was then grouped into rainfed land and irrigated land. The U-Net architecture consisted of encoder, bottleneck and decoder, and the hyperparameters, namely, the learning rate (n = 0, 0.005 and 0.001), batch size (n = 16) and the number of epochs (n = 50 – 250) were optimised through a grid search to enhance the performance of the model, based on the methods used by Waldner & Diakogiannis (2020) and Mpakairi et al. (2023). The hyperparameters were recognised through a cross-validation process (n = 8 times) with 80% of the training data, 10% of the training data was used to validate the model and 10% of the remaining data was used to test the model. The SVM model performs well in high-dimensional environments, and the model builds hyperplanes in a multidimensional space to efficiently divide various classes (Bey et al., 2020; Gxokwe, et al., 2022; Mpakairi et al., 2023). The Transformer model was applied to process the Sentinel-2 data and it was trained on the NDVI, MSAVI2 and NDVI, combined with MSAVI2 values, to compare their accuracies. These values formed the input sequence for the transformer model, which allowed the model to track changes in the vegetation and is vital for distinguishing rainfed smallholder farms from other land uses (Koutilya & Bandaru, 2023). The model was configured to enhance feature extraction, which focused on the patterns pertaining to rainfed smallholder farms. The input to the model was a time-series data stack of NDVI and MSAVI2 values for 12 months, which represents the growth stages of the agricultural cycle. The NDVI and MSAVI2 were combined to improve the model's ability to distinguish between crop types, which enhances the spectral signal, especially mixed land use areas, which are common in smallholder farming areas (Li et al., 2020; Yan et al., 2023). To avoid overfitting, the CNN used the drop-out regularisation technique to reduce the model's complexity (Li et al., 2020; Waldner & Diakogiannis, 2020). The GBDT and Transformer models underwent parameter tuning and early stopping, in order to prevent excessive training (Yan et al., 2023). Validation metrics were monitored to ensure that the models did not overfit to the training data and that they maintained their ability to generalise unseen data (Persello et al., 2019; Yan et al., 2023).

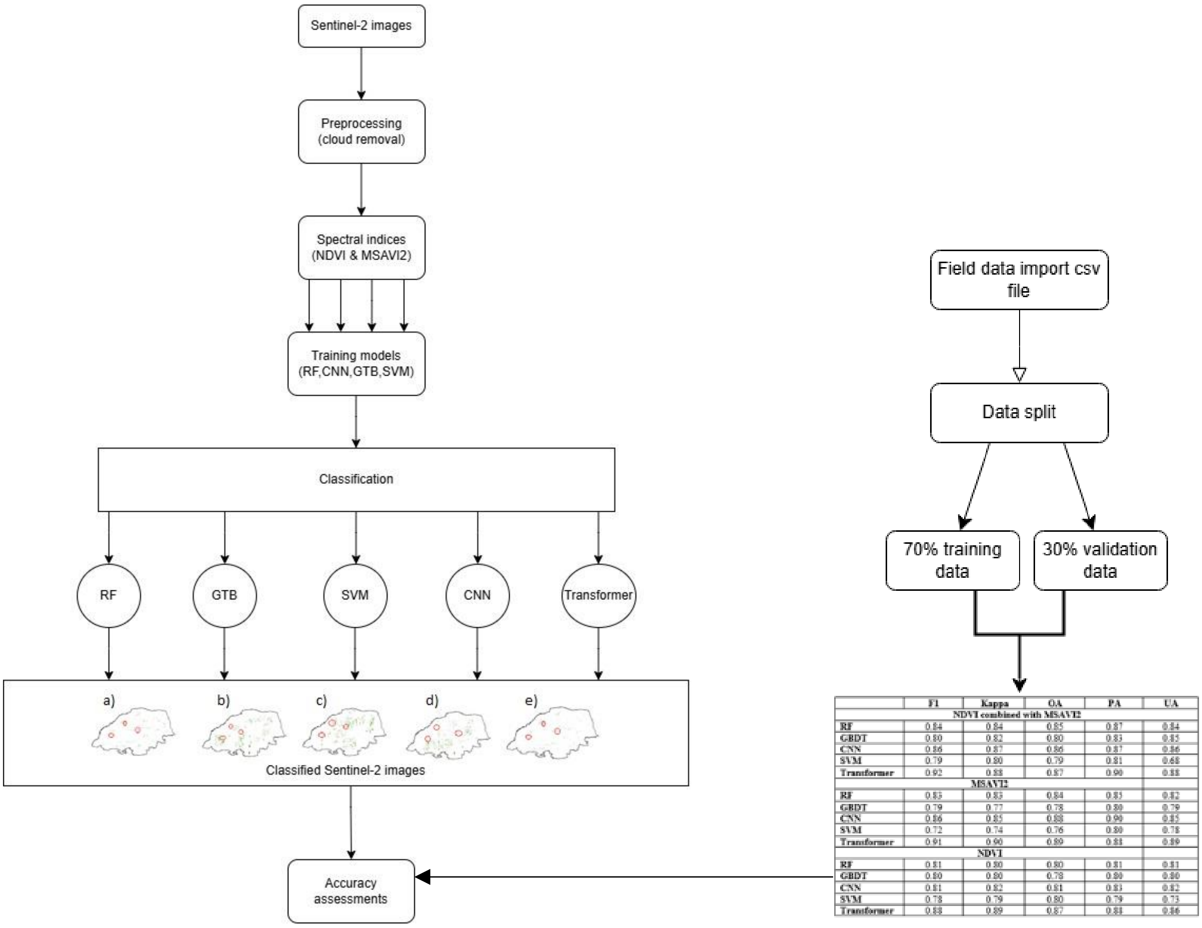

Figure 3.2 Flowchart of the work process

3.2.2.2 Accuracy assessment

Metrics, such as the F1 score, kappa coefficient, overall accuracy, producers' accuracy and users' accuracy, were used to assess the accuracy, based on the equations used by Congalton et al. (1983) and Seaton et al. (2020). These methods were chosen based on their application in studies conducted by Li et al. (2020), Estevez et al. (2022), Lin et al. (2022), Mpakairi et al. (2023) and Yan et al. (2023).

An assessment of the performance of the classification algorithms was tested by using the F1 score, which is the mean of the precision and recall. This score was useful in detecting and managing false positives and false negatives. The agreement between the observed and expected classifications was assessed by using the kappa coefficient, which provides a more reliable measure of accuracy that takes random classification into consideration (Congalton et al., 1983; Persello et al., 2019). The overall accuracy of the model, as measured by the ratio of samples that were classified correctly to the total number of samples, provided a clear indicator of its efficacy. The model's capacity to reliably map the rainfed smallholder farms was evaluated by using the producers' accuracy metric, which shows the likelihood that a reference pixel is correctly identified. The degree to which a pixel was categorised as belonging to a particular class, as indicated by the users' accuracy, gave an insight into how reliable the mapped classes were, from the user's point of view. A thorough assessment of the classification models was made possible by combining these methods, which demonstrates their ability to accurately identify rainfed smallholder farms (Li et al., 2020; Lin et al., 2022; Yan et al., 2023).

Furthermore, the mean Intersection over Union (mIoU) was used as a key metric to evaluate the performance of the models in accurately classifying and mapping rainfed smallholder farms. The mIoU quantifies the overlap between the predicted and ground-truthing areas by calculating the ratio of their intersection over their union, which averages across the different classes (Lin et al., 2022). This is vital for agricultural mapping, as it accounts for the spatial alignment and area-based accuracy of classified areas, which is important for delineating smallholder farms with irregular boundaries (Jin et al., 2019; Carelsen et al., 2021; Lin et al., 2022). This study evaluated the accuracy of the models in differentiating between rainfed and irrigated regions by using mIoU to estimate how well the model depicts the spatial extent of these rainfed areas. In addition, mIoU made it possible to compare various models by emphasising any improvement in segmentation accuracy that was specific to the spatial and temporal characteristics of the smallholder farms (Yan et al., 2023).

3.3 Results

3.3.1 Comparison of classification results across provinces

Figures 3.3, 3.4, 3.5 and 3.6 show the delineation results using the NDVI, combined with MSAVI2, of rainfed smallholder farms in the Limpopo, North West, Mpumalanga and Gauteng Provinces, by using the CNN, RF, GBDT, SVM and Transformer models. Limpopo and Mpumalanga had the highest presence of detected rainfed smallholder farms, while Gauteng had the lowest.

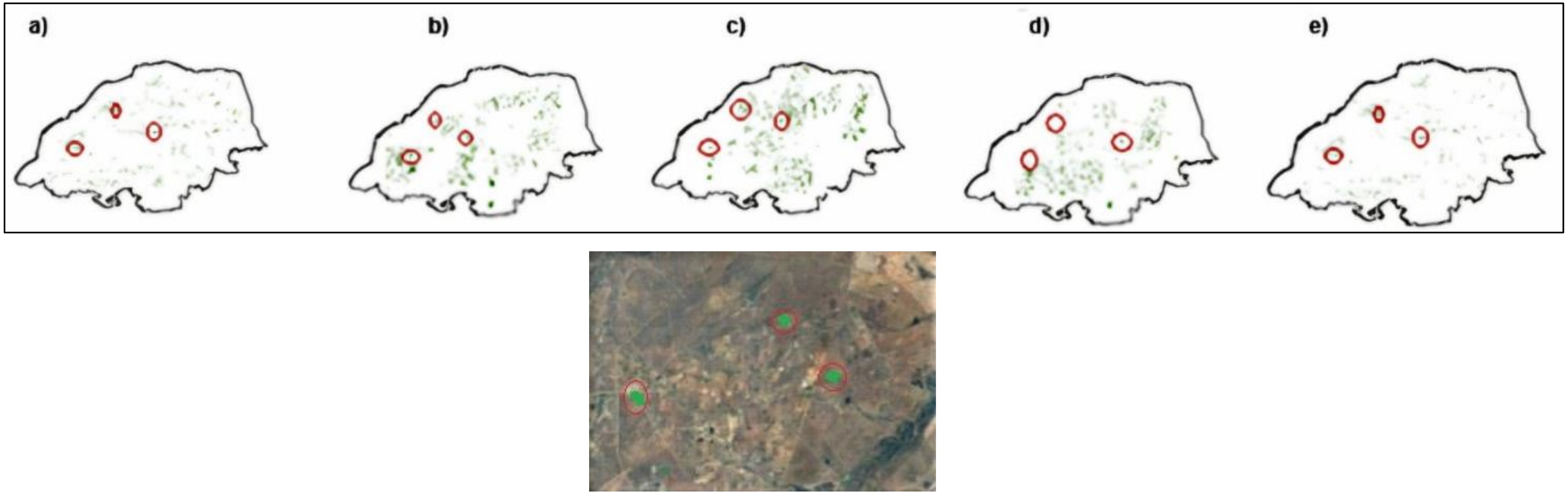

Figure 3.3 Rainfed smallholder farm delineation results for the Limpopo Province, using NDVI combined with MSAVI2 (a – CNN, b – RF, c – GBDT, d – SVM and e - Transformer), followed by a composite image

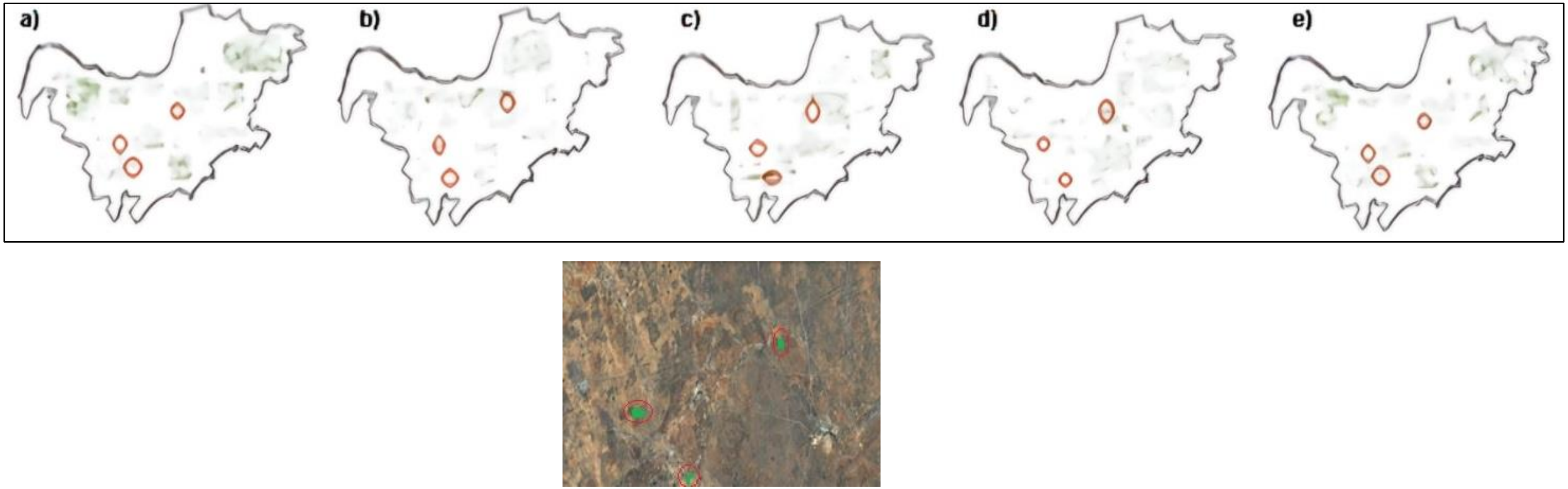

Figure 3.4 Rainfed smallholder farm delineation results for the North West Province, using NDVI combined with MSAVI2 (a – CNN, b – RF, c – GBDT, d – SVM and e - Transformer), followed by a composite image

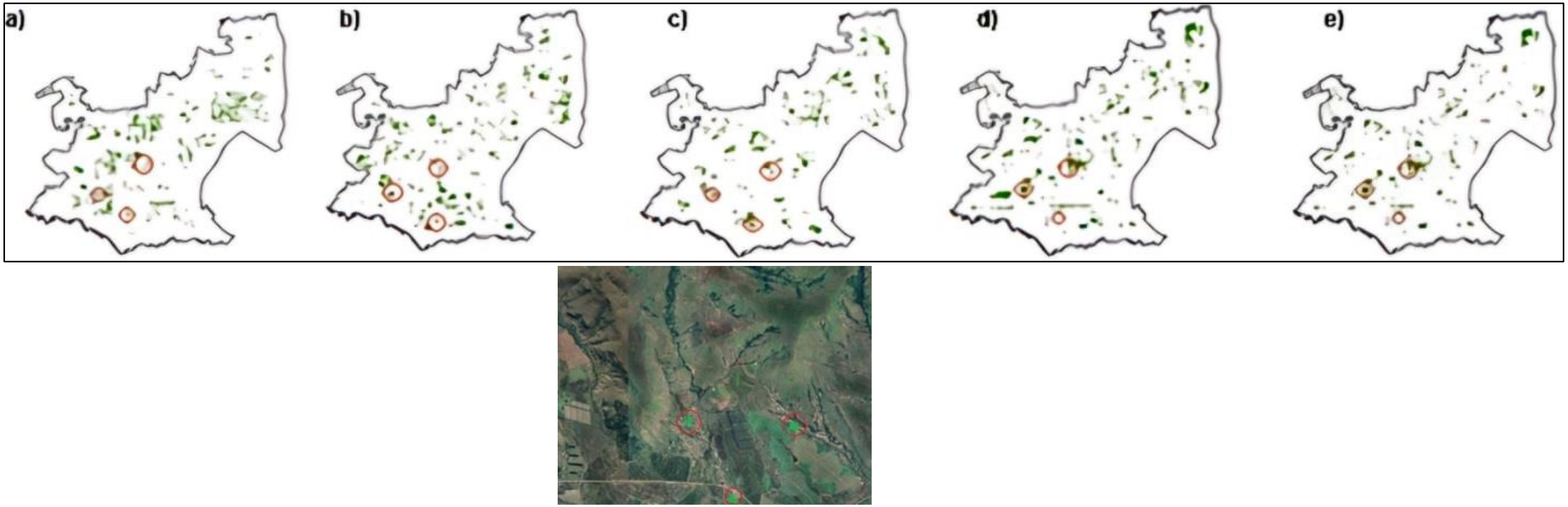

Figure 3.5 Rainfed smallholder farm delineation results for the Mpumalanga Province, using NDVI combined with MSAVI2 (a – CNN, b – RF, c – GBDT, d – SVM and e - Transformer), followed by a composite image

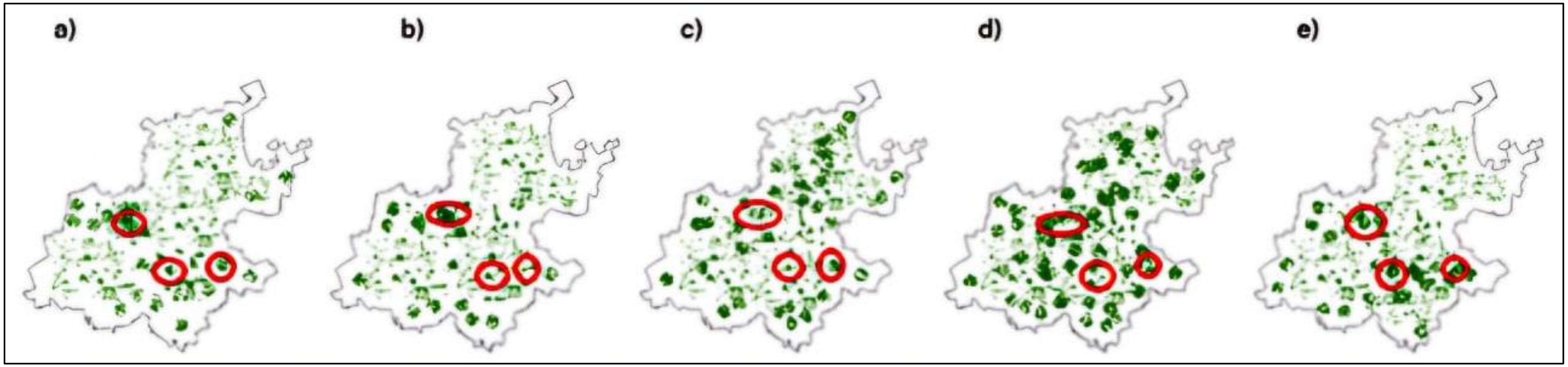

Figure 3.6 Rainfed smallholder farm delineation results for the Gauteng Province, using NDVI combined with MSAVI2 (a – CNN, b – RF, c – GBDT, d – SVM and e - Transformer), followed by a composite image

Rainfed smallholder farms across the provinces of Limpopo (Figure 3.3), North West (Figure 3.4), Mpumalanga (Figure 3.5) and Gauteng (Figure 3.6) were accurately mapped by using a combination of NDVI and MSAVI2. The combination of the two spectral indices proved to be highly effective in distinguishing rainfed smallholder farms and irrigated farms across all the machine learning algorithms considered in this study (Tables 3.2, 3.3, 3.4, 3.5, 3.6 and 3.7). When averaged across all the models, the results showed that the Limpopo (25.9%) and Mpumalanga (19.94%) Provinces had the largest area under rainfed smallholder agriculture, with the smallest presence in North West (13.64%), followed by Gauteng (14.02%) (Table 3.2). The superiority of the integrated spectral indices is demonstrated by higher accuracy metric values that include the OA, PA, UA and F1-score, regardless of the model that was used (Tables 3.3, 3.4, 3.5 and 3.6). When either of the spectral indices was used in the models, the classification accuracy reduces, except for a few instances.

Table 3.2 Total area occupied by rainfed smallholder farms as delineated by the different algorithms as a % of the province detected by NDVI combined with MSAVI2

	Limpopo	**North West**	**Mpumalanga**	**Gauteng**
RF	25.5	13.8	20.2	12.2
GBDT	26.2	12.9	15.8	16.4
CNN	25.3	14.6	19.8	11.5
SVM	26.7	11.8	24.7	19.2
Transformer	25.8	15.1	19.2	10.8

Surprisingly, NDVI was the superior spectral index for mapping smallholder farms in the Mpumalanga Province (Figure 3.5). NDVI was incorporated in the CNN model and the RF model. Surprisingly, when the same spectral index was integrated in the SVM model, it performed poorly across all three regions, with Mpumalanga having the least accuracy. The CNN model was used to discriminate between rainfed and irrigated agricultural areas. The OA, PA, UA and F1-score were used to validate the outcomes from the CNN model. The North West Province, followed by Mpumalanga, had a low presence of rainfed smallholder farms (Table 3.2), whereas the Limpopo Province had a high number of rainfed smallholder farms (Table 3.2).

3.3.2 Accuracy results of the classifications

A comparison of the performance of NDVI and MSAVI2 across the models showed that the models that incorporated NDVI with MSAVI2 outperformed the NDVI-based classification models (Tables 3.3, 3.4, 3.5 and 3.6). Table 3.3 indicates the accuracies for Limpopo, based on the RF, GBDT, CNN, SVM and Transformer results for the integration of NDVI with MSAVI2, MSAVI2 and NDVI. The NDVI results in all three provinces were poor, compared to the MSAVI2 results. NDVI combined with MSAVI2 detected the most rainfed smallholder farms in the northern regions of Limpopo, by all four models (Table 3.3).

Table 3.3 The levels of accuracy achieved for the Limpopo province, based on the five models adopted in the study based on NDVI, MSAVI2 and combined spectral indices

	F1	**Kappa**	**OA**	**PA**	**UA**
		NDVI combined with MSAVI2			
RF	0.84	0.84	0.85	0.87	0.84
GBDT	0.80	0.82	0.80	0.83	0.85
CNN	0.86	0.87	0.86	0.87	0.86
SVM	0.79	0.80	0.79	0.81	0.68
Transformer	0.92	0.88	0.87	0.90	0.88
		MSAVI2			
RF	0.83	0.83	0.84	0.85	0.82
GBDT	0.79	0.77	0.78	0.80	0.79
CNN	0.86	0.85	0.88	0.90	0.85
SVM	0.72	0.74	0.76	0.80	0.78
Transformer	0.91	0.90	0.89	0.88	0.89
		NDVI			
RF	0.81	0.80	0.80	0.81	0.81
GBDT	0.80	0.80	0.78	0.80	0.80
CNN	0.81	0.82	0.81	0.83	0.82
SVM	0.78	0.79	0.80	0.79	0.73
Transformer	0.88	0.89	0.87	0.88	0.86

Table 3.4 shows the accuracies achieved for the North West Province, whereby most rainfed smallholder farms were detected by NDVI combined with MSAVI2 in the eastern and central regions by all four models (Table 3.4).

Table 3.4 The accuracies achieved for the North West Province

	F1	Kappa	OA	PA	UA
NDVI combined with MSAVI2					
RF	0.83	0.82	0.84	0.85	0.83
GBDT	0.80	0.83	0.80	0.84	0.82
CNN	0.84	0.86	0.85	0.89	0.87
SVM	0.78	0.80	0.79	0.79	0.69
Transformer	0.87	0.87	0.86	0.89	0.88
MSAVI2					
RF	0.79	0.74	0.80	0.73	0.71
GBDT	0.79	0.73	0.76	0.69	0.69
CNN	0.82	0.81	0.84	0.83	0.82
SVM	0.76	0.71	0.79	0.69	0.70
Transformer	0.84	0.83	0.82	0.83	0.84
NDVI					
RF	0.82	0.81	0.83	0.84	0.80
GBDT	0.80	0.80	0.78	0.82	0.80
CNN	0.83	0.82	0.84	0.87	0.83
SVM	0.79	0.75	0.76	0.80	0.78
Transformer	0.84	0.83	0.81	0.83	0.84

Table 3.5 shows the accuracies achieved for Mpumalanga, whereby most rainfed smallholder farms were detected by NDVI combined with MSAVI2 in the eastern and central regions by all four models, and the SVM detected the least amount of rainfed smallholder farms (Table 3.5).

Table 3.5 The accuracies achieved for Mpumalanga Province

	F1	Kappa	OA	PA	UA
NDVI combined with MSAVI2					
RF	0.84	0.82	0.85	0.87	0.84
GBDT	0.80	0.83	0.84	0.83	0.83
CNN	0.85	0.85	0.86	0.89	0.86
SVM	0.70	0.79	0.81	0.80	0.79
Transformer	0.92	0.90	0.89	0.90	0.91
MSAVI2					
RF	0.83	0.81	0.82	0.86	0.83
GBDT	0.76	0.77	0.81	0.84	0.80
CNN	0.85	0.83	0.86	0.89	0.87
SVM	0.74	0.71	0.79	0.79	0.78
Transformer	0.89	0.87	0.85	0.87	0.86
NDVI					
RF	0.82	0.79	0.81	0.82	0.80
GBDT	0.79	0.76	0.80	0.79	0.78
CNN	0.82	0.80	0.83	0.84	0.81
SVM	0.80	0.79	0.80	0.78	0.77
Transformer	0.83	0.81	0.82	0.81	0.82

Table 3.6 indicates the accuracies achieved for Gauteng based on the RF, GBDT, CNN, SVM and Transformer results for the integration of NDVI with MSAVI2, MSAVI2 and NDVI. The Transformer model achieved the highest accuracies for all three indices, whereas the SVM achieved the lowest accuracy and detected the least amount of rainfed smallholder farms.

Table 3.6 The accuracies achieved for Gauteng Province

	F1	Kappa	OA	PA	UA
NDVI combined with MSAVI2					
RF	0.83	0.81	0.84	0.83	0.81
GBDT	0.79	0.80	0.81	0.80	0.79
CNN	0.82	0.84	0.83	0.87	0.85
SVM	0.80	0.79	0.77	0.80	0.75
Transformer	0.82	0.85	0.83	0.84	0.82
MSAVI2					
RF	0.78	0.73	0.75	0.70	0.69
GBDT	0.78	0.70	0.74	0.74	0.70
CNN	0.80	0.81	0.82	0.81	0.84
SVM	0.75	0.74	0.73	0.68	0.70
Transformer	0.80	0.81	0.80	0.82	0.81
NDVI					
RF	0.76	0.78	0.79	0.75	0.76
GBDT	0.75	0.72	0.75	0.76	0.74
CNN	0.79	0.69	0.70	0.72	0.78
SVM	0.69	0.62	0.65	0.63	0.64
Transformer	0.80	0.82	0.81	0.80	0.79

The CNN model was able to identify and delineate rainfed smallholder farms, and it achieved a high overall accuracy in all four provinces (Tables 3.3, 3.4, 3.5 and 3.6). The RF model achieved the second-highest accuracy, followed by the GBDT. The SVM achieved the lowest accuracy in all three provinces (Table 3.3). All four models achieved higher accuracies in the Limpopo (Table 3.3) and North West Provinces (Table 3.4), which are both classified as hot semi-arid climates (BSh). Mpumalanga, which is classified as a highland tropical climate (Cwb), achieved the lowest accuracies by all four models (Table 3.5), followed by Gauteng (Table 3.6). Gauteng has the least amount of rainfed smallholder farms and is mostly an urbanised region.

Table 3.7 indicates the mIoU results obtained by the RF, GBDT, CNN, SVM and Transformer models. The Transformer model performed the best in detecting and delineating rainfed smallholder farms, and it achieved the highest mIoU results across all four provinces using NDVI, MSAVI2 and NDVI combined with MSAVI2. The Transformer model with the NDVI combined with the MSAVI2 results, obtained the highest accuracies across all four provinces (Table 3.7). All five models performed the best in the North West Province and achieved the lowest accuracies in Mpumalanga. The North West Province achieved the highest mIoU result of 0.91, when using the Transformer model to compute NDVI combined with MSAVI2. The lowest mIoU result was 0.69 and was achieved by MSAVI2 under the SVM model in the Limpopo and Gauteng Provinces.

Table 3.7 mIoU results achieved by the models

	Limpopo	**North West**	**Mpumalanga**	**Gauteng**
		NDVI		
RF	0.79	0.80	0.76	0.79
GBDT	0.76	0.79	0.75	0.76
CNN	0.84	0.87	0.78	0.80
SVM	0.77	0.79	0.72	0.76
Transformer	0.87	0.89	0.79	0.78
		MSAVI2		
RF	0.76	0.85	0.75	0.72
GBDT	0.75	0.75	0.70	0.73
CNN	0.86	0.88	0.76	0.79
SVM	0.69	0.70	0.68	0.69
Transformer	0.89	0.90	0.88	0.88
		NDVI combined with MSAVI2		
RF	0.87	0.89	0.79	0.79
GBDT	0.86	0.88	0.76	0.80
CNN	0.90	0.90	0.87	0.89
SVM	0.77	0.79	0.75	0.79
Transformer	0.88	0.91	0.79	0.82

3.4 Discussion

3.4.1 NDVI and MSAVI2 based delineation of rainfed smallholder farms

Overall, the findings show how effective the GEE is at identifying and mapping rainfed smallholder farms across various climatic zones. The size and distribution of smallholder farms that rely on rainfed agriculture offer the baseline data and insights that are required for rural livelihoods, food security and poverty alleviation initiatives (Ruwanza et al., 2022; Wang et al., 2022; Dube et al., 2023). The existing techniques for identifying these boundaries are expensive for large areas. As an alternative, remotely-sensed data collected from open sources and agricultural databases can be employed. The findings of the study show how this methodology might be used more widely in future studies.

The NDVI maps were able to accurately delineate rainfed smallholder farms. The NDVI classification accuracy achieved an F1 score of 0.82, a kappa coefficient of 0.81, an OA of 0.82, a PA of 0.85 and a UA of 0.82. The study highlighted the usefulness of NDVI for mapping agricultural boundaries even more. It was easy to distinguish between the lower NDVI values in fallow or non-vegetated areas and the higher values found in agricultural areas. The overall accuracy of the study is consistent with earlier research findings, which indicates the validity of NDVI in agricultural mapping (Zeng, et al., 2020; Magidi et al., 2021a). In the North West and Mpumalanga Provinces, most of the rainfed smallholder farms are situated in areas where the climate and soil conditions are suited to rainfed agriculture and are impacted by the variability in rainfall and soil quality (Mpandeli et al., 2015; Mpakairi et al., 2023). In the North West Province, most of the rainfed smallholder farms are found in the eastern and central regions, which receive moderate rainfall during the summer months, and this supports the growth of maize, sorghum and sunflower (Cole et al., 2021; Amede et al., 2023). These regions are semi-arid and the farmers struggle with soil degradation and drought conditions (Cole et al., 2021; Mpakairi et al., 2023). The Limpopo Province has a large rainfed smallholder farming sector, which is prominent in the northern and central regions, due to its rural character and reliance on subsistence and small-scale farming (Mpandeli et al., 2015). Rainfed smallholder farmers are prominent in the eastern region of Mpumalanga, which receives high amounts of rainfall that are suitable for rainfed agriculture (Ebhuoma et al., 2020). The majority of these smallholder farmers grow maize, potatoes and various fruits (Mpakairi et al., 2023). In all three provinces, rainfed smallholder farms are vital for food security; however they are extremely vulnerable to varying weather patterns and soil conditions, which are impacted by climate change. The performance metrics did, however, also draw attention to certain shortcomings, notably in the North West and Limpopo Provinces, which are semi-arid areas and where the soil brightness can affect NDVI measurements and perhaps cause misclassifications. In the Gauteng Province, the models performed poorly, which could be due to the fact that it is a built-up area with a low presence of rainfed smallholder farmers (Carelsen et al., 2021; Mpakairi et al., 2023). This will lead to misclassification and low accuracies (Zeng et al., 2020; Carelsen et al., 2021); therefore, there is a need to improve the algorithms and classification methods in built-up urban areas.

The MSAVI2 achieved high accuracies in the North West and Limpopo Provinces, which are classified as hot semi-arid regions and where soil reflectance has a high impact on the vegetation index results. The MSAVI2 classification accuracy produced an F1 score of 0.84, a Kappa coefficient of 0.83, an OA of 0.86, a PA of 0.87 and a UA of 0.85. These MSAVI2 results indicate its superior performance in minimising misclassification and in detecting actual rainfed smallholder farms. When the NDVI and MSAVI2 results are compared, it becomes clear that, while both indices are useful for identifying rainfed smallholder farms, MSAVI2 has a minor advantage in areas where soil exposure is high. This benefit is especially noticeable in semi-arid zones, where the ability of MSAVI2 to adapt the soil lessens the effect of soil brightness, resulting in more precise mapping (Gxokwe et al., 2022). According to the MSAVI2 results, it made it easier to distinguish between the vegetated areas, particularly in the early- and late-growth seasons, when there is little to no vegetation cover. These findings are consistent with studies that demonstrate MSAVI2 outperforms NDVI in regions with significant soil exposure (Mpakairi et al., 2023). The enhanced capabilities of MSAVI2 demonstrate how ideal it is for mapping smallholder farms in semi-arid climates that get rainfall, where soil reflectance interference could be a problem for conventional vegetation indices.

When NDVI and MSAVI2 were directly compared, it became clear that, although both indices are useful, MSAVI2 has a clear advantage in regions where the soil brightness is high. Throughout the growing season, the temporal profiles of MSAVI2 showed an improved separation between farm and non-farm areas, which demonstrates its resilience in a variety of soil conditions. This benefit was especially noticeable in the Limpopo and North West Provinces, where the soil adjustment feature of MSAVI2 allowed for a more precise delineation. For smallholder farmers in these areas, this increased delineation accuracy with MSAVI2 is essential, since it allows for more accurate agricultural activity monitoring and management. For smallholder farmers, this increased precision leads to better crop management, better resource allocation and a higher yield. The MSAVI2 also achieved higher accuracies in the Gauteng Province, compared to the NDVI, despite it being a built-up area and a warm temperate climate (Cwa) region in the north and a subtropical highland climate (Cwb) in the south.

The delineation accuracy was further improved in all three provinces by the incorporation of NDVI combined with MSAVI2 values as features in the machine learning models (GBDT, RF, SVM, CNN and Transformer). By combining these indices, the models were better able to account for the effects of both the soil background and vegetation vigour, thereby producing more reliable classification results (Onyango et al., 2021). With the addition of NDVI and MSAVI2 characteristics, the overall accuracy of the Random Forest model increased to 0.80. The findings underscore the efficacy of integrating vegetation indices into machine learning processes, as they furnish supplementary spectral data that amplifies the discriminatory capacity of the model. While performing marginally worse than the Random Forest, the Gradient Tree Boosting and Support Vector Machine models also demonstrated notable increases in accuracy when NDVI and MSAVI2 were added. Out of all the models, the CNN, which is well-known for its outstanding understanding of textures and patterns in space, obtained the best accuracy, and similar results were achieved in studies by Li et al. (2020) and Walder and Diakogiannis (2020). Thanks to its deep learning architecture, CNN was able to use the spectral and spatial information offered by MSAVI2 and NDVI to automatically extract hierarchical features from the input data (Li et al., 2020). The enhanced performance of CNN highlights its potential as an effective mapping tool for agriculture, especially when paired with vegetation indicators.

The Transformer model enhanced the ability to map rainfed smallholder farms, by using time-series data more accurately than traditional models. The self-attention mechanism enabled the model to focus on critical time periods within the agricultural growing seasons. This allowed it to detect rainfed smallholder farms and to make it valuable and a promising approach in land classification. Compared to the other models, the Transformer's ability to process historical data is crucial for detecting rainfed farming, especially in semi-arid regions, where crops follow distinct seasonal growth patterns; this is consistent with the earlier research findings by Lin et al. (2022) and Yan et al. (2023).

Although these models achieved high accuracies, there are still several key sources of misclassification. The most prevalent issue was the confusion between rainfed and irrigated croplands, especially in regions with high vegetation cover throughout the year, for example in Mpumalanga, which is classified as having a tropical climate. Grasslands and shrublands were also misclassified as rainfed farms, especially in semi-arid regions where the natural vegetation exhibited similar spectral characteristics to those of crops. Spectral similarity, temporal variability in crop growth cycles that are influenced by climatic and seasonal changes, as well as limitations in the model in handling spatial complexity, are some of the possible reasons for misclassifications. These have also been experienced in previous studies by Jin et al. (2019), Persello et al. (2019), Bey et al. (2020), Waldner and Diakogiannis, (2020), Magidi et al. (2021), Mashaba-Munghemezulu et al. (2021), Lin et al. (2022), Wang et al. (2022), Koutilya and Bandaru (2023) and Mpakairi et al. (2023). To address these issues, future research should focus on enhanced feature engineering with extra vegetation indices (Yan et al., 2023). Future studies can also test hybrid models that combine temporal data and spatial data for temporal analysis, through seasonal time series studies and transfer learning with pre-trained models (Estevez et al., 2022; Koutilya & Bandaru, 2023). The collection of ground-truth data should also be expanded and post-classification filtering techniques can be used in future studies (Carelsen et al., 2021; Lin et al., 2022). By implementing these strategies, the accuracy and reliability of models can be improved when mapping rainfed smallholder farms.

When rainfed smallholder farms are defined precisely, there are major advantages for smallholder farmers and agricultural management. Accurate mapping helps farmers to plan and distribute their resources, like fertilizer and seeds, more effectively (Onyango et al., 2021). This results in higher agricultural yields, lower input costs and more effective farming techniques. The productivity and sustainability of farms are further increased by the capacity to keep an eye on crop health and to identify pest or disease outbreaks early (Mpandeli et al., 2015; Quandt, 2021). Precise farm maps are essential for agricultural management, because they give extension services access to vital information, which helps them to provide farmers with focused guidance and assistance (Fanadzo et al., 2021). This customised strategy assists with the adoption of best practices, it enhances crop management and it strengthens the resistance of farmers to climate variability. Furthermore, precise mapping ensures that policies are based on trustworthy data and it successfully meets the requirements of smallholder farmers by supporting policy-making and resource allocation at a regional and national level (Ruwanza et al., 2022; Wang et al., 2022).

3.4.2 Implications for scientific research and study limitations

The more accurate mapping of rainfed smallholder farms provides scientists with an abundance of trustworthy data for study and analysis. The reliability of research on land use, agriculture and environmental management is increased by precise mapping. It offers a strong basis for examining the dynamics and spatial distribution of smallholder farming systems, which allows researchers to investigate the relationship between the climate, soils and crops. By pushing the limits of remote sensing and GIS technology, the integration of vegetation indicators with machine learning models promotes innovation and advances the discipline. The accurate mapping of smallholder farms across a range of climatic zones facilitates multidisciplinary studies to be conducted in the future (Onyango et al., 2021; Dube et al., 2023).

The findings show that MSAVI2 and NDVI are effective methods for identifying smallholder farms that are rainfed, with MSAVI2 performing better in semi-arid areas. These indices, in combination with cutting-edge machine learning models, increases the classification accuracy even further and offers a trustworthy way to map smallholder farms throughout a range of climatic zones. Better agricultural management, resource allocation and policymaking are made possible by these enhanced mapping capabilities, which eventually raises the productivity and sustainability of smallholder farming systems (Dube et al., 2023). The Transformer model's performance, measured through mIoU, has indicated a superior ability to map and detect rainfed smallholder farms. Although deep learning models such as the CNN and the Transformer model achieved high accuracies in delineating rainfed smallholder farms, it is important to acknowledge the uncertainties inherent in these models. Sources of uncertainty include sensor limitations, ground-truth data sampling errors, limited representatives of the training data, spatial heterogeneity of rainfed smallholder farm landscapes and the random nature of the model training process (Gxokwe et al., 2022; Yan et al., 2023). Bayesian deep learning approaches, Dropout regularisation or ensemble methods can be incorporated into future studies to quantify predictive uncertainty (Heddam et al., 2022). This would assist in distinguishing between mixed pixels, which is vital for decision-making in agricultural applications.

Recent advancements in Cloud computing, GEE and remote sensing have enhanced the mapping and near-real-time monitoring of rainfed smallholder farms under various environmental conditions (Magidi et al., 2021a; Mashaba-Munghemezulu et al., 2021; Chiloane et al., 2023). The improved mapping of rainfed smallholder farms improves the farmers' insights for improving their farming practices and assists scientists and policy-makers to develop research and to shape policies even further. This, in turn, aids food security and sustainable agricultural development. Satellite images with a high resolution, such as RapidEye, QUICKBIRD, IKONOS and Worldview, can improve the accuracy of mapping and delineating rainfed smallholder farms; however, these data are expensive (Persello et al., 2019; Onyango et al., 2021). Another challenge with using remote sensing techniques to map rainfed smallholder farms in humid areas, is the overlap in spectral signatures, which makes it difficult to differentiate between rainfed and irrigated farming areas, as the vegetation is always green (Magidi et al., 2021a). To overcome the challenge of the temporal resolution of sensors, Unmanned Aerial Vehicles (UAVs) can be used to improve the mapping and delineation of rainfed smallholder farms (Dube et al., 2023). A key limitation is the applicability of this methodological framework to different sub-Saharan African countries with different climate classifications.

3.5 Conclusion

Remote sensing methods have been shown to be highly efficient in mapping and delineating rainfed smallholder farms. While the use of GEE in research is growing, there have not been many studies that utilise GEE to delineate rainfed smallholder farms in sub-Saharan Africa. Consequently, this work mapped and distinguished smallholder farms by using GEE across different South African provinces that have varying climatic classifications. The CNN model, along with the RF model, achieved a high accuracy, which indicates the potential for future studies to follow this approach on a larger scale, in different climatic regions. However, the Transformer model achieved the highest accuracies and is a vital advancement in the mapping of rainfed smallholder farms, especially when it is integrated with NDVI and MSAVI2. Its ability to analyse historical data enables the accurate delineation of rainfed smallholder farms in semi-arid regions, where the changes in vegetation are subtle and dependent on the rainfall variability. The results of this study highlight the potential of the Transformer model in agricultural mapping and detection, and it highlights the importance of integrating spectral indices and accuracy assessments, like mIoU, in detecting the small details of smallholder farms. The results of this study are vital for rainfed smallholder farmers to improve their farming practices, to assist with drought mitigation, as well as to assist scientists and policymakers to improve their research and shape their policies. Future studies can expand on these findings and can use time-series analyses to enhance the accuracy of rain-fed smallholder farm mapping and delineation, especially in humid regions with similar spectral wavelengths. This study has significant consequences for food security and sustainable development and shows the promise of machine learning algorithms and remote sensing data for rainfed smallholder farm delineation. Following the performance of the transformer model, there is a need for further on its applicability predominantly rural agricultural systems given their spatial complexity and configuration as well as varying microclimatic conditions.

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CHAPTER FOUR

DROUGHT FREQUENCY AND PROBABILITY ASSESSMENT IN DIFFERENT REGIONS IN SOUTH AFRICA

Abstract

This study evaluates the geographic extent, the likelihood of occurrence, as well as the severity of agricultural and meteorological drought conditions from 2004 to 2023, across the North West, Limpopo and Mpumalanga Provinces in South Africa. The Vegetation Condition Index (VCI) was computed by using SPOT VEGETATION 1 data from 2004 to May 2014 and PROBA-V data from June 2014 to December 2023. Based on CHIRPS data from January 2004 to December 2023, the Standardised Precipitation Index (SPI) was used to characterise droughts in the study area. The VCI and SPI were computed in Google Earth Engine (GEE) to illustrate drought severity throughout the three provinces and were classified according to the thresholds of previous studies. Of the three provinces, Limpopo emerged as the most affected province, as it experienced a severe drought of 0.91 for 15 years within the 19-year study period. The North West Province experienced a severe drought 11 times within the 19-year study period, while the Mpumalanga Province showed a relatively lower drought severity of 0.41. Validation metrics, such as the F1-score, True Skills Statistic and Matthews Correlation Coefficient, showed a strong agreement between the VCI and SPI results, which indicates the reliability of these indices for drought monitoring. These results are critical, not only for the agricultural sector but also for water-dependent sectors, especially in view of the anticipated influence of climate change on extreme events such as droughts. Thus, there is need to develop frameworks for integrating several variables, such as soil moisture and temperature, to conduct more accurate and comprehensive drought assessments.

Keywords: Drought impacts; drought vulnerability; remote sensing; South Africa; rural farmers

This chapter is based on the following manuscript:

Bhaga, TD, Shekede, MD, Shoko, C and Dube, T. (2024). Assessing drought frequency and probability across different regions in South Africa using satellite-derived metrics: a nineteen-year analysis. *Geomatics Natural Hazards and Risks*. [Under review -258955065]

4.1 Introduction

A drought is a natural disaster that has a major negative influence on socioeconomic stability, water supplies and agricultural productivity, especially in arid and semi-arid areas (Graw et al., 2017; Bekuma et al., 2022; Bogale & Erena, 2022). It is anticipated that droughts will occur more frequently, and with greater intensity, because of climate change, and that they will create more difficulties for sustainable development and food security (Mishra & Singh, 2010; Dube et al., 2023). Droughts have significant implications on the world at large, but they have had catastrophic effects in Africa, where many nations already struggle with food shortages and water constraints (Bhaga et al., 2020 Mpakairi et al., 2023). Therefore, understanding the frequency and probability of drought occurrence across different temporal scales is vital for effective water resource management, agricultural planning and disaster preparedness, especially in semi-arid regions, which are prone to droughts.

The African continent has seen the greatest number of drought-related fatalities since 1900, by accounting for a total of 800 000 deaths and directly impacting 262 million people (Sharara et al., 2022). For example, severe drought conditions struck Ethiopia between 2000 and 2020, impacting over 10 million people and triggering severe food shortages (Zeleke et al., 2017; Tareke & Awoke, 2022). Prolonged droughts in Somalia in 2017 have made the humanitarian disaster worse, causing acute food insecurity that affected about 6.2 million people (Giovetti, 2020; Keating, 2019). Drought-related disputes between farmers and herders over the limited resources have also got worse. Zimbabwe has experienced many droughts over the past few decades, which have had a significant effect on livelihoods and food security. For instance, the drought experienced in 2019 induced a 50% decline in agricultural output, and 5.5 million people were impacted (Matunhu et al., 2022). South Africa is susceptible to drought due to its varied climate and substantial reliance on rain-fed agriculture (Mpakairi et al., 2023). Recent years have seen South Africa experience a number of severe droughts, the worst of which was in recorded history in 2015-2018 (Bhaga et al., 2021). Currently, southern Africa is reeling from one of its worst droughts in years and has seen several countries declaring a state of national disaster. Understanding the possibility and frequency of drought events at various time scales is essential for the efficient management of water resources, the planning of agriculture and drought preparedness in these regions. Rainfed smallholder farms in these regions are severely affected by droughts and require timely drought monitoring, in order to mitigate their impacts (Bahta & Myeki, 2022).

Drought assessment encourages sustainable behaviour and well-informed decision-making, which supports long-term socioeconomic stability and environmental health and advances the progress toward a number of Sustainable Development Goals (SDGs). The key SDGs supported by drought assessments include eliminating poverty (SDG 1), reaching zero hunger (SDG 2), guaranteeing access to clean water and sanitation (SDG 6) and battling climate change and its effects (SDG 13). Monitoring the temporal and spatial patterns of droughts assists with the efficient allocation and management of water resources, that support SDG 6 and 13, respectively. Futhermore, assessing droughts is crucial for achieving the African Union's (AU) Agenda 2063, which aims to develop a prosperous and sustainable future for the continent. Satellite-based drought monitoring is vital for achieving the AU's 2063 goals, particularly for enhancing food security, agricultural production and economic stability (Adeyemi et al., 2023; Dube et al., 2023). This aligns with the AU's commitment to environmental sustainability, climate resistance and socioeconomic growth in Africa (de Araujo Junior et al., 2023; Prudhomme et al., 2024).

The monitoring, forecasting and analyses of the frequency of droughts have been completely transformed by remote sensing techniques, which also offer essential tools for long-term planning and real-time assessment (Huang et al., 2018; Agbehadji et al., 2023). With the use of remote sensing, large and remote areas may be continuously monitored with high temporal accuracy, which makes it possible to trace the progression and intensity of droughts, as well as to identify their early onset (Graw et al., 2017; Sharara et al., 2022; Adeyemi et al., 2023). These methods use satellite data to compute a variety of drought indicators, such as Land Surface Temperature (LST), which identifies the areas experiencing abnormal heat and water stress, and the Normalised Difference Vegetation Index (NDVI) and Vegetation Condition Index (VCI), which assess the health and greenness of thevegetation (Mishra & Singh, 2010; Bhaga et al., 2020). Furthermore, additional indicators, such as the Standardised Precipitation Index (SPI) and soil moisture data from the Soil Moisture Active Passive (SMAP) satellite mission enhance drought analysis (Huang et al., 2018; Tirivarombo et al., 2018; Li et al., 2020). The SPI is a drought indicator that measures abnormalities in precipitation over a range of time periods, from months to years (Adeola et al., 2021; Bhaga et al., 2023). Standardising precipitation data makes it possible to compare information from various climatic zones (Tirivarombo et al., 2018; Li et al., 2020; Wambura & Dietrich, 2020). Researchers are able to determine the frequency and length of drought events by examining past satellite data, which reveal the patterns and cycles that are essential for understanding long-term climate variability (Graw et al., 2017; Huang et al., 2018; Prudhomme et al., 2024).

The effectiveness of remote sensing indices, such as the Vegetation Condition Index (VCI) and Standardised Precipitation Index (SPI), in analysing the impact and pattern of droughts across sub-Saharan Africa has been highlighted in recent studies by Marumbwa et al. (2020), Adeola et al. (2021), Sharara et al. (2022) and Burka et al. (2024). Marumbwa et al. (2020) calculated the VCI and NDVI for 2015-2016 to determine the effect of droughts on land cover in southern Africa. The results of this study indicated that rural communities are more vulnerable to the impacts of drought, and they suggested that more studies need to be conducted to monitor and improve the mitigation strategies for these communities. Adeola et al. (2021) used rainfall data to calculate the SPI for the Free State Province in South Africa on a three-, six- and 12-month scale. It was found that the region experiences persistent drought conditions and that the VCI can be used to improve decision-making and to aid with drought early warning systems. Another study by Sharara et al. (2022) calculated the VCI and SPI in Zimbabwe from 2000 to 2018. Satellite data from SPOT Vegetation and PROBA-V were used to characterise droughts, while precipitation data were used to derive the SPI, and the results showed a positive correlation between the VCI and maize production ($r = 0.701$, $P = 0.000$). The results of this study indicate the significance of using satellite data and climate data to analyse the occurrence and patterns of drought, and they provide a framework for developing drought resilience and mitigation strategies in sub-Saharan Africa, while leaving room for these methods to be tested in South Africa. Similarly, Burka et al. (2024) calculated the VCI in the Google Earth Engine (GEE), using MOD13Q1 and MOD11A2 to identify the years drought occurred between 2000 and 2022, and they found a strong correlation between the VCI and rainfall (with Moran I and z scores of 0.23 to 0.79, respectively). The results of these studies can be used as a guide to improve the planning and management of water resources in South Africa, to build climate resilience and to test their applicability in drought-prone regions, in order to mitigate the effects of drought.

A thorough picture of the effects of drought is frequently not possible when climatological data are not integrated into the use of single indices, such SPI or VCI (Seaton et al., 2020; Bhaga et al., 2023; Abah et al., 2024). The accuracy of the measurements acquired from satellites is often unclear, due to a lack of ground validation data. Furthermore, little is known about how various crop varieties and land management techniques within these areas influence the satellite data (Mpakairi et al., 2023). To close these gaps and increase the precision and applicability of drought assessments in these crucial agricultural areas, high-resolution, multi-sensor satellite data must be integrated with in-situ data, particularly in sub-Saharan Africa, which is prone to droughts (Bhaga et al., 2021). Therefore, the aim of this study is to assess and determine the frequency and probability of drought occurrence over a nineteen-year period across rainfed smallholder farms in different regions in South Africa, namely, the Limpopo, North West and Mpumalanga Provinces, using multi-sensor satellite data and climatological data.

4.2 Methods and Materials

4.2.1 Study area

The research was carried out in three South African provinces, namely, Limpopo, North West and Mpumalanga (Figure 4.1). These three provinces are distinguished by their own soil, topographical and climatic characteristics, which influence their agricultural output and processes (Mpakairi et al., 2023). The subtropical climate of Limpopo, the northern-most province in South Africa, differs significantly from the climate in the east and the west of South Africa. The western part is more arid, while the eastern portions receive more rainfall, particularly in the summer (Mpandeli et al., 2015). Numerous agricultural endeavours, such as avocado plantations, citrus orchards and corn fields, are made possible by this heterogeneity. Limpopo is an important agricultural hub because of its subtropical temperature and diverse topography, which enable both dryland and irrigated cultivation. The North West Province, which located in the western part of the nation, is primarily semi-arid to arid, with large savannas and grasslands, and little-to-no rainfall. This climate makes it perfect for raising cattle and growing crops that are resistant to drought, such as sorghum and millet. According to Cole et al. (2021), its soils are often less fertile and better-suited for extensive grazing than intense agricultural production. The eastern Province of Mpumalanga has a variable climate, due to its diversified geography; the lowveld regions see warmer, drier weather, while the highveld regions see colder temperatures and frequent rains. With their rich soils and milder temperatures, the highveld regions are ideal for growing crops such as soybeans, potatoes and maize, while the lowveld is ideal for growing tropical and subtropical fruits, sugarcane and forestry because of its warmer temperature and less rainfall. The abundant biodiversity and different agricultural landscapes in the province are also a result of its diversified terrain, which includes the Drakensberg escarpment (Ebhuoma et al., 2020). The diverse climates and topographies of these locations significantly influence their agricultural production and drought susceptibility (Bhaga et al., 2020; Mpakairi et al., 2023).

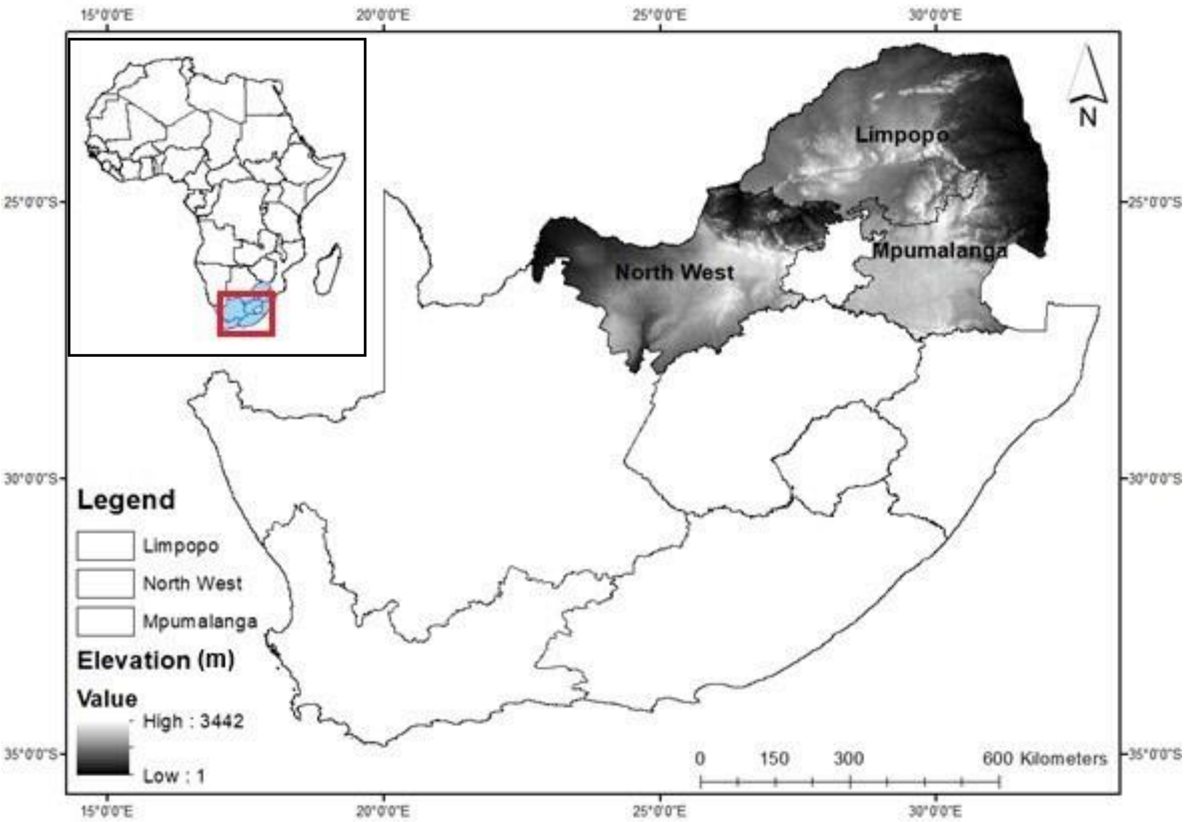

Figure 4.1 The location of the study area

4.2.2 Data collection

The Normalized Difference Vegetation Index (NDVI) was computed by using SPOT VEGETATION 1 data from 2004 until May 2014, and PROBA-V data was used from June 2014 until December 2023. Using the cloud mask tool in GEE, the imagery was processed to remove cloud cover, and seasonal patterns were captured by aggregating the data at monthly intervals.

In this study, the occurrence of droughts was characterised by using VCI, and the SPI was used to validate the characterised droughts derived from the VCI. The VCI was used because of its efficiency in monitoring vegetation health and detecting drought conditions, as well as its application and results across various regions around the globe (Quiring & Ganesh, 2010; Jiao et al., 2016; Kourouma et al., 2021; Valadao et al., 2021; Sharara et al., 2022; Burka et al., 2024). The VCI was derived from the NDVI, which was computed by using SPOT VEGETATION 1 and PROBA-V data (Figure 4.2).

The VCI is calculated by using the following formula:

$$\text{VCI} = \frac{NDVI - NDVImin}{NDVImax - NDVImin} \text{ x } 100, \qquad \text{Equation 4.1}$$

where NDVI is the Normalised Difference Vegetation Index and $NDVI_{min}$ and $NDVI_{max}$ represents the minimum and maximum NDVI values. High VCI values are indicative of healthy vegetation and low VCI values are an indication of stress, due to drought (Jiao et al., 2016; Burka et al., 2024). The VCI was calculated for each SPOT VEGETATION 1 and PROBA-V image in the time series, which allowed for the temporal and spatial analysis of drought conditions.

The SPI was computed to analyse deficits in the precipitation and to quantify the severity of the drought conditions. The SPI was calculated by using CHIRPS data collected from January 2004 to December 2023 on a three-month scale, in order to capture the variability of droughts. The calculation of SPI on a three-month scale reflects its close correlation to soil moisture, which influences crop growth (Sharara et al., 2022).

The SPI is calculated as $\text{SPI} = \frac{P - \mu}{\sigma}$, Equation 4.2

where P is the precipitation recorded at a location i, μ is the long-term mean precipitation for location i and σ is the standard deviation of the precipitation data at the same location. SPI values higher than 2 indicate wetter-than-average conditions and SPI values higher than -2 indicate drier-than-average conditions. The SPI was computed for each pixel within the study regions, to enable a spatial analysis of the drought patterns.

4.2.3 Data processing and analysis

The processed VCI and SPI data were analysed to determine the occurrence and intensity of droughts throughout the study region. In order to capture the temporal and spatial fluctuations in drought conditions, a trend analysis was conducted at a provincial level, to look at the VCI and SPI trends over the course of the 19 years. In addition, the data were combined to evaluate the frequency of droughts on an annual scale. GEE's spatial analysis tools were utilised to generate these maps, which illustrate the drought severity throughout the three provinces. A temporal analysis was undertaken to investigate the spatial and inter-annual variability of VCI and SPI, and the drought conditions were classified based on the previous thresholds (Mckee et al., 1993; Kogan, 1995) (Table 4.1).

Table 4.1 VCI and SPI drought classes

Drought severity	VCI	SPI
Mild	$30 \leq VCI \leq 40$	0 to -0.99
Moderate	$20 \leq VCI \leq 30$	-1 to -1.49
Severe	$10 \leq VCI < 20$	-1.5 to -1.99
Extreme	$0 \leq VCI < 10$	< -2

Next, the mild, moderate, severe and extreme drought thresholds were used to extract the occurrence and severity of droughts for each class across the years, based on VCI and SPI. The implementation of thresholds on drought maps resulted in binary maps, with 1 representing the occurrence of the specific drought type, and 0 representing no drought (Winkler et al., 2017; Sharara et al., 2022). The binary maps were then summed, before dividing them by the number of observations to yield probability maps for each drought type. Formally put, drought probability was calculated as:

$$\text{Drought probability} = \frac{\sum_i^n x}{N} \qquad \text{Equation 4.3}$$

Where x is the binary map and N are the total number of binary maps for each drought type. Drought detection was also independently tested, based on the VCI and SPI for each drought class by overlaying the corresponding drought classes in a GIS environment. This yielded a confusion matrix, which showed the frequency of agreement and disagreement in drought detection by the VCI and SPI. Six metrics of agreement were then calculated between these two indices, namely, the F1-score, the Matthews Correlation Coefficient, the Coefficient of Determination (R^2), the Root Mean Square Error (RMSE), the True skills statistic and the Accuracy. This offers a thorough method for tracking drought conditions in South Africa's Limpopo, North West and Mpumalanga Provinces by using SPOT VEGETATION 1, PROBA-V data and CHIRPS data processed in GEE.

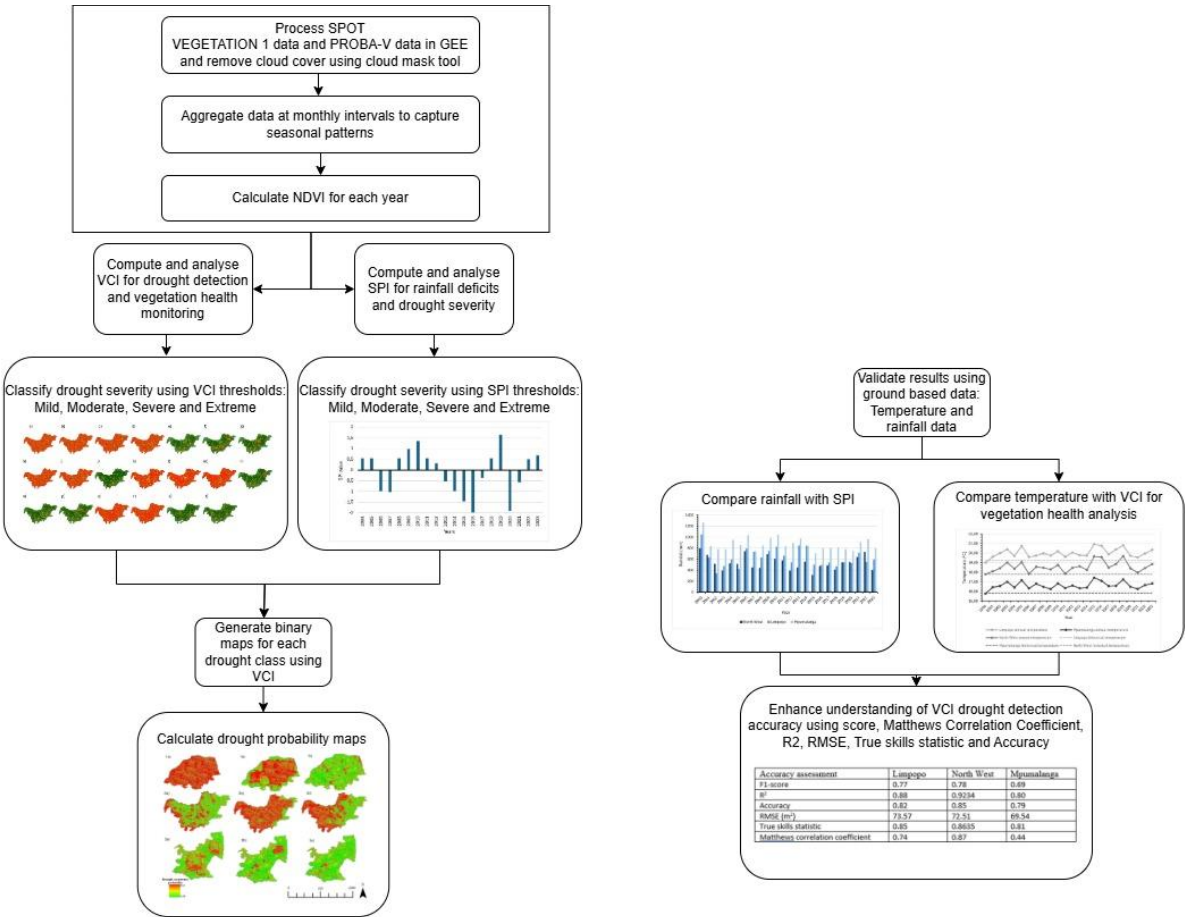

Figure 4.2 Flowchart of the workflow

4.2.4 Validation of drought indices

In this study, ground-based station rainfall and temperature data were also used to validate the VCI and SPI results (Sharara et al., 2022; Bhaga et al., 2023), along with the metrics that have been previously discussed. Ground-based rainfall data were collected from weather stations over the 19-year study period and compared to the SPI values derived from satellite-based CHIRPS data, to ensure that the SPI accurately reflected the observed rainfall rates. In order to determine if the SPI accurately reflected the observed times of drought or wetter-than-normal conditions throughout the study period, the monthly rainfall rates from weather stations were compared to the SPI values. This validation process improved the reliability of SPI in representing the rainfall deficits that contribute to drought conditions (Mishra & Singh, 2010). The VCI results were validated by using temperature data, as higher-than-average temperatures worsen vegetation stress, even when the rainfall rates are normal. The satellite-derived VCI results were compared with the ground-based temperature data, which is indicative of the vegetation's health. Instances when the VCI indicates severe vegetation stress (low values), despite the moderate rainfall levels, can be explained by the temperature data, which suggest that high temperatures may have exacerbated the ET and soil moisture depletion, which led to the dry conditions (Huang et al., 2018). By combining rainfall and temperature data from ground-based stations, the VCI and SPI are validated more thoroughly, which improves the validity of satellite-derived indices that indicate the climate conditions and how they affect the occurrence of drought (Jiao et al., 2016; Bhaga et al., 2023).

4.3 Results

4.3.1 Spatial and temporal frequency of droughts over the 19-year period

The trend analysis of the occurrence of droughts during the 19-year study period indicated a clear pattern in their frequency and intensity across the North West (Figure 4.3), Limpopo (Figure 4.4) and Mpumalanga (Figure 4.5) Provinces. Limpopo, which has a semi-arid climate, experienced the highest frequency of droughts, based on the severity of drought occurrence over the study period (Figure 4.4). Drought conditions were identified in 15 of the 19 years, with severe droughts occurring in 2004-2005, 2014-2016 and 2020-2021 (Figure 4.3). The 2014-2016 drought was the most severe, which coincided with a significant El Niño event that intensified the impacts of the drought across the Limpopo Province. The western region of Limpopo was most affected, where it impacted the agriculture and water resources. In 2018 and 2019, the province experienced severe drought conditions; however, there were regions in the south that were not affected and that did not experience any drought conditions. The rainfed smallholder farms were severely affected during the drought years, especially during 2004, 2005, 2006, 2007, 2011, 2012, 2014, 2015, 2016, 2019, 2020, 2021, 2022 and 2023. During 2009, 2010 and 2013, which were the years when the majority of the province did not experience drought conditions, a few rainfed smallholder farms experienced moderate-to-severe drought conditions in the north, north-west and middle regions, respectively. The North West Province experienced droughts in 13 out of the 19 years of the study period, with similar severe drought conditions being experienced during 2004-2007 and 2014-2016 (Figure 4.4). Moderate drought events occurred in 2010-2012 and 2018-2019, and during the years without a drought, the regions in the east and towards the south of the province still experienced moderate drought conditions. Many rainfed smallholder farms were impacted severely during the drought years in 2004, 2005, 2006, 2007, 2011, 2012, 2014, 2015, 2016, 2020 and 2021. A few rainfed smallholder farms in certain regions in the province were affected by severe drought conditions, despite the majority of the province not experiencing drought conditions.

Mpumalanga showed a lower drought frequency than Limpopo and the North West (Figure 4.5); however, during the 2014-2016 drought, it also experienced extreme conditions. The trend analysis identified drought hotspots in the northern and western regions of Limpopo and the central parts of the North West. In Mpumalanga, the drought conditions were more erratic, with a higher resilience noted in the eastern areas, due to frequent rainfall. However, during the years of severe drought, the central lowland areas in Mpumalanga were affected. In 2020 and 2021, there were severe drought conditions in the south-western part of the province. During the severe drought years (2011, 2012, 2014, 2015, 2016, 2018, 2019, 2022 and 2023), all the rainfed smallholder farms in the province experienced severe drought conditions. Mpumalanga experienced severe-to-moderate drought conditions in 2020 and 2021 in the south-western regions, and rainfed smallholder farms in these regions were also impacted by drought conditions. During 2004, 2005, 2006, 2007, 2008, 2009, 2010, 2013 and 2017, which were years without a drought, no rainfed smallholder farms were affected by drought.

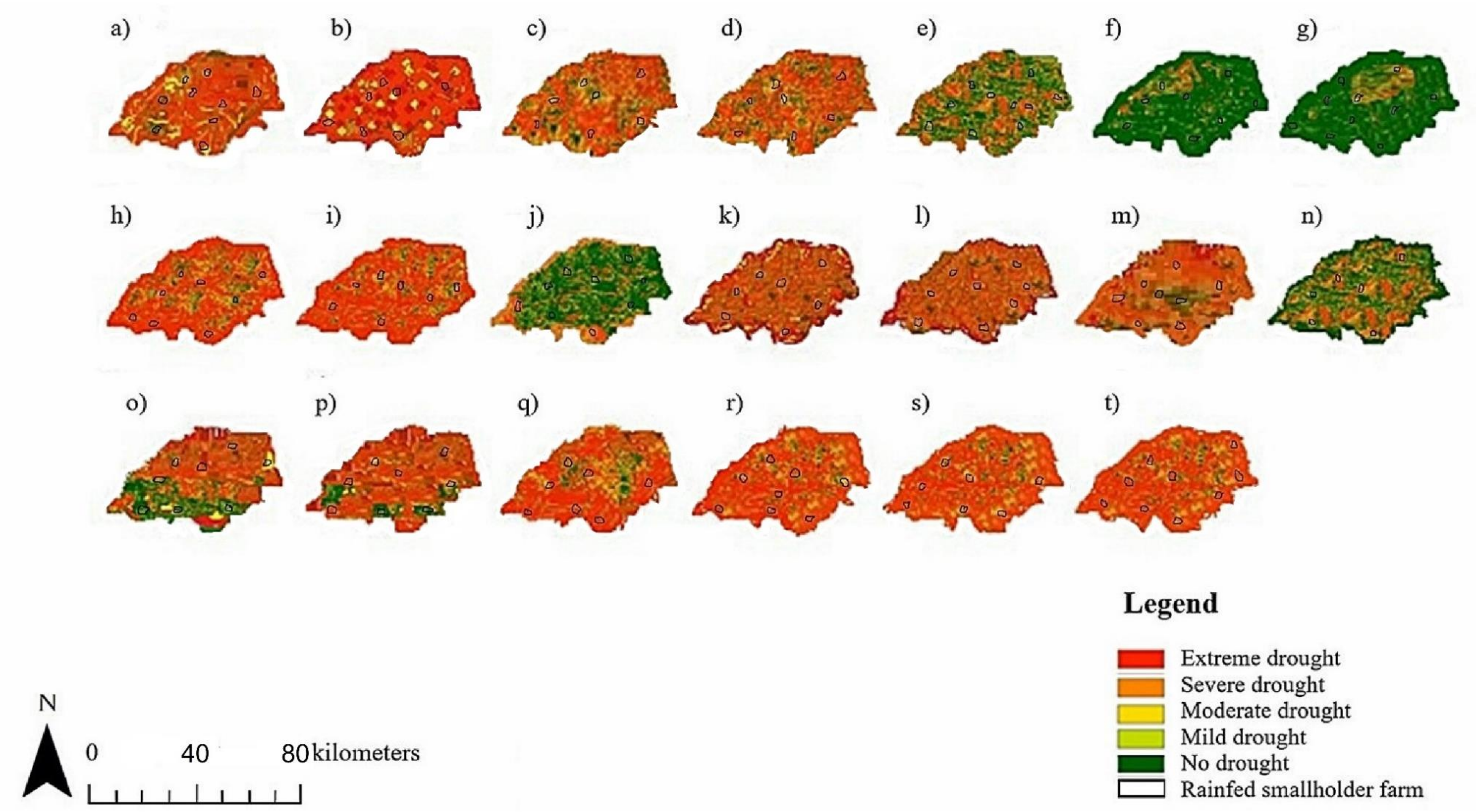

Figure 4.3 VCI results for Limpopo for the years 2004 to 2023 (a-2004, b-2005, c-2006, d-2007, e-2008, f-2009, g-2010, h-2011, i-2012, j-2013, k-2014, l-2015, m-2016, n-2017, o-2018, p-2019, q-2020, r-2021, s-2022, t-2023)

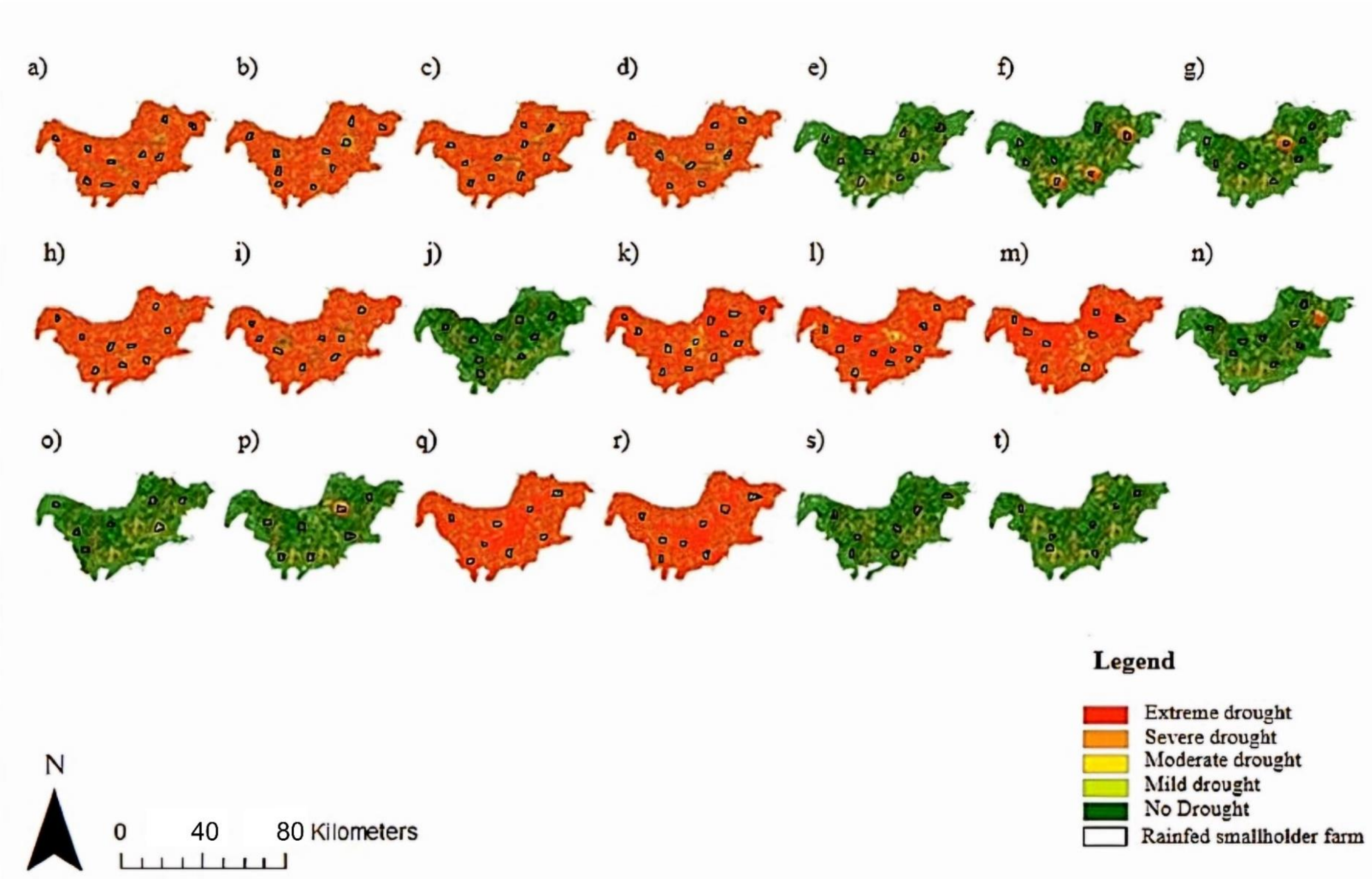

Figure 4.4 VCI results for the North West for the years 2004 to 2023 (a-2004, b-2005, c-2006, d-2007, e-2008, f-2009, g-2010, h-2011, i-2012, j-2013, k-2014, l-2015, m-2016, n-2017, o-2018, p-2019, q-2020, r-2021, s-2022, t-2023)

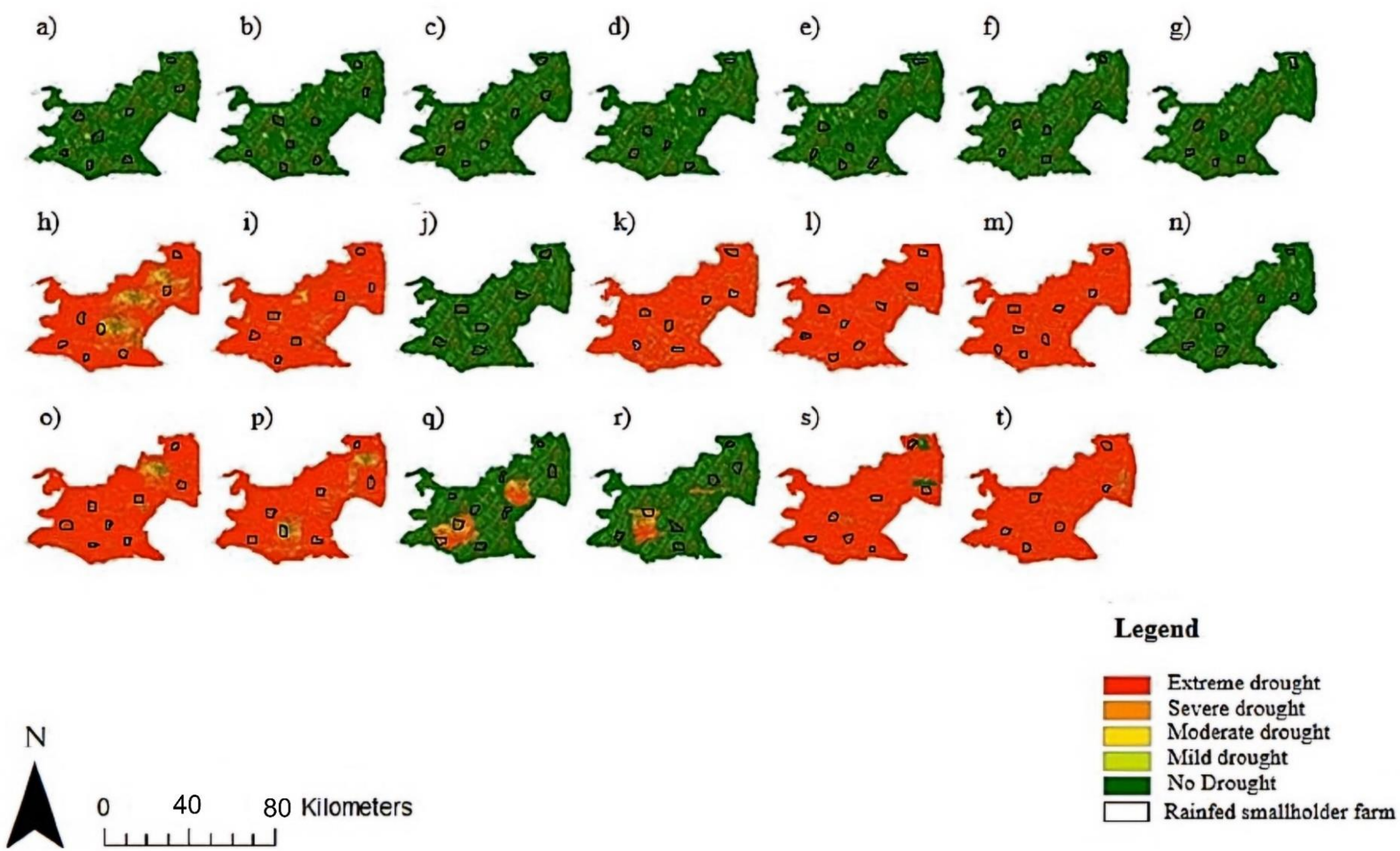

Figure 4.5 VCI results for Mpumalanga for the years 2004 to 2023 (a-2004, b-2005, c-2006, d-2007, e-2008, f-2009, g-2010, h-2011, i-2012, j-2013, k-2014, l-2015, m-2016, n-2017, o-2018, p-2019, q-2020, r-2021, s-2022, t-2023).

4.3.2 Drought occurrence probability

The results of the drought occurrence probability are illustrated in Figure 4.6 for Limpopo, the North West and Mpumalanga, respectively. The results are based on the historical data and the probability was classified into the three droughts of concern, namely, extreme drought, severe drought and moderate drought. Figure 4.6 illustrates the probability of drought occurrence for Limpopo and, based on these results, the probability of the province experiencing severe-to-moderate drought conditions in the future is high, namely 0.61 and 0.81. The probability of the province experiencing extreme drought conditions is low (0.5). The middle region of the province seems to be more susceptible to severe drought conditions, compared to the borders of the province and shows a higher probability of drought. The North West has a very high probability of extreme and severe drought. The probability of extreme drought is 0.62, and 0.89 for severe drought. The eastern regions of the North West Province have a lower probability of drought occurrence and the western regions have a higher probability of drought occurrence. Mpumalanga has the lowest probability of drought across the regions (Figure 4.6), and it has the lowest probability of extreme drought (0.24). The probability of a severe drought is 0.48, which means that the probability of severe drought occurring is moderate. The probability of moderate drought conditions is slightly higher (0.53). The eastern region of the province has a higher probability of severe drought conditions, and the middle, southern and eastern parts of the province have a higher probability of moderate drought conditions.

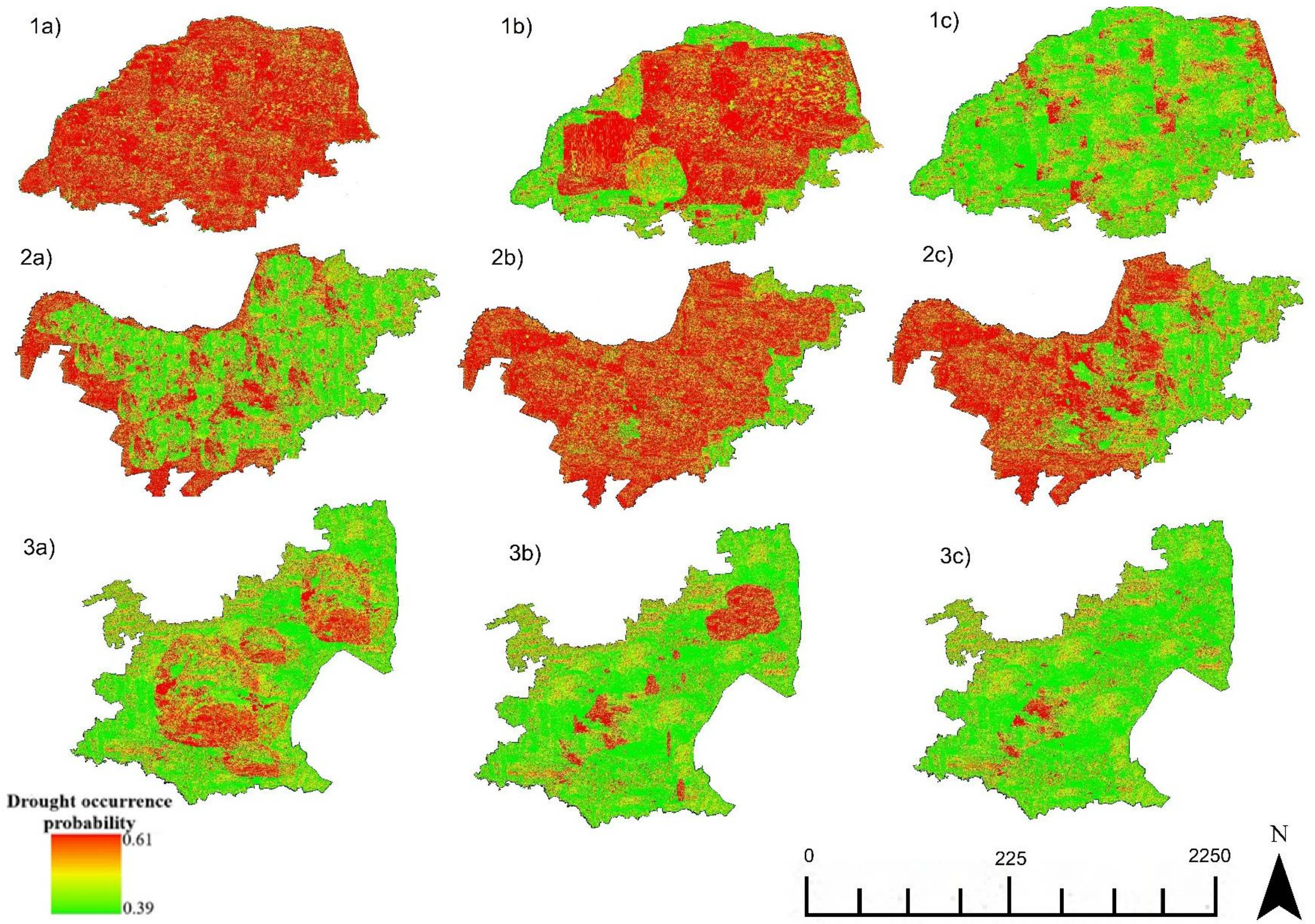

Figure 4.6 Drought occurrence probability maps for the Limpopo, North West and Mpumalanga Provinces (1 - Limpopo; 2 - North West; 3 - Limpopo. a - Moderate drought; b - Severe drought and c - Extreme drought)

4.3.3 VCI validation using SPI and ground-based meteorological data

The validation metrics, based on a three-month SPI generated from CHIRPS data and VCI results, are displayed in Table 4.2. The F1-Score results indicate that there is a strong agreement between the VCI and SPI, and this is further supported by the Matthew's correlation coefficient. The highest correlation was detected in the North West, which is the driest region, and the lowest correlation was detected in Mpumalanga, which is the wettest region. Overall, the True Skills statistic shows an excellent ability to detect drought conditions across all three provinces. Limpopo and the North West achieved similar results, whereas the results for Mpumalanga varied slightly.

Table 4.2 Validation of the VCI, based on the SPI derived from three different provinces in South Africa

Accuracy assessment	Limpopo	North West	Mpumalanga
F1-score	0.77	0.78	0.69
R^2	0.88	0.9234	0.80
Accuracy	0.82	0.85	0.79
RMSE (m^2)	73.57	72.51	69.54
True skills statistic	0.85	0.8635	0.81
Matthew's correlation coefficient	0.74	0.87	0.44

Figure 4.7 indicates the SPI results for Limpopo, which further validates the VCI results, as it shows the lack of precipitation during the drought years, especially during the 2014-2016 drought period, which was classified as an extreme drought in all three provinces. It also shows that 2008, 2009, 2013 and 2018 were the years during the study period in which enough precipitation was received to sustain normal conditions. However, the mild drought conditions were not detected as clearly as the severe drought conditions, or normal conditions.

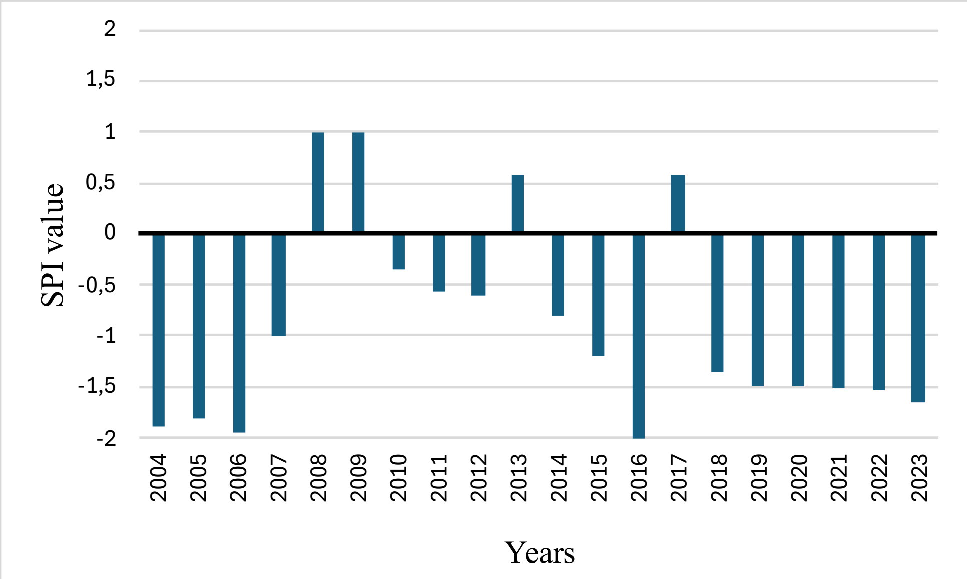

Figure 4.7 SPI values for Limpopo for the years 2004 to 2023

The SPI for the North West is illustrated in Figure 4.8. It shows that 2021 was the wettest year and 2016 was the worst driest year, followed by 2020. Figure 4.9 shows the SPI for Mpumalanga and it shows that 2004 to 2010 experienced normal to wet conditions; however, it was also severely affected by the 2012-2016 drought due to El Nino, and it experienced its driest year in 2015.

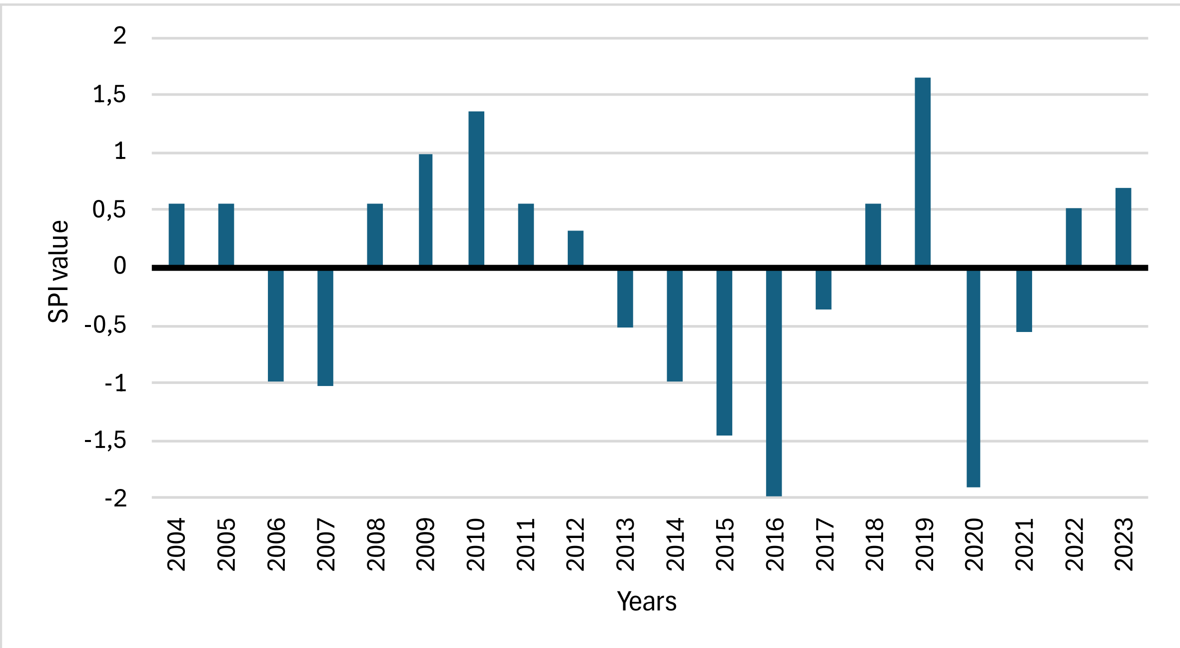

Figure 4.8 SPI values for the North West for the years 2004 to 2023

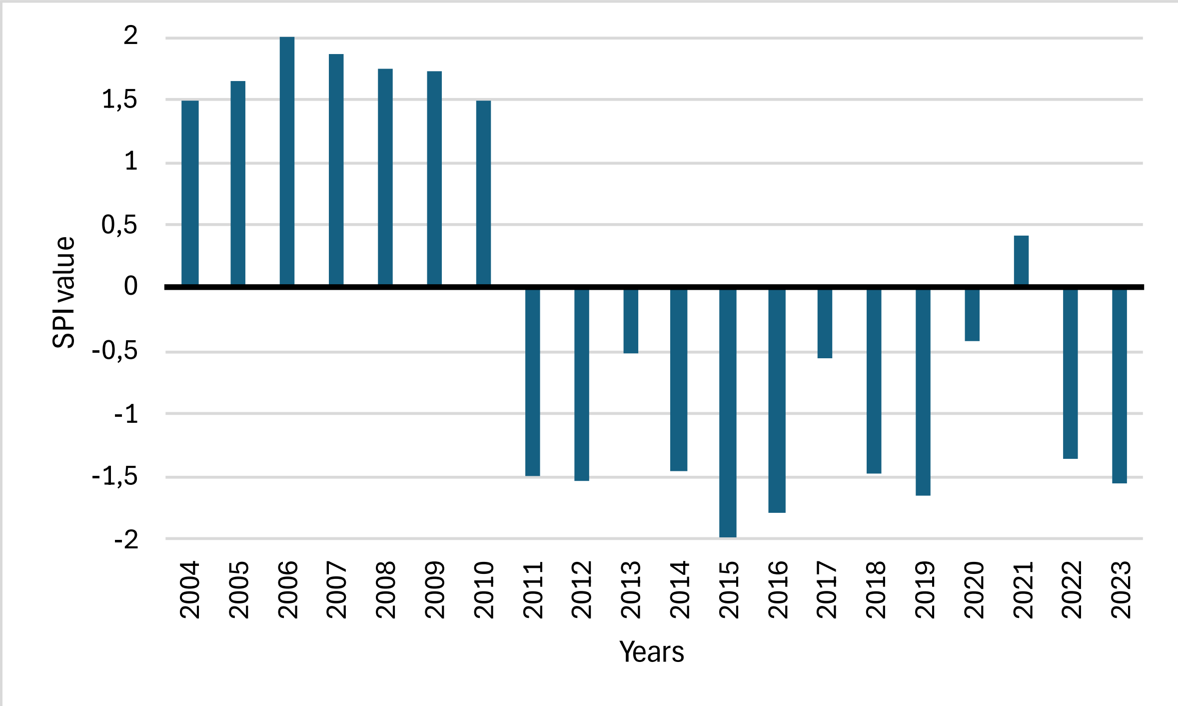

Figure 4.9 SPI values for Mpumalanga for the years 2004 to 2023

Figure 4.10 shows the annual rainfall data from 2000 to 2023 for the North West, Limpopo and Mpumalanga Provinces that were obtained from weather stations in the provinces. Throughout the study period, the provinces showed a variability in their annual rainfall, with fluctuations indicating climate variability and potential drought conditions. In the North West Province, the rainfall data indicates lower totals, compared to Limpopo and Mpumalanga, averaging between 400 mm and 800 mm, with peak years in 2000, 2010 and 2022, when it reached up to 900 mm. The North West indicated a high variability, with several years, such 2003, 2016 and 2019, having low rainfall totals that fell below 500 mm. These variations imply that the North West is more vulnerable to droughts, which correlates with the VCI and SPI results. The Limpopo Province had rainfall totals that ranged from approximately 400 mm to over 1000 mm, which indicates a high variability. The most noticeable peak years were 2002, 2006 and 2014, where the rainfall exceeded 900 mm. However, there were also years with a low rainfall rate, such as 2016 and 2021, which indicates periods of potential drought stress. The variability in rainfall patterns in Limpopo indicate a less stable trend. The rainfall levels in Mpumalanga were the highest of the three provinces, often exceeding 800 mm and reaching levels above 1000 mm in 2000, 2002 and 2010. Low totals of around 600 mm were received in 2003, 2015 and 2019. However, despite these fluctuations, Mpumalanga showed a stable rainfall pattern over time, which coincides with the humid climate that it experiences. Overall, Figure 4.10 indicates that

Mpumalanga receives the highest annual rainfall, followed by Limpopo and the North West. The ground-based data show periods of high rainfall and low rainfall across all three provinces, with 2016 being a common year of low rainfall for all three provinces. These trends indicate how the rainfall varies throughout South Africa, which has consequences for the agricultural planning, drought preparedness and water resource management in each province.

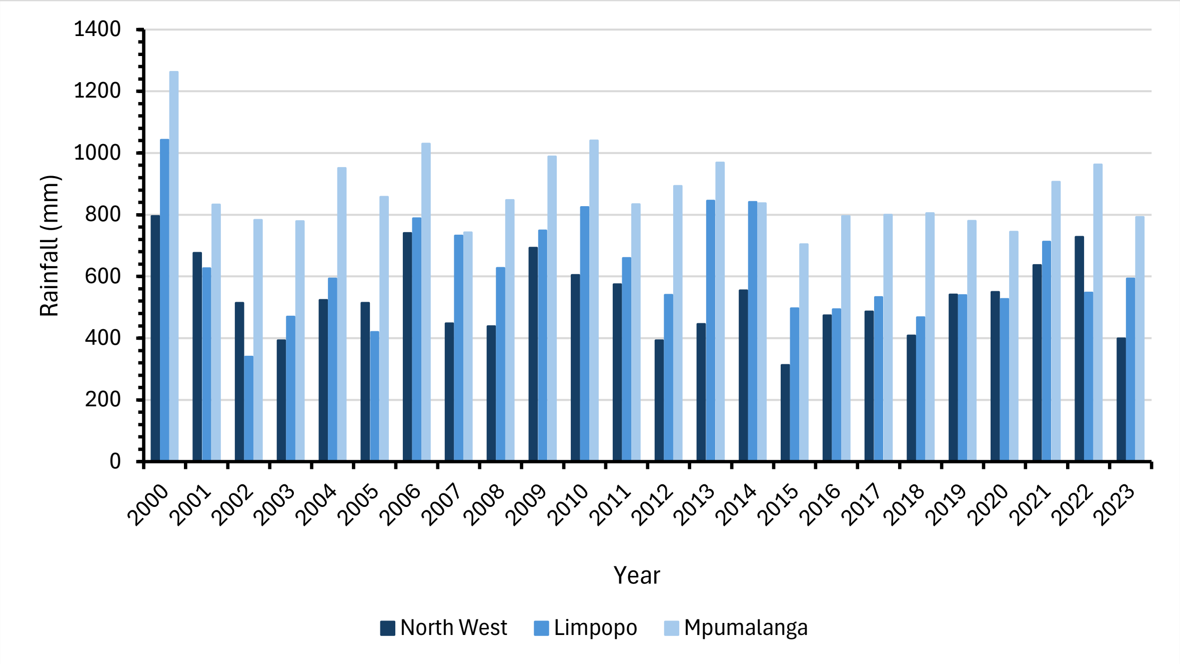

Figure 4.10 Annual rainfall data obtained from ground-based weather stations for the North West, Limpopo and Mpumalanga for the years 2000 to 2023

The temperature data displayed in Figure 4.11 indicate the annual trends for the North West, Limpopo and Mpumalanga Provinces from 2000 to 2023, together with their annual temperatures and historical averages. The North West experienced temperatures that ranged from 17°C to 19°C. Peaks in the temperature were observed in 2010 and 2015, which exceeded the historical average of 18°C. This province shows a more variable pattern, with alternate periods of cooling and warming, instead of a steady increase. The annual temperature in Limpopo varied between 19°C and 21°C, with a steady increase over time. The years of substantial warming are shown by periods of major temperature peaks, such those in 2005 and 2016, when values exceeded the historical averages. With recent years continuously indicating annual temperatures above the historical average, the trend in Limpopo highlights a general warming of the climate. In comparison to the other provinces, the temperatures experienced in Mpumalanga remained lower, ranging between 16°C to 18°C. The historical average for Mpumalanga is approximately 17°C. Although the temperature trend in Mpumalanga has been more consistent, slight increases in the temperature in recent years indicate warming, with readings above the historical average before 2020. According to the ground-based station data, all three provinces, especially Limpopo and Mpumalanga, indicate a general warming tendency, with Limpopo showing the most noticeable warming, which suggests the possible effect of climate change. These changes in temperature helps understand how the local climate affects ecosystem health, water resources and agriculture.

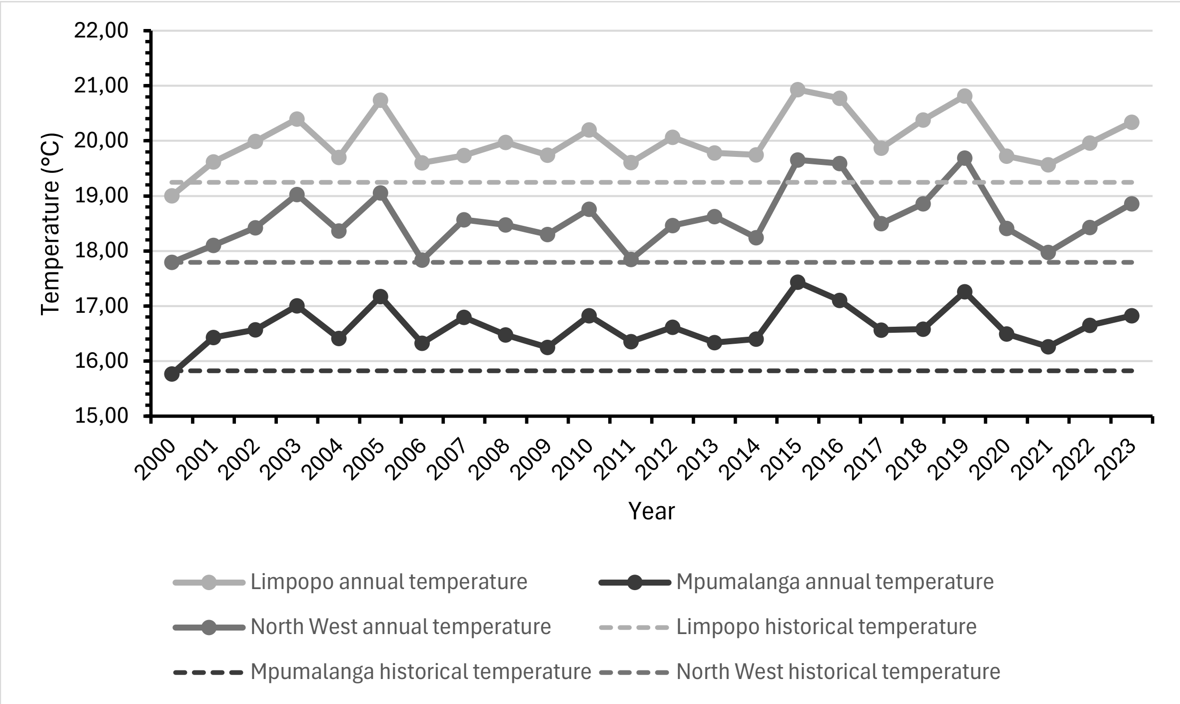

Figure 4.11 Annual temperature data obtained from ground-based weather stations for the North West, Limpopo and Mpumalanga for the years 2000 to 2023

4.4 Discussion

The analysis of drought conditions in the North West, Limpopo and Mpumalanga Provinces from 2004 to 2023, using the VCI and SPI, highlights the important patterns and trends in the occurrence of droughts. The validation of the VCI and SPI results with temperature and rainfall data improves this analysis, because temperature and precipitation are the main drivers of agricultural, hydrological and meteorological droughts (Mishra & Singh, 2010; Adeola et al., 2021; Bhaga et al., 2021; Sharara et al., 2022). This discussion contextualises the frequency and temporal changes in drought conditions over a 19-year period by looking at trends in the temperature and rainfall data. This helps to provide an insight into the relationship between climatic variability and the impacts of drought in these regions (Li et al., 2020; Bhaga et al., 2021).

Both the SPI and VCI showed widespread drought conditions during the severe drought period of 2014-2016, but the VCI values were very low, which indicated the combined stress of high temperatures and the decrease in rainfall. This finding suggests that the VCI may be a more comprehensive method for understanding the ecological impacts of drought, as it considers the thermal stress, which SPI is unable to measure. As a result, combining VCI and SPI offers a more comprehensive understanding of the effects of drought by accounting for the hydrological deficits and temperature-driven vegetation stress. The trend analysis also shows that mild droughts, which can happen once a year, are more common than the occurrence of rare, extreme droughts, which are linked to prolonged high temperatures and multi-year rainfall deficits. This distinction is crucial for drought monitoring, since extreme droughts have a more significant effect on the water supply, ecosystem stability and rural livelihoods, while mild droughts primarily influence the agricultural output. Based on the occurrence and probability of a drought, it is evident that rainfed smallholder farms are highly susceptible to, and impacted by, droughts. Drought probability occurrence varies significantly across the Limpopo, North West and Mpumalanga Provinces due to their climatic conditions (Ebhuoma et al., 2020). Limpopo has a semi-arid climate and experiences a high drought probability, especially in the western and northern regions, and this increases the vulnerability of rainfed smallholder farms in those regions. The North West is also a semi-arid province and the probability of the occurrence of a drought is therefore also high (Cole et al., 2021), with the western regions having a higher probability of severe drought occurrence, due to its climate and rainfall variability. Mpumalanga is prone to droughts in the eastern region, with a probability of moderate drought conditions of 0.53, due to the drier conditions in the highveld. Although Mpumalanga receives a high rainfall, certain regions are still prone to drought, due to its escarpment (Ebhuoma et al., 2020); however, rainfed smallholder farms in Mpumalanga are not as threatened by the probable occurrence of a drought, compared to those in Limpopo and the North West.

The North West and Limpopo Provinces, which are both classified as semi-arid regions, have experienced significant increases in temperature. Because the agricultural systems are less resilient to extended periods of high temperatures and low rainfall, these provinces are severely affected by this change. This increase in temperature increases the ET and the probability of heatwaves, which reduces agricultural productivity even further (Mishra & Singh, 2010; Valadao et al., 2021). The VCI results during periods of extreme temperatures indicate a decline in the vegetation health, which highlights that high temperatures are directly correlated with the reduced vegetation vigour and increased susceptibility to drought stress (Quiring &

Ganesh, 2010; Sharara et al., 2022; Burka et al., 2024). According to the ground-based station data, the mean annual temperatures of the North West, Limpopo and Mpumalanga have increased from 19°C, 17.9°C and 15.8°C in 2004 to 20.4°C, 18.9°C 16.9°C, respectively, in 2023. All three provinces are experiencing the same warming trend, with annual variations indicating short-term climatic events, but an overall increase in temperatures. For example, the peaks in the temperature from 2014 to 2016 and in 2022-2023 aligned closely with the SPI and VCI results, which indicated severe droughts during these years. The increases in temperature exacerbate the drought conditions by increasing the ET rate, therefore reducing the soil moisture and intensifying the water stress on the crops and natural vegetation (Quiring & Ganesh, 2010; Burka et al., 2024; Jiao et al., 2016). This warming trend suggests that droughts in these regions are likely to increase and become more severe over time, as small decreases in the rainfall are worsened by higher temperatures, which will lead to a decrease in water availability (Tirivarombo et al., 2018; Dube et al., 2023). The trend analysis shows that periods with a high increase in temperature coincide with decreases in the VCI; for example, the VCI decreased drastically in 2015 and 2016, which coincided with the peak temperatures in these years. This pattern indicates that the VCI is a useful indication for tracking drought conditions in conjunction with the SPI, since it is a vegetation health parameter that is sensitive to changes in the temperature. The hypothesis that higher temperatures have a direct, measurable effect on the condition and health of vegetation, especially during the occurrence of drought, is supported by the way that the temperature modifies the VCI results.

The rainfall data from a ground-based station data show significant variations in the annual precipitation, with long dry spells mixed with high rainfall periods. According to the trend analysis, the average rainfall has generally decreased, especially in years with a severe drought, as determined by VCI and SPI; for example, below-average rainfall was recorded in 2014-2016 and 2022-2023, which corresponded to the periods of severe drought identified by the SPI. When combined with an increase in the temperature, these dry spells worsened the drought conditions, since the little rainfall that was received was not enough to restore the groundwater and soil moisture that had already been depleted by the increased ET. The observed rainfall deficits are reflected in the SPI values that were computed for these years. Values below -1 indicate a moderate-to-severe drought, which makes the SPI an effective method for classifying the drought intensity. The SPI values in all three provinces were well below the threshold between 2014 and 2016, which confirmed the presence of a widespread drought. This research, which combines SPI and rainfall data, shows that the prevalence of droughts is strongly correlated with variations in the annual precipitation, with the dry years being characterised by significant rainfall deficits. There seems to be a cyclic pattern to the rainfall variability, especially in the North West and Limpopo Provinces, with severe droughts occurring roughly every five to seven years. Climate drivers, like El Nino, are known to influence the distribution of rainfall in southern Africa (Matunhu et al., 2022; Sharara et al., 2022; de Araujo Junior et al., 2023). The correlation between the SPI results and rainfall data suggests that SPI is a reliable metric for capturing the temporal dynamics of a drought and for accurately reflecting changes in the rainfall patterns, which is critical for understanding the availability of water and assisting with the farming patterns. The North West is particularly susceptible to recurring drought periods, due to its rainfall variability, which is reflected in the SPI fluctuations.

The high temperatures and low precipitation during drought years highlight how these factors affect the severity of droughts, as measured by both the SPI and VCI. SPI does not fully account for the effects of the high temperatures, but it is consistent with the reported drought situations because it predominantly reflects the rainfall deficiencies. However, VCI incorporates vegetation response to rainfall and temperature, which makes it an effective complementary indicator for evaluating the effects of a drought on agriculture and on the ecosystem (Quiring & Ganesh, 2010; Jiao et al., 2016). However, discrepancies between VCI and SPI were noted in several areas, especially in the drier parts of Limpopo and the North West, where vegetation may already be stressed, due to the ongoing water scarcity. This emphasises the challenge of using uniform drought-monitoring indices in different areas with different climatic and ecological characteristics (Kourouma et al., 2021; Agbehadji et al., 2023). In contrast, Mpumalanga demonstrated a higher degree of agreement between the SPI and VCI, especially in its wetter parts where precipitation is more directly related to vegetation health (de Araujo Junior et al., 2023). This variation highlights how crucial it is to take local ecological factors into account when interpreting drought indices, and it raises the possibility that localised calibration could increase the precision of drought detection in arid and semi-arid regions. These results are consistent with those of Tadross et al. (2007) and Sharara et al. (2022).

Although the research has effectively employed the measurements generated from satellites to track and identify droughts, several restrictions were identified. Although the RMSE method achieved the lowest accuracy results for all three provinces, compared to the other metrics, this is to be expected, as RMSE values that are lower than other comparable metrics in the same context suggest a better performance (Heddam et al., 2022). The level of accuracy in the provinces varied according to the validation of the VCI and SPI data; the North West and

Limpopo Provinces produced similar results and achieved the highest overall accuracy, whereas Mpumalanga produced lower accuracy scores. This implies that, in order to account for the various meteorological and ecological conditions found throughout the provinces, different indices might need to be used, depending on the specific location. Future studies should focus on enhancing these indices for enhanced regional relevance, especially by including more regionally-specific data sources, such as temperature and soil moisture (Marumbwa et al., 2020). Furthermore, to guarantee the reliability of satellite-derived drought indices in accurately identifying the beginning and progression of drought conditions, it is necessary to get additional validation by using ground-truthing data.

The need for integrated drought monitoring systems that take temperature and rainfall into consideration is highlighted by the recorded trends in the temperature and rainfall, as well as by the validation of these patterns, using SPI and VCI indicators. Future droughts may be more severe and frequent, especially in semi-arid regions that are not resilient to water scarcity, as indicated by the rising temperatures in the North West, Limpopo and Mpumalanga. Early warning systems and adaptive management plans can benefit from the comprehensive approach to drought monitoring offered by VCI and SPI measurements, which are verified by ground-based temperature and rainfall data. The results of this study highlight the importance of high-resolution, real-time data for monitoring and detecting droughts. Given the limitations of the spatial resolution, future studies can look at using datasets with a higher spatial resolution, which will provide a clearer understanding of the impacts of a drought on the vegetation; and by improving the temporal resolution of the SPI calculations, the detection of short-term drought events will improve drought monitoring and its future impacts on agriculture. The integration of rainfall and temperature data with the VCI and SPI results provides a comprehensive framework for understanding the spatiotemporal dynamics of droughts in South Africa (Dube et al., 2023). This study validates the use of satellite-derived drought indices and highlights the impact of climate factors on the severity of droughts. The results indicate that future studies should consider the temperature and precipitation trends, to improve the resistance against the threat of droughts in sub-Saharan Africa and to improve the early warning systems and mitigation strategies.

4.5 Conclusion

An analysis of the drought conditions in the South African provinces of Mpumalanga, Limpopo and the North West from 2004 to 2023, using the Vegetation Condition Index (VCI) and

Standardised Precipitation Index (SPI), has illustrated the spatiotemporal dynamics of droughts in these regions. The findings indicate that these provinces are especially susceptible to recurrent droughts, especially when El Niño and other climate-related phenomena occur. The agricultural sector, water resources and ecosystems were severely impacted by drought episodes like those that occurred in 2014-2016 and 2022-2023, with Limpopo and the North West being the most severely impacted, due to their semi-arid climates and their reduced capacity to withstand water stress. The observed rainfall and temperature data from ground-based weather stations added additional insights into the climate patterns of these regions and how they relate to drought and exacerbate their impacts. The rainfall and temperature trends showed variability, which contributes to the increased drought frequency and intensity. In order to mitigate the negative consequences of droughts on rural livelihoods and agricultural output, early warning systems and policy interventions are dependent on the efficacy of satellite-derived metrics in monitoring droughts over extended periods of time, as demonstrated by this study. The spatial resolution of the datasets that were used is a limitation of the study. Even if the study offers a fine-scale analysis, the geographical resolution of the VCI and SPI might still be insufficient to fully reflect the effects of localised droughts, especially in heterogeneous landscapes like the mixed agricultural regions of the North West, or the lowveld of Mpumalanga. More accurate drought evaluations may be possible by using higher-resolution satellite data, such as those from WorldView4, GeoEye and Quickbird, which could offer more in-depth details on the vegetation dynamics at a field or community level. Furthermore, the temporal resolution of the study could be improved to capture more frequent drought occurrences or brief dry periods that are not be represented in the SPI readings. It is crucial for future research to keep investigating the connection between the occurrence of droughts and climatic drivers like El Niño and La Niña. It will be essential to understand how these events affect the frequency and intensity of droughts, in order to create climate change-adapting measures. Future research should also concentrate on evaluating the socioeconomic effects of droughts on smallholder farmers, as they are more susceptible to reduced crop yields and water scarcity. Although the study offers a useful starting point for comprehending the dynamics of droughts in the North West, Limpopo and Mpumalanga, it also emphasises the need for more integrated, high-resolution and verified methods for monitoring them. By addressing these limits and concentrating on the important areas in future research, it will be feasible to enhance the management of water resources, to lessen the effects of droughts on vulnerable people and to create a more resilient agricultural sector in South Africa.

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CHAPTER FIVE

MODELLING THE OCCURRENCE OF DROUGHTS IN SOUTH AFRICA BY USING THE MAXIMUM ENTROPY MODEL

Abstract

The MSPI evaluates the short-, medium- and long-term effects of drought by integrating different timelines of the Standardised Precipitation Index (SPI). The probability of droughts occurring in various climatic locations was predicted by using key meteorological factors, such as the temperature, precipitation and evapotranspiration. To forecast the Multivariate Standardised Precipitation Index (MSPI) for the Limpopo, Mpumalanga and the North West Provinces for the years 2034, 2044, 2054, 2064 and 2074, this study used the Maximum Entropy (MaxEnt) model under the Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 scenarios. The findings showed significant spatial and temporal variations in drought occurrence probabilities across all three provinces. Limpopo exhibited the highest vulnerability under RCP 4.5, with severe drought probabilities increasing from 0.68 in 2034 to 0.82 in 2074. Mpumalanga showed a lower vulnerability, with moderate drought probabilities reaching 0.61 by 2074. The North West Province showed a moderate-to-severe vulnerability under RCP 4.5, with severe drought probabilities reaching 0.75 in 2074, especially in the western and southern regions. Under RCP 8.5, drought severity conditions increased across all three provinces, with extreme drought probabilities surpassing 0.80 in Limpopo and the North West by 2074. Accuracy assessments using the True Skill Statistic (TSS), the sensitivity, specificity and F1-score showed a high model reliability, with TSS values ranging from 0.79 in 2034 to 0.98 in 2074, under both scenarios. Limpopo consistently achieved the highest accuracies, which reflects its high susceptibility to drought. The findings of this study highlight the vital need for region-specific adaptation strategies for addressing and mitigating the escalating impacts of climate change on South Africa's drought-prone regions.

Keywords: Climate change; Drought; MaxEnt model; South Africa.

This chapter is based on the following manuscript:

Bhaga, TD, Shekede, MD, Shoko, C and Dube, T. (2025). Modelling the occurrence of droughts in South Africa using the Maximum Entropy Model. *Journal of Arid Environments.* [Under review - JAE25-113]

5.1 Introduction

Drought is a crucial environmental challenge that affects agricultural productivity, water resources and the socio-economic state of communities, especially on the African continent (Zhan et al., 2016; Ebhuoma et al., 2020; Ferchichi et al., 2024). Droughts are characterised by extended periods of insufficient precipitation, which have a severe effect on water resources, agriculture, ecosystems and livelihoods (Sheffield & Wood, 2008; Bhaga et al., 2020; Sharara et al., 2022; Ferchichi et al., 2024). The occurrence and severity of drought occurrences have escalated in recent decades as a result of climate change, which worsens the susceptibility of communities that rely on rainfed agriculture (Mpandeli et al., 2015; Ebhuoma et al., 2020; Zobeidi et al., 2021; Ruwanza et al., 2022). Water scarcity in sub-Saharan Africa, where more than 95% of agricultural land is reliant on rainfall, has significant consequences for food security, economic stability and sustainable development (Bhaga et al., 2020; Mpakairi et al., 2023; Ferchichi et al., 2024). The Horn of Africa, the Sahel region and parts of southern Africa are drought-prone regions that experience low levels of rainfall and high inter-annual rainfall variability (Bhaga et al., 2020; Ruwanza et al., 2022; Deivanayagam et al., 2022; Klisch & Atzberger, 2016). This negatively affects smallholder farmers who have a high presence in sub-Saharan Africa and who rely on rainfed agriculture, as it causes crop failure, the loss of livestock and reduced incomes, which leads to poverty and food insecurity in these vulnerable communities (Mpandeli et al., 2015; Mpakairi et al., 2023).

The Maximum Entropy (MaxEnt) model is a valuable tool for environmental modelling, especially in areas where data are sparse or incomplete (Khanum et al., 2013; Ju et al., 2023). The MaxEnt method has been used mostly for species distribution modelling, but it has also been modified for other uses in environmental science, such as drought prediction and vulnerability assessments (Khanum et al., 2013; Zhao et al., 2021). By using historical climate, topographic and vegetation indices as input factors, MaxEnt assists in predicting which regions are more vulnerable to drought (Ngarega et al., 2021; Roy et al., 2022). MaxEnt has also been used to analyse climatic factors and water availability, in order to determine which regions are most vulnerable to hydrological droughts (Roy et al., 2022). These studies usually combine soil moisture, temperature and precipitation data, in order to produce probabilistic predictions of drought occurrence (Kogo et al., 2019; Roy et al., 2022). The MaxEnt method has also been used in studies to understand the effects of drought on agriculture, particularly in areas that are vulnerable to drought conditions (Kogo et al., 2019; Aghelpour et al., 2020; Yang et al., 2022; Ju et al., 2023). By combining climatic data with agricultural productivity indices, MaxEnt has been used to forecast how different climate scenarios may impact crop yields, due to drought (Khanum et al., 2013; Kogo et al., 2019; Zhao et al., 2021; Roy et al., 2022). A study by Kogo et al. (2019) used the MaxEnt model to project the current and future suitability for rainfed maize farming in Kenya. The distribution of maize was significantly influenced by bioclimatic factors, such as the annual mean temperature, the annual precipitation and the mean temperature of the wettest quarter. According to the model, moderately-suitable areas will decline by 14.6% to 17.5% under Representative Concentration Pathways (RCP) 4.5 and RCP 8.5 scenarios for the year 2070, while unsuitable areas will increase by 1.9% to 3.9%. These results are important for policymakers who aim to develop adaptation plans for maize farming. These future predictions are vital for guiding agricultural planning and resource allocation in Kenya. This study highlights the potential of MaxEnt modelling in assisting agricultural resilience against climate change. Aghelpour et al. (2020) used the entropy theory and machine learning methods to forecast meteorological, hydrological and agricultural droughts by using the Joint Deficit Index (JDI) and Multivariate Standardised Precipitation Index (MSPI) in Iran. The model tested the Group Method of Data Handling (GMDH) and the Adaptive Neuro-Fuzzy Inference System (ANFIS) techniques by using data from ten weather stations that are spread throughout Iran's extremely arid climate. The most accurate predictor was the GMDH, with a Willmott Index (WI) of 0.955, a Root Mean Squared Error (RMSE) of 0.374 and a Mean Absolute Error (MAE) of 0.280. Because the MSPI can detect different drought types, its forecasts were more accurate, compared to the JDI results. The entropy-based input selection enhanced the model's prediction accuracy and decreased its complexity. This method makes it possible to evaluate several drought impacts at the same time, which is vital for drought mitigation and helps to improve drought prediction accuracy under complex climate conditions. A study by Yang et al. (2022) developed the Maximum Entropy Copula-Based Frequency Analysis (MECFA) to assess the bivariate drought risk and applied it to the Kaidu River Basin in China. MECFA improved the traditional Hydrological Index (HDI) frequency analysis by accurately modelling marginal distributions without pre-assumed curves. An analysis of the joint return periods and joint probabilities enhanced the understanding of the relationship between the duration and severity, which is vital for drought risk management, and the accuracy was tested by the Kendall and Spearman correlation tests. The findings from this study has assisted policymakers in drought resilience planning in arid regions. Although, the MaxEnt model is a powerful tool, it has several limitations, as mentioned by Kogo et al. (2019), Aghelpour et al. (2020), Yang et al. (2022) and Ju et al. (2023). If the data is biased towards certain areas or time periods, it will lead to the model's predictions being skewed (Ju et al., 2023). The spatial resolution of the input data that are used can also affect the accuracy of the model's predictions, especially for studies conducted on a small scale (Yang et al., 2022). The MaxEnt model is also prone to overfitting, particularly in studies that use complex models with many parameters, and this causes unrealistic predictions (Aghelpour et al., 2020; Roy et al., 2022). Climate models also have uncertainties and the choice of climate change scenarios can influence the predicted drought patterns (Kogo et al., 2019; Ju et al., 2023). However, despite these limitations, the MaxEnt model is a powerful tool for the prediction of droughts when it is used wisely, as it considers data quality, model complexity and the uncertainties associated with future climate predictions (Khanum et al., 2013; Aghelpour et al., 2020; Zhao et al., 2021; Ju et al., 2023).

With the frequency and intensity of droughts most likely increasing, due to climate change, there is an urgent need to use reliable and timely methods for predicting the occurrence of droughts and for assessing the drought risk, particularly in sub-Saharan Africa (Winkler et al., 2017; Xulu et al., 2018; Bhaga et al., 2020). Modelling the occurrence of droughts is vital for improving our understanding of their spatial and temporal patterns, which improves our preparedness and response (Henchiri et al., 2020; Bahta & Myeki, 2022). It also improves the development of early warning systems, which is essential for mitigating the impacts of drought, and lastly, accurate drought models can assist with water management policies and agricultural practices, which will ensure that resources are allocated efficiently and sustainably. Therefore, this study aims to model the occurrence of droughts in South Africa by using the Maximum Entropy model and to evaluate the impacts of such droughts on rainfed smallholder farmers.

5.2 Methods and Materials

5.2.1 Study area

South Africa has a highly-variable climate, which ranges from Mediterranean to subtropical climates (Vetter et al., 2020). The western and central regions are classified as arid and semi-arid (Xulu et al., 2018; Ebhuoma et al., 2020; Vetter et al., 2020). The regions of interest for this study were the Mpumalanga, North West and Limpopo Provinces in South Africa (Figure 5.1). Mpumalanga has a tropical highland climate in the eastern region of the province and a semi-arid climate in the western lowveld (Vetter et al., 2020). The province receives an approximate annual rainfall of 700 mm and the annual average temperature is 21.78°C (Weather and Climate, 2024). Mpumalanga has a high precipitation rate, particularly in the eastern highlands, which promotes high agricultural productivity and drought resilience. The North West Province has a semi-arid climate, with large savannas and grasslands, and hot, dry summers. The North West has an annual average temperature of 28°C and receives an annual rainfall of approximately 540 mm, which occurs mostly in October until March (Weather and Climate, 2024). These high temperatures, combined with the rainfall variability, leads to North West being highly-susceptible to drought conditions. Limpopo has a hot semi-arid climate in the west and a subtropical climate in the east of the province. The province has an average annual temperature of 22°C and an annual average precipitation of 55.48 mm, which exacerbates the drought conditions (Weather and Climate, 2024). The different climates experienced by these provinces make them ideal for modelling droughts, especially the North West and Limpopo Provinces, which are both semi-arid regions that are susceptible to drought and which is vital for developing effective mitigation strategies and sustainable agricultural practices.

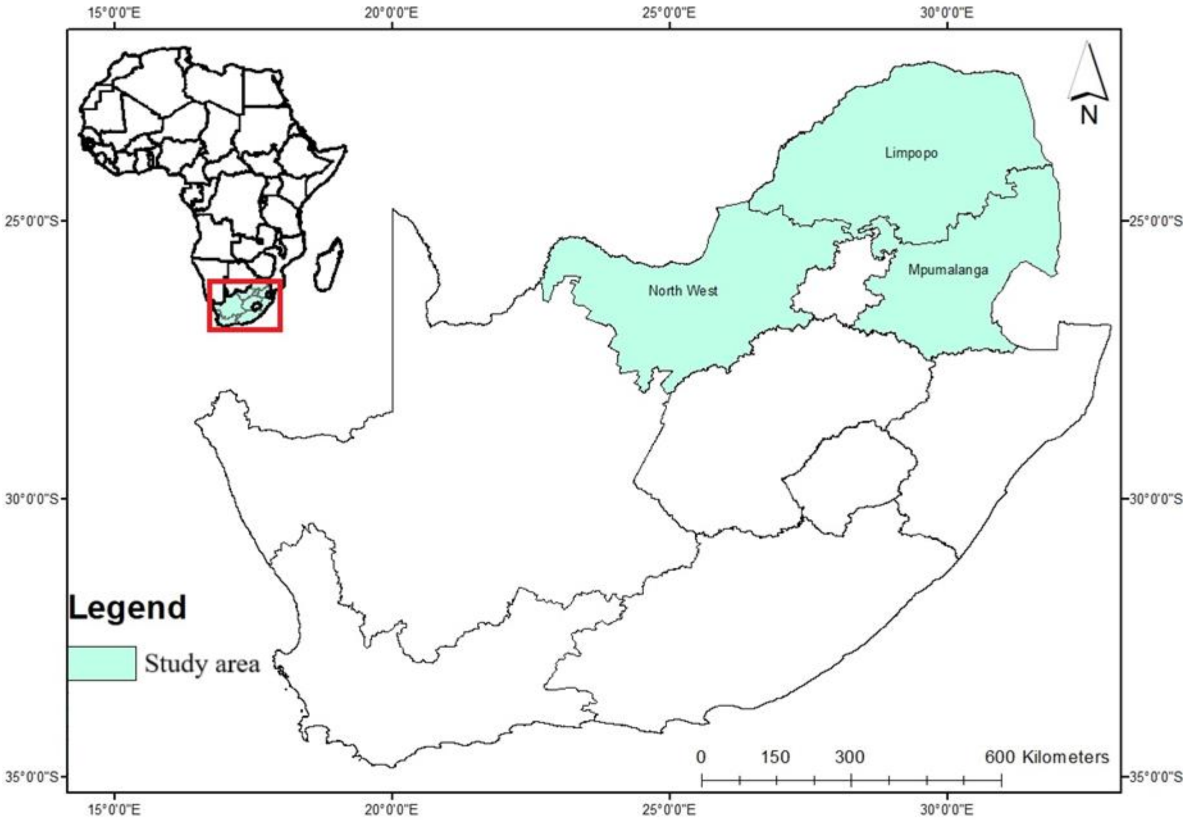

Figure 5.1 The study area

5.2.2 Data collection

This study applied the MaxEnt model to predict the Multivariate Standardised Precipitation Index (MSPI) across the Mpumalanga, North West and Limpopo Provinces in South Africa.

The MSPI is a drought index that measures the severity and variability of drought conditions over the short, medium and long timescales, by combining several timescales of the Standardised Precipitation Index (SPI). Based on environmental and meteorological factors, the MaxEnt model enables spatial projections of the MSPI-based drought severity for the years 2034, 2044, 2054, 2064 and 2074. Monthly precipitation data were collected from meteorological stations for the past 30 years (from 1993 until 2023), in order to calculate the historical precipitation statistics. Future precipitation data for the years 2034, 2044, 2054, 2064 and 2074 were obtained from climate model projections for the RCP 4.5 and RCP 8.5 scenarios. Key climatic variables, such as the temperature, soil moisture and evapotranspiration (ET), were included in the MaxEnt model as predictors, due to their influence on the drought conditions (Bhaga et al., 2020; Yang et al., 2022; Ju et al., 2023; Ferchichi et al., 2024).

5.2.2.1 Calculation of the Multivariate Standardised Precipitation Index (MSPI)

The MSPI integrates the SPI values across different timescales and captures different drought types, such as meteorological, agricultural and hydrological droughts. SPI values were calculated on a 1-, 3-, 6- and 12-month (SPI-1, SPI-3, SPI-6 and SPI-12) timescale at each meteorological station. These timescales reflect various drought types, which include the short-term for meteorological droughts, the medium-term for agricultural droughts and the long-term for hydrological droughts. Positive SPI values indicate wetter-than-normal conditions and negative SPI values indicate drier-than-normal conditions. The Principal Component Analysis (PCA) was applied to the SPI time series in order to integrate the SPI values across the different timescales. The MSPI is calculated as: $MSPI = \frac{PC1 - \mu PC1}{\sigma PC1}$, where PC1 is the primary component output, μPC1 is the mean of PC1, and σPC1 is its standard deviation. This normalisation process ensures that the MSPI values range similarly to SPI, where values <0 indicate dry conditions and values >0 indicate wet conditions. The MSPI values were categorised to indicate different levels of drought severity (Table 5.1) (Bazrafshan et al., 2017; Ghazipour & Mahjouri, 2022), and these categories were used as training labels in the MaxEnt model to identify the spatial patterns associated with different drought severities.

Table 5.1 Classification of MSPI values for drought severity

Drought severity	**MSPI value**
Normal	MSPI ≥ -0.5
Mild drought	-1 ≤ MSPI < -0.5
Moderate drought	-1.5 ≤ MSPI < -1
Severe drought	-2 ≤ MSPI < -1.5
Extreme drought	MSPI < -2

5.2.2.2 MaxEnt model configuration and training

The MaxEnt model was configured to use climatological and environmental variables as predictors and the MSPI values were the response labels. A Pearson correlation threshold of r >0.7 was applied in order to ensure the robustness of the model and to avoid issues of multicollinearity. Collinearity can cause the instability of model coefficients, a reduction in the precision of estimates and difficulty in interpreting the results (Ghazipour & Mahjouri, 2022). Model parameters, such as the regularisation muliplier and feature class, were used to improve the performance, based on the results of previous studies by Ghazipour and Mahjouri (2022) and Rezaei et al. (2022). The regularisation multiplier controls the complexity of the model; it prevents overfitting and improves its generalisation ability (Rezaei et al., 2022). The feature class determines the types of mathematical functions that are used to represent the relationship between the environmental variables and the probability of drought occurrence (Zhou et al., 2022). In order to maximise the model's predictive accuracy, various combinations of these parameters were experimented with (Ghazipour & Mahjouri, 2022). To ensure the robustness of the model, a five-fold cross-validation was used. This method involves dividing the dataset into five subsets, four of which are used for training and one for testing, and this process is then repeated five times, which lowers the chance of overfitting and assists in evaluating the model's performance on unseen data (Ngarega et al., 2021; Ghazipour & Mahjouri, 2022; Ferchichi et al., 2024). By employing parameter optimisation and cross-validation, the MaxEnt model can produce more accurate and reliable drought-occurrence predictions (Ghazipour & Mahjouri, 2022; Ferchichi et al., 2024). To forecast MSPI values for 2034, 2044, 2054, 2064 and 2074, future climate projections for each year were inputted into the trained MaxEnt model. These future scenarios were then used by the model to produce spatial forecasts.

5.2.3 Model evaluation

The performance of the MaxEnt model was evaluated by using the True Skill Statistic (TSS), Sensitivity and Specificity and the F1-score (Narkhede, 2018; Carrington et al., 2022). The TSS assesses the model's accuracy beyond random change and accounts for omission and commission errors (Zhou et al., 2022). Values range from -1 to 1, where higher values indicate a better predictive accuracy (Saha et al., 2022). The TSS method is valuable to the MaxEnt model, because it considers the balance between false positives and false negatives, which ensures the thorough validation of predictions (Carrington et al., 2022; Zhou et al., 2022). Sensitivity measures the model's ability to accurately predict areas that are prone to drought (Sharara et al., 2022). High sensitivity values indicate that the model is able to effectively identify the areas at risk of drought (Kogo et al., 2019). Specificity calculates the model's ability to accurately identify non-drought areas, and high-specificity values indicate minimal false predictions, which is vital for decision-making in drought management (Ghazipour & Mahjouri, 2022). The F1-score is the mean of precision and sensitivity and is therefore suitable for models that are used in datasets with unbalanced classes, such as drought versus non-drought conditions (Ngarega et al., 2021). When these metrics are combined, they provide a robust framework for assessing the performance of the MaxEnt model, which ensures its accuracy and suitability for forecasting the occurrence of drought and for assisting resource management (Kogo et al., 2019; Ngarega et al., 2021; Shikwambana et al., 2021; Ferchichi et al., 2024).

5.3 Results

Figure 5.2 shows the MSPI results under the RCP 4.5 for the Mpumalanga, North West and Limpopo Provinces for the years 2034, 2044, 2054, 2064 and 2074. The results for Mpumalanga show that the province is least likely to experience drought in the future, under RCP 4.5 (MSPI value of 0.32). In 2034 (1a), Mpumalanga has a low MSPI value (MSPI = 0.31), and therefore the drought occurrence probability is not high; however, the probability increases from 0.32 in 2044 to 0.79 in 2074. In 2044 (1b) there are mild drought conditions in certain regions in the north, east and south of the province. In 2054 (1c), the probability of drought occurrence increases to more mild and moderate drought conditions in the north-eastern and central parts of Mpumalanga (MSPI =0.48). In 2064 (1d), the probability of drought occurrence increases and spreads throughout the province to the western part of Mpumalanga (MSPI = 0.56). In 2074 (1e), the drought conditions are still expected to be mild-to-moderate; however, this is across most of the province and is not limited to certain regions in Mpumalanga (MSPI = 0.63).

The results for Limpopo showed that the probability of drought occurrence is high in the northern and western regions of the province, and that it is particularly high in 2054 and 2074 (MSPI = 0.79 and MSPI = 0.83, respectively). In 2034 (2a) the probability of drought occurrence is mild-to-moderate in the northern and western regions of the province; however, in 2044 (2b), the drought occurrence becomes more severe in those regions. In 2054 (2c), severe drought conditions are expected in the northern and western parts in Limpopo and mild-to-moderate conditions towards the central part of the province; however, these drought conditions decrease in severity in 2064 (2d) and mild-to-moderate drought conditions are expected in 2064. In 2074 (2e), these drought conditions increase, and severe drought conditions are expected in the northern, western and certain regions in the central and eastern parts of the province (MSPI = 0.89).

The results for the North West Province show a high probability of drought occurrence in the northern and southern regions of the province for each year of this study (2034, 2044, 2054, 2064 and 2074). In 2034 (3a), the province experiences mild-to-moderate drought conditions in the eastern, western and southern regions (MSPI = 0.76), and in 2044 (3b), the drought conditions spread and increase in these regions (MSPI = 0.78). In 2054 (3c) and 2064 (3d), the drought conditions are moderate in the eastern and southern regions and severe in the northern regions of the province. In 2074 (3e), the drought conditions are spread throughout the northern and southern regions of the province (MSPI = 0.80). Overall, all three provinces show the highest probability for the occurrence of drought in 2074, under RCP 4.5 conditions, and Limpopo shows the highest probability of drought occurrence and the highest vulnerability to drought, with severe conditions being projected for agriculture and water availability, followed by the North West. Mpumalanga shows a moderate vulnerability to drought conditions.

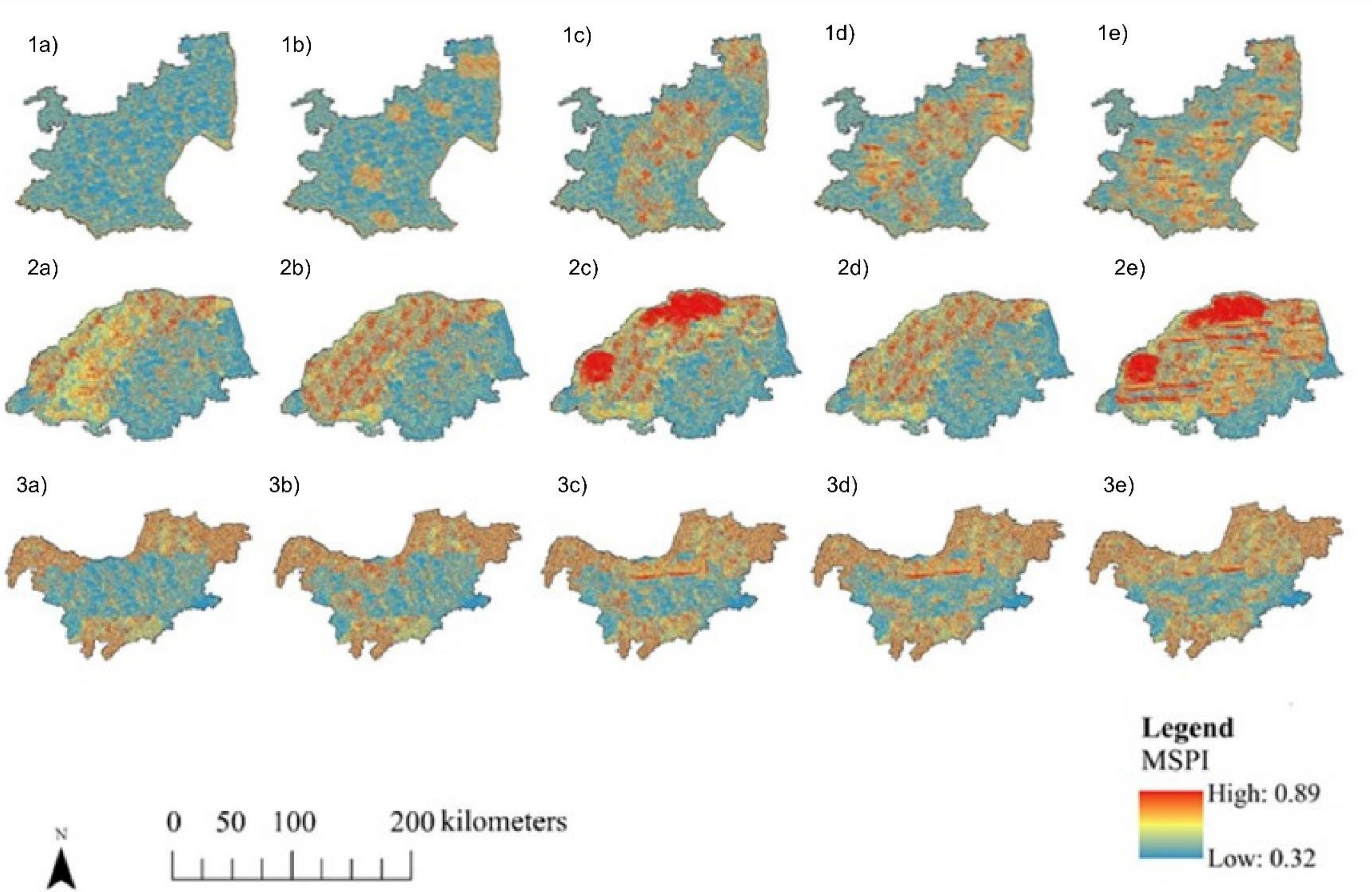

Figure 5.2 Derived MSPI from the Maximum Entropy (MaxEnt) model under Representative Concentration Pathways (RCP) 4.5 for Mpumalanga, Limpopo and the North West for the years 2034, 2044, 2054, 2064 and 2074 (1 – Mpumalanga, 2 – Limpopo, 3 – North West. a - 2034, b – 2044, c – 2054, d – 2064, e – 2074)

Figure 5.3 depicts the MSPI under RCP 8.5 conditions for Mpumalanga, the North West and Limpopo for 2034, 2044, 2054, 2064 and 2074. Mpumalanga is the least-vulnerable province to drought occurrence under RCP 8.5 conditions, and Limpopo is severely vulnerable to drought conditions, followed by the North West. In 2034 (1a), Mpumalanga has a low MSPI value and therefore the probability of drought occurrence is not high (MSPI = 0.56); however, the probability increases from 2044 to 2074. In 2044 (1b), there are mild drought conditions, less than in 2034 in certain regions in the north, east and west of the province (MSPI = 0.50). In 2054 (1c), the probability of the occurrence of a drought increases to more mild and moderate drought conditions in the north-eastern, central and southern parts of Mpumalanga (MSPI = 0.65). In 2064 (1d), the probability of drought occurrence increases to more severe in certain regions and spreads throughout the province (MSPI = 0.78). In 2074 (1e), the drought conditions are still expected to be moderate to severe (MSPI = 0.82).

The results for Limpopo show that the probability of drought occurrence is high in the northern and western regions of the province and that it is particularly high in 2054 and 2074 (MSPI = 0.81 and MSPI = 0.86, respectively). In 2034 (2a), the probability of the occurrence of a drought is mild-to-moderate in the northern and western regions of the province, and it increases in 2044 (2b), when the drought occurrence becomes more severe in those regions and over larger areas (MSPI = 0.76). In 2054 (2c), severe drought conditions expected in the northern and western parts in Limpopo; however, these drought conditions decrease in severity in 2064 (2d), where mild-to-moderate drought conditions are expected across the entire province (MSPI = 0.70). In 2074 (2e), drought conditions increase and severe drought conditions are expected in the northern and eastern parts of the province, while the rest of the province has moderate-to-severe drought conditions (MSPI = 0.89).

The results for the North West show a high probability of drought occurrence in the eastern and central regions of the province. In 2034 (3a), the province experiences moderate-to-severe drought conditions in the eastern and central regions (MSPI = 0.76), and in 2044 (3b), the drought conditions spread and increase in the central region (MSPI = 0.80). In 2054 (3c) and 2064 (3d), the drought conditions are moderate in the eastern, western, northern and southern regions (MSPI = 0. 85). In 2074 (3e), drought conditions are spread throughout the western and eastern regions of the province (MSPI = 0.89). Overall, all three provinces show the highest probability for drought occurrence in 2074 under RCP 8.5 conditions, and Limpopo shows the highest probability of drought occurrence and the highest vulnerability to drought, with severe conditions projected for agriculture and water availability, followed by the North West.

Mpumalanga shows a moderate vulnerability to drought conditions. The Limpopo Province has a high probability of drought occurrence under RCP 4.5 and RCP 8.5 conditions, and Mpumalanga has the lowest probability of drought occurrence. Conditions under RCP 8.5 are more severe across all three provinces, compared to the conditions under RCP 4.5 conditions.

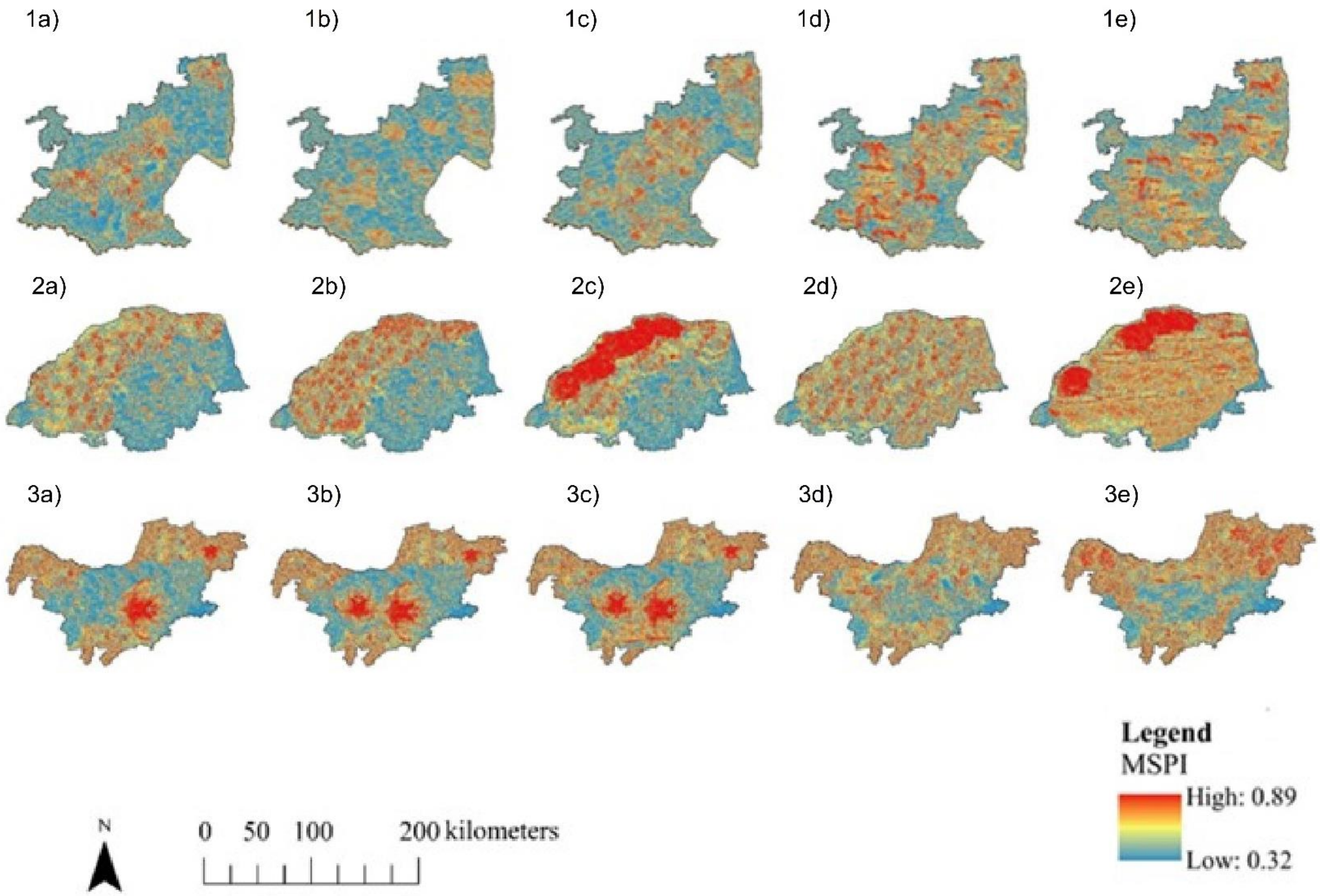

Figure 5.3 Derived MSPI from the Maximum Entropy (MaxEnt) model under Representative Concentration Pathways (RCP) 8.5 for Mpumalanga, Limpopo and North West for the years 2034, 2044, 2054, 2064 and 2074 (1 – Mpumalanga, 2 – Limpopo, 3 – North West. a - 2034, b – 2044, c – 2054, d – 2064, e – 2074).

Table 5.2 shows the accuracy assessment results for RCP 4.5 conditions, using the MaxEnt model to calculate the MSPI for the years 2034, 2044, 2054, 2064 and 2074. Limpopo achieved the highest accuracies for all five years and achieved a TSS of 0.89, 0.90, 0.93, 0.96 and 0.98 for 2034, 2044, 2054, 2064 and 2074, respectively. The North West Province achieved TSS results of 0.85, 0.89, 0.92, 0.94 and 0.96 for 2034, 2044, 2054, 2064 and 2074, respectively. Mpumalanga achieved the lowest accuracies for all five years across all four accuracy assessments and achieved TSS results of 0.79, 0.83, 0.91, 0.91 and 0.93 for the years 2034, 2044, 2054, 2064 and 2074, respectively. Under the RCP 4.5 conditions, the year 2074 achieved the highest accuracies. The year 2034 achieved the lowest accuracies for all four assessments across all three provinces.

Table 5.2 Accuracy assessments for RCP 4.5 conditions

Accuracy assessment	**Mpumalanga**	**Limpopo**	**North West**
2034			
TSS	0.79	0.89	0.85
Sensitivity	0.82	0.91	0.89
Specificity	0.80	0.87	0.84
F1-score	0.79	0.88	0.81
2044			
TSS	0.83	0.90	0.89
Sensitivity	0.90	0.98	0.93
Specificity	0.89	0.93	0.90
F1-score	0.85	0.89	0.87
2054			
TSS	0.91	0.93	0.92
Sensitivity	0.89	0.91	0.89
Specificity	0.90	0.92	0.91
F1-score	0.89	0.95	0.93
2064			
TSS	0.91	0.96	0.94
Sensitivity	0.89	0.93	0.90

Specificity	0.93	0.96	0.94
F1-score	0.90	0.95	0.92
2074			
TSS	0.93	0.98	0.96
Sensitivity	0.90	0.93	0.91
Specificity	0.93	0.96	0.95
F1-score	0.89	0.91	0.89

Table 5.3 shows the accuracy assessment results under RCP 8.5 conditions, using the MaxEnt model to calculate the MSPI. The RCP 8.5 accuracy assessment results were higher than those of the RCP 4.5 results. The Limpopo results were higher than those of the North West Province, and Mpumalanga achieved the lowest accuracies. Limpopo achieved TSS results of 0.92, 0.95, 0.93, 0.98 and 0.99 for the years 2034, 2044, 2054, 2064 and 2074, respectively, whereas Mpumalanga achieved TSS results of 0.80, 0.87, 0.91, 0.94 and 0.96 for 2034, 2044, 2054, 2064 and 2074, respectively, which are lower than the results achieved in Limpopo and the North West. The year 2074 achieved the highest accuracies across all metrics, whereas 2034 achieved the lowest accuracies across all metrics. TSS achieved the highest accuracies across all the years and provinces.

Table 5.3 Accuracy assessment for RCP 8.5 conditions

Accuracy assessment	**Mpumalanga**	**Limpopo**	**North West**
2034			
TSS	0.80	0.92	0.81
Sensitivity	0.89	0.93	0.90
Specificity	0.82	0.90	0.87
F1-score	0.79	0.88	0.81
2044			
TSS	0.87	0.95	0.92
Sensitivity	0.93	0.99	0.95
Specificity	0.89	0.94	0.91
F1-score	0.89	0.91	0.90

2054			
TSS	0.91	0.93	0.92
Sensitivity	0.89	0.91	0.89
Specificity	0.90	0.92	0.91
F1-score	0.89	0.95	0.93
2064			
TSS	0.94	0.98	0.96
Sensitivity	0.91	0.96	0.93
Specificity	0.94	0.98	0.93
F1-score	0.91	0.98	0.94
2074			
TSS	0.96	0.99	0.97
Sensitivity	0.93	0.97	0.95
Specificity	0.94	0.98	0.97
F1-score	0.92	0.96	0.95

5.4 Discussion

5.4.1 A comparative analysis of the results across the provinces

The MSPI for future drought conditions in the Mpumalanga, Limpopo and North West Provinces was predicted by using the MaxEnt model under RCP 4.5 and RCP 8.5 for the years 2034, 2044, 2054, 2064 and 2074. The results provided an insight into the regional drought dynamics under various greenhouse gas emission scenarios, and they highlighted the differences in the vulnerability and adaptation needs across these provinces.

Mpumalanga has a diverse climate that ranges from the humid highveld regions to the dry lowveld regions (Ebhuoma et al., 2020). This province showed a moderate drought vulnerability, compared to Limpopo and the North West. Under RCP 4.5 conditions, moderate drought conditions were prevalent, with the probability of reaching 0.61 by 2074. The eastern highveld regions showed drought resilience under this scenario, which is because the region usually experiences consistent rainfall and lower temperatures (Weather and Climate, 2024). The south-western and central lowveld regions showed an increasing probability of drought, which could be due to their warmer and drier conditions (Ebhuoma et al., 2020; van der Merwe et al., 2023). Under RCP 8.5 conditions, the projected changes in precipitation and temperature intensified the risks of drought significantly, especially in the lowveld regions. The severe drought probability reached 0.65 and the extreme drought probability increased to 0.49 by 2074. The central regions are projected to be hotspots for severe droughts, due to their higher ET rates and the decrease in rainfall under the high-emission scenario. These areas are critical for sugarcane and tropical fruit farming, which are extremely sensitive to water stress (van der Merwe et al., 2023; Zenda et al., 2024). The resilience in the highveld regions offers an opportunity to utilise the natural advantages, such as the higher rainfall and cooler temperatures, to minimise the impacts of drought. Expanding the irrigation infrastructure in the lowveld areas, which are vulnerable to drought, can stabilise the agricultural yield and preserve the natural water storage systems, which can enhance the regional water security. The eastern highveld regions showed drought resilience under both scenarios, as the region receives more consistent rainfall (Weather and Climate, 2024; Zenda et al., 2024). Mpumalanga achieved the lowest accuracies under RCP 4.5 and RCP 8.5 conditions across all three provinces, which could be due to the humid climatic conditions of the province (Zenda et al., 2024). However, the RCP 8.5 conditions achieved higher accuracies, compared to the RCP 4.5 conditions. The highest accuracy was 0.96, which was achieved by the TSS in 2074.

Limpopo exhibited the highest probability of drought occurrence under both RCP 4.5 and RCP 8.5, with a notable increase in the frequency and severity of extreme droughts over time, for all three provinces. This trend aligns with the semi-arid climate in the province (Dzurume et al., 2021; Weather and Climate, 2024). Under the RCP 4.5 scenario, moderate and severe drought conditions were more prevalent, with a probability of 0.68 by 2074. However, under the RCP 8.5, the likelihood of extreme droughts increased significantly and reached a probability of 0.82. The western parts of Limpopo are already prone to dry conditions and experienced the highest drought probability, which indicates their limited resilience to moderate climate shifts (Maponya & Mpandeli, 2012; Shikwambana et al., 2021). The eastern regions benefit from a slightly higher rainfall, due to subtropical influences, yet still showed an increasing vulnerability to moderate drought occurrences (Dzurume et al., 2021; Shikwambana et al., 2021). Under RCP 8.5 conditions, the severity and frequency of droughts increased drastically, which highlights the impacts of the increase in temperature and the decrease in rainfall (Shikwambana et al., 2021). The western region is a critical drought hotspot and experiences extended periods of vegetation stress and water scarcity (Mpakairi et al., 2023). Rainfed agricultural systems in this region, such as maize and sorghum, are highly likely to experience significant decreases in their agricultural yield, which will affect livelihoods and food security (Mpandeli et al., 2015; Ebhuoma et al., 2020; Shikwambana et al., 2021). The results highlight the importance of implementing targeted adaptation strategies for the western regions, which are vulnerable to drought. Limpopo's high drought vulnerability to drought under RCP 4.5 and RCP 8.5 highlights the need for integrated climate adaptation strategies. |It achieved the highest accuracy results under both RCP 4.5 and RCP 8.5 conditions, due to the arid climate, and the region is expected to experience extreme drought conditions. Similar results were achieved by Mpandeli et al. (2015) and Shikwambana et al. (2021). The lowest accuracies were recorded for the year 2034 under RCP 4.5 conditions. The highest accuracy was recorded by Sensitivity in 2034 (0.99) and the TSS in 2074 (0.99).

The North West Province is also highly vulnerable to drought under RCP 4.5 and RCP 8.5 conditions. The province is predominantly a semi-arid climatic zone and relies heavily on rainfed agriculture, which makes it highly susceptible to changes in the precipitation and temperature (Cole et al., 2021; Bahta & Myeki, 2022). Under RCP 4.5, the probability of a severe drought exceeds 0.75 by 2.74 and the probability of extreme drought reaches 0.62. This scenario indicates significant increases in the frequency of droughts, which mostly affects the western and northern regions, which are already characterised by low rainfall amounts and high ET rates (Botai et al., 2016; Cole et al., 2021). Sorghum and millet, which are more resilient to drought, are farmed in these regions; however, they are still vulnerable to prolonged drought conditions (Cole et al., 2021). Under RCP 8.5, the drought conditions worsened dramatically, with the extreme probability of drought exceeding 0.80 by 2074. The western regions of the North West experienced a decrease in vegetation health and soil moisture under RCP 8.5 conditions, which highlights the impacts of a decrease in rainfall and an increase in ET. Rainfed smallholder farms in these regions experience the greatest challenges, with impacts on the food security, rural livelihoods and ecosystem stability (Mpandeli et al., 2015; Botai et al., 2016; Ebhuoma et al., 2020; Zenda et al., 2024). Integrating climate adaptation into regional development is vital. The accuracy assessment results for the North West followed the results for Limpopo and achieved higher accuracies than those for Mpumalanga, due to its semi-arid climate and the severity of the projected drought occurrences. The 2074 results were the highest under both scenarios, compared to the rest of the years. The highest accuracy recorded was 0.97 in 2074 under RCP 8.5 conditions, and this was achieved by the TSS and Specificity.

5.4.2 Future research directions

Building on the results of this study, a number of areas warrant further research, in order to improve our knowledge on forecasting and managing droughts in South Africa, in the face of the changing climate conditions (Zhan et al., 2016; Aghelpour et al., 2020; van der Merwe et al., 2023). To improve the adaptive capacities in susceptible areas, future research should focus on incorporating more diverse and localised data sources, on improving the modelling techniques and on investigating the socio-economic factors (Zhao et al., 2021; Saha et al., 2022). The geographic accuracy of the MaxEnt model can be improved by using higher-resolution measurements on vegetation indices, soil moisture and precipitation, especially in areas with diverse landscapes like Mpumalanga and Limpopo. The more accurate monitoring of changes in landcover and drought-related vegetation stress can be made possible with the utilisation of Sentinel-2 and Landsat-9 imagery (Carrington et al., 2022; Ju et al., 2023). In addition, drought monitoring can be improved by incorporating near-real-time climatic data, which assists with early warning systems for proactive drought management (Bahta & Myeki, 2022; Ruwanza et al., 2022; Ferchichi et al., 2024). The use of hybrid models, which combine MaxEnt with other machine learning methods, such as Random Forest (RF) or Artificial Neural Networks (ANNs), should also be investigated in the future. These methods could improve the forecast accuracy of the models by reflecting the non-linear interactions between the environmental and climatic factors (Aghelpour et al., 2020; Carrington et al., 2022; Ferchichi et al., 2024). In addition, integrating the MaxEnt model with hydrological models may improve the insights into how meteorological droughts interact with their hydrological effects, which will lead to a more thorough understanding of drought dynamics (Bazrafshan et al., 2017; Ju et al., 2023; Ferchichi et al., 2024). By pursuing these research avenues and addressing these research directions, future research can greatly improve South Africa's drought preparedness and resilience, which will promote sustainable farming methods and accomplish the national and international development objectives, in the face of the growing climate hazards (Abah et al., 2024; Prudhomme et al., 2024).

5.5 Conclusion

This study employed the MaxEnt model to predict the probability of drought occurrence by using MSPI in the Mpumalanga, Limpopo and North West Provinces under the RCP 4.5 and RCP 8.5 scenarios for the years 2034, 2044, 2054, 2064 and 2074. The results highlighted the regional patterns and vulnerabilities to drought, which emphasised the vital need for targeted adaptation strategies to mitigate the future impact of droughts. Limpopo is the most vulnerable province under both RCP scenarios, with the high probability of severe and extreme droughts being predicted, especially in the western and northern regions. This aligns with its semi-arid climate and its dependence on rainfed agriculture, which is extremely sensitive to decreases in rainfall and increases in ET. The study highlights the need for interventions in water resource management, as well as the adoption of drought-resistant crops and improved irrigation systems, in order to support and sustain agricultural productivity and food security. Mpumalanga showed a lower drought vulnerability; however, the lowveld and central regions are projected to experience an increasing probability of droughts under RCP 8.5 conditions. The findings of this study highlight the role of integrated adaptation strategies that are suited to the unique climatic and agricultural conditions of each province. The projections under RCP 8.5 conditions highlight the severe consequences, and this study provides valuable insights for policymakers and stakeholders to develop proactive and region-specific interventions to improve drought resilience and to support sustainable farming.

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CHAPTER SIX

A SYNTHESIS: MACHINE LEARNING ALGORITHMS TO DEVELOP A REMOTELY-SENSED FRAMEWORK FOR DROUGHT MONITORING IN DIFFERENT CLIMATE REGIONS IN SOUTH AFRICA

6.1 Major Findings

Objective One: To review methods used to delineate rainfed smallholder farms and drought monitoring and impacts of droughts on predominantly rainfed farmers across different climatic regions.

This objective was addressed in Chapter Two by reviewing the available methods, approaches and challenges in delineating rainfed smallholder farms. The chapter highlighted the use of multispectral and hyperspectral remotely-sensed data in delineating rainfed smallholder farms. The use of spectral indices for monitoring vegetation health and delineating agricultural areas with high accuracy was discussed in detail. The findings in this chapter underscored the potential that remote sensing methods have in overcoming conventional challenges, such as gaps in the data and accessibility to varying landscapes. Machine learning algorithms, such as Random Forest and the Support Vector Machines, proved to be efficient tools for processing and analysing big datasets and achieved high accuracies when classifying and delineating rainfed smallholder farm boundaries. In addition, Chapter Two highlighted the gaps in applying these methods within the South African context, where climate variability requires scenario-specific approaches for effective agricultural and water resource management. It provided a detailed review of the progress of the various remote sensing methods that are used to delineate rural farms and for drought monitoring in sub-Saharan Africa, and it highlighted the impacts of droughts on rural farmers. The research gaps in drought monitoring were also highlighted, in order to provide insights for future studies, to assist in understanding droughts and to be prepared for the occurrence of droughts.

Objective Two: To assess the performance of multisource, remotely-sensed data and machine learning algorithms in delineating small-scale rainfed agricultural regions in different climate regions of rural South Africa.

This objective was addressed in Chapter Three by demonstrating the use of high-resolution remote sensing data, combined with advanced machine learning algorithms, to map and delineate rainfed smallholder farms in the North West, Limpopo, Mpumalanga and Gauteng Provinces in South Africa, by using Google Earth Engine (GEE). Chapter Three introduced a transferrable framework and achieved mapping accuracies that exceeded 90% in these provinces with different climate conditions. It expanded on the methodologies that were discussed in Chapter Two by assessing the use of cutting-edge machine learning models, such as the Gradient Boosting Decision Tree (GBDT), the Support Vector Machine (SVM), the Convolutional Neural Network (CNN), as well as the Random Forest (RF) and Transformer models, in conjunction with the Normalised Difference Vegetation Index (NDVI), the Modified Soil-Adjusted Vegetation Index 2 (MSAVI2) and the NDVI combined with MSAVI2 in the Google Earth Engine (GEE). This chapter shows that the mapping and delineation of rainfed smallholder farms is improved significantly when Sentinel-2 data are combined with the CNN, RF, SVM, GBDT and Transformer models, by using NDVI combined with MSAVI2. The findings highlighted the superior performance of the Transformer model, as it outperformed other algorithms and achieved an overall accuracy of 0.85 and a mean Intersection over Union of 0.86 across the Limpopo, North West, Mpumalanga and Gauteng Provinces. The results showed that Limpopo had the highest presence of rainfed smallholder farms (25.9%), followed by Mpumalanga (19.94%). The North West has an area of 13.64% of rainfed smallholder farms, whereas Gauteng had the lowest presence of rainfed smallholder farms of (4.02%). However, challenges with the landscape heterogeneity, as well as pixel mixing and changes in the planting and harvesting times, require further improvements and solutions.

Objective Three: To assess the frequency of drought occurrence at multiple temporal scales over a nineteen-year period across different ecological regions in South Africa, using satellite-derived metrics.

Chapter Four addressed Objective Three and focused on evaluating drought conditions across rainfed smallholder farms in Africa and it analysed their spatial extent, frequency and magnitude over 19 years, across the North West, Limpopo and Mpumalanga Provinces. From this chapter onwards, Gauteng was not included as a study area due to its low presence of rainfed smallholder farms and the lack of records on historical drought. By computing the Vegetation Condition Index (VCI) and the Standardised Precipitation Index (SPI) in GEE, drought severity classifications were conducted throughout the three provinces. The results of this study highlighted the fact that Limpopo faces the highest drought vulnerability due to its semi-arid climate and reliance on rainfed agriculture. The province experienced 15 years of severe drought of 0.91 within the 19-year study period. The North West Province experienced a severe drought 11 times within the 19-year study period, while the Mpumalanga Province showed a relatively lower drought severity of 0.41, because its climate is more humid. Validation metrics, such as the F1-score, True Skills Statistic and Matthews Correlation Coefficient, showed a strong agreement between the VCI and SPI results. Validating remotely-sensed drought indices by using ground-based meteorological data proved the robustness of this approach.

Objective Four: To model the occurrence of droughts in different climate regions in South Africa by using the Maximum Entropy (MaxEnt) model for the years 2034, 2044, 2054, 2064 and 2074.

Chapter Five addressed Objective Four by examining the potential of predictive modelling, using the Maximum Entropy (MaxEnt) model, to forecast the occurrence of drought under future climate scenarios. The study modelled the probability of drought occurrence for the years 2034, 2044, 2054, 2064 and 2074 and focused on the North West, Limpopo and Mpumalanga, by employing Representative Concentration Pathway (RCP) scenarios 4.5 and 8.5. The results indicated that there was a significant spatial variability in drought their vulnerabilities, and Limpopo was identified as the most susceptible, due to its arid conditions and heavy dependence on rainfed agriculture, as drought probabilities increased from 0.68 in 2034 to 0.82 in 2074, under RCP 4.5 conditions. The North West and Mpumalanga showed an increased risk under high-emission scenarios. The findings highlighted the need for region-specific adaptive strategies. This chapter also emphasised the effectiveness of integrating climate and environmental variables in forecasting future drought scenarios, as well as the need for proactive mitigation strategies.

Policymakers can develop targeted planning, mitigation strategies and climate resilience strategies, by mapping the presence of rainfed smallholder farms and understanding the historical droughts that occurred in these provinces, how they impacted these farmers and then forecasting the occurrence of droughts in the future. Therefore, these research chapters are all linked to each other, in order to create a framework.

6.2 Implications for Sustainable Agriculture and Water Resource Management

The methods that are covered in Chapters Two to Five are based on the integration of machine learning and remote sensing. These technologies addressed the difficulties faced by smallholder farmers in semi-arid and dry climates, by making it possible to monitor the regions that are prone to drought, and by accurately and efficiently mapping and delineating the rainfed smallholder farms (Abah et al., 2024; Enongene, 2024; Zenda et al., 2024). This study has addressed the knowledge gaps relating to the monitoring and management of drought conditions and their impact on agricultural productivity, by thoroughly examining the current methods and implementing new frameworks (Bekuma et al., 2022; Mpakairi et al., 2023; Zenda et al., 2024). This study has highlighted the need for climate adaptation strategies that focus on assisting rainfed smallholder farmers, as they are more vulnerable to drought conditions. Therefore, there is a need for policymakers to invest in remote-sensing-based early warning systems for droughts, to alleviate and prevent food insecurity, which will align with achieving Sustainable Development Goals (SDGs) 2 (Zero hunger), 13 (Climate action) and 15 (Life on land) (Bhaga et al., 2020; Mpakairi et al., 2023). The key findings of this research highlight the efficiency of the integration of high-resolution, freely-available satellite data with machine learning algorithms for the monitoring of agricultural vulnerabilities (Cui et al., 2021; Raihan, 2024; Heiss et al., 2025). The integration of the Google Earth Engine with machine learning algorithms has proven to be a cost-effective and efficient method for monitoring areas that are prone to droughts and for mapping rainfed smallholder farms. For example, this study has underscored the applicability of integrating Sentinel-1 and Sentinel-2 data to improve the accuracy of delineating rainfed smallholder farms and drought assessments. The use of NDVI and VCI has allowed for a holistic understanding of vegetation health and climatic indices, such as MSPI and SPI, and it has allowed for temporal drought monitoring over a 19-year time period. In addition, the use of machine learning models, such as RF and the Transformer method has proven to be capable of mapping rainfed smallholder farms. The monitoring of rainfed smallholder farms has undergone a paradigm shift with the incorporation of remote sensing and machine learning technologies, especially in areas that are vulnerable to climate extremes (Burka et al., 2024; Zenda et al., 2024). The implementation of these technologies in a South African setting was thoroughly examined in this study, with an emphasis on their ability to address vital agricultural challenges.

6.3 Prospects of Integrating Remote Sensing into Agricultural and Drought Management

The results of this study prove how incorporating cutting-edge machine learning and remote sensing technology into agricultural and drought management systems can have a revolutionary effect. This integration improves the accuracy of monitoring frameworks and assists decision-makers with information to support policy changes and sustainable practices (Abah et al., 2024; Burka et al., 2024; Zenda et al., 2024). The spatial framework developed in this study enables policymakers to identify and prioritise regions that are the most vulnerable to drought. By focusing the resources in these regions, it becomes possible to improve interventions, to improve resource allocation and to support climate-resilient farming (Masocha et al., 2018; Gxokwe et al., 2022; Heiss et al., 2025). The methods used in this study can help to determine the crops that are most appropriate for certain regions, based on the local soil and climate conditions, which can increase their productivity. The predictive models developed in this study are vital for developing drought early warning systems, which can provide timely alerts for farmers and will allow them to implement adaptive actions, such as changing their planting schedules, diversifying their crops or investing in technologies for water conservation (Cui et al., 2021; de Araujo Junior et al., 2023; Raihan, 2024). The integration of real-time data from weather stations also improves the precision and dependability of these systems (Meza et al., 2021).

The spatial modelling framework developed in this thesis has the potential to be integrated into local and national early warning systems. By linking real-time satellite monitoring with the outputs from machine learning models, drought conditions can be predicted in a timely manner and therefore assist decision-makers. The results from this study can be used by various government departments, such as the South African Weather Services (SAWS) and the Department of Water and Sanitation (DWS) and assist with crop insurance schemes and drought relief planning. Moreover, the data can support disaster risk management and allow for targeted support such as drought-tolerant seed distribution or early harvesting advisories.

6.4 Future Research Directions

Future research needs to investigate ways in which to improve classification accuracy, such as the use of multi-temporal and hyperspectral datasets, as well as ways to improve the computational methods and the ability to process and handle large datasets (Mpakairi et al., 2023; Heiss et al., 2025). Improving the deep learning methods can enhance the classification of rainfed smallholder farms. Future studies should also investigate hybrid models that integrate ground-based data and remotely-sensed data to improve the prediction accuracies. Future studies need to assess the integration of soil moisture indices, evapotranspiration metrics and microwave-based drought indicators, as well as the application of SAR data, to enhance mapping under cloudy conditions. There is also a need to consider integrating citizen science with drought-monitoring frameworks and to train communities to use mobile applications to assist with ground-truthing. Most importantly, there is a need to develop a risk assessment framework that can provide information for targeted drought relief programmes.

6.5 Conclusion

Across the four chapters, this research demonstrates the potential of integrating high-resolution satellite data, vegetation indices and machine learning models to significantly improve drought monitoring in smallholder contexts. This study assists policymakers with data to improve decision-making by accurately delineating rainfed smallholder farms and identifying drought conditions. For example, predicting and identifying drought occurrence in high-risk, rural areas directly supports drought mitigation. By improving the spatial and temporal resolution of drought assessments and identifying rainfed smallholder farms, this thesis enhances early warning systems, assists with targeted mitigation strategies and supports long-term adaptation strategies, which are critical for improving food security and livelihoods in vulnerable areas. This research helps to create farming systems in South Africa that are climate resilient and sustainable by filling the important research gaps. In order to evaluate the applicability and adaptability of the developed methodologies, future research needs to test and validate them in other sub-Saharan African regions. Socioeconomic data must also be included, in order to develop comprehensive models that address the various impacts of droughts. Policymakers need to assist with the creation of solutions, in order to ensure their relevance, applicability and sustainability. Future research needs to improve the methodologies, include more climatic factors and encourage collaboration between scientists, policymakers and local farming communities. The integration of advanced machine learning tools and participatory monitoring methods is also vital, to ensure that drought preparedness strategies are data-driven and community-centred. These initiatives will support the welfare of smallholder farmers and the broader agricultural sector by aiding food security and climate resilience. In conclusion, the findings of this thesis contribute to the fields of remote sensing, drought monitoring and agricultural resilience by providing solutions for enhancing the monitoring, food security and climate adaptation in drought-prone areas. It highlights the importance of an interdisciplinary approach for solving the problems caused by climate variability.

6.6 References

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