MAPPING THE MAIZE GROWTH PERIOD USING MULTI- TEMPORAL SENTINEL 1 AND 2 IMAGERY – A CASE STUDY IN KASISI AREA OF CHONGWE DISTRICT

by

Chenje Prassat Mtonga

A dissertation submitted to the University of Zambia in partial fulfilment of the requirements for the award of the Masters of Science in Geo-Information Science and Earth Observation

The University of Zambia

April 2025

Copyright Declaration

© 2025 Chenje Prassat Mtonga. All rights reserved.

Declaration

This thesis was written and submitted in accordance with the rules and regulations governing the award of the Master of Science in Geo-Information Science and Earth Observation in the School of Natural Sciences of the University of Zambia. I further declare that I am the sole author of this t dissertation and that all content is my original work that has not been presented before for any award at any university or learning institution:

Signed: ……………………………………………….

Date: ……………………………………………….

Certificate of Approval

The University of Zambia approves this dissertation of CHENJE PRASSAT MTONGA as fulfilling part of the requirement for the award of the degree of Master of Science in Geo-Information Science and Earth Observation.

Examiner 1: Name

Signature……………………………….. DATE……………………………………….

Examiner 2: Name

Signature ……………………………….. DATE ………………………………………

Examiner 3: Name

Signature ……………………………….. DATE ……………………………….........

Chairperson Board of Examiners: ………………………………………….

Signature: ……………………….. Date …………………………………..

Abstract

Effective agricultural monitoring is essential for ensuring food security and efficient resource management. This study aimed to use Synthetic Aperture Radar (SAR) from Sentinel 1 and Optical imagery from Sentinel 2 multi spectral instrument (MSI) for mapping and monitoring Maize fields in the Kasisi area of Chongwe District, Zambia, from November, 2019 to April 2020. This was done by capturing the temporal variations in maize growth and mapping its coverage from November 2019 to April 2020. The analysis focused on tracking maize phenological stages—sowing, emergence, vegetative growth, and maturity—through biweekly observations of SAR backscatter and NDVI. Dual-polarized SAR data (VV and VH) were analyzed to detect structural and moisture changes in maize, while NDVI and NDWI indices from Sentinel-2 provided complementary vegetation and water condition metrics. These indices also enhanced a Random Forest classifier used for land cover classification. Field-validated training data supported the classification, which achieved an overall accuracy of 96.97% and a Kappa coefficient of 0.95. Sowing was identified between 1st–15th November 2019, with emergence occurring by mid-December. Maturity was reached by mid-January 2020, followed by a post-maturity decline in backscatter from March to April, marking the harvesting phase. The results demonstrate the effectiveness of SAR and optical data fusion for identifying maize growth stages and mapping crop extent, particularly in cloud-prone tropical regions. This approach offers a scalable, weather-independent solution for precision agriculture and vital input for yield forecasting in Sub-Saharan Africa.

Keywords: *SAR, Crop Monitoring, Random Forest, Sentinel 1, Sentinel 2, NDVI, NDWI*

Acknowledgements

I would like to express my deepest gratitude to all those who contributed to the successful completion of this thesis.

First and foremost, I am profoundly grateful to my supervisor, Dr. Garikai Membele for their invaluable guidance, constructive feedback, and unwavering support throughout this research journey. Their insights and encouragement have been instrumental in shaping the direction and quality of this work.

I extend my heartfelt thanks to the Ministry of Technology and Science (Zambia) for awarding me the scholarship that helped me complete my studies. Your financial support and belief in my academic pursuits have been pivotal in enabling me complete this research.

A special thanks to my family for their unconditional love, patience, and encouragement. To my mother and wife, your support has been my anchor during this challenging yet rewarding journey.

I am also thankful to my colleagues and peers in the geospatial realm of Zambia for their advice, camaraderie, and shared knowledge. Your input and support during this time have been truly appreciated.

Finally, I am deeply grateful to all the researchers, authors, and contributors whose work provided the foundation and inspiration for this study. To all those not mentioned here but who played a part in my academic journey, your contributions will always be cherished.

Thank you all for your invaluable support.

TABLE OF CONTENTS

List of Tables

List of Figures

List of Abbreviations and Acronyms

AgRISTARS – Agriculture and Resource Inventory Surveys Through Aerospace Remote Sensing
AOI – Area of Interest
C-Band – Microwave frequency range used in SAR systems
DEM – Digital Elevation Model
EO – Earth Observation
ESA – European Space Agency
EMR – Electromagnetic Radiation
GEE – Google Earth Engine
GIS – Geographic Information Systems
GRD – Ground Range Detection (specific SAR product)
GPS – Global Positioning System
JECAM – Joint Experiment for Crop Assessment and Monitoring
LACIE – Large Area Crop Inventory Experiment
LAI – Leaf Area Index
MODIS – Moderate Resolution Imaging Spectroradiometer
MLP – Multilayer Perceptron (a type of neural network)
MSI – MultiSpectral Instrument
NASA – National Aeronautics and Space Administration
NDVI – Normalized Difference Vegetation Index
NDWI – Normalized Difference Water Index
NIR – Near-Infrared
NOAA – National Oceanic and Atmospheric Administration
OA –Overall accuracy
PA – Producer's Accuracy
RF – Random Forest
RS – Remote Sensing
SAR – Synthetic Aperture Radar
SRTM – Shuttle Radar Topography Mission
SVM – Support Vector Machine
TIR – Thermal InfrareUAV – Unmanned Aerial Vehicle (often referred to as drones)
UA – User accuracy
USDA – United States Department of Agriculture
VH – Vertical Transmit, Horizontal Receive (SAR polarization)
VV – Vertical Transmit, Vertical Receive (SAR polarization)
VV/VH Ratio – Ratio of Vertical Transmit-Receive to Vertical Transmit-Horizontal Receive polarization.

CHAPTER ONE: INTRODUCTION

1.1 Background

The increase in world population and demand for more food with limited resources have led to a demand for efficient and enhanced agricultural systems. Globally, the state of food security is a complex and evolving issue. According to (FAO, IFAD, UNICEF, WFP, WHO;, 2022) the number of people facing chronic food deprivation has been increasing since 2014 and in 2021, it was estimated that around 828 million people worldwide faced hunger with a sharp increase since the Covid-19 pandemic. The report also showed that nearly one in three people or 2.31 billion people were moderately or severely food insecure in 2021.

In Africa, the food security situation varies across countries and regions. Africa faces numerous challenges such as population growth, climate change, conflicts, and limited access to resources and infrastructure, which impact food production and availability. According to (FAO, IFAD, UNICEF, WFP, WHO;, 2022), Africa has the highest prevalence of undernourishment, with over 250 million people suffering from chronic hunger. The report also showed that Zambia in 2017 had 14.8 million people who could not afford a healthy diet. This number grew to 15.2 million in 2018, 15.7 million in 2019 and 16.2 million in 2020. This shows as of the estimate from 2020 that close to 90 percent of the Zambian population are unable to access or afford a healthy diet.

The global, continental and country statistics on population growth and the increasing demand for food show that there is a greater need to ensure food security and meet the growing demands for agricultural products. The accurate assessment of crop sizes and monitoring of crop health are crucial for effective resource allocation, production planning, and addressing potential food shortages. This process can tend to be expensive and tedious if done manually through ground surveys. Earth observation satellites provide an alternative source of data capture that is cost effective and available at varied temporal scales. The understanding of the dynamic progress of the composition and spatial distribution of crops is essential for numerous agricultural monitoring activities such as crop acreage, yield modelling and harvest operations schedule (Wardlow, et al., 2007).

Earth observation (EO) technologies, such as satellite imagery, play a vital role in providing valuable data for crop monitoring and management. By utilizing EO data, such as Sentinel-1 Synthetic Aperture Radar (SAR) and sentinel 2 MSI imagery, this study aims to contribute to the accurate estimation of the size and spatial distribution of maize fields in Chongwe District. This information is essential for understanding the agricultural landscape, optimizing resource allocation, and improving crop yield predictions and can act as a basis for decision-making at a wider spatial scale (Löw & Duveiller, 2014). This information can be gathered in near real-time depending on the type of satellite imagery employed. The information from crop maps can also be used in sustainable land management and more resilient food production systems and provide vital statistics for yield prediction and crop area estimation (Ghazaryan, et al., 2018).

Remote sensing has been a useful tool in mapping, assessing and monitoring of agricultural crop conditions and production (Moran, 2000). Airborne and Space borne imaging platforms are used at varied spatial and temporal scales to provide data for different mapping objectives and implementation levels (Apan, et al., 2002). Since the earliest times of digital remote sensing numerous approaches of crop classification that are based on supervised and unsupervised classification techniques have been used to map geographic distributions of crops and characterize cropping practices (Nellis, et al., 2009).

In Zambia, crop monitoring and forecasting was the responsibility of the Ministry of Agriculture (MoA). Prior to 1990, the ministry performed this function exclusively through crop monitoring surveys (CMS) executed by its field staff in the districts and camps. Since 1990, the ministry has been implementing two parallel monitoring systems: district-level CMS, as before, and through crop forecast surveys (CFS). Unlike CMS, implementation of the CFS is largely conducted by the Central Statistical Office (CSO), which is now Zambia Statistical Agency or Zamstats (Tembo, et al., 2014). The CFS are also based on probability sampling (Megill, 2004) and is designed to produce valid production forecasts at national level. Crop production estimates are drawn from the Crop Forecast Surveys (CFS) and Post-Harvest Surveys (PHS), which are the official estimates of the Government of the Republic of Zambia (GRZ). The nationally representative surveys were started in the 1990/91 crop season and conducted thereafter annually by the Zamstats. The CFS and PHS are based on a sample frame of about 13,600 small-scale and medium-scale agricultural households selected from the census Standard Enumeration Areass (SEAs) (GRZ, 2015).

Small-scale farmers are those who cultivate between 0.1 and 5 hectares while medium-scale farmers cultivate between 5 and 20 hectares of land. The methods currently employed are unable to give accurate yield information, especially during the growing period (December to March) in Zambia. This impedes vital early warning information to make decisions for better food security in the country. Tembo, et al., (2014) showed that resources both human and capital to facilitate data gathering by CFS field staff were inadequate to gather information on yield in smaller spatial units and this causes inherent variations due to differences in farming systems and agro ecological systems around the country. A more diverse sampling mechanism was suggested that would cater to the different farming systems but the required resources would make it practically impossible (Tembo, et al., 2014).

The use of geospatial science to carry out crop mapping and yield estimation would standardize the mapping as physical parameters of each crop would be used in the mapping and therefore increase the quality and amount of information on crops grown in different districts around the country. Using satellite imagery would also save on both human and capital resources as the data could be generated using a considerably smaller amount of field data for training and validation. The amount of time taken to generate the crop maps and yield information would also be greatly reduced using geospatial information.

Maize is the main staple in Zambia and most small-scale farmers around the country plant rain fed fields during the growing period and rely on the harvest for food during the year. This makes the plant very important in ensuring food security in the country. Against this background, this study aimed to map maize fields and monitor the growth using Sentinel 1 and 2imagery in Chongwe District.

1.2 Statement of the problem

Zambia's economy is showing signs of recovery, with GDP growth improving from 5.2% in 2022 to 5.8% in 2023, driven in part by agriculture alongside mining and trade. However, despite this, agriculture's contribution to GDP has declined significantly, from 9.3% in 2012 to just 3.3% in 2022, even though the sector still employs 24% of the labor force (African Development Bank Group, 2024). This shrinking economic footprint reflects broader structural issues, including low productivity, climate vulnerability, and limited modernization. This decline underscores the growing need for modernization and investment in the sector, particularly through the adoption of technologies such as remote sensing for improved crop monitoring and yield forecasting. While the Crop Forecast Survey (CFS) conducted by ZAMSTAT remains the primary official method for national crop yield estimation in Zambia, it is not the only approach used in practice. Other stakeholders, including researchers and development partners, increasingly rely on crop modeling and remote sensing methods to supplement and validate survey-based estimates. For instance, Zambia's Third National Communication to the UNFCCC highlights the use of simulation modeling and Earth Observation (EO) data to estimate maize yield under varying climate scenarios, reflecting a shift toward geospatial tools for agricultural assessment (GRZ, 2020).

This current official system relies on face-to-face interviews with farmers and most information gathered is based on probability sampling as is the case in PHS (Megill, 2004) and gives little information on the physical dynamics of the crop and puts little emphasis on real-time crop conditions and environmental variables. The crop forecast surveys are time-consuming and require vast amounts of human and capital resources to carry out every year. The results from the Crop Forecast Surveys tend to be delayed due to challenges in reaching remote areas, especially during the rainy season as well as logistical issues. This may lead to the information not being as useful for planning and decision-making on food security in the country. Therefore, there is a need for an approach that can be used to derive statistics and information in a timely and cost-effective manner to foster decision-making and policy formulation. Therefore, this study seeks to explore the potential of using SAR images in mapping maize fields in Kasisi area of Chongwe District.

1.3 Main objective

To explore the potential of using Sentinel Synthetic Aperture Radar (SAR) images in mapping and monitoring the progression of maize fields in Kasisi area of Chongwe District

1.4 Specific objectives

1. To establish the size of land under maize cultivation in the study area.
2. To investigate the spatial-temporal variations of maize during the growing period.
3. To explore the challenges and opportunities of using SAR imagery in estimating maize yield.

1.5 Research questions

1. What is the size of land under maize cultivation in the study area?
2. How is the maize fields distributed in the study area over time?
3. What are the challenges in using SAR imagery in estimating maize yield?
4. What are the opportunities for using SAR imagery in estimating maize yield?

1.6 Significance of study

Maize is Zambia's staple crop, central to national food security and rural livelihoods. This study offers a scalable, remote sensing-based framework for monitoring maize growth stages and estimating crop inventories using Sentinel-1 SAR and Sentinel-2 optical imagery. By replacing labor-intensive field surveys with near real-time satellite analysis, it reduces costs, enhances efficiency, and supports early warning systems for droughts, pests, and other climate-related stressors.

The information generated from this research will be useful to stakeholders such as the Ministry of Agriculture, Zambia Statistics Agency (Zamstats), Conservation Agriculture Unit, insurance companies, and climate resilience platforms like the Zambia Climate Change Network. These institutions can use the data to improve seasonal crop inventories, inform policy decisions, optimize resource allocation, and support climate-smart agriculture.

The study also contributes to Zambia's broader agricultural modernization goals by demonstrating how machine learning and Earth Observation (EO) data can be integrated to produce actionable, field-level insights. Its methodological contributions will be valuable for future research on crop mapping, yield modeling, and risk assessment, particularly under changing climate conditions.

CHAPTER TWO: LITERATURE REVIEW

This literature review explores the current survey techniques used to carry out Crop Forecast Surveys and Post Harvest Surveys by the Ministry of Agriculture and Zamstats. The section further explores the role and evolution of remote sensing technologies in agricultural monitoring, with a particular focus on crop classification and growth monitoring using Synthetic Aperture Radar (SAR) and optical imagery. Over recent decades, advancements in remote sensing have provided valuable tools for precision agriculture, enabling efficient management of crop health, water resources, and yield predictions. Key studies are examined to highlight both foundational techniques and recent innovations, emphasizing the utility of SAR and multispectral imagery in overcoming challenges posed by atmospheric conditions and varying agricultural landscapes. This review sets the foundation for understanding how remote sensing has developed as a reliable, data-driven approach in agriculture, especially for maize monitoring in regions similar to Zambia.

2.1 Theoretical framework

This study is anchored in two complementary theoretical perspectives of systems thinking and remote sensing theory, which together provide a robust foundation for the integration of multi-source geospatial data in crop mapping and monitoring.

Systems thinking offers a structured lens through which complex, interdependent components of an agricultural monitoring system can be understood (Arnold & Wade, 2015). In this context, maize growth monitoring is viewed as a dynamic system comprising input data (e.g., Sentinel-1 SAR, Sentinel-2 MSI, field observations), transformation processes (e.g., machine learning classification, temporal trend analysis), and decision-making outputs (e.g., maps of sowing, emergence, and maturity). This systems-oriented perspective emphasizes feedback loops and cause-effect relationships, which are critical in understanding crop responses to environmental variables over time. The framework supports the idea that satellite data, when processed in a continuous feedback system like Google Earth Engine (GEE), can improve responsiveness and precision in agricultural decision-making, which is an essential need in Zambia’s climate-vulnerable regions.

Remote sensing theory underpins the spectral and structural interpretation of vegetation using satellite data. Specifically, SAR backscatter theory explains how microwave energy interacts with crop structures based on parameters like canopy height, leaf water content, and surface roughness (Li, et al., 2018; Venkatesan, et al., 2019). VV and VH polarizations, and their ratio (VV/VH), provide unique temporal signatures for different vegetation. Likewise, optical remote sensing theory supports the use of NDVI and NDWI to detect chlorophyll content and water availability, essential indicators of crop vigor and stress (Kumar, et al., 2021; Jin, et al., 2019). These concepts collectively justify the integration of dual-polarized SAR data with spectral indices from MSI to map and, capture both structural and biochemical changes during the maize phenological cycle.

Together, these theories reinforce the methodological rationale of this study which combining SAR and optical data within a systems-based processing environment enables accurate, scalable, and timely maize mapping and monitoring. This approach is particularly suitable for Zambia, where limited field capacity and frequent cloud cover undermine conventional survey and optical-only monitoring systems.

2.2 Remote Sensing in Agriculture

Remote Sensing has been an important tool for agriculture even before the term Remote Sensing was coined in 1958. Aerial photographs were part of the data used in crop inventories and soil surveys by different departments in the United States. Technological advancements during World War II brought about an evolution in Remote Sensing Techniques and saw the introduction of infrared photography. This consequently allowed scientists access to greater information on crop status, crop soil condition and water availability (Nellis, et al., 2009).

Remote Sensing technology has revolutionized the agricultural sector. It has provided exceptional insight into our crops, water, soil and other resources. The ability to monitor crop growth, crop health, nutrient levels and soil moisture has given us the ability to spot possible stress regions using remotely sensed data. Using the information gathered from platforms such as drones, planes and satellites, farmers can make informed decisions about fertilization, crop management, pest control and irrigation in near real-time. This information ultimately leads to higher yields for the farmer and reduces their costs by minimizing waste (Kumawat, et al., 2023).

2.2.1 Historical overview of Remote Sensing in Agriculture

The genesis of using remote sensing in agriculture can be traced back several decades, with efforts being largely experimental in the early years. In the 1960s, as satellite technology began to develop, scientists recognized the potential of using aerial imagery to monitor and manage agricultural practices.

A landmark in this evolution was the Large Area Crop Inventory Experiment (LACIE) in the late 1970s. Sponsored by NASA, USDA, and NOAA, LACIE was an ambitious attempt to estimate wheat production in the United States, Canada, and the Soviet Union using data from Earth-observing satellites, such as the Landsat series. The program was pioneering in integrating satellite data, meteorological information, and ground observations (MacDonald & Hall, 1980). The success of LACIE was monumental for several reasons in the history of Agricultural Monitoring. It demonstrated that large-scale crop monitoring using satellite data was technically feasible. LACIE project also led to the development of new algorithms and methods for crop classification, growth stage estimation, and yield prediction. The experiment further laid the groundwork for subsequent remote sensing programs in agriculture such as Agriculture and Resource Inventory Surveys through Aerospace Remote Sensing (AgRISTARS) which aimed to create an early warning system and the widespread acceptance and implementation of precision agriculture around the globe (Moran, et al., 1997).

In the wake of the groundbreaking LACIE initiative, the subsequent decades, the 1980s and 1990s witnessed a surge in technological advancements in the realm of remote sensing. The launch of advanced satellite systems, such as SPOT, coupled with the continuation of the iconic Landsat series, brought forth higher spatial and spectral resolutions. This heightened resolution empowered researchers and agricultural experts to discern crop types and their conditions with unprecedented clarity and specificity (Nellis, et al., 2009). Concurrently, the emergence of Geographic Information Systems (GIS) technology and Global Positioning Systems (GPS) amplified the prowess of remote sensing, making data analysis and interpretation more dynamic and context-specific for agriculture. This synergistic merger of GIS and remote sensing opened doors to a multitude of precision agricultural applications. From meticulously managed crops and efficient irrigation techniques to real-time pest and disease monitoring, the landscape of agriculture began to transform. This technological renaissance not only bolstered sustainable agricultural practices but also significantly enhanced the protective measures for the environment while concurrently boosting profitability (Moran, 2000).

The late 1990s and 2000s marked the rise of new satellite systems. These systems include MODIS (Moderate Resolution Imaging Spectrometer) in 1999 and Sentinel satellite systems (2014). Commercial High-resolution satellite Systems also became available such as Quickbird (2001) and WorldView-1 (2007) (Cracknell, 2018)

Over the years, the technological advancements in Synthetic Aperture Radar (SAR) have been notable and its utility in earth observation has grown exponentially. SAR became a focal point in remote sensing, especially with the deployment of satellites like Radarsat-2, Advanced Earth Observing Satellite (ALOS), and missions such as Shuttle Radar Topographic Mission (SRTM) during the late 1990s and 2000s. The true potential of SAR lies in its ability to capture data under conditions where traditional optical sensors fail. Its capacity to penetrate cloud cover ensures uninterrupted, all-weather surveillance, a boom for sectors like agriculture and meteorology where continuous monitoring can be critical. This capability of SAR is not limited to just overcoming atmospheric challenges; its interaction with the Earth's surface, particularly vegetation, has ushered in new methodologies in remote sensing. By leveraging the way SAR signals interact with different vegetation types and structures, researchers can extrapolate data to estimate parameters like biomass, offering invaluable insights into forest health, carbon sequestration, and other environmental metrics. Such unique advantages of SAR technology have made it indispensable in the rapidly evolving field of earth observation (Moreira, et al., 2013).

Advancements in multispectral as well as hyperspectral technology enabled more detailed analysis of land features and vegetation by capturing a wide range of the electromagnetic spectrum. This provided detailed data for spectral signature analysis in agricultural crop management (Cracknell, 2018).

The launch of Google Earth in 2005 provided a unique tool for visualizing the world and ushered in a new era of digital globes. Google Earth provided a seamless new way for scientists, researchers and indeed common people could add and share spatial data to the platform. This new visualization tool coupled with the advancements in data processing software such as ArcGIS and Erdas Imagine catapulted RS and GIS capabilities into a new paradigm. People were now able to process, analyze and model vast amounts of spatial data and visualize it in virtual globes (Butler, 2006).

Today, with the integration of technologies like Artificial Intelligence and drones, remote sensing in agriculture is not just about large-scale monitoring but also about farm-level precision agriculture, offering unprecedented levels of detail and accuracy. Drones have made it possible to monitor and assess plant stress such as drought stress, diseases, nutrition inadequacy, weeds and pests at a very high resolution. This level of precision gives farmers the ability to intervene in areas of stress with pin point accuracy (Dutta & Goswami, 2020).

In conclusion, from the pioneering efforts of LACIE to the sophisticated tools of today, remote sensing in agriculture has evolved immensely, offering invaluable tools for sustainable and efficient farm management.

2.2.2 Role of Remote Sensing in Agriculture Monitoring

Remote sensing data plays several critical roles in providing information for decision-making. The complexity and uses of the information vary greatly. In agriculture remote sensing is used widely at different spatial scales from farm level to regions and indeed globally to generate information for decision-making.

2.2.2.1 Crop Inventory and Mapping

Remote Sensing (RS), Global Positioning System (GPS) and Geographical Information Systems (GIS) play a key role in crop mapping and surveying. For key policymakers such as governments, information on what crops have been planted, how they have been distributed spatially, the area planted and estimated yield is crucial in agricultural planning and early warning systems (Kumawat, et al., 2023). Proper identification of crops is crucial for crop acreage and production estimation. Remote sensing provides an efficient method of achieving this as remote sensing data provides unique responses for different crops at different growing stages.

Mapping the agro ecological landscape involves the application of classification algorithms (which can be supervised and unsupervised) and results in discrete categories of spatialized remote sensing measurements (Weiss, et al., 2019). These measurements when repeated over time provide insight into the spatial temporal characteristics of the landscape and hence one obtains the capacity to monitor change over time. This ability allows policy makers and other stakeholders to understand the prevailing trends within the agricultural sector and make data-based decisions and plans on food security.

2.2.2.2 Irrigation Management and Monitoring

Remote sensing can assess soil moisture levels, evaluate irrigation systems' effectiveness, and determine areas requiring more or less irrigation. With this information, farmers can optimize water use, reducing waste and improving crop yields.

The portion of the electromagnetic radiation (EMR) that is visible and its interaction with vegetation provides useful information on the condition of the vegetation. The leaf or chlorophyll absorbs blue and red light but reflects the green of the EMR. A healthy leaf will hence will appear green and this can provide a basis for investigation of water availability. When a plant is stressed, little chlorophyll will be available for photosynthesis and the leaf will have little green to reflect (Bello, et al., 2014).

This information based on the middle infrared and thermal infrared portion of EMR can give detail to how much water is in the leaf, soil and atmosphere in the area and provides vital input into irrigation scheduling. Water is a good absorber in the middle infrared portion of EMR and so leaves with high moisture content will have low reflectance in this portion and high reflectance will signify low moisture content (Bello, et al., 2014).

Irrigation is an important component of agriculture and proper management and utilization of water resources is pivotal to the successful implementation of any agricultural project. Information based on remote sensing is important in drought monitoring, water resource management and irrigation scheduling as farmers can efficiently use water when and where it is required. This reduces wastage and costs in the field (Dutta & Goswami, 2020).

2.2.2.3 Pests and Disease Detection

Before visible symptoms manifest on plants, remote sensing can detect stresses caused by pests and diseases. Early detection can lead to timely intervention, preventing widespread crop losses.

The ability of remote sensing multispectral and hyperspectral sensors to see the internal conditions of plants has provided us the ability to diagnose early signs of disease and pest infestation in crops when human assessment is not possible. Remote sensing gives us the ability to recognize disease and stress due to pests at very early stages before they are visible to the human eye (Dutta & Goswami, 2020).

Precision intervention is made possible with data from remote sensing. Site-specific Agro drone application of weedicides and other intervention measures are possible with the geolocated information produced. The intervention measures are applied where they are needed and in exactly the right amounts, thereby reducing the costs of mitigation and subsequently increasing the yield of the farmer (Huang, et al., 2009).

2.2.2.4 Yield Prediction and Harvest Forecasting

Modern agricultural practices often employ yield-monitoring systems, which are mounted on combines during harvest to gather yield data. These systems, however, cover multiple crop rows at once, resulting in a more generalized, coarse resolution of yield maps. It can be challenging to discern the yield for individual rows with this approach (Kumawat, et al., 2023).

Remote sensing (RS) has shown significant potential to address this issue by producing high-resolution yield maps. By harnessing Vegetation Indices (VIs) from RS imagery and integrating them with machine learning algorithms, it is possible to estimate crop yields with notable accuracy. However, the precision of these yield prediction models varies with the growth stage of the crop; models tend to be more accurate during the mid-season than in earlier growth stages. Yet, predicting yield early in the season is vital to mitigate potential crop yield losses. To enhance yield forecasting further, there's an emerging interest in assimilating RS data into detailed crop growth models. This integration factors in seasonal weather forecasts and specific field management practices. Despite the potential benefits of this approach, it remains relatively underexplored. However, with the growing accessibility to RS data and advancements in data analytics, the agricultural sector is expected to make more strides in developing sophisticated crop yield forecasting systems. (Khanal, et al., 2020).

2.2.3 Advantages of Remote Sensing in Agriculture

Since its early adoption, remote sensing has proven its importance in agriculture. This has been due to the several properties of remotely sensed data that allow its use in key functions in the agricultural industry.

Scalability in the context of remote sensing for agricultural purposes refers to the capacity of satellite systems to monitor varying scales of land areas, from localized farm plots to extensive regional landscapes. This ability to adjust to different scales provides a flexible solution for agricultural management needs (Khanal, et al., 2020). Remote sensing allows the coverage of vast areas unlike ground-based surveys, which can be labor-intensive and time-consuming. Remote sensing platforms can quickly and routinely cover thousands of square kilometers in a single pass. This vast coverage makes it possible to monitor extensive agricultural regions and even assess regional trends or threats such as pest outbreaks or drought conditions (Weiss, et al., 2019),

Satellite data guarantee consistent time-series captures, which is invaluable for trend analyses, pest predictions, and studying crop seasonality (Weiss, et al., 2019). Satellite data has proven to be cost-effective, especially for remote and inaccessible regions. Satellite imagery emerges as a far more economical solution than conventional ground-based surveys, reducing both time and resources as pointed out by (Khanal, et al., 2020).

Remote sensing can record data beyond the visible spectrum, providing insights into plant health, soil conditions, and moisture content that are invisible to the naked eye. This ability to view the Multispectral and Hyperspectral characteristics of the phenomenon has given us the ability to see beyond what is visible with the naked eye and helps us monitor processes that would otherwise be invisible (Bello, et al., 2014).

Real-time decision-making based on quick access to accurate data enables farmers and policymakers to make timely decisions regarding irrigation, pest control, and harvest timings. The common properties of remote sensing are spatial, temporal and spectral resolution. Spatial refers to the pixel size of an image and determines the size of the objects that one can detect. Spectral refers to the number and size of spectral sampling intervals and this determines the ability of the sensor to resolve features in the EMS. The temporal resolution is how often the sensor acquires data (Khanal, et al., 2020). A satellite system with a high temporal resolution provides information that farmers and policymakers can base decisions on. Drones are being used for monitoring crops throughout the growing period and can give different information on demand. By using different sensor systems with visible, Near Infrared (NIR) and thermal bands can be used to compute different multispectral indices depending on the reflection patterns in the field at different wavelengths. This information is a vital input into any early warning system so that vital decisions are made (Dutta & Goswami, 2020).

2.2.4 Google Earth Engine and Remote Sensing

Google Earth Engine or GEE is a planetary scale cloud-based geospatial analysis platform. It uses Google's monumental computational abilities in a variety of high-impact social-economic themes such as drought, deforestation, disaster management, food security, water resource management, climate monitoring and environment protection. GEE is a platform that brings together geolocated data, high computational abilities and Application Programming Interfaces (APIs) to perform cloud-based parallelized geospatial data analysis (Franceschini & Ali, 2022). This has an advantage over classic methods of Remote Sensing data analysis that require downloading and analyzing individual tiles that require a lot of computing power (hardware) and local storage. GEE has a vast archive of public time series satellite imagery that is constantly being updated. These data sets include Earth Observation (EO) data such as Sentinel 2 and Landsat, Radar data such as Sentinel 1 SAR, Land Cover data such as the ESA Global land cover data and Weather and Climate data such as Climate Hazards Center InfraRed Precipitation with Station data (CHIRPS) (Franceschini & Ali, 2022). The massive catalogue of data allows users to apply a variety of data analysis techniques in agriculture, water management, disaster risk and mitigation, forest studies, weather and climatic studies.

A study by Lemoine, et al., (2017) emphasized the revolutionary impact of Google Earth Engine (GEE) in operationalizing large-scale geospatial analysis. By leveraging inbuilt cloud-based infrastructure, GEE enables seamless integration of varied datasets, providing researchers with a platform capable of analyzing global-scale environmental phenomena without the limitations of localized computational resources. The study validated GEE's ability to manage and process multi-sensor datasets, including optical, hyperspectral, and radar imagery. The platform facilitate comprehensive analyses in various thematic domains.

GEE has proven instrumental in agricultural mapping and monitoring by providing high-resolution imagery, such as Sentinel-1 and Sentinel-2, for accurate crop classification and area estimation. Its applications extend to urban planning, forest health assessments and disaster risk management, demonstrating its adaptability in addressing complex geospatial phenomena. The platform has a vast library of analytical tools and its open, collaborative, script-sharing community foster innovation and efficiency in tackling large-scale geospatial challenges (Lemoine, 2017).

Building on the advancements highlighted by Lemoine et al., (2017), recent studies have demonstrated the potential of object-based (OB) classification methodologies for improving crop mapping accuracy and the use of GEE. Vizzari et al., (2024) successfully employed an OB approach using Sentinel-2 L2A (Level 2 A- surface reflectance) and Sentinel-1 GRD data within Google Earth Engine (GEE) to classify crops in central Italy's Lake Trasimeno area. By integrating spectral bands, vegetation indices, backscatter (VV/VH), Radar Vegetation Index (RVI) from the SAR imagery and textural features derived from the Gray-Level Co-occurrence Matrix (GLCM), the study achieved classification accuracies as high as 89% at the first level of aggregation. The optimized Random Forest (RF) classifiers highlighted the critical role of textural features, particularly for distinguishing between complex crop types such as winter cereals and warm-season cereals.

This approach not only demonstrates the scalability of OB methods for agricultural mapping but also underscores the significance of incorporating multi-sensor data for improved accuracy. The findings from their study align with the growing emphasis on leveraging geospatial tools for precision agriculture, providing a robust framework for applications in diverse agricultural contexts, including Zambia (Vizzari, et al., 2024).

By adopting such innovative methodologies, agricultural monitoring programs can achieve high-accuracy classifications, reduce reliance on resource-intensive traditional surveys, and enhance the timeliness of crop forecasts, particularly in areas with fragmented or heterogeneous landscapes. This positions OB classification as a pivotal advancement in utilizing cloud-based platforms such as GEE for agricultural monitoring and decision-making.

2.2.5 Limitations and Challenges

Remote sensing in agriculture has revolutionized the way farmers and agronomists assess and manage their fields, but it is not without its limitations and challenges.

Atmospheric conditions, cloud cover, and sensor calibration can influence the accuracy of remote sensing data. These facets can potentially lead to inconsistent or inaccurate results. The temporal resolution of imagery, especially with satellite-based systems, may not always align with crucial agricultural decision-making timelines. Furthermore, the sheer volume of data generated can be overwhelming, requiring significant computational resources and expertise for processing and interpretation (Khanal, et al., 2020).

Additionally, there are challenges in converting remote sensing data into actionable insights for farmers. Specific nuances like crop variety differences, soil variability, and local pest and disease pressures may not be fully captured or understood just from aerial or satellite imagery. Thus, while remote sensing offers remarkable potential, its effective implementation in agriculture requires careful consideration of these challenges (Khanal, et al., 2020).

2.3 SAR imagery for crop mapping

While optical sensors capture reflected sunlight from the Earth's surface, Synthetic Aperture Radar (SAR) sensors emit their radiation, making them independent of sunlight conditions. This capacity gives SAR a significant edge in monitoring agricultural fields under cloudy conditions, where optical sensors fall short (Nagraj & Karegowda, 2016). Furthermore, SAR's sensitivity to moisture conditions has proven invaluable in monitoring irrigation, soil moisture, and even differentiating crop types in certain conditions (Bello, et al., 2014). Moreover, the moisture levels in various crops can differ, allowing for the potential differentiation of crop types based on their water content. This can be particularly valuable in regions where multiple crops are grown in close proximity (Bello, et al., 2014).

A study by Kussul, *et al.*,(2014) that was conducted in Ukraine offers a compelling illustration of the potential of SAR imagery in crop classification. Collaborating with the Joint Experiment for Crop Assessment and Monitoring (JECAM) project, the researchers employed multitemporal SAR images from RADARSAT-2 to classify summer crops. Ukraine, being one of the world's most prominent wheat exporters, has dominant cultivation of crops like maize, soybean, and sunflower. The study compared three classification techniques: a feed-forwarded neural network (often referred to as Multilayer Perception or MLP), a Support Vector Machine (SVM), and a Decision Tree (DT). The unique properties of SVMs, where the determination of model parameters aligns with a convex optimization problem, ensure that any localized solution also reaches a global optimum. Notably, the classifications were executed on a per-pixel basis, revealing MLP to be the superior classifier with an 80.4% accuracy, followed closely by SVM at 78.6%, and DT at 78.1% (Kussul, et al., 2014).

This study demonstrates the early use of machine learning algorithms in SAR-based crop classification, establishing a baseline for performance across classifiers. However, the accuracy ceiling of ~80% achieved in that study reflects the limitations of earlier SAR systems and classification models like MLP. Importantly, Kussul et al., (2014) conducted pixel-based classification without incorporating multi-sensor fusion or spectral indices such as NDVI or NDWI. This study builds on their work by integrating SAR and optical data, using Random Forest rather than MLP or SVM, and achieving a higher accuracy (96.7%) while focusing specifically on temporal backscatter trends for maize phenology, rather than general seasonal mapping.

A study by Li et al., (2018) in the North China Plain to address challenges posed by cloud cover, which often disrupts optical remote sensing during crucial maize growth periods. Utilizing Sentinel-1A time series data, their research centered on maize cropland mapping for the year 2016. Leveraging the Support Vector Machine (SVM) method with this SAR data, they achieved a commendable classification accuracy of 93.57% and a kappa coefficient of 0.929 (Li, et al., 2018).

Their findings underscored the pivotal role of polarization mode in the radar signal's interaction with maize structures. Specifically, changes in VH and VV polarization from April to July were notably distinct from other land covers. The VH cross-polarized backscatter, in particular, proved instrumental in discerning maize croplands from forests. Multi-polarization modes, especially the combination of VH and VV dual-polarization, consistently outperformed the single-polarization modes.

In evaluating temporal datasets, the time series images from Sentinel-1A SAR emerged as decidedly more effective than single temporal phase SAR images, especially for differentiating varied maize cultivation techniques. The study suggests that while augmenting the number of single-phase acquisitions can bolster classification, there is a diminishing return with excessive additions. Li and colleagues highlighted the untapped potential of Sentinel-1A SAR data for precise maize identification in the region. They also advocated for exploring alternative classification methodologies to potentially elevate the accuracy further (Li, et al., 2018). This study highlights the potential of integrating SAR data, specifically from the Sentinel-1 satellite, with optical data from Sentinel-2 and PlanetScope satellites for crop type and land cover mapping in Northern China. The authors leveraged the unique capabilities of SAR data to penetrate cloud cover (a common challenge in sub-Saharan Africa) enhancing the reliability of agricultural mapping in cloud-prone regions. The use of Sentinel-1 SAR data, characterized by its C-band frequency and capability to capture dual-polarization (VV and VH) images, was crucial in overcoming limitations posed by high cloud cover during critical crop growth stages. By combining SAR data with high-resolution optical images, the study achieved significant improvements in mapping accuracy, demonstrating the complementary strengths of radar and optical sensors.

The study provided a critical insight into the behavior of SAR polarizations in crop mapping. Their results underscore how multi-polarization SAR (VV and VH) can outperform single-polarization for maize discrimination. However, their study was confined to the 2016 growing season in a mechanized, temperate-zone system, which may not generalize well to smallholder, rainfed systems like Zambia’s. Additionally, they used SVM for classification, which, while effective, may require extensive tuning and does not inherently perform internal feature selection like Random Forest.

Kpienbaareh et al.'s (2021) findings underscore the value of SAR data in enhancing the spatial and temporal resolution of agricultural mapping in sub-Saharan Africa, where cloud cover can impede the use of solely optical remote sensing methods. The study provides a compelling case for the operational integration of SAR with optical data in agricultural and environmental decision-making processes, paving the way for more accurate and reliable agricultural monitoring systems in cloud-dense and resource-poor settings (Kpienbaareh, et al., 2021).

The research employed the random forest algorithm for classification, trained with both in-situ collected data and digital samples from high-resolution satellite imagery. The integration of Sentinel-1 SAR data with optical data resulted in higher overall accuracies and Kappa coefficients, outperforming the use of single-source data sets. This multi-sensor approach not only improved the accuracy of crop and land cover maps but also offered insights into the distribution of agricultural practices in the region, with maize identified as the dominant crop.

This contribution is particularly relevant for sub-Saharan Africa, where accurate and timely agricultural data are essential for food security planning and environmental management. The methodology and findings from this study offer a blueprint for leveraging the synergies between SAR and optical data to address the challenges of agricultural mapping in regions with frequent cloud cover and limited ground-based data collection capabilities. (Kpienbaareh, et al., 2021).

This study provides the most directly comparable context to the current research, highlighting the operational benefits of combining SAR and optical data in a sub-Saharan environment. Like this study, it used Random Forest for classification, validating the choice of classifier. However, Kpienbaareh et al., (2021) focused on broad crop type classification and land use, not the temporal evolution of specific crops like maize. They also did not analyze backscatter changes over time or attempt to link them to growth stages.

2.4 SAR imagery in maize growth monitoring

Monitoring maize growth stages using SAR (Synthetic Aperture Radar) imagery is a comprehensive process that covers the entire lifecycle of maize, including stages such as germination, vegetative growth, tasseling, and reaching physiological maturity (Arslan, et al., 2022). The unique capability of SAR to penetrate the soil surface and its sensitivity to backscatter changes offers distinct advantages in observing these growth stages, particularly under diverse weather conditions where optical sensors may not be effective (Venkatesan, et al., 2019). For example, during germination and early vegetative growth, SAR can detect slight changes in the soil's surface texture as maize seedlings begin to emerge. The different polarizations in SAR imagery, that is VV(vertical transmit, vertical receive) and VH(vertical transmit, vertical receive), provide varying sensitivities to soil moisture and vegetation, with VV-polarization being more responsive to soil moisture and surface roughness, thus ideal for early growth stages, and VH-polarization more indicative of vegetation presence, beneficial for later growth stages (Venkatesan, et al., 2019).

The study by Venkatesan et al.,(2019) in Tamil Nadu, India demonstrated that the spectral dB of growth stages of Maize was at minimum at sowing and maximum at vegetative or tasseling stage of the crop with values of -21.26 to -13.18 in VH and -14.05 to –6.54 in VV polarization. The study achieved also generated a maize area map and achieved an overall accuracy of 91 % and a Kappa score of 0.82 (Venkatesan, et al., 2019).

Arslan, et al., (2022) demonstrated in their study that before planting backscatter values were low and did respond to planting operations, especially with larger incident angles. The study noted that the backscatter values also responded to early growth and increased after irrigation operations and rain events. The backscatter values generally also increased until tasselling and maturity. When the backscatter values began to decrease it indicated a drop in moisture content of the canopy and the grain maize had passed growth stages that indicated that it was time to harvest (Arslan, et al., 2022).

By performing a temporal analysis of SAR data, one can track the maize's growth over time, with changes in backscatter values indicating key growth milestones.

This advanced monitoring approach enhances the understanding of maize growth patterns and supports effective agricultural management strategies. This method has significant potential for improving crop yield assessments and informing decision-making processes in maize cultivation. This approach, utilizing SAR imagery for monitoring maize growth, represents a significant advancement in precision agriculture, allowing for a more detailed and accurate understanding of crop development stages and their impact on yield (Arslan, et al., 2022; Venkatesan, et al., 2019).

Both studies confirm the sensitivity of SAR backscatter (VV and VH) to maize phenology, with Venkatesan et al., (2019) showing clear backscatter trends from sowing to tasseling, and Arslan et al., (2022). Relating backscatter fluctuations to rainfall and irrigation events. However, these studies were conducted in climatically and structurally different regions, using large-scale or irrigated maize fields. Moreover, neither integrated NDVI or NDWI or offered a multi-sensor analysis platform like Google Earth Engine.

In their groundbreaking study, Jin et al., (2019) utilized the Google Earth Engine platform to map maize yields across Kenya and Tanzania with unprecedented detail. By integrating Sentinel-1 radar and Sentinel-2 optical data, the research successfully addressed challenges such as cloud cover and landscape heterogeneity, common in smallholder farming regions. The study employed a novel approach by leveraging machine learning algorithms and crop model simulations to predict maize yields, revealing significant spatial variability within these countries. This method not only demonstrated high accuracy in distinguishing maize from non-maize crops but also highlighted the critical role of soil nitrogen levels in influencing yield variations. The findings underscore the potential of satellite-based technologies in enhancing agricultural productivity and informing policy decisions in smallholder maize systems, offering valuable insights for agronomic practices and food security strategies (Jin, et al., 2019).

2.5 Advances in crop classification and phenological monitoring

Past studies have emphasized the robustness of machine learning algorithms, particularly Random Forest (RF) and Support Vector Machines (SVM), in enhancing the classification of agricultural land cover using satellite data (Kussul, et al., 2014; Li, et al., 2018; Kpienbaareh, et al., 2021; Jin, et al., 2019). RF has gained preference due to its ability to handle high-dimensional data, reduce overfitting through ensemble learning, and deliver high classification accuracy without extensive parameter tuning. In various contexts that range from the temperate, mechanized maize farms of the North China Plain (Li, et al., 2018) to the smallholder landscapes of Malawi (Kpienbaareh, et al., 2021), RF has consistently outperformed or matched SVM and Decision Trees in overall accuracy. Moreover, the integration of SAR and optical data has been widely recognized as crucial for improving classification performance, particularly in regions with persistent cloud cover such as sub-Saharan Africa (Jin, et al., 2019; Kpienbaareh, et al., 2021).

In terms of crop growth phenological mapping, research has shown that temporal patterns in SAR backscatter, especially VV and VH polarizations, closely align with maize growth stages. Across studies in India and Turkey, the VV, VH and NDVI trends have been instrumental in identifying key growth phases such as sowing, vegetative growth, and maturity (Venkatesan, et al., 2019; Arslan, et al., 2022). These findings validate the use of multi-temporal SAR metrics for monitoring maize development, even in data-scarce or cloud-prone areas. What distinguishes the present study is its combined use of VV, VH, VV/VH, NDVI, and NDWI time-series data within Google Earth Engine, offering an operationally scalable and cloud-ready approach to both classification and phenological mapping under Zambian conditions.

2.6 Machine learning

Machine Learning (ML) has emerged as a powerful subset of artificial intelligence for analyzing complex spatial datasets in remote sensing and GIS. Among its four primary approaches, supervised, unsupervised, semi-supervised, and reinforcement learning supervised learning is most relevant for land cover classification, as it relies on labeled training data to learn patterns and make predictions (Upreti, 2022). In remote sensing, supervised classification methods such as Support Vector Machines (SVM), Decision Trees (DT), Naïve Bayes (NB), and Random Forest (RF) have gained prominence due to their adaptability and high classification accuracy. Random Forest, a non-parametric ensemble learning algorithm, constructs multiple decision trees using bootstrapped subsets of data and aggregates their outputs for final prediction. This approach not only reduces overfitting but also increases generalization accuracy, particularly in high-dimensional remote sensing data (Upreti, 2022).

RF has been widely used for land use/land cover mapping, crop classification, and even hydrological modeling due to its robustness and minimal parameter tuning requirements. In the current study, RF was chosen because of its ability to handle large volumes of satellite-derived input variables such as VV, VH, NDVI, and NDWI, and produce high-accuracy classifications while minimizing bias and variance in results.

Random Forest (RF) is an ensemble learning method used for both classification and regression tasks. RF belongs to the family of decision tree-based algorithms and has gained popularity for its robustness, scalability, and ability to handle high-dimensional data (Defourney, 2017). Random Forest is widely used in various fields, including image segmentation, remote sensing, healthcare, finance, and more. Random Forest is based on constructing a multitude of decision trees during training and outputting the class that is the mode of the classes (for classification) or mean prediction (for regression) of the individual trees.

This algorithm uses bootstrapped datasets (randomly sampled with replacement) to build each tree. Additionally, when splitting each node during the construction of a tree, the best split is found either from all input features or a random subset, making it less susceptible to overfitting compared to a single decision tree (Breiman, 2001).

2.7 Satellite platforms for agricultural monitoring

Remote sensing data can be sourced from two primary types of sensors namely active and passive instruments. Passive sensors also known as optical remote sensing work by detecting natural radiation that is reflected or emitted by the object under observation. Reflected sunlight is the most common type of radiation that is measured by passive sensors. Active sensors also known as microwave remote sensing involve instruments providing their energy to illuminate the object that is being observed. An active sensor works by emitting radiation in the direction of the target and measuring the backscatter from the target (Nagraj & Karegowda, 2016).

Airborne systems are mostly used for specialized survey applications such as Light Detection and Ranging in terrain modelling (LIDAR), Detailed spectral signature analysis and field-level precision agriculture. These systems have the advantage of being easy to configure and launch on demand. The increased use of Unmanned Aerial Vehicle (UAVs) or drones has brought with it even more efficient platforms for data collection for remote sensing analysis. UAVs have the advantage of being lightweight and have the capability of collecting data at a very high spatial resolution on demand. These systems however do have drawbacks especially when data is required over larger areas. Safety regulations such as line of sight operation and flight altitude can hinder the amount of data that can be collected by UAVs (Lemoine, 2017).

Satellite-based remote sensing hinged off the space race between the Soviet Union and the United States of America. The first satellite was launched by Russia in 1957 and was named Sputnik 1 (Cracknell, 2018). The United States launched the Explorer 1 in 1960 and Landsat 1 in 1972. This marked the beginning of earth observation satellite systems. The Landsat program has continued since and is the longest-running satellite data collection program and has since Landsat 9 (Adamo, et al., 2020).

The first real success in remote sensing came in the field of meteorology with the launch of Vanguard 2 in 1959 and the Television Infrared Observation Satellite (TIROS 1) in 1960. These marked the start of a long series of polar-orbiting spacecraft which later led to the development of the Improved TIROS Operational Satellite (ITOS) and the National Oceanic and Atmospheric Administration (NOAA) (Cracknell, 2018). These satellite systems provided information that could be used in agriculture on prevailing weather conditions.

Polar-orbiting earth observation (EO) satellites such as Landsat, Sentinel and SPOT provide certain advantages over meteorological data for monitoring and yield modelling of crops. The EO satellites can provide course, moderate and high-resolution coverage of different areas of the globe (per crop field up to global scale) at different return periods. EO data also provides the ability to capture the effects of factors of growth that are not meteorological in nature such as the pest infestations on crop growth and yield (Dadhwal, 2005).

The European Space Agency (ESA) launched its Sentinels as a means to meet the Earth Observation needs of the European Union (EU) under the Global Monitoring for Environment and Security (GMES) – Space component. Sentinel 1 was launched in April 2012 and carries on it a C-band Synthetic Aperture Radar (SAR) active instrument and has a temporal resolution of 12 days and a wavelength of 5.6cm. (Torres, et al., 2012).

2.8 Crop Survey Methods in Zambia

Agricultural crop surveys in Zambia predominantly rely on field-data collection methodologies, including post-harvest surveys (PHS) and manual area frame sampling (Megill, 2004). These traditional methods involve extensive field data collection, where enumerators measure crop areas and conduct interviews with farmers. While the effective to some extent, these approaches require vast amounts of capital and human resources; they are also prone to human error and are logistically constrained, especially in remote or inaccessible regions.

The Zambian government's crop monitoring systems heavily depend on the Crop Forecast Survey (CFS). This annual survey is conducted through structured interviews and physical measurements of crop plots, which are aggregated to estimate production levels in different areas. This process faces several challenges, including delays in data collection, high operational costs, and inconsistencies in yield estimates due to variability in enumerator expertise and weather disruptions during survey periods (Tembo, et al., 2014). These limitations often result in delayed or unreliable outputs, undermining effective planning and policy formulation.

While Crop Forecast Surveys (CFS) and Post-Harvest Surveys (PHS) remain the official methods for national crop yield estimation by the Zambia Statistics Agency (Zamstats), researchers have increasingly supplemented these with remote sensing and crop modeling techniques. For instance, the Third National Communication to the UNFCCC explicitly recognizes the use of simulation models and EO data for estimating crop yield under different climate scenarios (GRZ, 2015).These advancements represent a shift toward integrating geospatial tools to enhance the accuracy and timeliness of yield assessments, particularly in light of logistical and resource limitations faced by traditional survey methods.

The integration of geospatial technologies, particularly remote sensing and Geographic Information Systems (GIS), offers a robust alternative to traditional methods of crop yield estimation. Remote sensing, with its ability to capture thematic, multi-temporal, and spatially explicit data, can significantly improve the timeliness and accuracy of crop surveys. Satellite imagery such as Sentinel-1 SAR and Sentinel-2 MSI imagery provides us with the ability to carry out continuous monitoring of crop phenology, area estimation, and yield forecasting, even in regions with persistent cloud cover (Kumawat, et al., 2023). Geospatial tools can also be used to complement ground surveys by providing baseline data for constructing Area Frame Sampling (AFS), stratifying land cover classes, and identifying crop-specific patterns over large areas.

Integrating geospatial tools can address the existing gaps in Zambia’s crop monitoring systems by reducing the reliance on time-consuming field surveys, enhancing the spatial resolution of crop distribution data, providing timely and accurate estimates of crop health or yields and reducing operational costs while helping improve resource allocation. By adopting such technologies, Zambia’s agricultural sector can transition from reactive, post-harvest data collection to proactive, real-time crop monitoring systems (Kumawat, et al., 2023). This paradigm shift is particularly crucial for addressing food security challenges, optimizing resource use, and supporting evidence-based policymaking in the face of climate variability.

CHAPTER THREE: DESCRIPTION OF STUDY AREA

3.1 Location

The study will be carried out in Kasisi and Kanakantapa areas about 20 kilometres from the capital city of Lusaka. Kasisi is Located in the North of Kenneth Kaunda International Airport in Chongwe district. The study area is between 15.163048°S, 28.388709°E; 15.154127°S, 28.561868°E; 15.292445°S, 28.569147°E; and 15.292309°S, 28.380232°E. The area has evidence of both small-scale and large-scale farming activity, which will be important in the study (Figure 1).

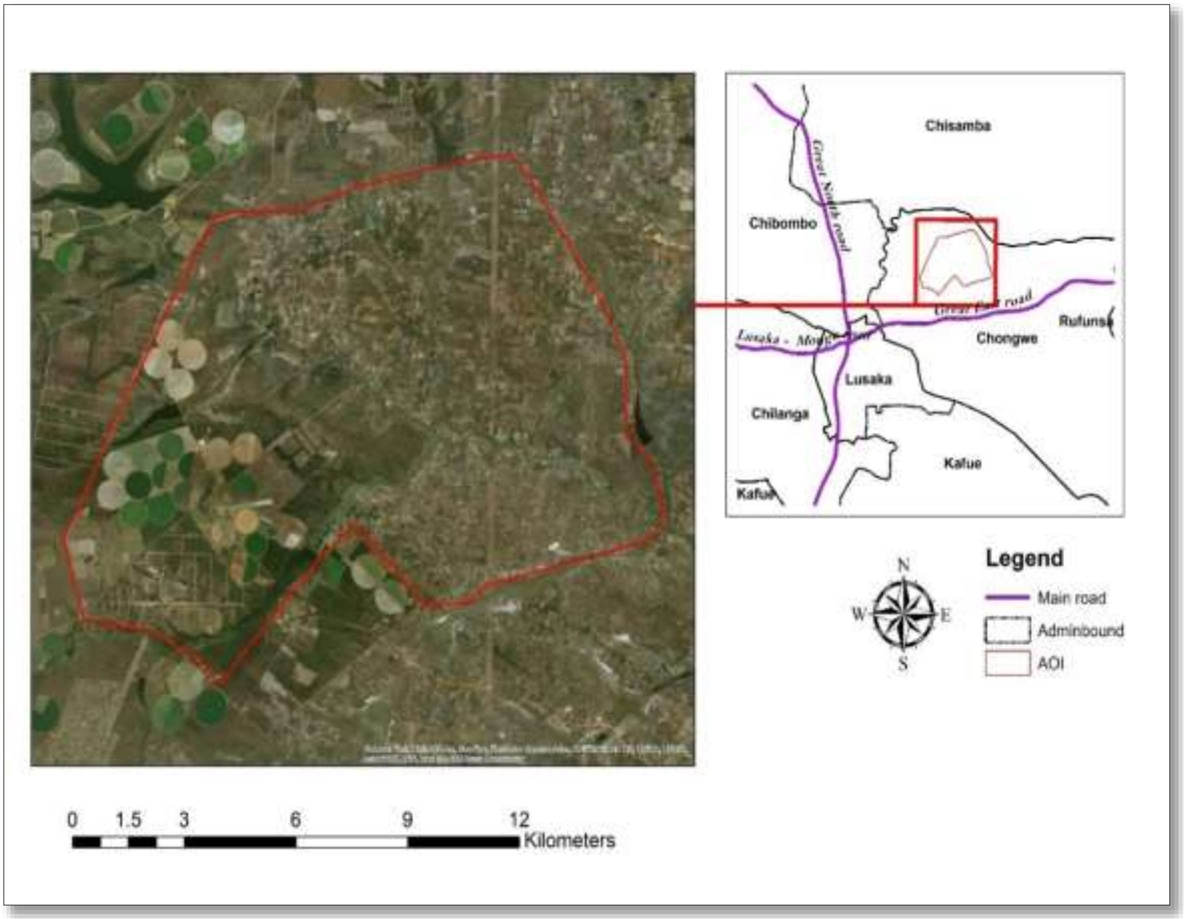

Figure 1: Study area in Chongwe district, Lusaka

Source: Author, 2024

Chongwe District is located in Lusaka Province. It shares boundaries with Chibombo District in the north, Rufunsa District in the east, Kafue District to the south and Lusaka District to the west (Figure 2). It has a total area of 2,447 km2, of which lies between latitudes -15.1 and -15.6 degrees South and longitudes 28.2 and 28.96 degrees east.

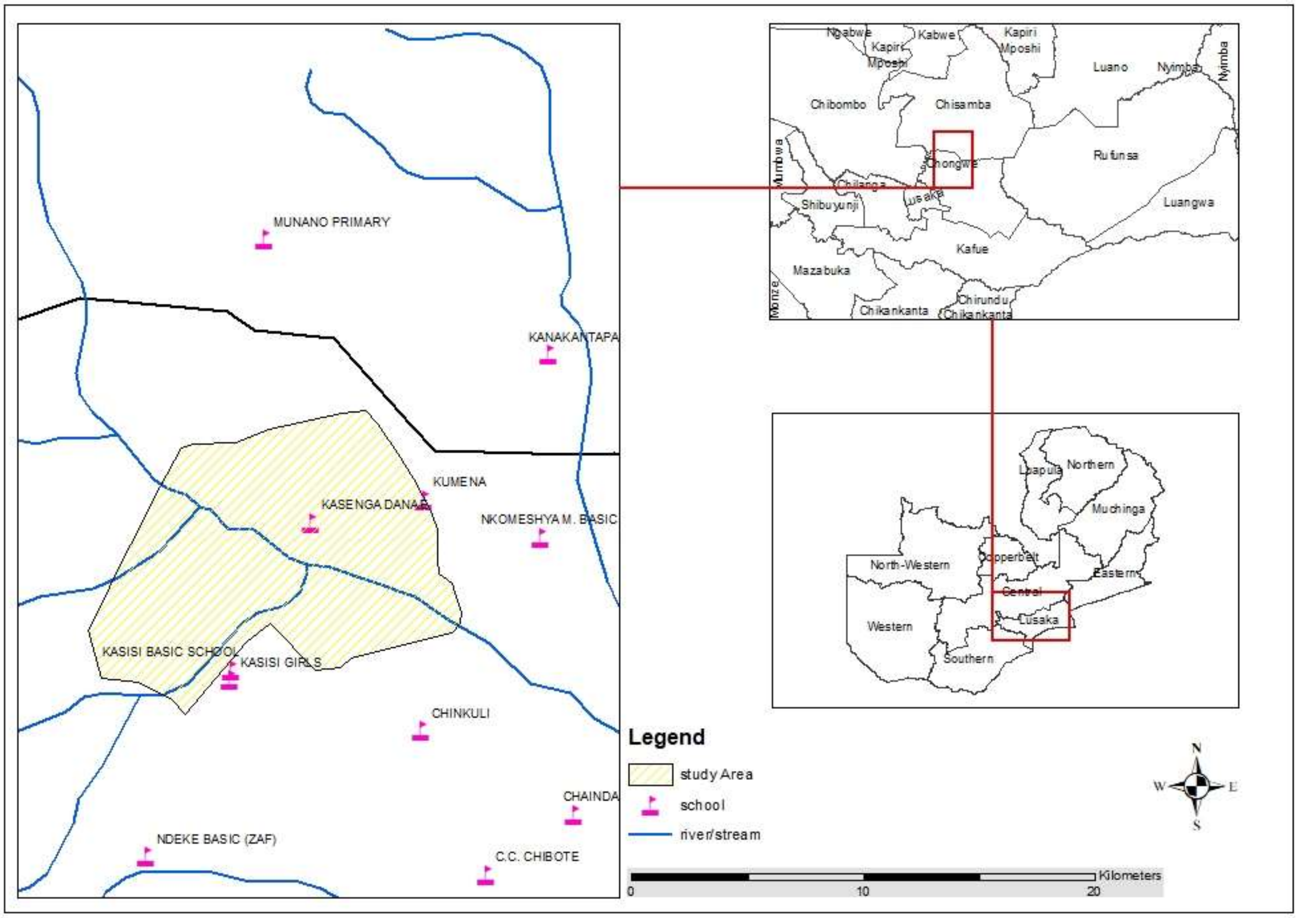

Figure 2: Location of the study area in Chongwe District, Lusaka Province

Source: Author, 2024

3.2 Topography

The topography of Chongwe District is generally characterized by a combination of flat to gently rolling terrain with some hilly areas that are between 900 and 1400 meters above sea level (NASA JPL, 2013). The presence of hills and slopes affects water drainage patterns and soil erosion (Figure 3).

3.3 Soils

Chongwe District can be separated into three main descriptions of soil characteristics which are as follows: These soils exist mainly in the Northern region of the District. The soils are described as being well-drained, deep to very deep, yellowish red to dark brown, friable, fine loamy to clayey soils (dominated by Gleysols). They have a clear clay increase with depth; with inclusions (20%) of moderately well-drained to imperfectly drained, deep to moderately shallow, gravelly clay soils (Soil Survey Section Research Branch, 1999).

These soils are found mostly in the Central Region of Chongwe District and are described as being well-drained, shallow to moderately shallow, dark brown, friable, fine loamy to clayey soils with humic topsoil (orthi-eutric LEPTOSOLS and moderately well drained, deep to very deep, red to strong brown, friable, moderately leached, fine (Soil Survey Section Research Branch, 1999).

The southern region of the District is described as excessively drained to well-drained, shallow to moderately shallow, and dark brown to yellowish brown. The soils are friable, stony, gravelly, coarse to fine loamy soils (orthi-eutric LEPTOSOLS; rudic phase; with lithic LEPTOSOLS)

3.4 Weather and climate

The area experiences a tropical climate with distinct wet and dry seasons. The rainy season typically occurs from November to April, with the highest precipitation levels recorded in December and January. The dry season extends from May to October of every year. The annual average rainfall estimated over a thirty-two-year period provided by the World Meteorological Organization is 930mm (Nick, 2015).

The climate and rainfall in Chongwe are divided into 3 categories. The first is mid-April to mid-August. It is cool and dry with mean day temperatures between 14°C and 18°C, with minimum temperatures falling below 4°C in June and July. The second category runs from mid-August to mid-November. It is characterized by hot and dry conditions with temperatures ranging between 20°C in the earlier months and up to 32°C around October and November. The last category starts around mid-November through to mid-April and this is the period where 96% of the annual precipitation occurs (Nick, 2015).

3.5 Hydrology

The study area is in a District that is intersected by several rivers and streams within the Chongwe catchment, including the Chongwe River, which flows through the area. These water bodies play a vital role in irrigation and water supply for agricultural activities.

The Chongwe catchment is part of the Middle Zambezi catchment. It covers a total area of 5,150 km^2. It is divided into Upper Chongwe – 1,234 km^2, Kanakantapa – 483 km^2, Ngwerere – 299 km^2, Chalimbana – 645 km^2, Middle Chongwe – 762 km^2, Lwimba – 590 km^2 and the Lower Chongwe – 1,131 km^2. It covers the Lusaka District (Ngwere and Chalimbana sub-catchments), Chongwe District (all sub-catchments, at least partially), Chibombo District (Upper Chongwe and Kanakantapa) and Kafue District (Lower Chongwe and Lwimba). A very small fraction of the Luangwa district is inside the Lower Chongwe subcatchment (Nick, 2015).

The rivers which are mainly used for agriculture purposes are the Ngwerere and Chalimbana, as well as the Upper and Middle parts of Chongwe River with several dams on these rivers, Ray's dam on the Upper Chongwe reach being the largest (Figure 3). The Chongwe River catchment has potential aquifers with the most productive ones in the western and central parts (Nick, 2015).

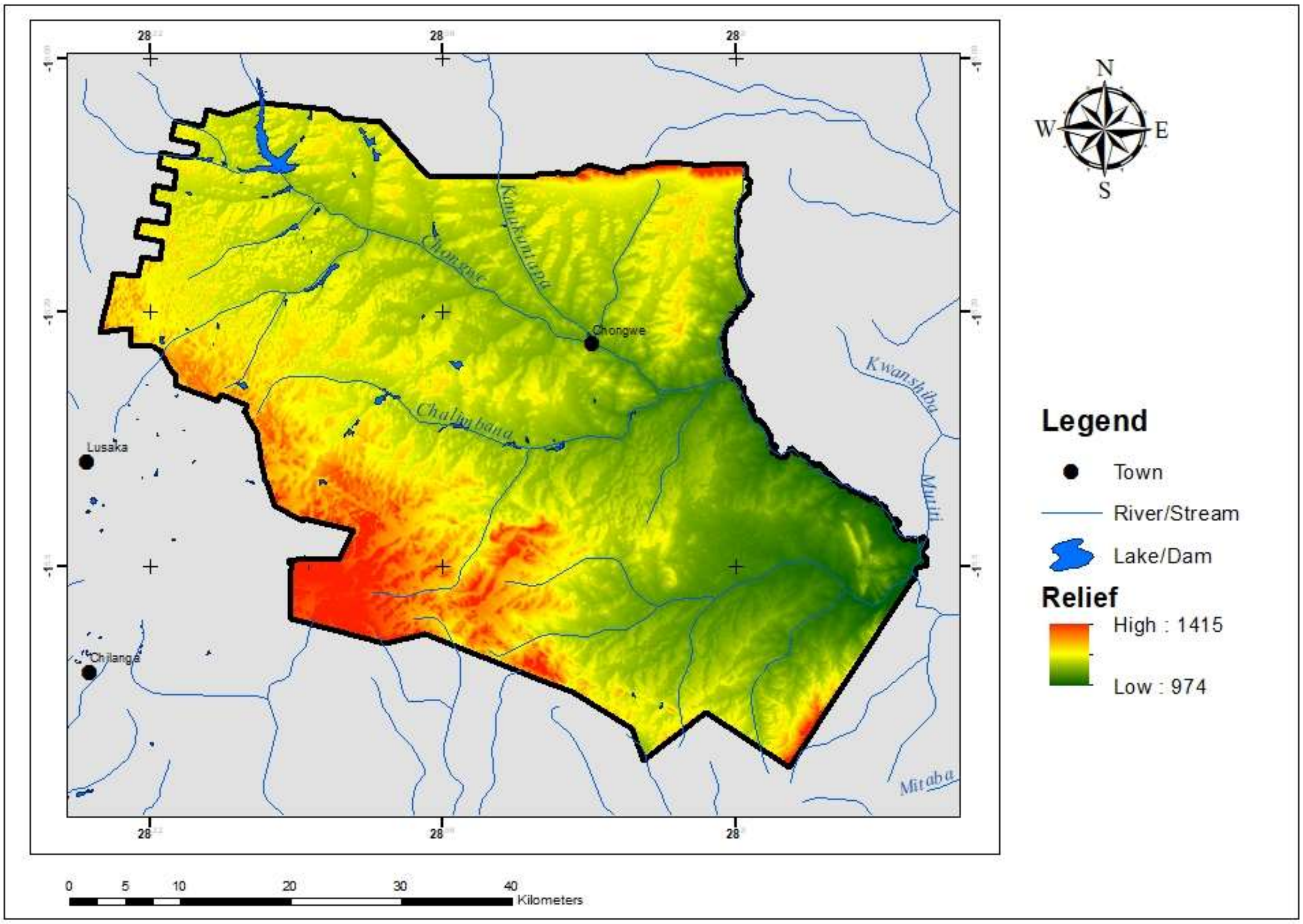

Figure 3: Relief and drainage of the Chongwe Catchment in Chongwe District

Source: Author, 2024

3.6 Demography, economy and livelihoods

Land in Chongwe District is primarily under customary tenure, with communal and individual land ownership. The original inhabitants of the district are the Soli people under the chieftainship of Nkomeshya Mukambo II (Milupi, et al., 2020).

The population in Chongwe District is estimated to be 313,389 (Zambia Statistical Agency, 2022). Due to its proximity to Lusaka, the District has experienced rapid population growth in recent years and the main push has been the need for residential plots in the districts. Agriculture is a significant economic activity in the District, with a focus on subsistence farming and small-scale commercial farming.

Maize cultivation is widespread, along with other crops such as vegetables, legumes, and fruits (Milupi, et al., 2020)

3.7 Land cover

The land cover in Chongwe can be classified into eight classes namely Water, Treecover, Shrub, Grass, Flooded vegetation, Cropland, Built up and Bare land (ESRI, 2022). Two forest reserves existed in the district namely, No.75 (Soli) and No.99 (Kanakantapa). They were both converted to agricultural resettlement schemes in 1992 to resettle unemployed urban youth and some members of the public (Milupi, et al., 2020). The majority of the District is covered in Shrub and cropland. Tree cover was the third most dominant class followed by Built up areas (Figure 4).

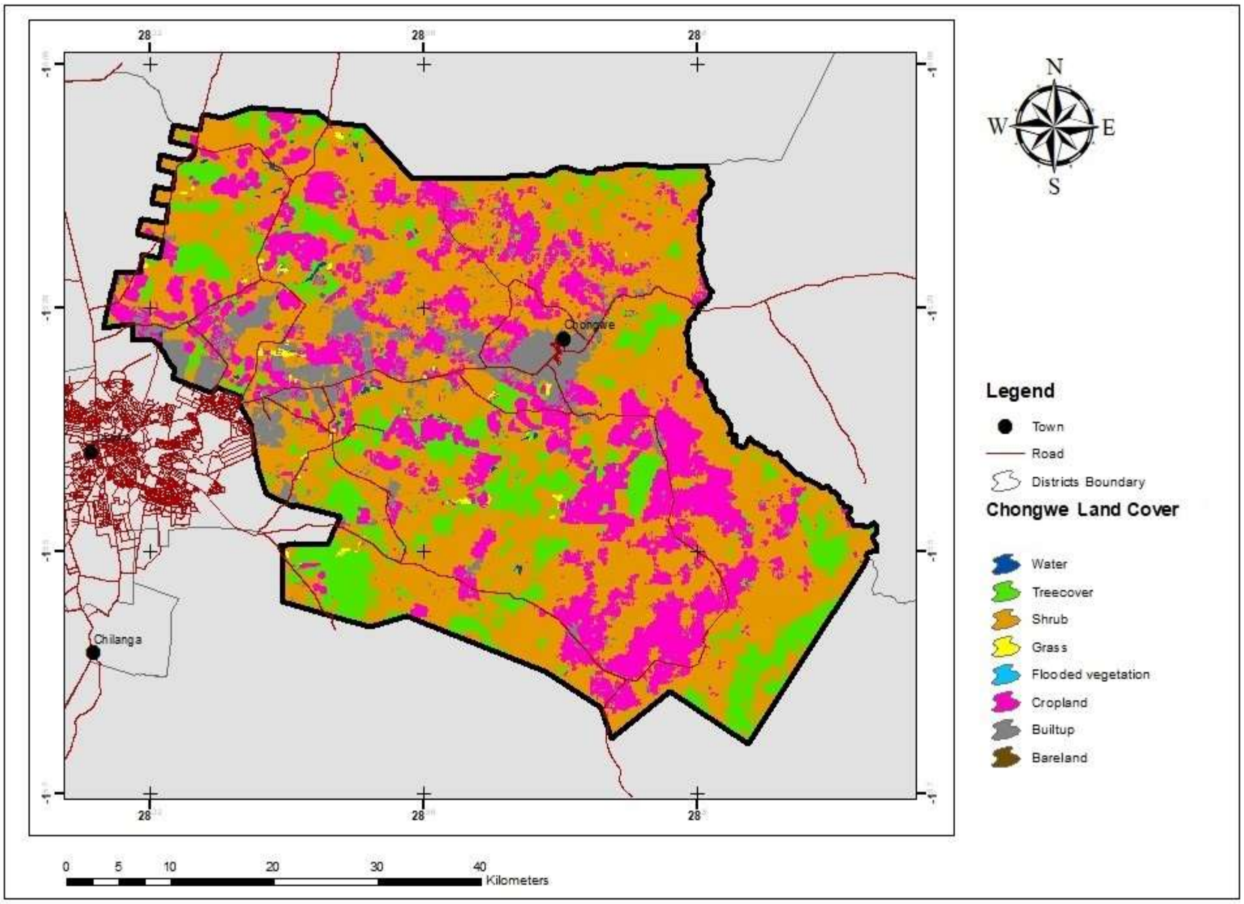

Figure 4 Land Cover Map of Chongwe District
Source: Author, 2024

Three main types of vegetation exist in the district and these include dry miombo (*Brachystegia*) woodland, mopane (*Colophospermu mopane*) woodland, and munga (*Acacia*) woodlands. The natural vegetation has been affected in the recent past by a growing number of settlements, charcoal production and an increase in vegetation (Milupi, et al., 2020). This is further highlighted from the Land Cover map as the majority of the land is mostly shrub and cropland, giving evidence of tree cutting for agricultural use in the District (Figure 4).

CHAPTER FOUR: METHODOLOGY

4.1 Philosophical orientation of the study

This study if framed within positivism, pragmatic and systems thinking to provide a robust methodological framework for mapping maize-growing periods using multi-temporal Sentinel-1 SAR imagery and Sentinel-2 Multi spectral imagery.

4.1.1 Pragmatism

Pragmatism serves as the overarching philosophical orientation of this study. Unlike the rigid paradigms of positivism or constructivism, pragmatism focuses on what works to address the research question effectively (Maarouf, 2019). Maarouf (2019) further described pragmatism as a bridge between the divide of positivist and interpretivism approaches, allowing researchers to adopt methods best suited to address research questions. Pragmatism legitimizes the integration of diverse datasets, such as radar imagery, optical data and ancillary ground truth measurements, to develop actionable insights for maize mapping and monitoring. It allows the researcher to adopt a mixed-method approach where quantitative remote sensing outputs are validated against field observations.

Pragmatism emphasizes practical solutions to real-world problems. In this study, the use of Google Earth Engine (GEE) demonstrates the power of cloud-based computational platforms to handle big data challenges in geospatial analysis. This pragmatic approach ensures that the study produces timely, reliable, and scalable results to support decision-makers in Zambia's agricultural sector.

The pragmatic emphasis on actionable insights also makes this study particularly relevant for policymakers, farmers, and stakeholders like insurance companies, as the results directly contribute to timely decision-making, yield estimation, and crop risk assessments.

4.2 Research design

This research utilized a quantitative method, specifically focusing on remote sensing techniques, combining Synthetic Aperture Radar (SAR) and optical imagery to classify and monitor maize fields. The methodology integrated advanced image processing, feature extraction, and classification workflows through Google Earth Engine (GEE), enabling the effective use of

Sentinel-1 SAR and Sentinel-2 multispectral imagery. The data was processed bi-weekly from November 1, 2019, to April 30, 2020, providing insights into the spatial-temporal dynamics of maize growth and the Random Forest classification accuracy. The process is illustrated in Figure *5: Methodology flow diagram* the analysis focused on VV (vertical transmit, vertical receive), VH (vertical transmit, horizontal receive) and VV/VH (vertical transmit, vertical receive)/ vertical transmit, horizontal receive) ratio values. These were used in classifying the landscape into four key classes: 1. Maize Fields, 2. Other Vegetation, 3. Urban/Bareland, and 4. Water. The Sentinel-2 Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) data, which improved the water and vegetation discrimination in the classification process were also used.

4.3 Sampling procedure

For this study, a clustered sampling method of field data collection was used. This method was chosen due to its suitability for the region's challenging terrain and limited road network. This method involved selecting central nodal points around which clusters with minimum 4 sample points were established to provide detail on prevailing land cover in the area. The key advantages of this approach in our context, included maximizing data collection efficiency in inaccessible areas and significantly reducing field time by minimizing travel between sampling sites. Despite the practical nature of this method, it retains statistical rigour through a randomized selection of nodes and satellite sites (McCoy, 2006). To mitigate the risk of autocorrelation and ensure accurate map representation, sampling sites were strategically spaced to reduce spatial dependence. This approach aligns with recent findings by Watson (2021), who highlight the significance of accounting for spatial autocorrelation in the design of geographically defined clusters. Their study demonstrates that careful consideration of cluster parameters can enhance the efficiency and accuracy of spatial data collection, particularly in studies where spatial dependence is a concern (Watson, 2021) .

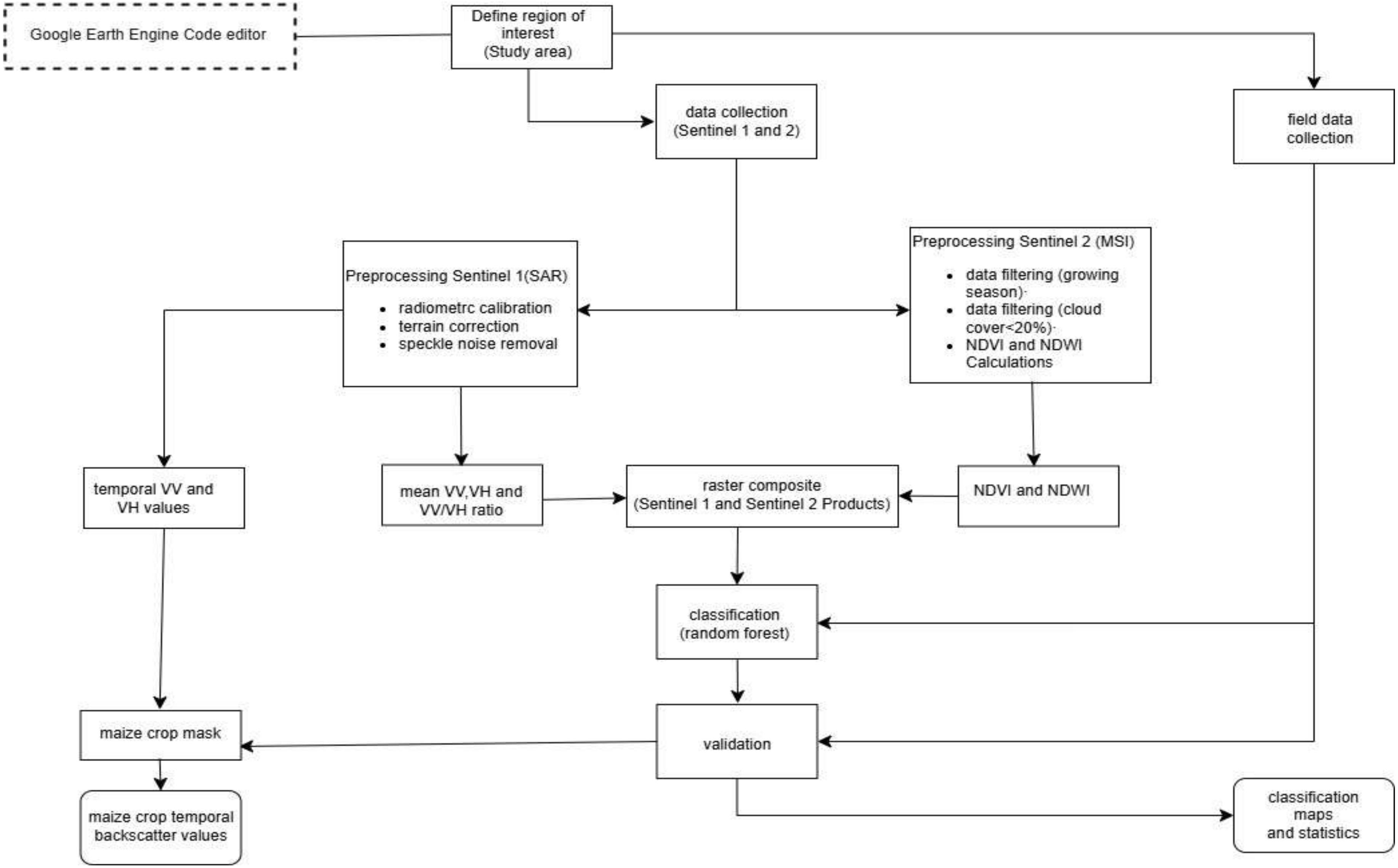

Figure 5: Methodology flow diagram
Source: Author, 2024

4.4 Data collection

4.4.1 Sentinel-1 SAR data

For this study, dual-polarized C-Band Sentinel-1 Ground Range Detection (GRD) products for the 2019/2020 growing period were used. These products, offer 10m spatial resolution in Interferometric Wide Swath (IW) mode were accessed through the GEE platform, providing cloud-based processing capabilities (Torres, et al., 2012). This study applies both VV (Vertical-Vertical) and VH (Vertical-Horizontal) polarizations, which are essential for differentiating land cover types, including maize fields and water bodies.

4.4.2 Sentinel-2 multispectral data

Sentinel 2 satellites have on board an optic sensor called a Multi-Spectral Instrument (MSI) which acquires data in 13 spectral bands of varying resolution. The 10 meter resolution bands are the visible and near-infrared bands, the 20 meter resolution bands are the red edge and shortwave infrared bands while the atmospheric bands have 60 meter spatial resolution (Jin, et al., 2019). The level 2 Surface reflectance products were used. The optical imagery from Sentinel-2 was used to compute vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI). The multispectral data offered additional spectral insights that complemented the SAR imagery for accurate classification (Kpienbaareh, et al., 2021). The NDVI data provided vegetation health information while the NDWI provided water content information for the different land cover features. This provided the algorithm with more layers to aid in distinguishing the different land cover types for the classification (Kpienbaareh, et al., 2021).

4.4.3 Field Data

A handheld tablet with GPS capabilities was used during the field data collection exercise. The land cover considered was maize crop fields, other vegetation, built up areas/settlements/bare land and water. The Field data points were collected using Softwel or SW maps mobile application. The collected information was used as training and validation data during the analysis using a 70%

to 30% split of the data (Li, et al., 2018). A total of 102 samples were collected in December 2019 and used for the classification and validation of the produced land cover map.

Figure 6 Data collection during vegetative growth
Source: Author, 2024

4.5 Preprocessing

4.5.1 SAR Image enhancement and MSI Index generation

Preprocessing steps available through Google Earth Engine (GEE) include radiometric calibration, terrain correction using SRTM DEM, and noise removal. Further noise removal was required due to Sentinel-1 imagery inherently having a form of noise called speckle-noise. Speckle noise is unique to SAR imagery and is caused by backscatter interaction between adjacent returns (Jin, et al., 2019)

Processing was done using the Google Earth Engine platform (GEE) to ease the amount of processing power required through cloud computing. The GRD data in the GEE catalogue was pre-processed and has thermal noise removal, radiometric calibration and terrain correction done using the Sentinel-1 toolbox. Terrain Correction of SAR data was done using the 30m SRTM DEM to correct for terrain distortions using the DEM as a basis for elevation and slope. These parameters adjusted the SAR image to its correct geographic position (Li, et al., 2018).

Speckle filtering was done to remove noise from the scattering of signals off rough surfaces and electronic noise in the imaging system of the SAR sensor. A 3x3 lee speckle filter was applied as it has been proven to be efficient in preserving edges, which are important for mapping crop fields. It also provides better smoothing while it preserves important details in the images (Al- Zuhairi, et al., 2016). A mean composite image was then generated to be used for the land cover classification for the entire growth period.

MSI Images with cloud cover of more than 20% were filtered out of the analysis. A temporal filter was also used to match the growing season period from November 2019 to April 2020 (Tembo, et al., 2014), ensuring that only relevant data is used. This period was chosen due to the unavailability of Sentinel 1 SAR data from 2021 to date (GRZ, 2020). The Normalized Difference Vegetation Index (NDVI) was then calculated using the equation:

$$NDVI = \frac{NIR - RED}{NIR + RED}$$

Equation 1 NDVI equation

Where : NIR: Near-infrared band (Sentinel-2: Band 8).
RED: Red band (Sentinel-2: Band 4).

NDVI is a common vegetation index used to assess the health and density of vegetation and will help in the identification of plant cover.

The Normalized Difference Water Index (NDWI) was calculated using the green (B3) and near-infrared (B8) bands, which is useful for identifying water bodies.

$$NDWI = \frac{GREEN - NIR}{GREEN + NIR}$$

Equation 2 NDWI equation

Where : GREEN: Green band (Sentinel-2: Band 3).
NIR: Near-infrared band (Sentinel-2: Band 8).

This index was useful for identifying water bodies in order to mask out water areas in the classification process (Andreu, et al., 2021). A mean composite of the NDVI and NDWI images was then generated for the vegetative stages of the maize, representing the average vegetation and water conditions over the study period.

4.6 Feature extraction

Feature extraction plays a crucial role in capturing relevant information from the SAR data that can discriminate different land cover types including maize fields and non-maize fields. Feature extraction transformed raw SAR data into a set of meaningful and representative features that can be used as input for the classification (Defourney, 2017). Feature extraction from SAR data within defined Regions of Interest (ROIs) which involved computing various statistical and textural measures. These features captured the SAR signal's intensity, texture, and spatial distribution. (Zhang, et al., 2021). This was crucial for distinguishing different land cover classes. The process transformed raw SAR data into meaningful features that accurately represented the distinct characteristics of each land cover class, providing valuable input for machine learning classifiers. Consequently, this facilitated the precise classification and mapping of maize fields.

The feature extraction process involved calculating key indicators from Sentinel-1 and Sentinel-2 imagery. Vertical transmit/Vertical receive, Vertical transmit/Horizontal receive, and the VV/VH ratio are derived from Sentinel-1 to capture different surface scattering properties of varied land cover features (Mullisa, et al., 2021). The VV/VH Ratio (σVV/σVH) helps distinguish different vegetation types and their structural characteristics during classification and is measured with the formula:

$$VV/VH\ Ratio = \sigma VV/\sigma VH$$

Equation 3 VV/VH ration

σVV : This is the backscatter coefficient for VV polarization. It represents how much of the radar signal is scattered back to the satellite after being transmitted and received in vertical polarization.

σVH : This is the backscatter coefficient for VH polarization (cross-polarized).

This ratio enhances the ability to distinguish different land cover types, particularly vegetation with varying structure and biomass. While VV polarization is more sensitive to surface roughness and canopy volume, VH polarization tends to reflect the presence of volumetric scattering elements such as leaves and branches. By normalizing VV against VH, the VV/VH ratio accentuates structural and moisture-related differences in vegetation and provides further input for the random forest classifier. (Mullisa, et al., 2021).

NDVI and NDWI from Sentinel-2 provided insights into vegetation health and water body delineation, respectively. The feature values are computed to capture temporal variations of backscatter throughout the growing season, providing a detailed analysis of crop growth and land cover changes based off the changes in backscatter due to crop condition and vigor. The mean growing period values for each parameter (spectral indices, VV, VH and VV/VH) over the season was used to run the classification (Kpienbaareh, et al., 2021; Arslan, et al., 2022).

4.7 Image segmentation and classification

Image segmentation was done to partition an image into meaningful and homogeneous regions based on certain characteristics such as intensity, texture, spatial coherence and spectral properties. Segmentation is an important step in SAR data processing. This step facilitates the identification of homogeneous areas like maize fields and water bodies (Bicego, et al., 2003)

The processed features from Sentinel-1 and Sentinel-2 were used as input for a Random Forest classifier. The classification involved training the model on labelled ground truth points (collected from field data and GEE) and applying it to the entire study area. The classifier incorporates features such as VV, VH, VV/VH ratio, NDVI, and NDWI to distinguish between the different Land cover classes. The generated maize crop class was used to create a maize crop mask. The maize crop mask was then used for the subsequent NDVI and backscatter temporal analysis to ensure that the backscatter and NDVI values that were calculated had no distortions form the other land cover classes (Immitzer, et al., 2016).

4.8 NDVI temporal analysis

The generated maize crop field land class was used as an input mask for the subsequent NDVI and backscatter analysis. The NDVI temporal analysis involved using the maize crop field mask generated using the random forest classifier to calculate the maize NDVI value over the study area at different dates during the season. The temporal analysis of the NDVI values give insight into sowing period, maximum vegetation period and maturity period of the crop as well as the harvesting period (Kumar, et al., 2021).

4.9 Backscatter analysis

The backscatter values for VV (vertical transmit, vertical receive) and VH (vertical transmit, horizontal receive) was computed two times a month throughout the growing season. The VV Backscatter (σVV) measures the radar signal's reflection off the surface in the vertical transmit/vertical receive mode. It is sensitive to surface roughness and vegetation structure. The VH Backscatter (σVH) measures the radar signal's reflection in vertical transmit/horizontal receive mode, useful for distinguishing between surface features like crops and water. VH can also show changes in biomass/ water content in crops.

The temporal analysis was divided into two intervals for each month. The VV and VH backscatter values which provided critical insights into the maize development phases, confirming literature findings such as the sensitivity of VH to biomass (Li, et al., 2018) and the importance of dual-polarization in distinguishing crops (Kussul, et al., 2014).

4.10 Dataset preparation for training and testing

A clustered sampling method was employed for field data collection, focusing on accessible nodal points and surrounding satellite points. Random water samples were generated using NDWI thresholds to supplement the dataset. The training dataset was used to train the Random Forest classifier, while the validation dataset provided an independent assessment of classification accuracy (Li, et al., 2018).

4.11 Validation and reliability

The classification results were evaluated using an error matrix, which calculates overall accuracy, producer’s accuracy, user’s accuracy, and the Kappa coefficient. The producer’s accuracy indicates how well the model correctly classifies each land cover type, while the user’s accuracy assesses the reliability of the classification. The Kappa coefficient provides a measure of agreement between the predicted and observed classifications beyond random chance (Defourney, 2017).Accuracy assessment is crucial in evaluating the performance of classification models, especially in remote sensing, where image data is classified into different land cover classes.

4.11.1 Overall accuracy (OA)

Overall Accuracy measures the proportion of correctly classified samples to the total number of samples. It is a straightforward indicator of classification performance but can sometimes be misleading in cases of imbalanced datasets (Defourney, 2017).

$$Overall\ Accuracy = \frac{Number\ of\ Correctly\ Classified\ Samples}{Total\ Number\ of\ Sample} = \frac{\sum_{i=1}^{n} C_{ji}}{N} \qquad \text{Equation 4}$$

Where:

C_{ji} are the diagonal elements of the confusion matrix (correct classifications).

N is the total number of samples.

4.11.2 Producer's accuracy (PA):

Producer's Accuracy refers to the probability that a certain land cover class i is correctly classified as that class (Defourney, 2017). It reflects how well the classification model predicts a given class (from the producer’s point of view). This is calculated for each class individually and is essentially the recall or sensitivity for that class.

$$Producer's\ Accuracy\ for\ Class\ i = \frac{Correctly\ Classified\ Samples\ for\ Class\ i}{Total\ Reference\ Sample\ for\ Class\ i} = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ji}} \qquad \text{Equation 5}$$

The Producer’s Accuracy for maize fields is 1.0, meaning all maize fields (Class1) in the reference data was correctly identified by the classifier. The Producer’s Accuracy for other vegetation (class 2) is 0.75. This means that only 75% of the reference vegetation samples were correctly classified, indicating some confusion between this class and others (likely with maize fields). Producer’s Accuracy for built-up (class 3) areas is 1.0, indicating perfect classification of urban regions. The producer’s Accuracy for water (class 4) is also 1.0, which means all reference water samples were correctly identified.

4.11.3 User's accuracy (UA):

User's Accuracy represents the probability that a pixel classified into a given class *i* belongs to that class (Defourney, 2017). It reflects the reliability of the classification from the user's point of view and is essentially the precision for that class.

$$User's\ Accuracy\ for\ Class\ i = \frac{Correctly\ Classified\ Samples\ for\ Class\ i}{Total\ Samples\ Classified\ as\ Class\ i} = \frac{C_{ii}}{\sum_{j=1}^{n} C_{ij}} \quad \textit{Equation 6}$$

The User's Accuracy for other vegetation is 0.8571, meaning that 85.71% of the areas classified as other vegetation actually correspond to the class in reality. This shows some minor misclassification (likely with maize fields).

4.11.4 Kappa coefficient (Kappa):

Kappa is a statistical measure of agreement or consistency between predicted and observed classifications, adjusted for the agreement that could happen by chance (Defourney, 2017). It provides a more robust evaluation of the classifier, especially for imbalanced data.

$$Kappa = \frac{p_{o-}\,P_e}{1-\,P_e} \qquad \textit{Equation 7}$$

Where:

p_o is the observed agreement (same as Overall Accuracy).

p_e is the expected agreement by chance.

The value of Kappa ranges from -1 to 1 where a Kappa value of 1 indicates perfect agreement between the classification and the ground truth. A value of 0 indicates no agreement beyond chance. Negative values indicate worse-than-random agreement. The total maize field area was calculated by clipping the buffered raster layer to the area of interest (AOI) and converting the resulting GeoTIFF files into polygons using ArcGIS Pro Geoprocessing tools.

CHAPTER FIVE: RESULTS

This chapter presents the results of the analysis, focusing on maize field mapping and monitoring in the Kasisi area of Chongwe District using Sentinel-1 Synthetic Aperture Radar (SAR) imagery.

5.1 Accuracy Assessment

The land cover random forest classification was evaluated using an error matrix to assess the overall, producer's, and user's accuracy. The classification outputs were validated using a 30% test dataset (Table 3).

Table 1: Producer and User accuracy for the study

Class	**User's Accuracy (%)**	**Producer's Accuracy (%)**
Maize Fields	100%	100%
Other Vegetation	85.7%	75%
Urban/Bareland	100%	100%
Water	100%	100%

Source: Data analysis, 2024

The overall accuracy of the random forest random classification was 96.7%, with a Kappa coefficient of 0.95, demonstrating high agreement between predicted and actual land cover. The Producer's accuracy for other vegetation was slightly lower than expected, indicating some misclassification between maize and other vegetation (Figure 11).

5.2 Backscatter, normalized difference vegetation and water indices for identifying maize fields

The NDVI analysis shows that the highest mean NDVI value within the area of interest was 0.73 and from the map, it was found that the highest NDVI values were mostly in the southwest of the study region (Figure 7). These areas indicate places which have natural and protected vegetation cover. The lowest mean NDVI value was -0.169 and this was found in dams and other water bodies in the study region.

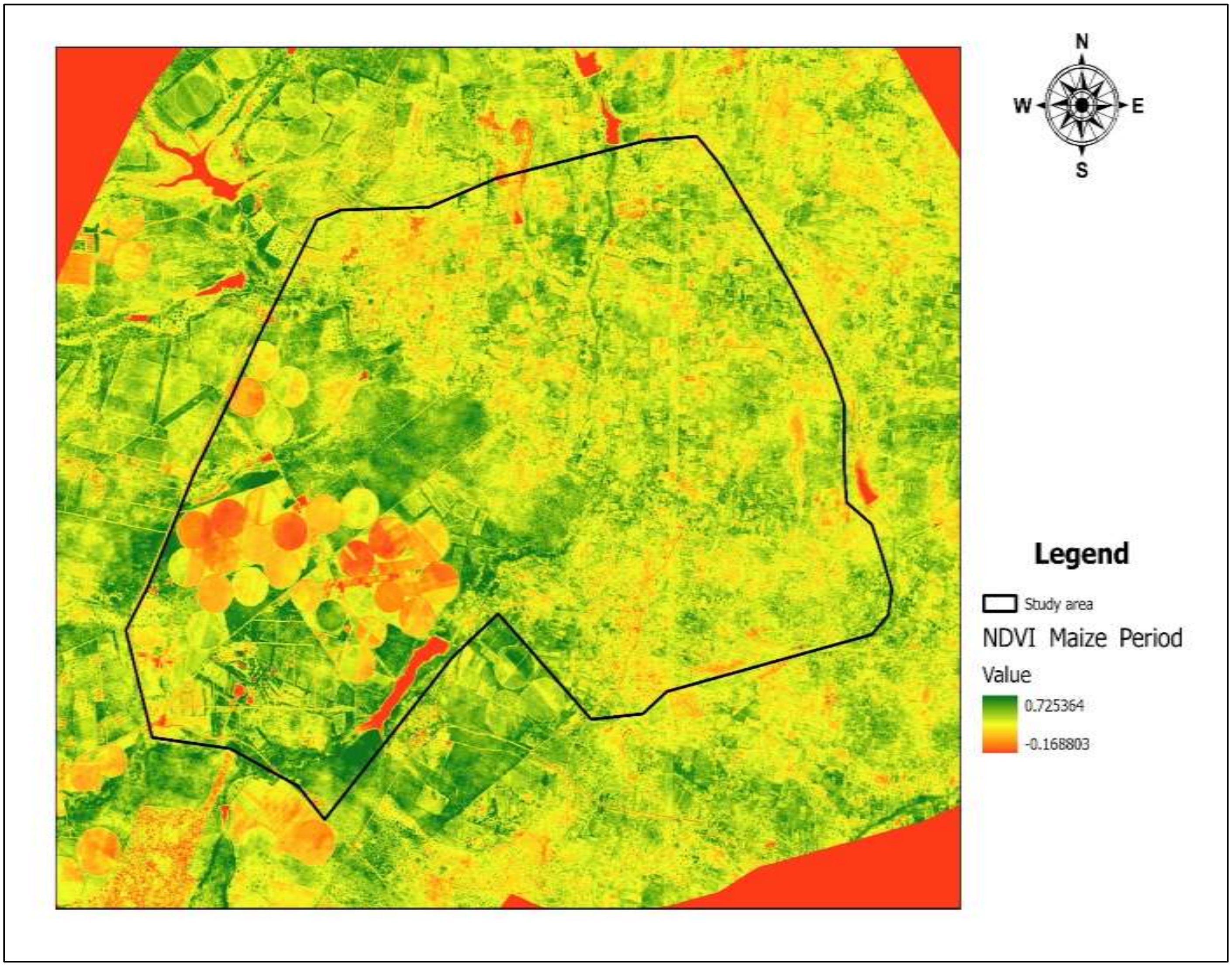

Figure 7 NDVI Mean Composite Map

Source: Author, 2024

From the Random Forest classification run in GEE, the results show that Maize fields were successfully distinguished from other land cover types (Figure 8).

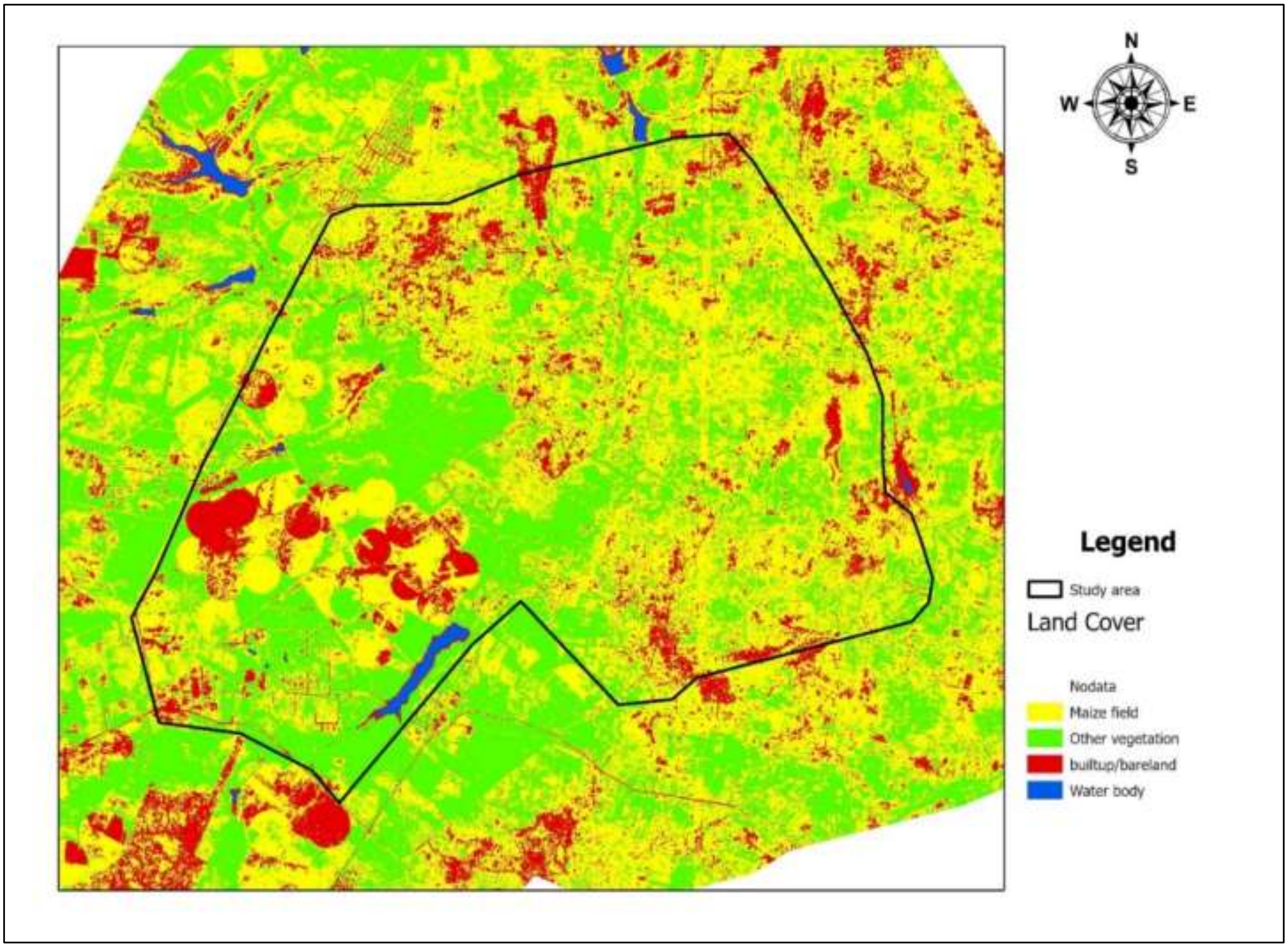

Figure 8 Land Cover Classification map over the study area
Source: Author, 2024

The mean NDWI analysis in Figure 9 shows that the area has several large dams, one being within the study region. Several reservoirs of water were also identified. The dams were used to generate training and validation water samples that were used during classification.

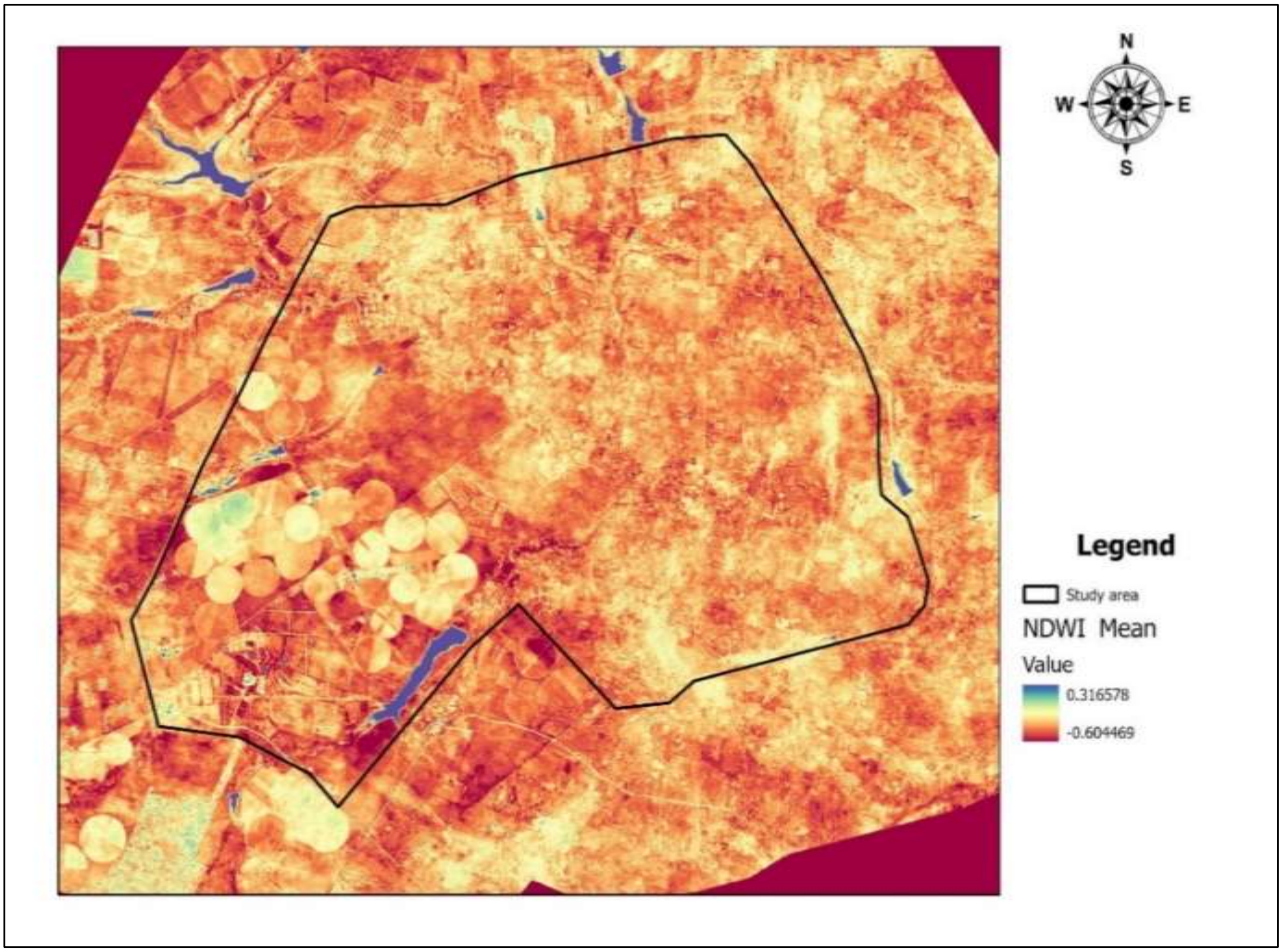

Figure 9 NDWI image
Source; Author, 2024

5.3 Area under maize cultivation

It was estimated that the total cultivated area of maize was 6721.46 hectares in the study area representing 54.55% of the total land cover. This represents the fields that had maize during the growing period as the mean composite values were used to run the classification. The produced land cover map Figure 9, visually distinguishes maize fields from other land cover types which are built-up areas/ bareland, other vegetation, and water bodies. The generated maize field class was used as a maize crop mask to extract the backscatter and NDVI temporal values. The land cover quantities for the different land cover classes were also determined (Table 2 Land Cover Quantities in the Study Area) and reflect the area distribution of land cover in the area.

Table 2 Land Cover Quantities in the Study Area

Land Cover	**Area_Ha**	**Percentage**
builtup/bareland	1493.84	11.90255749
Maize fields	6721.46	53.55497515
Other vegetation	4276.4	34.07332569
Water bodies	58.88	0.469141665
Total	12550.6	100

Source: Data analysis, 2024

5.4 NDVI temporal characteristics

The NDVI time series analysis showed the gradual increase in NDVI values over the maize crop area within the study area. The mean NDVI values during early November was estimated at 0.145. This value rose to 0.406 by mid-December. The value was estimated to have dropped slightly to 0.3822 around mid-January and by mid-march it had rose to 0.495 and this was the highest value recorded for the season. A drop to 0.382 was seen in early April which dropped further to 0.315 by end of April. The trends are shown in Figure 10 and a map depiction of the spatial variations of NDVI values over time is further shown in Figure 12 which illustrates how the how the maize crop performed in the different areas over time. Figure 11 shows the backscatter values relating to the NDVI time step data

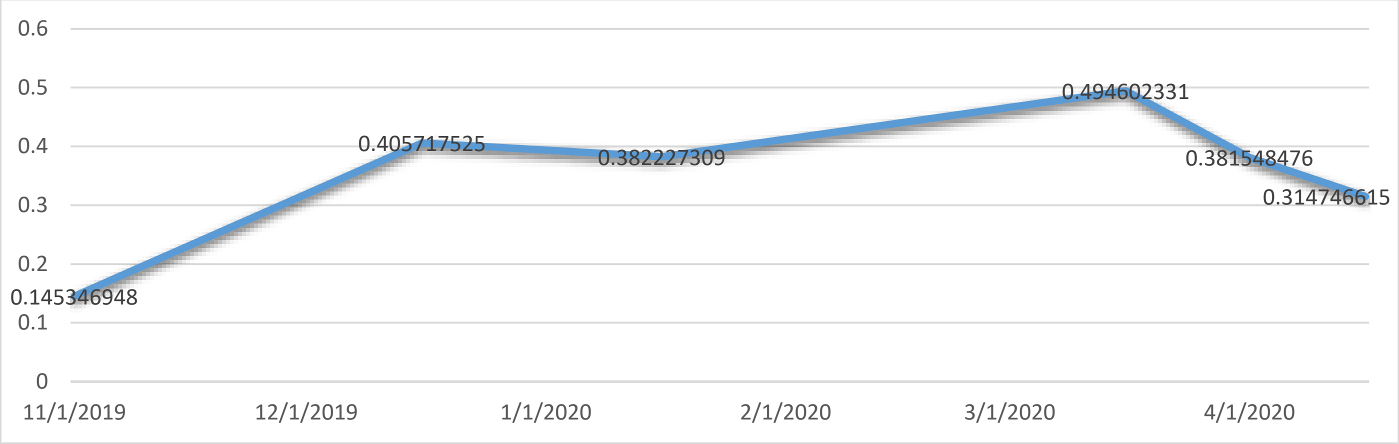

Figure 10 NDVI time series variation of maize in the study area
Source: Data analysis, 2024

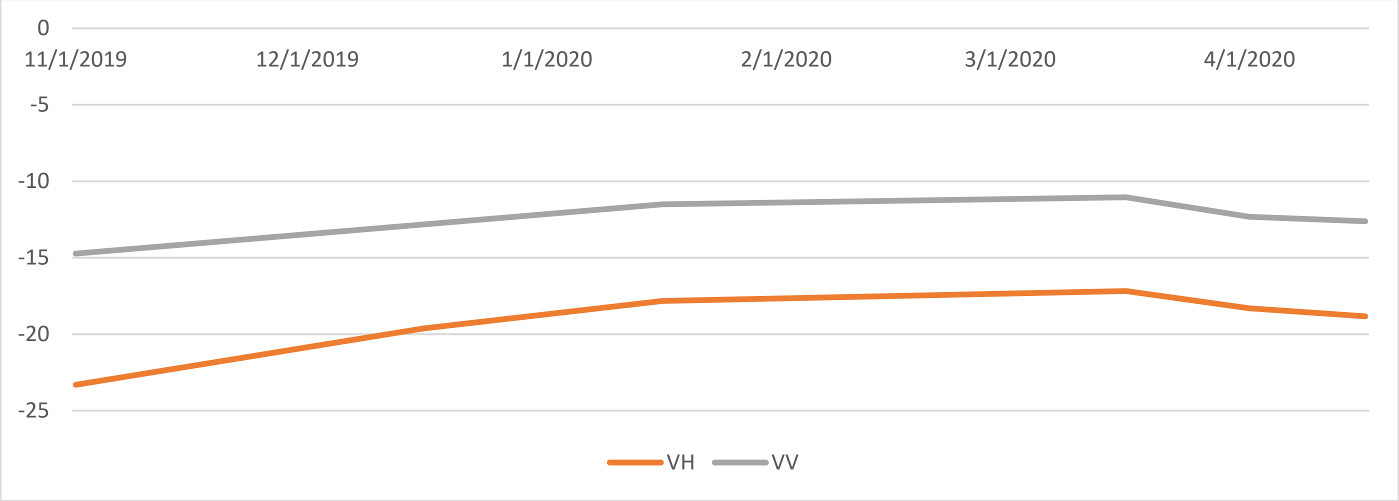

Figure 11: VV and VH values in comparison to the NDVI time steries values
Source: Data analysis, 2024

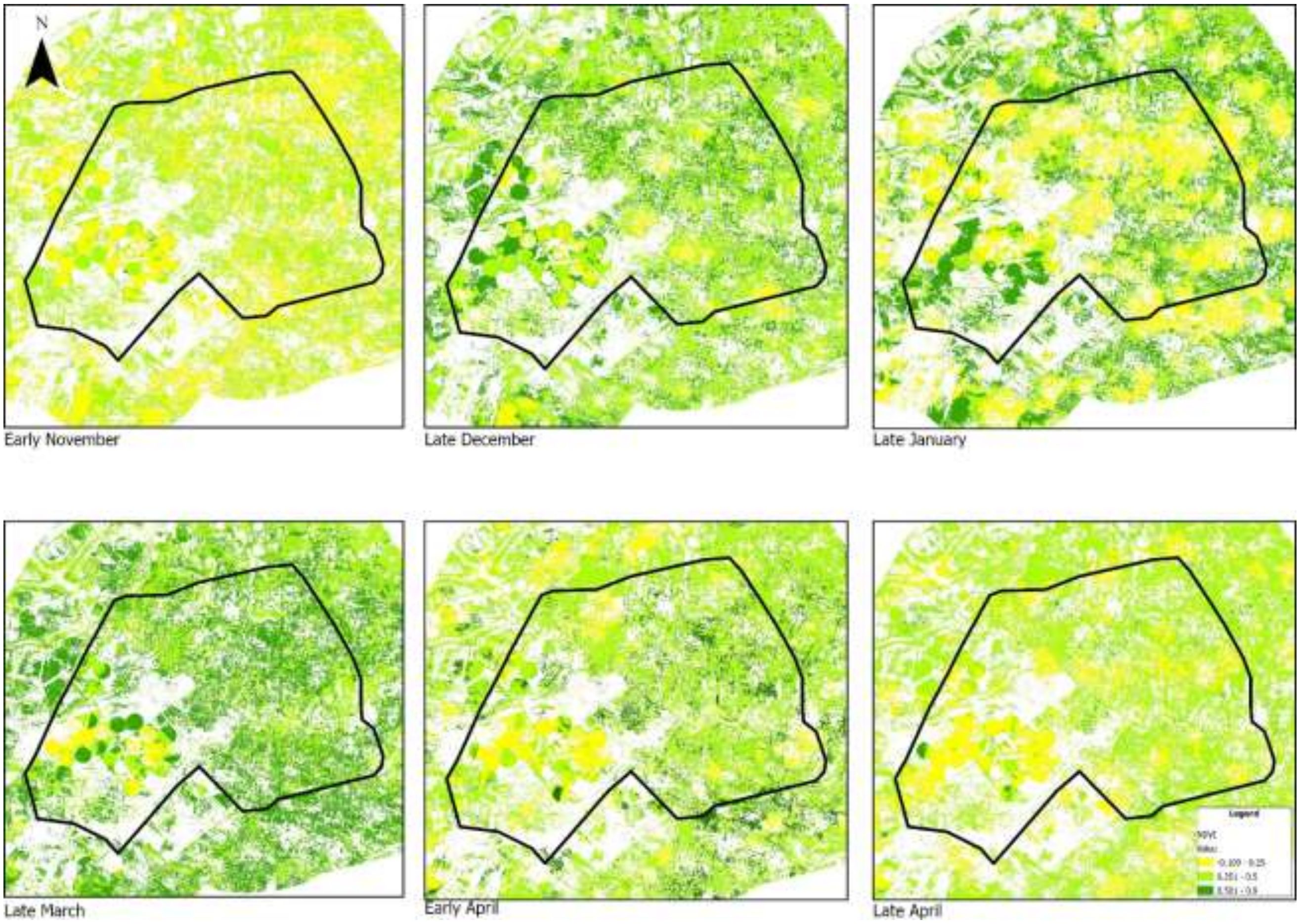

Figure 12 NDVI spatial- temporal variation during the growing period
Source: Data analysis, 2024

5.5 Backscatter characteristics of maize during the growing period

The backscatter values in show significant variations during the key maize growth stages.

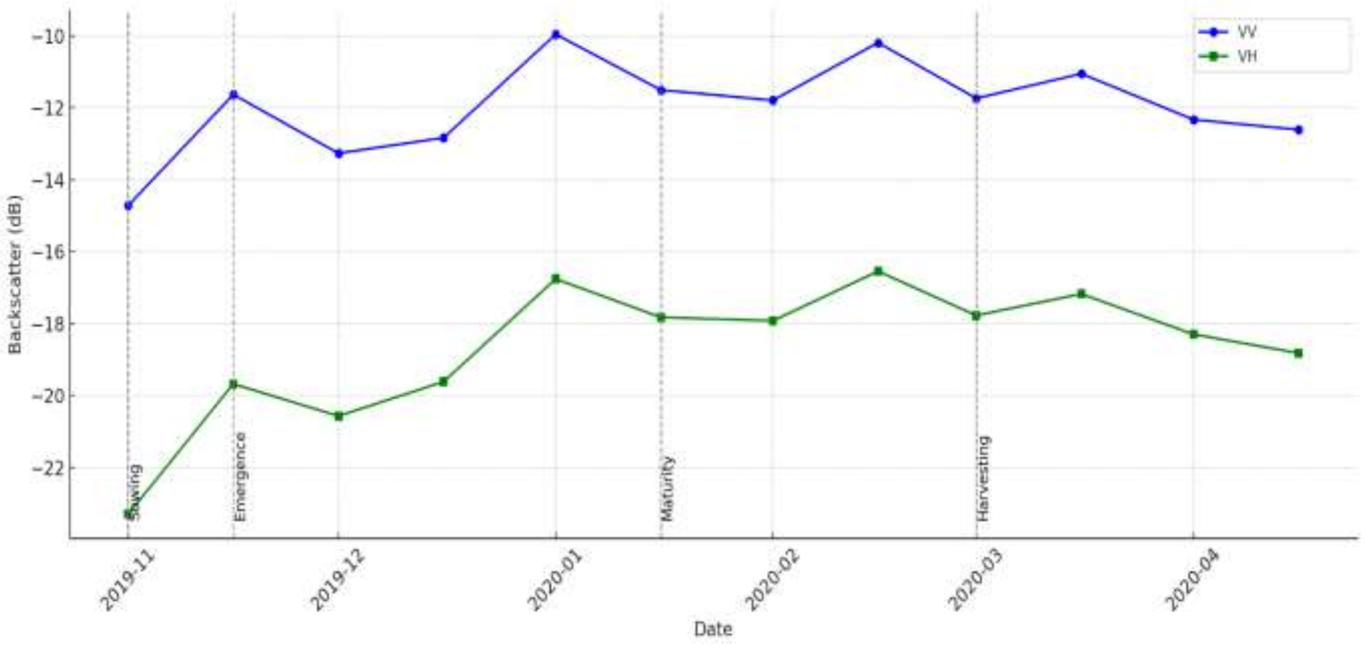

Figure 13 Temporal Variation of SAR backscatter of maize in the study area

5.5.1 Sowing

Using the VV and VH backscatter values, sowing was found to have occurred between 1st and 15th November 2019, as indicated by the low VV (-14.72 dB) and VH (-23.30 dB) values (Figure 13**Error! Reference source not found.** and Table 3 Sentinel-1 temporal backscatter values).

5.5.2 Seed emergence

The seed emergence was identified through an increase in backscatter values as maize seedlings started to appear. This was reflected in the bi-weekly backscatter values, which gradually increased during the second half of November and into December. The seed emergence occurred between November 16th and December 16th, 2019. This period showed an increase in VV (from -14.72 dB to -12.83 dB) and VH (from -23.30 dB to -19.61 dB), indicating vegetative growth (Figure 13).

5.5.3 Maturity

The Maize reached maturity when the backscatter values were at maximum and consistent. This indicated vegetative or tasseling stage of crop growth. During January and February, the VV and VH values remained consistent, indicating full canopy closure and a stable crop structure. Maize reached maturity between 15th January and 15th February 2020, with the VV backscatter values ranging between -11.50 dB and -11.79 dB and VH backscatter from -17.82 dB to -17.92 dB. This can also be seen in (Figure 13) as the values stabilized during this period.

5.5.4 Harvesting

Harvesting was detected by a decrease in backscatter values as the maize biomass was removed. The reduction in VV and VH backscatter values during March and April confirmed the harvesting period. Harvesting occurred between March 1st and April 30th, 2020, as indicated by a decrease in VV from –11.74 dB to -12.61 dB and VH from -17.77 dB to -18.82dB (Figure 13)

CHAPTER SIX: DISCUSSION

The results of this study support the utility of combining Synthetic Aperture Radar (SAR) and optical imagery (Sentinel-1 and Sentinel-2 data) for effective maize growth monitoring and land cover classification. These findings align closely with various studies that emphasize the effectiveness of SAR data, particularly in regions with frequent cloud cover such as is the case in Zambia during the growing period.

The integration of SAR and optical data has proven valuable in capturing different maize growth stages in the study area. The study has revealed clear trends in backscatter values for each phase. GEE's capacity to handle Sentinel-1 and Sentinel-2 data efficiently is particularly relevant for agricultural studies. By integrating high-resolution time-series data with analytical tools, GEE supports precision agriculture practices such as monitoring crop health, identifying stress regions, and predicting yield (Lemoine, 2017). This functionality aligns with the goals of improving food security and resource management in data-scarce regions like Zambia. GEE offered a powerful combination of accessible data, advanced computational capabilities, and flexible APIs which, enabled complex manipulation and analysis of SAR and MSI data to provide a crop map and growth information with unprecedented efficiency and precision.

The mean NDWI analysis and map produced, as illustrated in Figure 9revealed the presence of several large dams in and around the study area, with one of the prominent dams located within the study region. These dams and reservoirs are critical water resources for agricultural and domestic use, particularly in a region where water availability significantly influences crop productivity and livelihoods.

Further, the analysis highlighted multiple smaller reservoirs scattered across the landscape, providing valuable insights into the spatial distribution of water bodies. This suggests a potential decline in water availability during the study period, possibly due to factors such as prolonged dry spells, over-extraction for irrigation, or limited rainfall recharge (Andreu, et al., 2021).

6.1 Maize field mapping

The findings on maize crop mapping from this study are in line with results achieved by Li et al., (2018), who monitored and mapped maize crops using Sentinel-1 data in the North China Plain.

In their study, they achieved a classification accuracy of 93.57% using a Support Vector Machine (SVM), compared to the 96.7% accuracy obtained in this study using a Random Forest classifier. Both studies highlight the capacity of Sentinel-1 SAR data to accurately identify maize growth stages. In their study, Li et al., (2018) observed that dual-polarization SAR data enhances the ability to distinguish maize from other crops, aligning with the study's use of VV and VH backscatter values to differentiate stages in maize growth.

Kussul et al., (2014) also demonstrated high accuracy in crop classification using RADARSAT-2 SAR data within the JECAM project, achieving 90% accuracy. However, while they focused more on the classification, this study has extended into the growth stage analysis, offering a detailed perspective on backscatter trends specific to maize, particularly during vegetative and reproductive phases. (Kussul, et al., 2014).

The results have shown that Maize is a major crop in the study are, representing a total of 54% of the land cover during the growing period. Figure 8 has shown that majority of the small to medium scale fields are located mostly in the Eastern and Northern regions of the study area and the large scale fields evidenced by the distinct round crop fields indicating center pivots are located in the South-Western region of the study area. This information is important as it can help in planning for extension and resource allocation. Ultimately, this information can lead to enhanced productivity and better yields for farmers across the country.

6.2 NDVI trend analysis during the growing period

The results from the NDVI profile of maize in this study showed a clear pattern that align closely to the finding by Kumar et al., (2021). It was observed in this study that NDVI values were initially low (0.15) in early November, indicating bare soil or early sowing which coincided with the low VV and VH noted in this study. A marked increase to 0.41 by mid-December suggested rapid canopy development and vegetative growth which also agreed with the findings from the backscatter analysis. NDVI stabilized around 0.38 in mid-January, implying canopy closure and onset of maturity or tasseling. From Figure 10, it was observed that peak NDVI value of 0.49 was observed in mid-March, after which values declined to 0.31 by mid-April coinciding with the harvesting period observed in the SAR backscatter analysis. These trends align with the observations of Kumar et al. (2021), who found that maize NDVI values rose to above 0.7 during peak vegetative stages and fell below 0.5 during senescence and harvest phases in their study in Telangana, India. This consistency supports the applicability of NDVI time-series analysis for identifying maize growth stages across different regions and agroecological regions.

The NDVI time series information has given vegetation health statistics for maize in the study region. This information provides actionable insight for crop performance at different crop growth stages and acts as an early warning for crop failure. Timely decisions can therefore be made towards achieving food security as a nation.

6.3 Backscatter sensitivity with maize growth stages

The temporal analysis of VV and VH backscatter values observed in this study for the different maize growth stages found that the backscatter values increased from sowing to germination and this trend continued throughout growth until maturity was reached, The values only began to decrease once the Maize was ready for harvest. This aligns with findings in Venkatesan, et al., (2019); Ghazaryan, et al., (2018); Li, et al., (2018) and other relevant studies who also found saw similar trends during the studies on temporal backscatter of Maize crops.

In this study, the VV backscatter value was recorded at -14.72 dB and VH at -23.30 dB during early November, indicating low biomass and canopy cover. Venkatesan, et al., (2019) reported a similar trend, with VH polarization values ranging from -21.26 dB to -17.51 dB and VV values around -14.05 dB to -11.45 dB for emerging maize. These values align closely with our study, reinforcing the significance of low VV and VH backscatter values as indicators of sparse crop cover and early growth (Venkatesan, et al., 2019). The analysis results agree with common practice around Chongwe and provide a method of assessing crop germination. This information is critical as it can guide planning decision for food security. Early information on maize germination gives actionable insight into crop perfomanc for the growing period.

As the maize canopy developed, backscatter values in this study increased, reaching -12.83 dB (VV) and -19.61 dB (VH) by December. These increases correspond with the accumulation of biomass and canopy density, suggesting that VV polarization is sensitive to structural growth, while VH reflects increased water content and leaf area index (LAI) during this stage (Venkatesan, et al., 2019; Arslan, et al., 2022). This information provided insight into crop performance during vegetative growth and provide clues on how the season has perfomed so far. A deviation from expected values can give a basis for further investigation to the cause of variation which can be an early warning for pest infestations, dry spells and other parameters which may hinder optimal yield.

During the study period, the VV backscatter values stabilized between -11.50 dB and -11.79 dB from around mid-January, indicating full canopy closure, with VH values around -17.9 dB. This stabilization coincides with the tasseling and maturity phases, where plant structure remains consistent, and canopy closure is near-complete. Li et al (2018) observed similar patterns during maize maturity stages in temperate regions of the North China plain which is a temperate region characterized by mechanized, large-scale maize cultivation with controlled irrigation. Their study found that the VV values stagnated around -11.0 dB to -10.5 dB, and VH values stabilized at around -16.0 dB due to moisture saturation in the canopy. The current research was conducted in a tropical agro-climatic zone with predominantly smallholder rainfed systems. The similarity in backscatter trends despite the differing environmental and management conditions suggests that SAR-based phenological monitoring is robust across diverse agro-ecological settings, extending the applicability of these methods to Sub-Saharan Africa. (Li, et al., 2018; Arslan, et al., 2022).

This study recorded a decrease in backscatter values during the harvesting period, with VV backscatter dropping to -12.3 dB and VH to -18.3 dB by early April. This decline is attributed to moisture loss and structural breakdown as the maize dries post-maturity. Li et al. (2018) also observed similar reductions in VV and VH values during harvest, where VV dropped to around -12.5 dB and VH to approximately -17.5 dB, emphasizing the strong correlation between backscatter decreases and biomass reduction as the crop nears the end of its life cycle. These observations were also in agreement with results from Arslan et al., (2022) who found similar figures in the descending orbit imagery during the harvesting phase of the plant cycle. This information is important as it allows for farmers and stakeholders to plan for appropriate storage and business decisions to be made as the growing period draws to an end.

The VV and VH backscatter values provide distinct insights into maize phenology, enabling accurate tracking of growth phases. In this study, the VV backscatter, which is responsive to canopy structure, showed consistent increases through the vegetative phase. In November, VV was

-14.7 dB, reaching –10.0 dB by January. This pattern corroborates findings from Ghazaryan et al. (2018), who noted similar increases in VV backscatter during vegetative growth. The increased backscatter reflects the denser canopy, which increases surface roughness and signal reflectance. The VH backscatter was particularly useful in distinguishing the moisture characteristics across phenological stages. Starting at -23.3 dB in November, VH rose to -16.54 dB by February, indicating moisture and biomass accumulation during the vegetative and maturity stages. This aligns with Kussul et al. (2014), who reported similar trends in maize due to the interaction between SAR signals and water-rich, dense canopies during maturity (Ghazaryan, et al., 2018; Kussul, et al., 2014; Arslan, et al., 2022).

6.4 Classification of maize crop area using random forest classification algorithm

The random forest classification of the study area into four primary land cover classes (maize fields, other vegetation, urban/bareland, and water bodies) yielded results in line with other studies, demonstrating an overall accuracy of 96.7% and a Kappa coefficient of 0.95. These metrics underscore the effectiveness of the Random Forest classifier for maize mapping. This study estimated maize coverage at 53.55% of the total area, reflecting the dominance of maize in the region and reiterating the importance of maize in the rural agriculture economy. This analysis identified fewer water bodies (0.47% of the total area), potentially due to the 10m spatial resolution of Sentinel-2 imagery used for NDWI analysis. Kpienbaareh, et al., 2021 experienced similar challenges in their study conducted in Northern Malawi, as certain land cover features such as tarred roads were harder to detect. Future studies may benefit from higher-resolution data or alternative indices to better capture narrow water features. The results of the Maize crop classification also play a critical role in Maize yield estimation methods as demonstrated by Jin, et al,. (2019) who used similar methods to classify crop and Maize fields in Kenya and Tanzania before using field data to model yield.

These results also align with the study by Vizzari, et al., (2024) who used integrated Sentinel 1 and Sentinel 2 data to run an OB classification using the Random forest classifier. The study used mean backscatter values from SAR data as was the case in this study, and created a composite with the median vegetative Indices from the optical imagery. The study used median Radar Vegetative

Indices (RVI) in the classification to provide more information for the RF classification and the achieved overall accuracy was up to 89% (Vizzari, et al., 2024).

6.5 Summary of key findings

This study demonstrated the effectiveness of integrating Sentinel-1 SAR and Sentinel-2 optical imagery to map maize phenological stages in Kasisi, Chongwe District. By analyzing biweekly backscatter trends (VV and VH) and NDVI values from November 2019 to April 2020, the study identified four key growth phases: sowing, emergence, maturity, and harvest. The classification model, trained using Random Forest and multi-source features (VV_Lee, VH_Lee, VV/VH ratio, NDVI, NDWI), achieved a high overall accuracy of 96.7% with a Kappa coefficient of 0.95. Additionally, maize fields were successfully delineated, and NDWI-derived water bodies were detected and incorporated into land cover classification.

6.6 Interpretation of results

The increasing backscatter values (VV and VH) from early November to mid-January indicate progressive maize canopy development, consistent with findings by Li et al. (2018) and Venkatesan et al. (2019). The stability of VV and VH in mid-January to February marked maturity, while their decline in March and April signaled harvesting. NDVI trends mirrored this pattern, confirming vegetative health and growth transitions. These results support the sensitivity of SAR metrics to structural biomass changes and the complementary role of NDVI in validating vegetative dynamics. The VV/VH ratio enhanced class separability by capturing both structure and water content variations across maize growth stages.

6.7 Practical implications for policy makers and other stakeholders

The results from the study demonstrate the capacity of multi-temporal Sentinel 1 SAR imagery to monitor the maize growing period in Zambia. The study aligns with current global trends emphasizing and advocating for increased use of geospatial technology in crop monitoring and agricultural management. These results have significant implications for Zambia’s agricultural systems, decision-making, and stakeholders, such as Zamstats, the Ministry of Agriculture and insurance companies. Traditional methods of data collection, such as field surveys and crop forecasting surveys (CFS), often face challenges related to logistical constraints, delayed reporting, and limited sample sizes that may not accurately represent district-level variations ((Tembo, et al., 2014). The integration of Sentinel-1 SAR imagery addresses these challenges by providing high-resolution, timely, and consistent data. Zamstats and MoA can use the estimated area under maize cultivation to improve the yield prediction based off average yield data gathered during crop forecast surveys.

6.7.1 Crop forecasting

The study has shown the utility of Sentinel SAR and MSI imagery for accurate crop classification and growth monitoring, which can significantly enhance Zambia's crop forecasting systems. Zamstats and the Ministry of Agriculture who are responsible for national agricultural statistics, can integrate the technology used in this study to improve the reliability and timeliness of crop estimates. Unlike traditional surveys that are labour-intensive and subject to delays, SAR-based methods enable real-time monitoring and scalable area estimations. Improved detection of planting dates and growth stages, such as those seen in this study, allows for early-season production forecasts. Temporal backscatter values observed in this study during the vegetative stage correspond with increases in biomass, indicating healthy crop growth. This aligns with findings by Jin et al. (2019) and Arslan et al. (2022), showcasing robust methodologies that can be adapted for the current crop monitoring framework. The introduction of high-resolution SAR imagery, coupled with field verification, can refine district-level crop yield estimates, addressing the limitations of current sampling methods highlighted in Zambia's early warning systems (Tembo, et al., 2014).

6.7.2 Crop insurance

In crop insurance, SAR-enabled systems provide critical inputs to quantify yield variability across different regions, enabling insurers to design tailored policies that address localized risks. A study by Setiyono et al. (2014) highlighted how SAR data can effectively capture the spatial and temporal dynamics of crop phenology, which are crucial for accurate risk assessment in smallholder farming systems. The study further demonstrated how SAR-based systems can identify flood or drought-affected areas with high reliability, offering insurers an efficient way to validate claims.

The study's findings have shown how insurance companies operating in the agricultural sector can leverage the results to develop or refine insurance products. These products rely on measurable indices, such as rainfall or vegetation indices, to trigger payouts, reducing the need for field assessments and mitigating the risks of moral hazard and adverse selection (Setiyono, et al., 2014).

The precise monitoring of maize growth stages and biomass through SAR backscatter data provides an objective and reliable index for insurance purposes. Accurate mapping of maize-cultivated areas and growth stages enables insurance stakeholders to perform more detailed risk assessments. By understanding the spatial distribution of crops and their vulnerability to climatic events, insurers can calculate premiums more accurately and design products that reflect the actual risk levels in different regions around Zambia. This precision benefits both the insurers, through better risk management, and the farmers, by providing fairer premium rates.

6.7.3 Food security and agricultural planning

Policymakers need accurate and timely data to formulate effective agricultural policies, allocate resources to different regions, and plan interventions. The ability to monitor maize growth stages and predict yields with high accuracy allows for better anticipation of potential food shortages or surpluses. This proactive approach is essential for ensuring national food security and can inform decisions on grain reserves, import/export policies, and distribution of agricultural subsidies (Kumawat, et al., 2023). The study's results can provide valuable information on the amount of agricultural land that has Maize in different regions of Zambia and its integration into the policy frameworks would provide policymakers with quantified information for better planning and decision-making.

6.7.4 Climate change adaptation and disaster risk management

Zambia, like many other countries in Sub-Saharan Africa, is vulnerable to the impacts of climate change, which can exacerbate food insecurity (FAO, IFAD, UNICEF, WFP, WHO;, 2022). The study's methodology provides tools for monitoring the effects of climate variability on crop production such as Maize. By identifying areas affected by drought, flooding, insect infestations or other events in near real-time, policymakers can implement targeted adaptation strategies, support affected communities, and develop long-term resilience plans.

The integration of SAR data into early warning systems enhances the country's capacity to respond to agricultural disasters. The ability to detect anomalies in crop growth stages allows for early intervention, potentially mitigating the impact of pests, diseases, or extreme weather events. This proactive disaster risk management aligns with global best practices and supports the objectives outlined in Zambia's National Disaster Management Policy (Government of Zambia. , 2015).

6.7.5 Agricultural extension services

Agricultural extension officers can utilize the detailed growth stage information to provide timely and location-specific advice to farmers. For instance, if SAR data indicates delayed crop development in certain areas, extension services can investigate potential causes such as nutrient deficiencies or pest infestations and recommend appropriate interventions (Nellis, et al., 2009) . The precise mapping of maize cultivation areas as done in the study helps in the efficient allocation of resources such as fertilizers, improved seed varieties, and irrigation infrastructure. Development programs and government initiatives can prioritize regions based on actual data, ensuring that interventions reach the farmers who need them most. This targeted support enhances agricultural productivity and sustainability as resources are effectively distributed based on requirements ensuring no wastages or shortages.

6.7.6 Agribusiness and market intelligence

For agribusinesses involved in the procurement, processing, and distribution of maize and other crops, the ability to predict yields and understand spatial production patterns is very important for effective business decisions. Private sector partners and stakeholders can optimize their supply chains, manage inventories, and plan logistics more effectively when equipped with accurate production forecasts (Jayne, et al., 2007). Accurate yield predictions contribute to better market price forecasting. Anticipating surpluses or shortages allows market participants to make informed decisions, potentially stabilizing prices and reducing instability. This stability benefits both producers and consumers by ensuring fair prices and consistent supply around Zambia.

6.8 Implications of the findings

The ability to accurately detect growth stages from satellite data in near real-time has several operational benefits. First, it enables early warning and mid-season decision-making, which is critical for food security and resource allocation. Second, this approach reduces reliance on labor-intensive field surveys, offering a cost-effective solution for monitoring in data-scarce regions. Third, the method can support agricultural insurance schemes through objective yield-related indicators, enhancing risk assessment. Lastly, the water body mapping using NDWI supports irrigation planning and agro-hydrological assessments.

6.9 Research contribution and alignment with previous work

This study builds on and expands previous work in tropical crop monitoring using EO. While studies such as Kpienbaareh et al. (2021) demonstrated the effectiveness of combining SAR and optical data for maize classification in Malawi, and Li et al. (2018) focused on phenology in temperate zones, this research contextualizes those findings within Zambia's smallholder rainfed systems. Unlike earlier efforts, this study integrates a high-frequency (biweekly) analysis of SAR and NDVI trends to map phenological stages with high accuracy and strong field validation. It provides a template for scalable agricultural monitoring and sets a precedent for integrating such methods into national systems like Zamstats.

CHAPTER SEVEN: CONCLUSION AND RECOMMENDATIONS

The main goal of this study was to explore the potential of using Sentinel Synthetic Aperture Radar (SAR) images in mapping and monitoring the progression of maize fields in the Kasisi area of Chongwe District. This study effectively delineated maize crop fields and provided phenological monitoring of growth stages within the study area.

This was done by using multi-temporal Sentinel 1 SAR and Sentinel 2 MSI data to extract the backscatter as well as NDVI values at different periods during the growing season. The sowing, seed emergence, crop maturity and harvesting dates were successfully estimated using SAR and Optic data. The work contributes to the broader scholarship by demonstrating how using Satellite derived imagery with training data has the capability to enhance Maize monitoring and mapping in Zambia. A Maize classification map was also generated using the VV, VH and VV/VH from Sentinel 1 SAR and NDWI and NDVI indices from Sentinel 2 MSI. The maize classification map and ndvi time series maps showed the spatial temporal variations in the study area through the growing season. A composite was generated using the SAR and MSI outputs and a Random forest classifier was trained and validated using the field data.

This study demonstrates that Sentinel-1 SAR data, particularly with dual-polarization (VV and VH) and Sentinel 2 MSI data, is highly effective for monitoring maize growth stages. The Sentinel-2 optical data also complements this by providing essential vegetation and water indices. The results have shown that 6721.46 Hectares representing 55% of the study area had maize cultivated during the growing period. The align with findings from diverse agroecological contexts, suggesting this method's broad applicability for mapping maize fields across different climates and geographic regions. Integrating higher-resolution imagery would enhance the delineation of smaller land cover features, such as streams and rural houses, thereby providing more accurate water resource mapping, effective resource utilization planning and supporting precision agriculture practices.

The study also opens opportunities for integrating yield prediction models, where the classified maize field maps can serve as key inputs for forecasting crop yields. Field-level data, including plant height and biomass, could be collected during different growth stages to enhance the yield estimation models. Expanding the temporal scope of analysis beyond the 2019–2020 growing season will also provide more comprehensive insights into long-term agricultural trends.

In conclusion, this study highlights the potential of using SAR and optical data for agricultural monitoring in Zambia, offering a scalable, reliable solution for crop mapping in regions with high cloud cover. These findings can inform future agricultural policy and planning, supporting efforts to improve food security and optimize resource management in Zambia's agricultural sector.

It is recommended that Zamstats, the Ministry of Agriculture, WARMA and other stakeholders adopt methods that use geospatial data in the framework of resource management, especially in the Agricultural sector.

Zambia’s national crop yield estimation system, managed by the Zamstats, primarily depends on the Crop Forecast Survey (CFS) and the Post-Harvest Survey (PHS). These surveys rely on field-based enumerators collecting data from small and medium scale farming households annually. While these methods provide useful national-level estimates, they suffer from several limitations, including delays in data availability, limited spatial resolution, and the subjectivity of self-reported yield data, which may be influenced by recall bias or social desirability. Additionally, CFS estimates are typically released once per season, limiting their utility for in-season interventions.

In contrast, this study employed a remote sensing-based approach using Sentinel-1 SAR and Sentinel-2 MSI data, combined with field-based training samples, to map maize fields and monitor growth stages with biweekly temporal granularity and 10-meter spatial resolution. The integration of VV, VH, and VV/VH ratio metrics with NDVI and NDWI indices allowed for the accurate detection of key phenological stages such as sowing, emergence, maturity, and harvest, aligning with field observations and well-established crop calendars. The resulting land cover classification achieved an overall accuracy of 96.7% and a Kappa coefficient of 0.95, surpassing the spatial and temporal accuracy typically achievable through survey-based methods.

Moreover, this approach allows for early detection of anomalies, such as delayed planting or early senescence, which are difficult to capture using static field surveys. While Zamstats estimates are reported post-season, the methods applied in this study offer the ability to conduct mid-season monitoring and produce near real-time updates, supporting early warning systems and adaptive response strategies.

By demonstrating that timely, spatially explicit, and cost-effective agricultural monitoring is achievable through Earth Observation and machine learning, this study validates the use of remote sensing as either a complementary tool to Zamstat's surveys or as a potential foundation for a more modernized crop monitoring framework in Zambia. This aligns with national and regional goals of strengthening data-driven decision-making in agriculture and improving food security forecasting under changing climatic conditions.

7.1.1 RECOMMENDATIONS

- Zambia's crop monitoring systems under Ministry of agriculture should integrate Synthetic Aperture Radar (SAR) and optical satellite imagery to enhance the accuracy and timeliness of data collection on crop conditions and yield. This approach eliminates the need for labour-intensive ground surveys and provides near-real-time insights into crop growth dynamics.
- The Ministry of Agriculture and other relevant stakeholders should invest in training programs to equip technical staff at all levels with skills in remote sensing, geospatial analysis, and machine learning. This will ensure the effective implementation and utilization of advanced agricultural mapping and monitoring systems.
- Policymakers should adopt geospatially informed crop growth monitoring systems as part of Zambia's national food security strategy
- Insurance companies should adopt the SAR amd NDVI based monitoring to help in compensation for farmers. This will ensures fair compensation for farmers affected by adverse weather events, reducing uncertainties in the insurance industry.

The methodology developed in this study should be expanded to other major crops such as cassava and soybeans in the agro-ecological regions of Zambia.

7.2 Recommendations for future research

- The study period was constrained due to the unavailability of Sentinel-1 SAR data from 21st December 2021 until the present for the study area, significantly impacting the ability to analyze a more recent growing period. This limitation highlighted the need for alternative or complementary data sources to bridge such temporal gaps in future research.
- Future research should focus on refining the classification model by incorporating higher-resolution data, such as commercial satellite imagery with finer spatial resolution or drone imagery. The integration of such data can reduce misclassification errors, particularly in delineating smaller land cover features like narrow streams, rural houses, and smallholder farms.
- Research should also be done on exploring the use of higher-frequency SAR data or multi-frequency radar data (e.g., C-band and L-band combinations). This could enhance the sensitivity of classification to different crop growth stages and vegetation structures, further improving accuracy and applicability.
- Additionally, exploring temporal datasets that combine optical and radar data from alternative sources could help provide continuous monitoring in cases of data gaps like those experienced in this study. Platforms such as PlanetScope which offer high temporal and spatial resolution, could be explored as potential alternatives to complement Sentinel-1 data for agricultural monitoring.
- Expanding the study's methodology to other crops and agroecological regions of Zambia is also crucial. Validating this methodology across the four agroecological regions of the country would enable a broader understanding of its applicability and performance under varying climatic, soil, and management conditions. This approach could provide more generalized and robust insights into crop dynamics across Zambia’s diverse agricultural landscapes.
- Further research should also focus on developing a robust yield prediction model that integrates SAR and optical data, high-resolution imagery, ground-truth measurements, and environmental variables such as soil type, precipitation, and temperature. Incorporating advanced machine learning algorithms and crop growth simulation models can significantly enhance the precision of these yield forecasts. Such models could operate at

smaller spatial units, such as agricultural camps, allowing for more targeted interventions and informed decision-making by policymakers and stakeholders.

Future research based on these results can enhance mapping and monitoring capabilities and aid in water resource management, precision agriculture practices, and climate resilience planning. The inclusion of socioeconomic data, such as farmer profiles and market access, in future research could also help integrate geospatial analysis into comprehensive frameworks for sustainable agricultural development in Zambia

LIST OF REFERENCES

Adamo, N. et al., 2020. Dams Safety: Review of Satellite Remote Sensing. *Journal of Earth Sciences and Geotechnical Engineering,* 11(1), pp. 347-438.

African Development Bank Group, 2024. *Zambia Country Economic Outlook 2024.* [Online] Available at: https://www.afdb.org/en/countries-southern-africa-republic-zambia/zambia-economic-outlook
[Accessed 15 April 2025].

Al- Zuhairi, M., Nahas, F., Hussein, F. & Pradhan, B., 2016. A refined classification approach by integrating Landsat Operational Land (OLI) and RADARSAT-2 imagery for land-use and land-cover mapping in a tropical area. *International Journal of Remote Sensing.*

Andreu, F. J. L., Erena, M., Gómez, J. A. D. & Morales, J. A. L., 2021. Sentinel-2 Images and Machine Learning as Tool for Monitoring of the Common Agricultural Policy: Calasparra Rice as a Case Study. *agronomy,* 11(621).

Apan, A. et al., 2002. Spectral Discrimination And Separability Analysis Of Agricultural Crops And Soil Attributes Using Aster Imagery. *" in Proc 11th Australas. Remote Sens. Photogramm. Conf,* Volume 2, pp. 396-411.

Arnold, R. D. & Wade, J. P., 2015. A Definition of Systems Thinking: A Systems Approach. *Procedia Computer Science.*

Arslan, I., Topakci, M. & Demir, N., 2022. Monitoring Maize Growth and Calculating Plant Heights with Synthetic Aperture Radar (SAR) and Optical Satellite Images. *Agriculture,* 12(6), p. 800.

Bello, M., Nasidi, N. M. & Shanono, N. J., 2014. *Remote Sensing as a Tool for Irrigation Water Management.* Bayero University, Kano, Nigeria, s.n.

Bicego, M., Christani, M., Fusiello, A. & Murino, . V., 2003. *Watershed based unsupervised clustering..* Lisbon, Springer, Berlin, pp. 83-94.

Breiman, L., 2001. Random Forests. *Machine Learning,* pp. 5-32.

Butler, D., 2006. The web-wide world. *Nature,* Volume 439, pp. 776-778.

Cracknell, A. P., 2018. The development of Remote Sensing in the last 40 years. *International Journal of Remote Sensing,* 39(23), pp. 8387-8427.

Dadhwal, V., 2005. *Crop Growth And Productivity monitoring And Simulation Using Remote Sensing And GIS.* s.l., s.n.

Defourney, P., 2017. Land cover mapping and monitoring. In: *Handbook on Remote Sensing for Agricultural Statistics(Chapter 2).* Rome: FAO, pp. 21 - 50.

Dutta, G. & Goswami, P., 2020. Application of drone in agriculture: A review. *International Journal of Chemical Studies,* Volume 8, pp. 181-187.

ESRI, 2022. *Sentinel-2 10m Land Use/Land Cover Timeseries.* [Online] Available at: https://www.arcgis.com/home/item.html?id=d3da5dd386d140cf93fc9ecbf8da5e31 [Accessed 27th June 2022].

FAO, IFAD, UNICEF, WFP, WHO;, 2022. *The State of Food Security and Nutrition in the world 2022. Repurposing food and agricultural policies to make healthier diets more affordable,* Rome: FAO.

Franceschini , G. & Ali, M., 2022. *Introductory Course to Google Earth Engine.* Rome: FAO.

Ghazaryan, G. et al., 2018. A rule-based approach for crop identification using multi-temporal and multi-sensor phenological. *European Journal of Remote Sensing,* 51(1), pp. 511-524.

Goertzen, M. J., 2017. Introduction to Quantitative Research and Data. *Library Technology Reports,* 53(4), pp. 12-18.

Government of Zambia. , 2015. National Disaster Management Policy. In: s.l.:Office of the Vice President..

GRZ, 2015. *Post Harvest Survey,* Lusaka: Central Statistical Office.

GRZ, 2020. *Third National communication to the United Nations Framework Convention on Climate Change(UNFCCC),* s.l.: s.n.

Huang, Y. et al., 2009. Development of a spray system for unmanned aerial vehicle platform. *Applied Engineering in Agriculture,* 25(6), pp. 803-809.

Immitzer, M., Vuolo, F. & Atzberger, C., 2016. First Experience with Sentinel-2 Data for Crop and Tree species Classification in Central Europe. *remote sensing.*

Jayne, T., Chapoto, A. & Govereh, J., 2007. *Grain Marketing at at the Crossroads: Challenges For Eastern and Southern Africa.* Rome, FAO.

Jin, Z. et al., 2019. Smallholder maize area and yield mapping at national scales with Google Earth Engine. *Remote Sensing of Environment,* Volume 228, pp. 115-128.

Khanal, S. et al., 2020. Remote Sensing in Agriculture—Accomplishments, Limitations and Opportunities. *Remote Sensing,* Volume 12.

Kpienbaareh, D. et al., 2021. Crop Type and Land Cover Mapping in Northern Malawi Using the Integration of Sentinel-1, Sentinel-2, and PlanetScope Satellite Data. *Remote Sensing,* Issue 13.

Kumar, A. D. et al., 2021. Monitoring of Spectral Signatures of Maize Crop using Temporal SAR and Optical Remote Sensing data. *International Journal of Bio-resource and Stress Management.*

Kumawat, L. et al., 2023. Remote Sensing Approaches and Application in Agriculture.. *Recent Trends In Agriculture,* Volume 7.

Kussul, N., Skakun, S., Shelestov, A. . Y. & Kussul, O., 2014. *The use of satellite SAR imagery to crop classification in Ukraine within.* s.l., s.n.

Lemoine, G., 2017. Data Access and data analysis software (Chapter 1). In: *Handbook of the Global Strategy to improve Agricultural and Rural Statistics(GSARS).* Rome: s.n.

Li, L. et al., 2018. Precise identification of maize in the North China Plain based on Sentinel-1A. *International Journal of Remote Sensing.*

Löw, F. & Duveiller, G., 2014. Defining the Spatial Resolution Requirements for Crop Identification Using Optical Remote Sensing. *Remote Sensing,* Volume 6, pp. 9034-9063.

Lys, P., 2010. *The Current State of Cost of Production Estimates- A Review of Country Practices in Ethiopia, Mali and Zambia,* s.l.: s.n.

Maarouf, H., 2019. Pragmatism as a Supportive Paradigm for the Mixed Research: Conceptualizing Ontological, Ontological, Epistemological, and. *International Business Research,* 12(9).

MacDonald , R. B. & Hall, F. G., 1980. Global Crop Forecasting. *Science,* Issue 208, pp. 670-679.

McCoy, R. M., 2006. *Field Methods in Remote Sensing.* New york: Guilford Press.

Megill, D., 2004. *Recommendations on Sample Design of Post-Harvest Surveys in Zambia Based on 2000 Census, Working Paper No.11, Food Security Research Project.* Lusaka: s.n.

Milupi, I., Chileshe, B., Moonga, M. S. & Monde, P., 2020. Women and Natural Resource Conservation: A Study of hongwe District, Zambia. *International Journal of Humanities Social Sciences and Education (IJHSSE).*

Moran, M. S., Inoue, Y. & Barnes, E. M., 1997. Opportunities and Limitations for Image-Based Remote Sensing in Precision Crop Management. *@article{Moran1997OpportunitiesAL,,* Volume 61, pp. 319 -346.

Moran, S., 2000. Image-based remote sensing for agricultural management: perspectives of image providers, research scientists and users. p. 29.

Moreira, A. et al., 2013. A tutorial on synthetic aperture radar. *IEEE Geoscience and Remote Sensing Magazine,* 1(1), pp. 6-43.

Mullisa, A. et al., 2021. Sentinel 1 SAR Backscatter Analysis Ready Data Preparation in Google Earth Engine. *remote sensing,* 13(1954).

Nagraj, G. M. & Karegowda, A. G., 2016. Crop Mapping using SAR Imagery: An Review. *International Journal of Advanced Research in Computer Science,* 7(7).

NASA JPL, 2013. *NASA Shuttle Radar Topography Mission Global 1 arc second [Data set].* s.l.:s.n.

Nellis, D., Price, K. & Rundquist, D. C., 2009. Remote Sensing of Cropland Agriculture. *Papers in Natural Resources.*

Nick, A., 2015. *Groundwater Resources for Lusaka and selected Catchment Areas,* Lusaka: s.n.

Setiyono, T., Nelson, A. & Francesco Holecz, 2014. Remote sensing based crop yield monitoring and forecasting. In: M. K. Srivastava, ed. *Crop monitoring for improved food security.* Vientiane, : FAO and Asian Development Bank, pp. 123 - 132.

Soil Survey Section Research Branch, M. o. A., 1999. *Exploratory Soil Map of Zambia, Scale 1 : 1,000,000.* Lusaka: Ministry of Agriculture.

Tembo, G., Chimai, B., Nathan, T. & Ndiyoi, M., 2014. Observations on Zambia's Crop Monitoring and Early Warning Systems. *Journal of Agricultural Science* , 6(3).

Torres, R. et al., 2012. GMES Sentinel-1 mission. *Remote Sensing of Environment,* Issue 120, pp. 9-24.

Upreti, A., 2022. Machine Learning Application in G.I.S. and Remote Sensing: An Overview..

Venkatesan, M., Pazhanivelan, S. & Sudarmanian, N. S., 2019. Multi-Temporal Feature Extraction for Precise Maize Area Mapping Using Time-Series Sentinel 1a SAR Data. *ISPRS - International Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences,* Volume 423, pp. 169-173.

Vizzari, M., Lesti, G. & Acharki, S., 2024. Crop classification in Google Earth Engine: leveraging Sentinel-1, Sentinel-2, European CAP data and object- based machine learning approaches. *Geo-spatial Information Science.*

Wardlow, B. D., Egbert, S. & Kastens, J., 2007. Analysis of Time-Series MODIS 250 m Vegetation Index Data for Crop Classification in the U.S. Central Great Plains. *Remote Sensing of Environment,* pp. 290-310.

Watson, S., 2021. Efficient design of geographically-defined clusters with spatial autocorrelation. *Journal of Applied Statistics.*

Weiss, M., Jacob, F. & Duveiller, G., 2019. Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment,* p. 236.

Zambia Statistical Agency, 2022. *Zambia Executive Monitor Application,* Lusaka: s.n.

Zhang, Q. et al., 2021. Comparative Analysis of Edge Information and Polarization on SAR-to-Optical Translation Based on Conditional Generative. *Remote Sensing*, 13(128).

Appendix

Table 3 Sentinel-1 temporal backscatter values

Date	**VV (dB)**	**VH (dB)**
01/11/2019 -15/11/2019	-13.823	-21.625
16/11/2019 -	-11.110	-18.520
01/12/2019	-12.487	-19.396
16/12/2019	-12.139	-18.649
01/01/2020	-9.802	-16.395
16/01/2020	-11.031	-17.210
01/02/2020	-11.287	-17.310
16/02/2020	-10.004	-16.207
01/03/2020	-11.250	-17.214
16/03/2020	-10.704	-16.728
01/04/2020	-11.784	-17.684
16/04/2020	-12.007	-18.096

Source: Data analysis, 2024

Table 4 NDVI time series analysis

Date	NDVI
01/11/2019	0.145347
16/12/2019	0.405718
16/01/2020	0.382227
16/03/2020	0.494602
01/04/2020	0.381548
16/04/2020	0.314747

Source: Data analysis, 2024

Table 5 Sentinel 1 SAR images used

Date	ID	Orbit	Platform	RelativeOrbit
29/01/2020	S1A_IW_GRDH_1SDV_20200129T163328_20200129T163351_031017_039019_D2E6	ASCENDING		145
12/11/2019	S1B_IW_GRDH_1SDV_20191112T163250_20191112T163315_018896_023A42_C6BA	ASCENDING		145
24/11/2019	S1B_IW_GRDH_1SDV_20191124T163249_20191124T163314_019071_023FE2_9BDC	ASCENDING		145
06/12/2019	S1B_IW_GRDH_1SDV_20191206T163249_20191206T163314_019246_02456D_498F	ASCENDING		145
18/12/2019	S1B_IW_GRDH_1SDV_20191218T163248_20191218T163313_019421_024B05_715C	ASCENDING		145
30/12/2019	S1B_IW_GRDH_1SDV_20191230T163248_20191230T163313_019596_025094_BC5B	ASCENDING		145
11/01/2020	S1B_IW_GRDH_1SDV_20200111T163247_20200111T163312_019771_025625_83ED	ASCENDING		145
23/01/2020	S1B_IW_GRDH_1SDV_20200123T163247_20200123T163312_019946_025BB8_65D8	ASCENDING		145
04/02/2020	S1B_IW_GRDH_1SDV_20200204T163247_20200204T163312_020121_026162_7043	ASCENDING		145
16/02/2020	S1B_IW_GRDH_1SDV_20200216T163246_20200216T163311_020296_026704_FB27	ASCENDING		145
28/02/2020	S1B_IW_GRDH_1SDV_20200228T163246_20200228T163311_020471_026CA2_2727	ASCENDING		145
11/03/2020	S1B_IW_GRDH_1SDV_20200311T163246_20200311T163311_020646_027234_1098	ASCENDING		145
23/03/2020	S1B_IW_GRDH_1SDV_20200323T163246_20200323T163311_020821_0277BA_6631	ASCENDING		145
04/04/2020	S1B_IW_GRDH_1SDV_20200404T163247_20200404T163312_020996_027D44_1513	ASCENDING		145
16/04/2020	S1B_IW_GRDH_1SDV_20200416T163247_20200416T163312_021171_0282CF_0B7F	ASCENDING		145
28/04/2020	S1B_IW_GRDH_1SDV_20200428T163248_20200428T163313_021346_028854_374F	ASCENDING		145

Table 6 Sentinel 2 MSI images used

Date	**ID**	**Platform**	**Cloud**
01/11/2019	20191101T080051_20191101T082333_T35LPD	Sentinel-2A	3.0041
06/11/2019	20191106T080029_20191106T081440_T35LPD	Sentinel-2B	0.3259
16/12/2019	20191216T080239_20191216T082039_T35LPD	Sentinel-2B	4.1439
25/01/2020	20200125T080119_20200125T082048_T35LPD	Sentinel-2B	10.0972
25/03/2020	20200325T075609_20200325T082005_T35LPD	Sentinel-2B	2.8528
30/03/2020	20200330T075611_20200330T082055_T35LPD	Sentinel-2A	0.0072
14/04/2020	20200414T075609_20200414T082144_T35LPD	Sentinel-2B	8.6259
24/04/2020	20200424T075609_20200424T082227_T35LPD	Sentinel-2B	14.8045
29/04/2020	20200429T075611_20200429T082102_T35LPD	Sentinel-2A	0