UNIVERSITY of RWANDA

College of Science and Technology

School of Architecture and Built Environment

MSc in Geo-Information Sciences for Environmental and Sustainable Development

By

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Using remote sensing to monitor growth and estimate yield of maize crop in Nyagatare district, Eastern Rwanda

Thesis submitted to the University of Rwanda: College of Science and Technology in partial fulfillment of the requirements for the award of the Degree of Master of Science in Geo-Information for Environment and Sustainable Development.

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Kigali, ………………….

DECLARATION

I hereby declare that this thesis is the result of my original research work and that all sources used for reference have been duly acknowledged. This work has not been submitted for any other degree, nor has it been previously published in any form.

I confirm that this thesis represents my work according to the University's regulations on plagiarism and that I have not used any sources, written or otherwise, except where due acknowledgment has been made in the text.

I further certify that the research work presented in this thesis has been carried out according to the ethical principles and guidelines laid down by the University and the relevant regulatory bodies.

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Signed:

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APPROVAL

It is hereby confirmed that this thesis entitled **“Using remote sensing to monitor growth and estimate yield of maize crop in Nyagatare district, Eastern Rwanda”** submitted by **Obed BIMENYIMANA** has been assessed and accepted by the post-graduate coordination team in the School of Architecture and Built Environment.

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ABSTRACT

The adverse impacts of climate change on food security and agriculture are especially severe in Sub-Saharan Africa. Monitoring and analyzing crop yield accurately is crucial for food security and enhancing farming practices. Remote sensing technology, particularly the Normalized Difference Vegetation Index (NDVI), offers valuable insights into vegetation health, which correlates closely with crop yield. This study examines Nyagatare District in Eastern Rwanda, focusing on the spatial and temporal variations of NDVI and maize greenness, and their relationship with crop yield.

Landsat images from 2016, 2019, and 2022 were utilized to calculate NDVI values for agricultural Seasons A and B, using the red and near-infrared (NIR) bands. A linear regression model was applied to evaluate the correlation between NDVI values and maize crop yield, using the R-squared value as a measure. Additionally, household surveys and interviews with maize farmers provided supplementary data.

The study found that in 2016, maize yield was largely within the Medium to Very High NDVI range during Season A, but in the Low to Medium range during Season B. By 2019, NDVI values suggested the potential for above-average yields, with Season A values ranging from 0.13 to 0.57 and Season B from 0.11 to 0.51. In 2022, the NDVI values were mostly in the Medium to Very High range, indicating areas with high crop yields. The positive correlation between NDVI levels, maize greenness, and crop yield was strong, with an R-squared value of 0.871 for both seasons. The linear regression model showed a moderately strong relationship, with an R-squared value of 0.7812, supporting NDVI's effectiveness as a predictor of agricultural productivity.

These results underscore the potential of remote sensing technology for predicting crop yield and optimizing crop management, contributing to improved agricultural productivity and sustainability in Nyagatare District. Policymakers can use these insights to enhance maize crop monitoring systems and implement targeted interventions such as fertilization programs, irrigation management, and early warning systems for drought or pest outbreaks. Integrating NDVI-based monitoring into agricultural policies could lead to better resource allocation, timely farmer support, and sustainable practices that secure food availability.

Keywords: Maize, NDVI, Remote Sensing, Crop Yield, Nyagatare District, Rwanda

LIST OF ABBREVIATIONS AND ACRONYMS

CIP	Crop Intensification Program
CO2	Carbon Dioxide
FAO	Food and Agriculture Organization of the United Nations
GDP	Gross Domestic Product
GIS	Geographic Information System
MSAVI	Modified Soil Adjusted Vegetation Index
NISR	National Institute of Statistics Rwanda)
NDVI	Normalized Difference Vegetation Index
REGL	Red-Edge Chlorophyll Vegetation Indices
RVI	Ration Vegetation Index
RS	Remote Sensing
SAS	Seasonal Agriculture Survey
USGS	United States Geological Survey
VI	Vegetation Indices

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CHAPTER 1: INTRODUCTION

1.1. Background

The agriculture sector is the backbone of the Rwandan economy, with more than 85% of the active population engaged in this economic activity. It represents 33% of the Gross Domestic Product (GDP) (Murindahabi, Li et al. 2017). Maize, a globally significant agricultural grain, is a staple food in many countries and a key feed for livestock. By 2050, the demand for maize in developing countries is expected to double, and by 2025, maize is projected to become the crop with the greatest production globally. Introduced to Africa around 1500 AD, maize has become a vital staple for over 300 million Africans and is used for both food and non-food purposes (Shiferaw, Prasanna et al. 2011).

In Rwanda, maize is a priority under the Crop Intensification Programme (CIP), launched in 2007 to enhance food security and boost agricultural productivity(Rwibasira, 2019). This program focuses on agricultural land consolidation, increased input use, mechanization, improved extension services, and better cultivation practices (Uwiragiye, 2016). Maize ranks third in cultivated area and agricultural production in Rwanda, following beans and bananas (MINAGRI, 2019)

It is grown in both hills and bottomlands, often in monoculture on large farms managed by cooperatives or intercropped with other food crops, especially beans (Finley, 2021).Suitable for almost all agro-climatic zones of the country, maize is cultivated by 62% of farm households nationwide. It plays a crucial role in the socio-economic life of Rwandans, being grown for direct human consumption, local market sales, millers, and as a food security stock (NISR, 2012).

Since 2013, the Ministry of Agriculture and Animal Resources (MINAGRI) has collected agricultural data through Seasonal Agricultural Surveys (SAS) conducted by the National Institute of Statistics of Rwanda (NISR), with input from local stakeholders. However, these surveys lack a spatial component and detailed yield predictions, limiting their utility for decision-making during critical maize crop growth periods(NISR, 2019).

Effective monitoring of maize crop growth and early yield prediction is essential for informed decision-making, enabling planners and policymakers to anticipate import needs during shortages, manage exports during surpluses, and establish contingency plans for equitable food distribution during famines (Panek, 2020)

Traditional maize crop yield estimation methods, relying on ground-based field visits and reports, are often subjective, costly, and time-consuming, leading to inaccuracies (Debalke, 2022). While various empirical models, such as the EPIC model, have been developed for yield estimation, their complexity and data demands make them impractical, especially at the field level (Ramos, Simionesei et al. 2018)

Remote sensing, particularly with satellite imagery, offers a promising alternative by providing spatial information on maize crop growth and yield estimation in near real-time. It can identify crop classes, assess crop vigor, and provide data on spatial variability, thereby enhancing field scouting efficiency. Through vegetation indices like the Normalized Difference Vegetation Index (NDVI), remote sensing data can indicate maize crop health, biomass production, and phenological changes, offering insights into maize crop growth stages and overall productivity(Zinhle, Munghemezulu, et al. 2024).

Nyagatare District in eastern Rwanda is a major maize-producing area. However, challenges such as diverse landscapes, inadequate ground-based monitoring infrastructure, and variable weather patterns complicate accurate crop growth monitoring and yield prediction. Remote sensing techniques appear promising for addressing these challenges, providing valuable insights into maize crop growth and yield potential in Nyagatare.

This case study aims to evaluate the effectiveness of remote sensing data in monitoring maize crop growth and estimating maize yields in the Nyagatare District. By analyzing multi-temporal satellite images, vegetation indices, and phenological data, this study seeks to establish correlations between remote sensing parameters and ground-based measurements, including field observations and yield studies. The findings can enhance understanding of maize growth patterns and productivity factors, aiding agricultural managers in making data-driven decisions. Ultimately, this study underscores the importance of integrating remote sensing into agricultural monitoring and planning in Rwanda, potentially improving food security and promoting sustainable farming practices.

1.2. Problem Statement

Maize is cultivated in both uplands and lowlands, often as a monoculture on large farms managed by cooperatives or alongside other crops like beans. In marshlands, maize monoculture is particularly prevalent under a land consolidation strategy, requiring state authorization through local authorities (Umutoni, 2013).

Estimating maize crop yield is a critical metric for assessing agricultural productivity and identifying yield gaps. The National Institute of Statistics of Rwanda (NISR), in collaboration with the Ministry of Agriculture and Animal Resources (MINAGRI), conducts the Seasonal Agriculture Survey (SAS) to monitor agricultural programs and policies and address key issues for policymakers and stakeholders. Traditionally, crop yield estimation has focused on the total reported harvest relative to the harvested area, often overlooking other factors influencing production (NISR, 2014)

Most recent efforts to estimate maize crop yield have focused on the total reported quantity harvested over the harvested area, often neglecting other factors that may impact yield (NISR 2014). In Rwanda, conventional methods such as crop cuts, on-station and on-farm trials, statistical techniques, farmer estimates, whole plot harvest methods, ground-based visits, and sampling of harvest units are used for yield estimation. However, these methods are time-consuming, expensive, subjective, and may not accurately account for factors such as poor germination, pest and disease damage, animal grazing, and floods, which can lead to inaccuracies in yield estimates (Ngaruye, von Rosen et al. 2016)

The use of remotely sensed data has become increasingly important in agricultural studies, including crop condition monitoring, crop yield forecasting, crop phenology monitoring, and more recently, crop insurance schemes (Benami, Jin et al. 2021). By measuring vegetation reflectance, valuable information about the crop can be obtained. Vegetation indices (VIs), derived from spectral data, are indicators of the biophysical and biochemical parameters of a crop and have been linked to variables such as above-ground biomass (Goris, 2017)

Nyagatare District, located in the eastern part of Rwanda, is a major maize-producing area. However, accurately measuring crop growth and predicting maize yield in this region is challenging due to diverse landscapes, insufficient ground-based monitoring infrastructure, and changing weather patterns. Therefore, remote sensing techniques offer a promising approach to address these challenges. This study aims to utilize remote sensing methods to estimate maize yield in Nyagatare District, developing precise mechanisms based on the interpretation of remote sensing data and vegetation indices. The goal is to track maize growth, estimate yields accurately, and provide reliable data to policymakers for informed decision-making in the maize commodity value chain.

1.3. Research Objectives

1.3.1 General Objectives

The primary objective of this study is to utilize remote sensing techniques to monitor the growth and estimate the yield of maize crops in Nyagatare district, Eastern Rwanda.

1.3.2 Specific Objectives

Specifically, this study embarks on a comprehensive exploration of maize landscapes, employing advanced spatial-temporal analyses and remote sensing techniques to achieve four primary objectives.

1. To analyse the spatial extent and the temporal changes of maize fields in the Nyagatare district between 2016 and 2022.

2. To identify the indicators for monitoring maize phenology.

3. To analyse the correlation between maize health indices and production.

4. To predict maize yield production using time series remote sensed data.

1.4 Hypotheses

The study hypothesizes that there has been a significant spatial expansion of maize fields in Nyagatare district between 2016 and 2022 with temporal changes closely associated with agricultural policies and climatic factors. It is also posited that key remote sensing indicators, such as NDVI, are reliable for tracking maize phenology and growth stages, effectively differentiating between various growth stages to allow for accurate monitoring throughout the growing season. Additionally, the research anticipates a strong positive correlation between remote sensing-derived vegetation indices and actual maize yield, suggesting that these indices can accurately predict yield. Lastly, it is hypothesized that time series remote sensed data can accurately forecast maize yield production, improving prediction accuracy when multi-temporal data is utilized compared to single-date observations.

CHAPTER 2. LITERATURE REVIEW

Agricultural modernization sets the stage for industrialization by improving labor productivity, generating agricultural surplus for capital accumulation, and increasing foreign exchange through exports. It also supports humanitarian goals by enhancing the incomes and productivity of impoverished farmers, reducing food prices, and improving nutrition. By modernizing agriculture, we can enhance human capital by providing better nutrition, which helps prevent the long-term effects of malnutrition, such as child stunting. A well-nourished child is more likely to develop fully, be more productive, and earn higher wages in adulthood compared to a malnourished child. Increased agricultural productivity and income also boost consumers' ability to purchase manufactured goods and reinvest in agricultural modernization (Lin, 2018). The National Agriculture Policy (2018) aims to create a nation that enjoys food security, nutritional health, and sustainable agricultural growth through a productive, environmentally sustainable, and market-driven agrarian sector by 2030 (MINAGRI, 2018).

Nyagatare district is among the first maize-producing districts in the country but the problem is that it may be attached to different scenarios such as poor harvesting and understanding their climate condition concerning maize product health landscape. This draws my attention to carrying out this research as a Geo-researcher who needs to address these kinds of problems through statistical analytics by integrating the geospatial technology of GIS and remote sensing (NISR, 2011)

Introducing remote sensing for crop growth and yield estimation provides accurate predictions of maize harvests and facilitates plantation management. It also aids in risk management and future harvest predictions, which are essential for both current and future decision-making, ultimately contributing to the development of maize cultivation (Basso, 2022)

2.1. Crop Phenology and Vegetation Cycle

Phenology is the study of periodic events in the life cycle of living species. In the case of crops, understanding the timing of these periodic events is crucial for various activities, such as irrigation scheduling, fertilizer management, evaluating crop productivity, and analyzing seasonal ecosystem carbon dioxide (CO_2) exchanges (Gao, 2021)

Phenology information detection is the basis for other remote-sensing-based agriculture applications. So far, there have been a lot of phenology estimation models based on remote-sensing data, but little attention paid microscopic mechanism of crop and environmental factors. Especially, in an increasingly food-insecure world, a comprehensive understanding of global croplands is a critical need, and crop phenology is a very important element in it (Dey *et al.,* 2019).

In recent years, the detection of phenological events using high temporal resolution satellite data (e.g., NOAA-AVHRR normalized difference vegetation index (NDVI) and Terra/Aqua-MODIS EVI) has emerged as an important tool for ecological and climate change studies over large areas. Many methods have been developed to detect significant phenological events based on remote sensing information. The majority of these methods involve two key steps: expanding the satellite-derived vegetation indices into a time series and then using this time series to determine specific phenological events based on a set of rules (Xiang, Liu et al. 2024).

Phenology describes the seasonal timing of events in the life of an organism. In the DGVM (Dynamic Global Vegetation Model) context, the key phenological events that are modeled include the timing of budburst, the length of time required to reach the full ‘leaf-on’ state, and the timing of leaf senescence and/or abscission. Although these events occur in all green plants, most DGVMs consider them only for deciduous woody plants in seasonal climates and perennial herbaceous plants with a seasonal display of above-ground biomass. The importance of modeling these specific cases lies in their control over the seasonal pattern of ‘greenness,’ i.e., the fraction of absorbed photosynthetically active radiation, which is a principal control of the rate of photosynthesis at the ecosystem level (Guo, Chen et al. 2022)

2.2. Factors Affecting Crop Growth and Yield Estimate

Crop growth is the irreversible increase in size where the development is the continuous change in plant form and function with characteristics transition phases. Liliane & Charles, (2020), have explained the factors affecting crop growth as follows:

2.2.1. Light

Plants have evolved throughout time in different locations throughout the world. Some plants developed in tropical locations under the canopy of large trees while others developed on slopes of harsh mountain ranges. For this reason, plants have adapted to different types of light. Some plants cannot adapt easily to new conditions. It is important to understand the type of light that your plants need and then provide it for them if you want them to grow(Guo, Chen et al. 2022).

2.2.2. Water

To survive, plants have to have water. Most plants are made up of nearly 90 percent water. Without the appropriate amounts of water, plants will be stressed and eventually die. Even plants that live in the desert such as the cactus need water, they just need less of it than other types of plants. Water provides plants with nourishment and hydration. Water that is in the soil will break down minerals and other elements of the soil. When the plants absorb water through their roots, they will also pick up nutrients that will travel to the cells of the plant (Dugas, Arkin et al. 2020)

2.2.3. Temperature

Temperature plays an important role in plant growth. Plants will slow down or speed up their growth rate based on the temperature. Warm temperatures encourage growth and germination. A warmer temperature will trigger a chemical reaction inside the cells of a plant and this will speed up respiration, transpiration, and the photosynthesis process. Plant growth is faster during warmer periods and will slow down or become dormant in a cooler period (Zhao, Liu et al. 2017)

2.2.4. Nutrients

Plants require certain nutrients to grow. Carbon, oxygen, and hydrogen are three essential nutrients that plants obtain from water and air. The other necessary nutrients are found in the soil. If a plant lacks any of these nutrients, its growth can be stunted (Bhatla, A. Lal et al. 2018)

2.2.5. Rainfall

Rainfall significantly impacts agriculture, as all crops need at least some water to survive, making rain crucial for farming. While regular rainfall is vital for healthy plants, too much or too little can be harmful or even devastating to crops (Kumar, Rayar et al. 2014)

2.2.6. Humidity

Humidity is very important to make photosynthesis possible. If the plant loses too much water, the stigmata will close the result of photosynthesis. Reduction of photosynthesis leads to low crop yields. High air humidity is favourable for many plant diseases and insect pests. It increases the growth of shoots and leaves at the expense of crop yields (Lad, Bharathi et al. 2022).

2.3. Vegetation Indices

Vegetation indices play a crucial role in crop monitoring, providing essential information and significantly contributing to agricultural operations. These indices use remote sensing data to measure crop health and development, assisting farmers, researchers, and policymakers in making informed decisions for sustainable agriculture. Vegetation indices are mathematical combinations of various light bands or wavelengths collected by remote sensing sensors, which provide information about the condition and vitality of vegetation (Liangliang, Zhang et al. 2021)

The use of vegetation indices in crop monitoring, such as NDVI, NDRE, and MSAVI, is revolutionizing agricultural methods. These indices provide valuable, real-time data on crop health and environmental conditions, allowing for better-informed decision-making, increased production, and a more sustainable farming approach. We are getting closer to securing food security and environmental conservation for future generations by utilizing the power of remote sensing and vegetation indices.(Li, Pei et al. 2020).

2.3.1. Normalized Difference Vegetation Index (NDVI)

In this algorithm, the red and near-infrared (NIR) bands of imagery are evaluated to calculate a vegetation index value. It's designed to detect differences in green canopy areas, emphasizing the green colour of a healthy plant. It's commonly used as an indicator of chlorophyll content in several different types of crops, including maize, soybean, and wheat.

NDVI= (NIR-RED)/ (NIR+RED)

The near-infrared (NIR) and red bands of the electromagnetic spectrum are used to calculate NDVI. Healthy vegetation strongly reflects near-infrared light while absorbing red light for photosynthesis. NDVI values range from -1 to 1, with higher positive values indicating healthier and more abundant vegetation (Huang, Tang et al. 2021).

2.3.2. Red-Edge chlorophyll vegetation Index (RECL)

The Recall vegetation index is responsive to chlorophyll content in leaves that is nourished by Nitrogen. Recall shows the photosynthetic activity of the canopy cover.

Recall= (NIR/RED)-1

Because chlorophyll content directly depends on the nitrogen level in plants, responsible for their greenness this vegetation index in remote sensing helps detect areas with yellow or shed foliage.

Recall values are most useful at the stage of active vegetation development but are not suitable for the season of harvesting (Fenghua, Tongyu et al. 2020).

2.3.3. Normalized Difference Red Edge Vegetation Index (NDRE)

The NDRE index combines the Near-infrared (NIR) spectral bands and a specific band for the narrow range between the visible red and the red-NIR transition zone (the so-called red-edge region). For the best data precision, it is recommended to use NDRE in combination with NDVI.

NDRE= (NIR-RED EDGE)/ (NIR+RED EDGE)

The given vegetation index applies for high-density canopy cover.

NDRE is typically used to monitor crops that have reached the maturity stage (Nadjla, Assia et al. 2022).

2.3.4. Modified Soil –Adjusted Vegetation Index (MSAVI)

The MSAVI vegetation index is designated to mitigate soil effects on crop monitoring results. Therefore, it is applied when NDVI cannot provide accurate values, particularly, with a high percentage of bare soil, scarce vegetation, or low chlorophyll content in plants.

MSAVI= (2*Band 4+1-sqrt ((2*Band 4+1)2-8*(Band4-Band3)))/2

Since MSAVI is adjusted to soil effects and is sensitive to early vegetation in the field, it works even when the earth is hardly covered with crops.

MSAVI is useful at the very beginning of crop production season when seedlings start to establish.

The Ratio Vegetation Index (RVI) improves the contrast between vegetation and ground cover. It is less affectionate toward the effects of illumination but more sensitive to the optical properties of the ground(Qi, Chehbouni et al. 2023).

Among these indices, we select NDVI as the most suitable because it effectively indicates the amount of green plant material present in a field. NDVI is particularly advantageous since green leaf area is a strong predictor of yield potential, reflecting the available light energy that drives photosynthesis, which is directly linked to grain filling and development. While other indices like NDRE and MSAVI have specific advantages, especially in late growth stages or in minimizing soil effects, NDVI's ease of use, widespread data availability, and established relationships with maize yield make it the most practical choice for large-scale agricultural monitoring (Singh, Komal et al. 2020)

2.4. Remote Sensing with Crop Growth and Yield Estimate

In recent years, remote sensing technology has been increasingly developed for modeling crop yield and monitoring agricultural drought due to its high temporal and spatial resolution in acquiring water, soil, and plant data, as well as its ability to evaluate different crop stresses (Karthikeyan, Chawla, et al. 2020)

2.4.1. Vegetation indices

A vegetation index is a numerical value that represents the biomass and health of vegetation for each pixel in a remote sensing image. It is calculated using specific spectral bands that are responsive to plant biomass and vitality. Vegetation indices derived from remote sensing canopies are straightforward yet powerful tools for assessing vegetation cover, health, and growth dynamics, among other applications (Xue,2017).

2.4.2. Crop Growth Monitoring

Crop health is one of the cornerstones of a successful farming season. Traditionally, crop health assessment was a very time-consuming and labour-intensive process to carry out. With the help of remote sensing technology and advanced sensors like the Sequoia multispectral sensor, farmers no longer need to spend hours or days surveying on foot. Instead, they can collect data, run analyses, and act on their problems all on the same day (Rasti, Bleakley et al. 2022).

Developed for modelling of crop yield and monitoring agriculture drought because of high temporal and spatial resolution in acquiring water, soil, and plant data and the ability to evaluate different crop stresses thus crop growth management (Ni, Zhang et al. 2018).

2.4.3. Crop Yield Estimate

Crop yield is defined as the quantity of crop harvested per unit of land area (Kg per hectare) which is used to determine the efficiency of food production (NISR, 2019). Crop yield estimate is an important subject of research in agriculture. Every farmer needs to know how much yield he/she should get from his/her expectations. The agriculture yield primarily depends on environmental factors such as weather conditions and agricultural inputs. Accurate Information about the history of crops is also an important thing for making decisions related to agriculture risk management(Cauvery,2018).

In general, there are two categories of methods to estimate crop yield by use of remote sensing being the empirical models, which fit a regression equation to predict crop yield based on vegetation indexes (VIs) such as NDVI, NDWI, EVI, RVI, MSAVI, etc. and a semi-empirical Methods (Ennouri 2019). Crop yields in developing countries do not benefit from the same level of agricultural technology as richer countries. Therefore, these countries have much lower yields. For example, corn yields in the US have doubled since 1970 from 5 to 10 t/ha (metric tonnes/hectare) due to improvements in agricultural technology such as irrigation, pesticides, herbicides, fertilizers, and plant breeding. Worldwide, yields of staple grains have doubled in the same time due to these same factors (Chunhua, 2024)

Remote sensing can be integrated with geographic information system (GIS) technologies or with satellite methods. The estimation method relates the vegetation indices with the final yield at a specific growth stage of the plant (vegetative and reproductive stages) during the growing season (Richards, 2022)

Vegetation indices refer to the spectral transformation of two or more bands designed to enhance the contribution of vegetation properties and allow reliable spatial and temporal inter-comparisons of terrestrial photosynthetic activity and canopy structural variations. These vegetation indices are derived from remotely sensed data. Remote sensing can also relate the final yield with the cumulative values of vegetation indices obtained during the whole growing season or a specific plant growth period (vegetative or reproductive stages) depending on the model used (normalized difference vegetation index, NDVI (Solymosi, 2019).

Remote sensing has become an asset for detecting environmental changes that impact crop health since initial studies in the 1980s and 1990s. Today, satellite imagery costs less and is more easily accessible, making remote monitoring more broadly available to scientists and the general public. The majority of previous research on crop monitoring is in developing countries where there are many yield and production data at high resolution. Such data significantly improve agricultural research, but are only affordable by wealthier nations (Fulton, 2020).

Remote sensing forms a foundation for estimating parameters of spatial variability over a large area using a frame sample design. It provides efficient and low-cost stratification based on crop proportions derived from visual interpretation or digital classification of remote sensing data. Remote sensing facilitates estimates based on ground surveys, near-real-time crop monitoring, easy derivation of vegetation data (including hilly terrain), and reduces the amount of field data that needs to be collected (Quattrochi, 2023)

2.5. Maize growth in Nyagatare District

Maize farming is crucial in Rwanda's agricultural environment, with Nyagatare district emerging as a leading player in maize agriculture. According to the Seasonal Agricultural Survey 2018 Annual Report (NISR, 2018), the Nyagatare district had around 47,000 hectares of maize production land. This significant region accounted for nearly 15% of the country's total 296,000 hectares of maize production in 2018. Several reasons contribute to the district's importance in maize growing. The region's ideal agro-climatic conditions and a growing emphasis on agricultural development have encouraged maize production expansion. Furthermore, the district's good soils and irrigation connections contribute to its maize-producing capacity (NISR, 2014).

Several reasons contribute to the district's importance in maize growing. The region's ideal agro-climatic conditions, combined with a growing emphasis on agricultural development, have encouraged maize production expansion. Furthermore, the district's good soils and irrigation connections contribute to its maize-producing capacity.

Nyagatare district's significant contribution to Rwanda's maize cultivation underscores the importance of studying maize growth in this region. This study aims to leverage remote sensing technology to assess crop production, growth, and yield estimation for maize cultivation in Nyagatare and offer valuable insights that can enhance agricultural practices and decision-making processes at both local and national levels.

Chapter 3: MATERIAL AND METHODS

This chapter deals with the details of the study area, remote sensing techniques, and their application in yield estimation. The details of materials used and the methodology adopted for using remote sensing to monitor growth and estimate yield of maize crop in Nyagatare district, Eastern Rwanda.

3.1. Study Area Description

Nyagatare district, located in the Eastern Province of Rwanda, is predominantly characterized by agriculture and livestock farming. The district comprises 14 sectors and 628 villages and has a vast area of 1,741 square kilometers, making it the largest district in the country in terms of land area. With a population of 653,861 as of 2022, Nyagatare is the second most populous district in Rwanda after the Gasabo District in Kigali City. The district shares borders with Uganda to the North, Tanzania to the East, Gatsibo to the South, and Gicumbi to the West.

The soil in Nyagatare District is characterized by a tightly bound humified layer due to the grassy savannah. Although the soil is rich in nutrients and mineral elements, it lacks organic substances. These soils can be effectively utilized with modern agricultural techniques and can support the creation of artificial pasture camps for livestock. Half of the Akagera National Park by area falls within Nyagatare District and is renowned for its wildlife, including lions, elephants, rhinoceroses, giraffes, buffaloes, antelopes, hippopotamuses, and other species. The park also supports a diverse range of birds, such as birds of prey, guinea fowl, partridges, and more (Panek, 2022).

Nyagatare District experiences low rainfall and high temperatures. According to the 2009 district climate survey, the district has two main seasons: a long dry season that lasts between 3 and 5 months, with an annual average temperature ranging from 25.3°C to 27.7°C. Monthly rainfall distribution varies from year to year, with an annual average of 827 mm, which is relatively low compared to other regions of the country. This variability makes it challenging to meet the needs of agriculture and livestock, particularly for modern livestock and mechanized farming (Mugunga, Wali et al. 2021).

The economy of Nyagatare District is primarily characterized by agriculture and livestock production, with agriculture predominantly taking place in wetlands through irrigation. According to a 2016 inventory, Nyagatare District contains ten marshlands, of which four are used for agricultural production, while six remain undeveloped (Green, 2019).

The savannah surrounding wetlands such as the Muvumba wetland is mainly used for livestock grazing by the local community and products from livestock breeds like milk and meat are sold to generate income to the local population. In addition, Nyagatare District's Economic situation is mostly dominated by agriculture and livestock production activities. This is done through the existence of huge plains and small hills that favor agricultural mechanization. Besides, its topography slows down soil erosion thus increasing the fertility of the soil and therefore agricultural development. Nyagatare is known for its industrial exploitation of granite, and its proximity to Akagera National Park, which brings touristic opportunities.

Rwangingo was selected in Nyagatare district as a study area that explicit the conditions of Nyagatare district. It was selected based on its agro-climatic zone, rainfall, and on its state of maize production where its production takes center stage. Cooperative agriculture effectively manages and develops maize planting in this area. Rwangingo Marshlands is 15.13% of Rwanda's land and is classified as part of the Dry Low Land agro-climatic zone. The region has a bimodal rainfall pattern, with an annual mean rainfall of about 863.5 mm (ranging from 827mm to 900mm). The major rainy season lasts from February to mid-June, with March receiving the most precipitation, with more than 120 mm per month. Furthermore, the second rainy season, which lasts from October through December, provides heavy rains, particularly in November. August, on the other hand, is the driest month, with rainfalls that are both feeble and irregular, frequently insufficient to meet the demands of agriculture and animal activities.

Rwangingo marshlands are in the Nyagatare Sector of Rwanda's Eastern Province, at UTM coordinates E0532260 N9824406 and E0532200 N9824173. This 900-hectare marshland, accessible via the National paved road Kigali – Kayonza - Kagitumba, serves as a significant resource for agriculture in the region, spanning both the Nyagatare and Gatsibo districts. The Umuvumba River and surrounding marshes are noteworthy because they permit agricultural mechanization, considerably increasing agricultural and livestock productivity. Notably, the Kagitumba valley has irrigation machinery such as pivots and splinters installed, which considerably contribute to agricultural development.

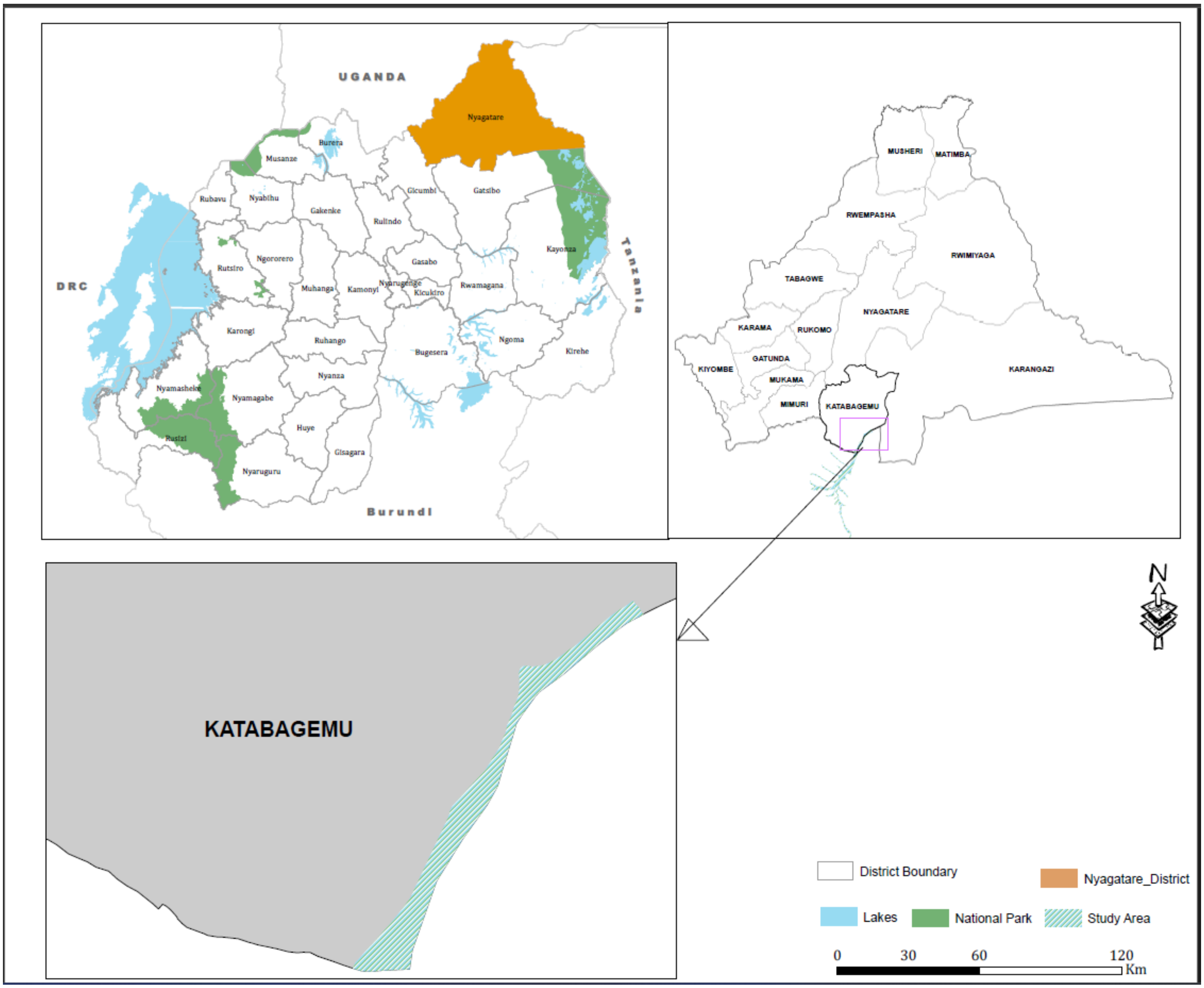

Figure 1 Study Area Location

3.2. Data Collection Methods

This section details the data collection methods used in this research, incorporating both primary and secondary data sources. Various techniques were employed, including interviews with key stakeholders in the Rwangingo cooperative such as maize farmers and the cooperative president as well as household surveys and observations to capture insights into harvest outcomes resulting from Seasons A and B of agricultural activity.

In this study, remote sensing was also employed to monitor growth and estimate maize crop yield in the Nyagatare district of Eastern Rwanda. GIS functionalities were utilized for processing and classifying data to reveal environmental and geographical factors influencing maize plantation development. Data collection was based on locations sampled during the 2021 Seasonal Agriculture Survey in Rwanda, focusing on larger fields dedicated solely to maize, smaller intercropped fields typical of smallholder agriculture, and natural areas. Data was gathered on three dates during the peak of the 2016 Season A growing season.

3.2.1 *Secondary* Data Collection

To obtain the required secondary data for satellite imagery, and vegetation indices the following collection tools and sources were utilized: Satellite Imagery: Landsat Images from the United States Geological Survey (USGS) were obtained. The USGS website (www.usgs.gov/landsat) served as the collection tool to access the desired satellite imagery. Vegetation Indices: The satellite imagery obtained from the USGS was utilized to calculate vegetation indices such as the normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), or leaf area index (LAI). These indices provide information about vegetation health and vigor.

3.2.2 Primary Data Collection

3.2.2.1 Interviews

Interviews were conducted with farmers from the cooperative to gain insights into their farming activities. The interviewees were selected based on their active involvement in maize agriculture and their ability to provide relevant information from their daily practices. These selected farmers are expected to offer valuable insights into several key aspects, including the area of maize cultivated, the irrigation methods and sources, the types of fertilizers used, pest and disease management, harvest dates, and the yields obtained.

3.2.2.2 Ground Truth Data Collection

Field visits were planned and conducted according to the exact factors that are seasonally influencing maize plantations in the Nyagatare district. A field conducted in Nyagatare District based on complete coverage of the farm level is a better way of collecting the agriculture data and the findings are much more precise. The main data that is collected is information on the phenological stage of maize and maize planting and harvesting data.

3.2.2.3 Survey

The target population of this study were the farmers in cooperative known as Rwangingo Rice Grower involved in maize farming. To get the sample size, n, needed to estimate a population proportion, p. The following formula

Names of cooperative	**Number of Farmers**
Rwangingo Rice Growth	88

Source: Katabagema Sector (2023)

The sample size required were calculated according to the fallowing formula

$\boldsymbol{N} = \frac{n0}{1+\frac{n0}{N}}$ Where, n0=$\frac{t^2 * pq}{d^2}$

Where n= required sample size.

N= Number of farmers in Rwangingo Cooperative (N=88)

p =probability equal to 0.5 and offer the reliable results.

q =Probability of value equal to 0.5

d =Margin error at 10%.

T= Confidence level at 95%(standard value of 1,6~2)

No =Constant calculated from the above expression.

N0=$\frac{(2^2)*0.5*0.5}{(0.10)^2}$=100

By replacing no and N by their values, The total number of required sample size will be equal to 47 as shown below:

n=$\frac{100}{1+\frac{100}{88}}$=$\frac{100*88}{88+100}$=46.80~ 47

Thus the sample size N=47 Farmer

3.3. Data Processing and Analysis

In our investigation of using remote sensing techniques to estimate crop growth and yield, we have opted to use Landsat 7 and Landsat 8 satellites as our primary data sources instead of other satellite images such as Sentinel-2. This choice is driven by two key factors: spatial resolution and temporal resolution. Landsat 7 and Landsat 8 offer a spatial resolution of 30 meters in their visible and near-infrared bands, whereas Sentinel-2 provides a higher spatial resolution of 10 meters (visible) and 20 meters (near-infrared). We find the coarser spatial resolution of Landsat to be sufficient for our study, which not only streamlines data management but also reduces the computational burden. Furthermore, in terms of temporal resolution, Landsat satellites provide more frequent global coverage, with updates approximately every 16 days, compared to Sentinel-2's 5-day coverage cycle. These factors collectively make Landsat 7 and Landsat 8 more suitable for our research objectives.

3.3.1 NDVI Calculation

We used Landsat 7 and Landsat 8 satellite images available from the USGS Earth Explorer website (https://earthexplorer.usgs.gov/) to perform a series of data processing processes to examine the spatial-temporal greenness of maize landscapes. The aim was to learn how the greenness of maize changes during the agricultural season. From the USGS Earth Explorer website, we downloaded Landsat 7 and Landsat 8 images corresponding to the appropriate agricultural season. These satellite photos give useful information on the Earth's surface, such as the health and distribution of plants. We performed atmospheric correction on the Landsat photos to assure data accuracy and remove atmospheric contamination. This procedure aids in the collection of trustworthy and consistent data for future analysis. We also mosaicked and georeferenced the preprocessed images, resulting in a geographically accurate seamless composite.

We created RGB composite images using the appropriate bands from Landsat images, such as near-infrared, red, and green. These composite images enable visual analysis by detecting and enhancing the presentation of greenness and other agricultural aspects. The NDVI was computed as follows: NDVI = (NIR - Red) / (NIR + Red), where NIR represents the near-infrared band and Red represents the red band. We learned a lot about the greenness levels of the maize landscape by creating NDVI raster layers for each Landsat image. We used ArcGIS or other Geographic Information System (GIS) software to investigate the spatial-temporal trends of maize greenness NDVIs throughout the agricultural season. The NDVI has been selected because several researchers (Fernandez-Ordonez & Soria-Ruiz, 2017; Nagy et al., 2021; Panek & Gozdowski, 2020) have highlighted and demonstrated the NDVI as an effective tool for monitoring and forecasting agricultural yield.

3.3.2. Statistical Test of Indicators of Healthy Maize Plant and the Factors Affecting Phenology.

This technique allowed us to see how the greenness of maize changes over time. Time series plots of NDVI values were created, revealing seasonal changes in maize vegetation health. We used a systematic data processing technique to examine the link between maize health indices and production metrics, which included constructing a comprehensive questionnaire aimed to collect data on various maize health indices and production metrics.

3.3.3. Statistical Test – Correlation

The questionnaire was carefully prepared to include pertinent questions concerning aspects that could affect maize crop health and production.

With the obtained data in hand, we used time series data analytics approaches to investigate the relationship between maize health indices and yield prediction. One of the key analyses we carried out was linear regression, which assisted in determining the association between particular health indices and crop yields. This research enabled us to analyze the influence of changes in health indices on maize production.

In addition, we used statistical analyses, such as correlation coefficient analysis, to determine the significance of the discovered relationships. These tests contributed to the validation of the strength and direction of the connections between maize health indices and production measures.

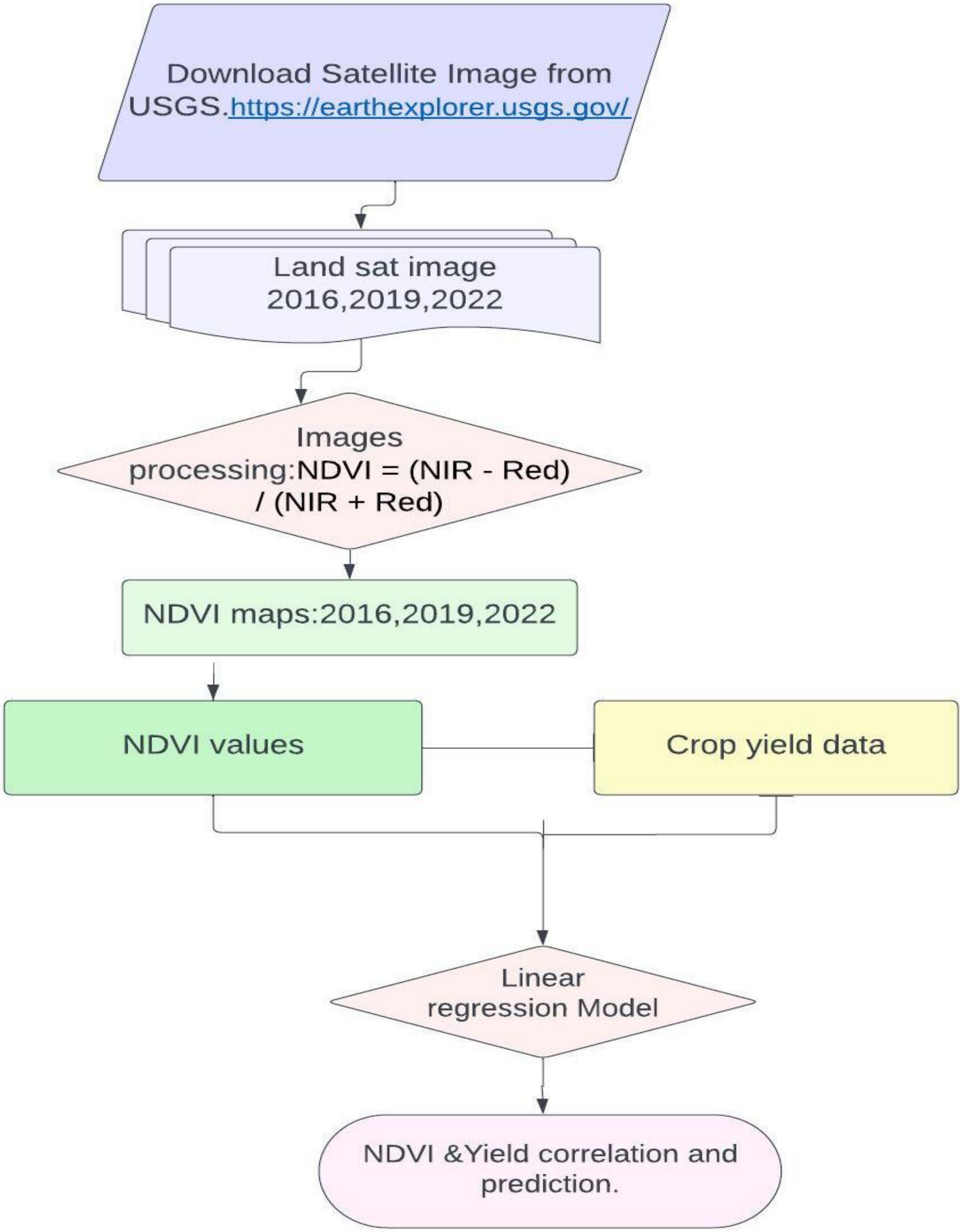

Figure 2: Methodology flowchart

Chap. 4. DISCUSSION AND RESULTS

4. 1. Introduction

This chapter explores the use of remote sensing to monitor the growth and estimate the yield of maize crops in Nyagatare District, Eastern Rwanda. The primary objective is to analyze and interpret the findings derived from field data collection. This was mainly achieved through questionnaires and field observations, which aimed to capture the farmers' perspectives. Data were collected from forty-seven farmers who responded to the questionnaire. The sample included 27 females out of the 47 respondents. The higher number of female participants reflects their predominant involvement in maize farming, while men are more engaged in both crop farming and livestock activities.

The respondents mentioned that the crops experienced water stress, pest pressures from armyworms, and damage from hippos, with the highest impact occurring during Season B, leading to a reduction in yields. Additionally, the high rainfall experienced in 2019 and 2021 caused flooding, which had a significant impact on the crops. Respondents noted that irrigation and canalization were steps taken to address these issues. The results indicate that crop yields increased in 2019 and 2021.

4.2. Spatial-temporal Greenness of Maize Landscape

4.2.1. Evolution of the Greenness of Maize for 2016 Season A&B

The greenness of the maize landscape was analyzed in this study, focusing on two seasons: Season A and Season B in 2016. Table1 presents the data for maize greenness, NDVI values, and the percentage they occupy in each season. The results indicate that the NDVI values for maize crops were generally higher in Season A compared to Season B, with better crop growth and productivity during this period.

Furthermore, the crop yield was mostly in the Medium to Very High NDVI class in Season A, while in Season B, the crop yield was mostly in the Low to Medium NDVI class. This suggests that the greenness and NDVI values of maize can serve as an indicator of crop yield and overall productivity.

Overall, the data provided in Table 1 and Figure 3 demonstrate the spatial-temporal variation of maize greenness and NDVI values in the two seasons analyzed. These findings can be useful for predicting crop yield and optimizing crop management practices.

Table 1: Spatial and temporal variation of maize greenness (2016 Season A&B)

2016 Season A			
Value	NDVI Area (%)	NDVI Values	NDVI class/ greenness of maize
1	7	0.02	Very Low
2	12	0.11	Low
3	25	0.21	Medium
4	35	0.28	High
5	21	0.59	Very High
2016 Season B			
Value	NDVI Area (%)	NDVI Values	NDVI class/greenness of maize
1	4	0.01	Very Low
2	40	0.07	Low
3	25	0.14	Medium
4	18	0.20	High
5	12	0.40	Very High

The given data in Figure 3 presents the NDVI values for the 2016 Season A and Season B for the maize crop. In Season A, the NDVI values range from 0.02 to 0.59, with the highest percentage of the area falling under very high greenness (21%) compared to Season B. In Season B, The Very High NDVI class, which represents the healthiest and very high greenness, covers only 12% of the area. This indicates that the maize crop in Season A is healthier and more abundant overall, with a higher potential for crop yield.

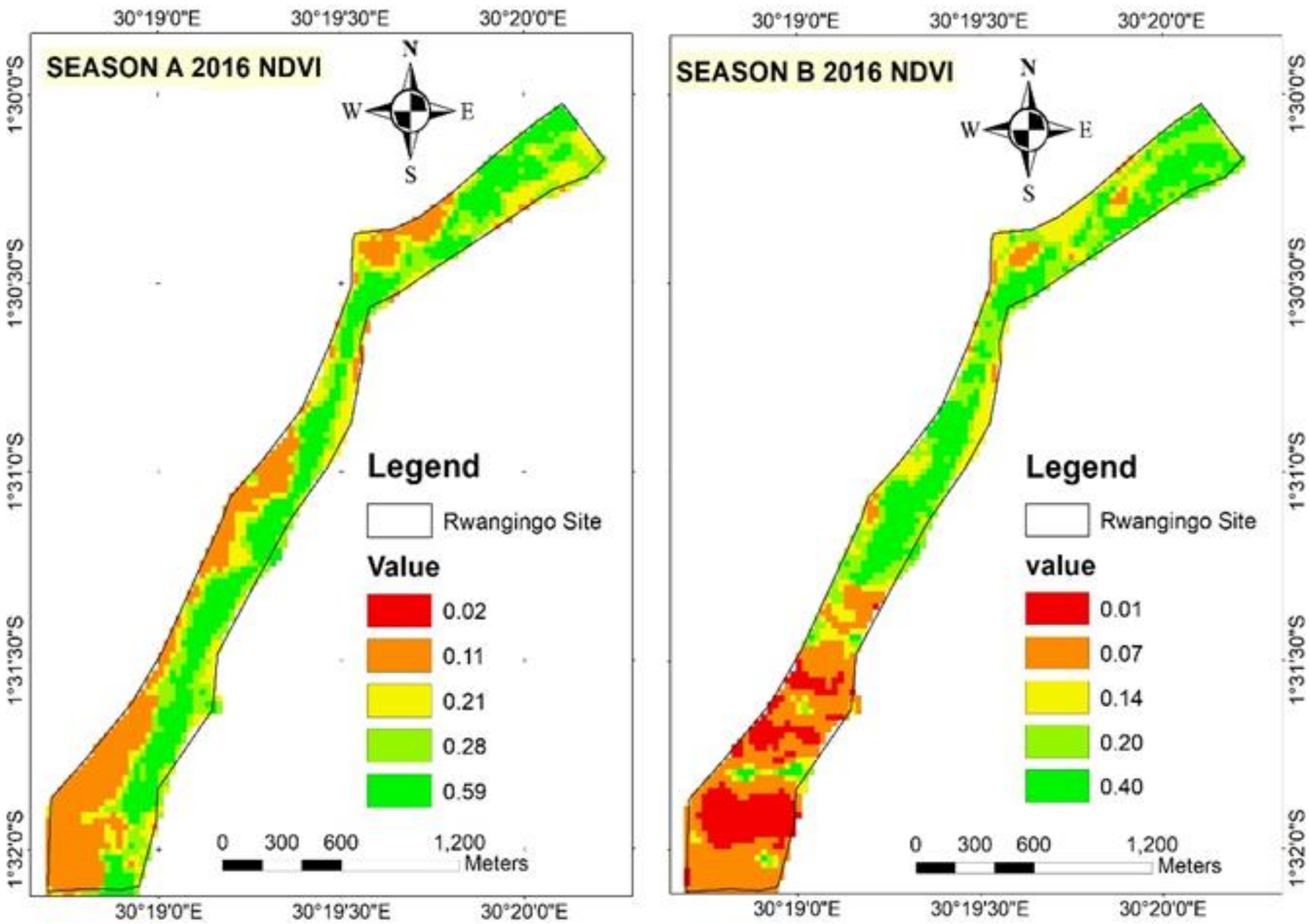

Figure 3: NDVI and maize greenness 2016 Season A&B

4.2. 2. Evolution of the Greenness of Maize for 2019 Season A&B

The results presented in Table 2 show a positive correlation between NDVI values, the greenness of maize, and crop yield in both Season A and Season B.

As you can see from the data, in Season A, the highest crop yield was obtained from the area with the highest NDVI value (0.57), while the lowest crop yield was obtained from the area with the lowest NDVI value (0.13). Similarly, in Season B, the area with the highest NDVI value (0.51) also had the highest crop yield, while the area with the lowest NDVI value (0.11) had the lowest crop yield

These findings suggest that there is a strong relationship between the health and abundance of maize crops, as indicated by NDVI values, and their resulting crop yield. These results can be used to develop better agricultural practices that maximize crop yield and help farmers in the Nyagatare district to increase their income.

Table 2: **Spatial and Temporal Variation of Maize Greenness (2019 Season A&B)**

2019 Season A			
Value	NDVI Area (%)	NDVI Values	NDVI class/greenness of maize
1	5	0.13	Very Low
2	17	0.27	Low
3	16	0.35	Medium
4	33	0.42	High
5	29	0.57	Very High
2019 Season B			
Value	NDVI Area (%)	NDVI Values	NDVI class/greenness of maize
1	4	0.11	Very Low
2	27	0.22	Low
3	14	0.31	Medium
4	30	0.38	High
5	26	0.51	Very High

Figure 4, shows the NDVI values and corresponding greenness of maize for the 2019 seasons A&B. As you can see from the map, for Season A, the NDVI values range from 0.13 to 0.57. The lowest value of 0.13 indicates very low greenness or unhealthy vegetation, which may suggest lower crop yields. On the other hand, the highest NDVI value of 0.57 indicates very high greenness and abundant vegetation, which may suggest the potential for above-average crop yields.

Similarly, for Season B, the NDVI values range from 0.11 to 0.51. The lowest NDVI value of 0.11 suggests relatively very low greenness or unhealthy vegetation, which may suggest lower crop yields. However, the highest NDVI value of 0.57 indicates very high greenness and healthy vegetation, which may suggest the potential for above-average crop yields

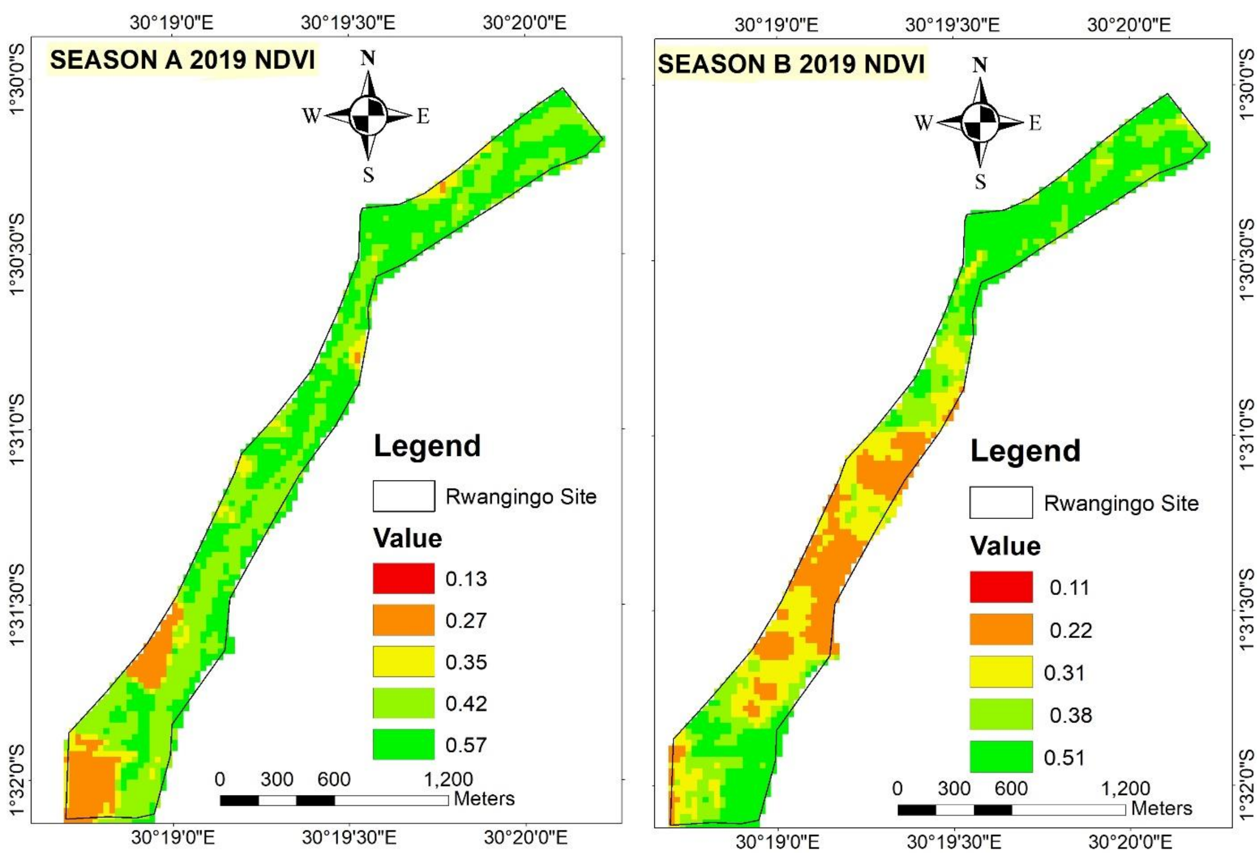

Figure 4**:** NDVI and maize greenness 2019 Season A&B

4.2.3. Evolution of the Greenness of Maize for 2022 Season A&B

The NDVI values and greenness of maize are depicted in Table 2, For Season A the NDVI values fall within the Medium to Very High range, with a few in the Very Low range. This indicates that the maize crop is likely to have good growth and a high yield. Additionally, the highest NDVI value is 0.56, which is in the Very High range, suggesting that there may be some exceptional areas of the crop with even higher yields. For Season B, the majority of the NDVI values fall within the Medium to Very High range, with a few in the Low range. This indicates that the maize crop is likely to have good growth and a high yield. Additionally, the highest NDVI value is 0.49, which is in the Very High range, suggesting that there may be some exceptional areas of the crop with even higher yields.

Table 3: **Spatial and Temporal Variation of Maize Greenness (2022 Season A&B)**

2022 Season A			
VALUE	NDVI Area (%)	NDVI Values	NDVI class/greenness of maize
1	5	0.06	Very Low
2	11	0.23	Low
3	24	0.32	Medium
4	32	0.49	High
5	27	0.55	Very High
2022 Season B			
VALUE	NDVI Area (%)	NDVI Values	NDVI class/greenness of maize
1	4	0.08	Very Low
2	22	0.17	Low

3	34	0.23	Medium
4	22	0.42	High
5	18	0.49	Very High

The map in Figure 4 shows the NDVI values and maize greenness for the 2022 Season A&B in the Rwangingo site. It provides information on the distribution of NDVI values and their corresponding NDVI classes across the study area. For the 2022 Season A, the map shows that the majority of the study area (59%) had NDVI values in the high to very high range (0.49-0.55), indicating healthy and abundant vegetation, which may suggest the potential for above-average crop yields. About 24% of the study area had NDVI values in the medium range (0.32-0.49), which may be sufficient for average crop yields. Only a small proportion of the study area (16%) had NDVI values in the low to very low range (0.06-0.23), which may indicate relatively sparse or unhealthy vegetation and may suggest lower crop yields.

For the 2022 Season B, the map shows that the majority of the study area (40%) had NDVI values in the high to very high range (0.42-0.49), indicating healthy and abundant vegetation, which may suggest the potential for above-average crop yields. About 34% of the study area had NDVI values in the medium range (0.23-0.42), which may be sufficient for average crop yields. A small proportion of the study area (26%) had NDVI values in the low to very low range (0.08-0.17), which may indicate relatively sparse or unhealthy vegetation and may suggest lower crop yields. The map suggests that the 2022 Season A&B had relatively healthy vegetation in most parts of the study area, with the majority of the area having NDVI values in the high to very high range. This may suggest the potential for above-average crop yields in the study area.

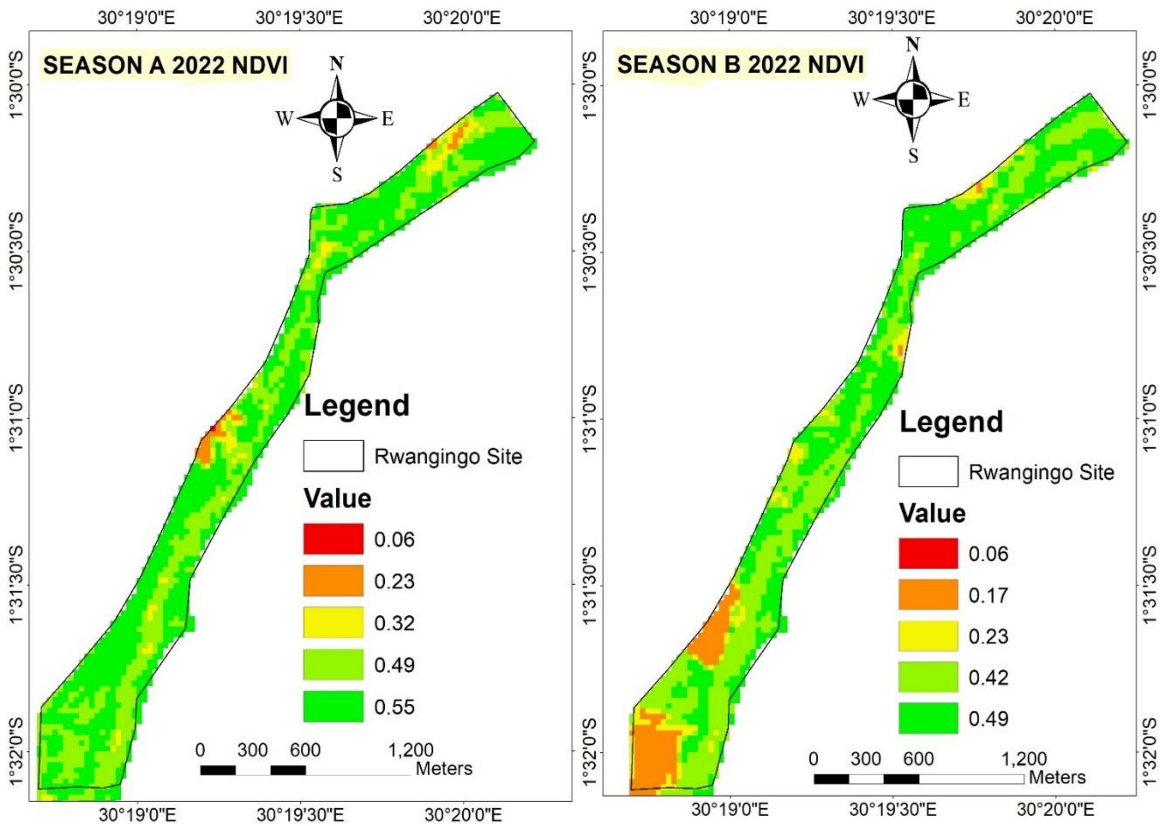

Figure 5: NDVI and Maize Greenness 2022 Season A&B

In summary, utilizing data from Earth observation satellites allows for effective monitoring of agricultural production at the local level and the forecasting of crop yields (Nagy, 2021). Numerous researchers globally have emphasized that NDVI and satellite data are valuable tools for predicting crop yields (Panek, 2020). The NDVI (Normalized Difference Vegetation Index) measures vegetation or greenness in an area and can be used to assess the health and productivity of crops (Ahmad, 2018).

The above information presents NDVI values for maize crop greenness across three different seasons 2016, 2019, and 2022 and compares them to evaluate crop growth and potential yield. The data reveal that areas with higher NDVI values and greenness corresponded to higher crop yields, while areas with lower NDVI values had lower yields. In all observed seasons, NDVI values were generally higher in Season A compared to Season B, indicating better crop growth and productivity in Season A.

These results can be further explained by plant phenology factors discussed in Section 4.1.2. It was observed that average rainfall during Season A was greater than during Season B, and soil fertility was higher in Season A, leading to better plant growth and higher yields. Conversely, Season B faced challenges from various pest and disease pressures, such as armyworm (NKONGWA) in 2016, which adversely affected plant growth. Additionally, extreme weather events, including flooding and drought conditions in 2019 and 2021, disrupted plant phenology and contributed to lower yields.

To accurately assess crop yield using NDVI results, it is crucial to consider the phenological characteristics of the crop, as these factors significantly influence NDVI values and the interpretation of results (Jiao, Gao et al. 2021)

4.3. Factors Affecting Crop Phenology on Rwangingo Site

A major biophysical component influencing crop phenology is water stress. Reduced yields can result from drought circumstances at crucial stages including tasselling, silking, and grain filling. This is consistent with the respondent's statement that maize crops experienced water stress during Season B. The relevance of irrigation and other water management measures in reducing the harmful consequences of water stress is highlighted by research (Yang, Tao et al. 2021).

Flooding and other extreme precipitation events can potentially mess with crop phenology. The impact of flooding on maize crops has been researched by (Chen, Dai et al. 2024), and the respondent's statement that excessive rainfall leads to flooding is consistent with their findings. When plants are flooded, it can hinder their ability to grow, absorb nutrients, and produce fruit.

Aside from weather, soil fertility is a major component in determining crop phenology. The timing of phonological occurrences may have been influenced, as noted by the respondent, by the fact that soil fertility was high in Season A and medium in Season B. Crop development, including phenology, is profoundly impacted by nutrient availability and soil fertility, as evidenced by several studies such as those conducted by (Ji, Pan et al. 2021). The answer noted that armyworms and hippo eating crops are two examples of pest stressors that might affect agricultural phenology. Pests can cause problems for crops at any point in their development. To reduce the negative effects on crop phenology and productivity, pest management measures are emphasized by the research of (Ji, Pan et al. 2021). The respondent identified irrigation and canalization as measures adopted to manage or reduce the effects of these biophysical elements on maize crop phenology. Irrigation can reduce water stress and maintain moisture levels crucial for growth. The risk of floods can be reduced and water flow managed via canalization. In terms of making seed choices, the respondent studied the characteristics of resilient seedlings. The maize strains RHM1409, WH507, WH403, and WH407 were selected as the top options. This is in line with findings from Li et al. (2018), which highlight the significance of choosing crop types that are adapted to certain environmental conditions, such as the availability, of water and the level of fertility in the soil (Paula,2022).

According to the respondent, getting a fuller picture of how crops are developing is possible by combining NDVI with information from crop phenology. In addition to what can be learned from phenological data, NDVI can also capture the vitality and health of the plants. The work by (Shammi,2020) highlights the value of integrating NDVI and phenology data for crop monitoring and yield forecasting. Ultimately, phenology in maize crops can be affected by biophysical factors as water stress, flooding, soil fertility, and insect pressures. The effects of these factors on agricultural growth and development can be managed and mitigated by taking measures like irrigation, canalization, optimal seed selection, and the incorporation of NDVI.

4.4. Relationship between Maize Health Indices (NDVI) and Crop Yield

The equation in Figure 6, $y = 0.06x + 0.3233$ is the regression equation for the relationship between NDVI (x) and crop production (y) for the Rwangingo sites. The R-squared value of 0.871 indicates that 87.1% of the variation in crop production can be explained by the variation in NDVI. The slope of the line (0.06) indicates that for every unit increase in NDVI, there is a predicted increase of 0.06 units in crop production. The R-squared value (0.871) indicates that the model fits the data reasonably well, as 87.1% of the variation in crop production can be explained by the variation in NDVI.

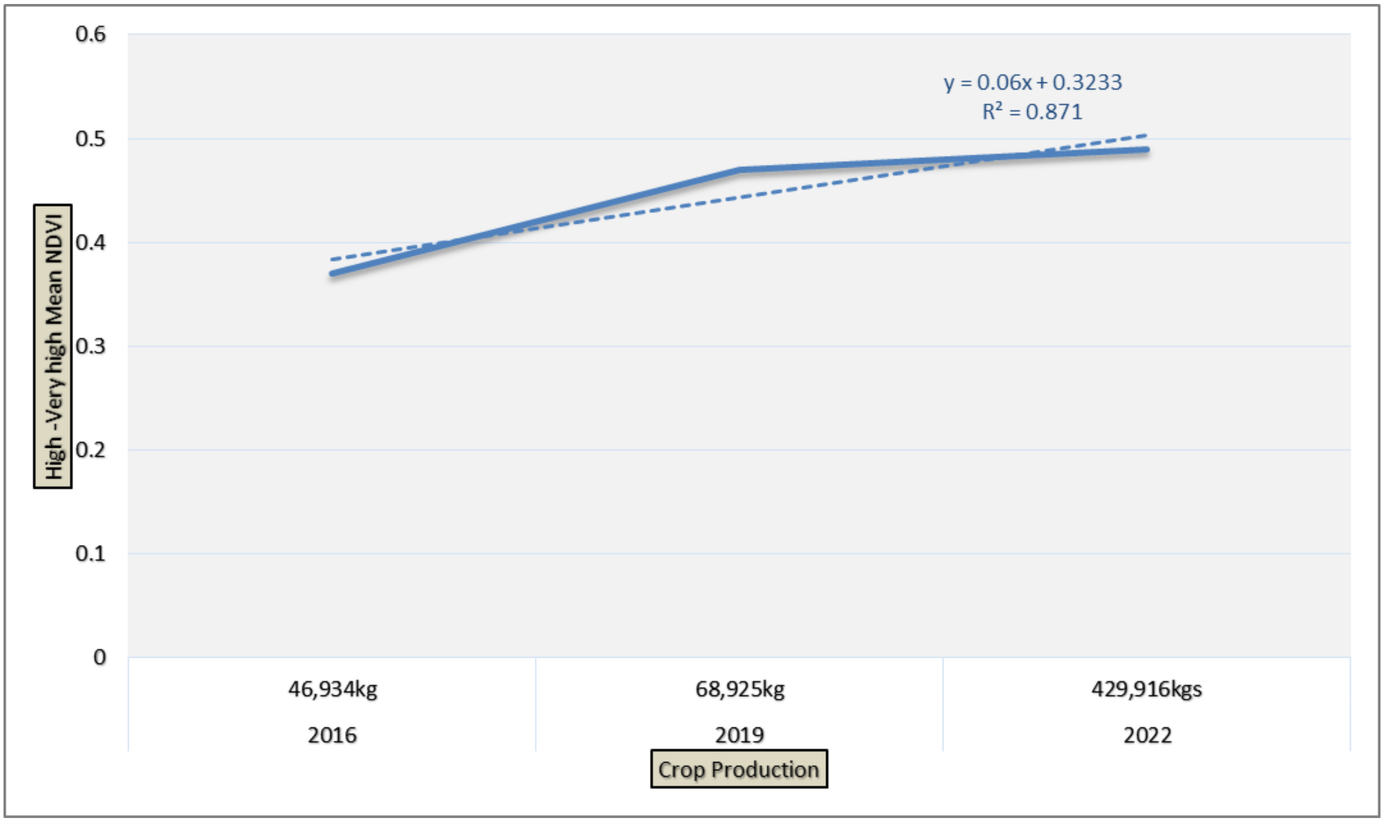

Figure 6: **Correlation of NDVI and Crop Yield**

The high correlation coefficient and coefficient of determination suggest that there is a strong positive relationship between NDVI and crop production in the Rwangingo sites. As NDVI values increase, so does crop production. This indicates that NDVI can be a reliable predictor of crop production in this region. However, it is important to note that correlation does not necessarily imply causation, and other factors such as weather, soil quality, and management practices could also influence crop production.

4.5. Yield Prediction

The average Normalized Difference Vegetation Index (NDVI) is expected to rise from now until 2050, which is consistent with the yield forecast (Figure7). When it comes to plant life, a greater NDVI value is indicative of stronger growth. The association between NDVI and crop yield is revealed by the regression model used to make predictions based on past data. Extrapolating the model to 2050, it is suggested that there is an anticipated rise in crop yield when the mean NDVI increases.

However, additional factors that can affect crop yield must be considered. These include climate change and shifts in management practices.

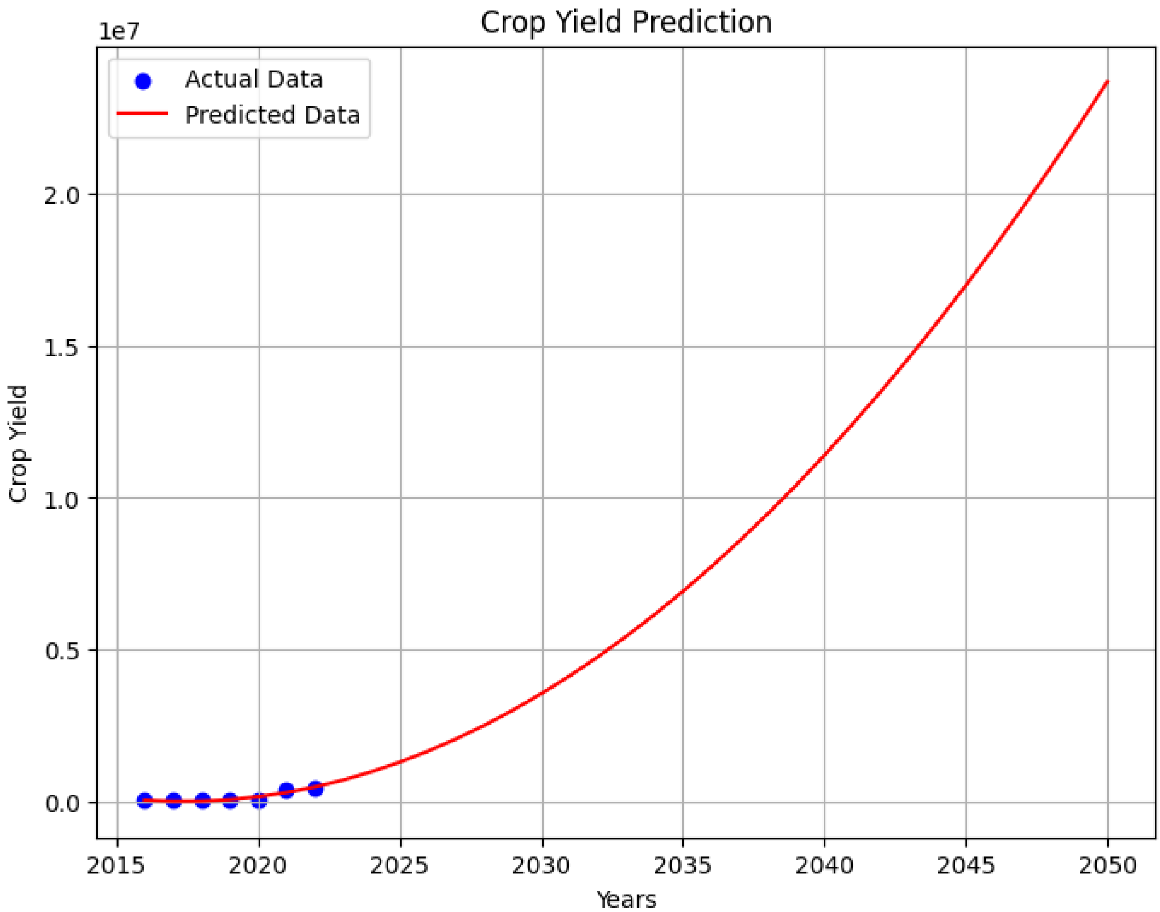

Figure 7: Crop Yield Prediction

The predicted crop output in Figure 8 has an R-squared (R2) score of 0.7812. The percentage of the variance in crop production that can be explained by the predictor variables (NDVI and years) used in the linear regression model is indicated by the R2 value. Crop yield and the predictor factors have a reasonably good association, as indicated by the R2 score of 0.7812. It's important to remember that the R2 score by itself cannot tell you if the model is overfitting the data or whether the predictions are accurate. The model's reliability and predictive power should be ensured by interpreting it in conjunction with other evaluation metrics and other analyses, even though it offers insightful information about the model's performance.

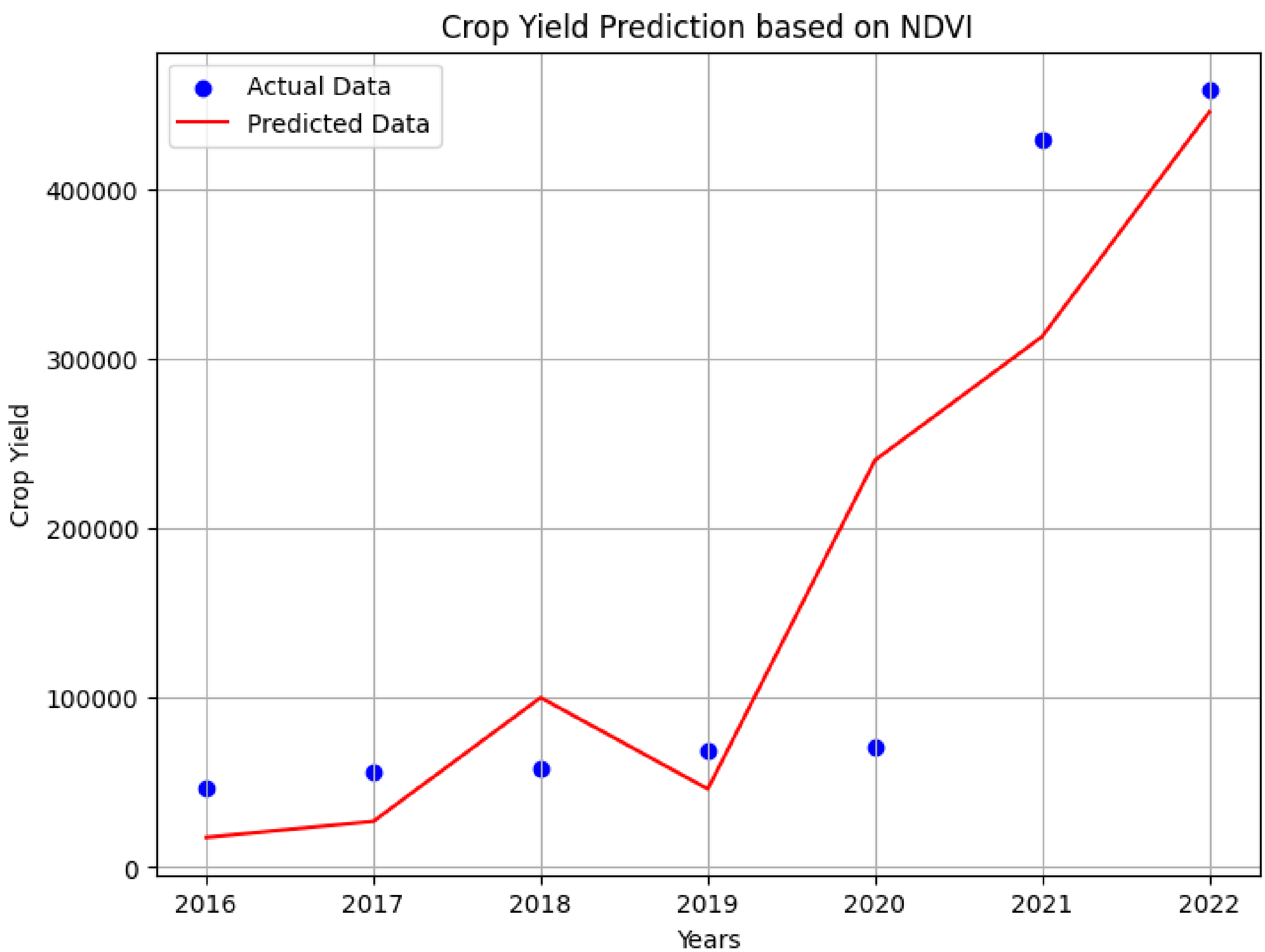

Figure 8: Crop Yield Prediction based on NDVI

The prediction made in Figure 8 suggests that crop production is likely to increase over time as the mean NDVI increases. In order to better understand how to predict yield using NDVI, Johnson and Brown (2016) analysed historical data to determine the correlation between NDVI and crop yield. A positive correlation between NDVI and crop yield was found. They extrapolated their regression model to predict rising mean NDVI, and thus higher crop yields in The future.

5. CONCLUSION

In general, this study demonstrates the effectiveness of remote sensing, specifically the use of NDVI (Normalized Difference Vegetation Index), in monitoring maize crop growth and estimating yield in Nyagatare District, Eastern Rwanda. By analyzing NDVI values across different growing seasons, the research reveals a strong positive correlation between vegetation health and maize productivity. The linear regression analysis, with a high R-squared value, confirms that higher NDVI values are indicative of increased maize yield, highlighting the potential of remote sensing technology for agricultural monitoring in the district.

However, while NDVI is a valuable tool for predicting crop performance, it is essential to consider that maize yield is influenced by various factors, including rainfall, crop phenology, soil quality, and farming practices. Therefore, NDVI should be used in conjunction with other agricultural indicators to develop comprehensive crop management strategies.

The findings from this study contribute to a deeper understanding of maize crop dynamics in Nyagatare District and lay the groundwork for sustainable agricultural practices in the region. By integrating NDVI-based monitoring with traditional farming knowledge, farmers and policymakers can improve decision-making processes, optimize resource allocation, and enhance food security in Nyagatare.

In the face of global challenges such as climate change and population growth, this research emphasizes the importance of adopting innovative, technology-driven approaches like remote sensing to ensure sustainable agricultural productivity in Nyagatare District and beyond.

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7. APPENDICES

7.1 Letters and Questionnaire

Obed BIMENYIMANA

Tel:0789860442

bimeobed@gmail.com

LETTER OF THE INFORMED CONSENT.

Dear Respondent,

I am a student at the University of Rwanda Nyarugenge Campus, I am studying the last year of my Masters of Geo-Information Science for Environment and Sustainable Development, Geography and Urban Planning department, in addition, I am conducting research entitled the use of remote sensing for crop growth and yield estimate of maize case study Nyagatare District.

The aim of this research is to access crop phenology and indicators of hearth plants.

You have been selected randomly as one of the respondents of this study. The information you will give us will be treated with the utmost confidentiality and used purely for academic purposes. The findings and recommendations from this study area are likely to benefit all farmers, Please spare some of your valuable time to answer these questions.

Thank you for your participation.

Obed BIMENYIMANA

UNIVERSITY of RWANDA

CST-SCHOOL OF ARCHITECTURE AND BUILT ENVIRONMENT

OFFICE OF THE COORDINATOR OF POST GRADUATE STUDIES

Recommendation for Obed BIMENYIMANA

This is to recommend Mr. Obed BIMENYIMANA, a final year student in the MSc of Geo-Information Science for Environment and sustainable Development (GI-ESD) under the School of Architecture and Built Environment (SABE), College of Science and Technology, University of Rwanda. He is working on the topic *"the Use of remote sensing for crop growth and yield estimate in Rwanda. Case Study of Nyagatare District"*. He will be collecting field data in Nyagatare from March to September 2023. In addition, He will need datasets on:

- Maize yields of Rwangingo, Kagitumba, and Muvumba in Nyatare District from 2016, 2019, and 2022;
- Shapefiles of the Site surveyed by SAS;
- Orthophoto of Nyagatare District in (2016,2019 and 2022).

Any assistance to him will be highly appreciated. For additional information do not hesitate to contact me on the tel. or email below.

Done at Kigali, the 7th March 2023.

Sincerely yours,

Dr Théophile NIYONZIMA
P.o.Box .377 BUTARE
TEL: +250 788450488

Questionnaire for Maize Farmers

Section 1: Respondent Identification

Names: ……………………	
Sex ☐	District: ………………………
Male ☐	Sector: …………………………..
Female ☐	
Telephone: …………………..	Cell: ……………………………
	Village: ………………………

Section 2: Assessment of crop phenology and indicators of healthy plants

Information from the farmers

Information on Maize plantation	**Location (X, Y).**
Location of the site and Plot (With XY coordinates): **Sector:** **Cell:** **Village:** **Site:** **Plot Id:**	

Area in Ha: **Plot size**	
Maize crop variety name and duration: Kigega (ZM607), ISARM081 (Pool15_ QPM_SR), Ndaruhutse (Pool 32), H513, SC513, SC525, ISARM101, ISARM103, RHM101, RHM102, RHM103 and WH505.	
Date of sowing and Sowing density	
Details on irrigation (if any)	
Rate of fertilizer application and details of quantity and stage of the application	
Organic amendments used (If any applied)	
Pest and disease attack and control (if any)	
Date of harvesting	
Yield estimation of the plot	

Source: Credited by Author 2023

7.2. Interaction with the farmers for the collection of crop management data

…**………………………………………………………..**

7.3: Crop prediction code.

```
import numpy as np

import matplotlib.pyplot as plt

from sklearn.linear_model import LinearRegression

# Given data

years = np.array([2016, 2017, 2018, 2019, 2020, 2021, 2022])

crop_yield = np.array([46934, 55768, 58540, 68925, 71053, 429916, 459353])

ndvi = np.array([0.218, 0.273, 0.295, 0.383, 0.342, 0.364, 0.355])
```

```python
# Convert years and NDVI to a 2D array for linear regression
X = np.column_stack((years, ndvi))
# Fit a linear regression model
model = LinearRegression()
model.fit(X, crop_yield)
# Predict crop yield for the year 2050 based on NDVI
year_2050_ndvi = np.array([[2050, 0.355]])  # Change NDVI value based on the actual NDVI for 2050
crop_yield_2050 = model.predict(year_2050_ndvi)[0]
print("Predicted crop yield in 2050 based on NDVI:", crop_yield_2050)
# Create a graph to visualize the predicted crop yield over the years based on NDVI
plt.figure(figsize=(8, 6))
plt.scatter(years, crop_yield, color='blue', label='Actual Data')
plt.plot(years, model.predict(X), color='red', label='Predicted Data')
plt.xlabel('Years')
plt.ylabel('Crop Yield')
plt.title('Crop Yield Prediction based on NDVI')
plt.legend()
plt.grid(True)
plt.show()
import numpy as np
from sklearn.linear_model import LinearRegression
from sklearn.metrics import r2_score
# Given data
years = np.array([2016, 2017, 2018, 2019, 2020, 2021, 2022])
crop_yield = np.array([46934, 55768, 58540, 68925, 71053, 429916, 459353])
```

ndvi = np.array([0.218, 0.273, 0.295, 0.383, 0.342, 0.364, 0.355])

 # Convert years and NDVI to a 2D array for linear regression

X = np.column_stack((years, ndvi))

 # Fit a linear regression model

model = LinearRegression()

model.fit(X, crop_yield)

 # Predict crop yield for the year 2050 based on NDVI

year_2050_ndvi = np.array([[2050, 0.355]]) # Change NDVI value based on the actual NDVI for 2050

crop_yield_2050 = model.predict(year_2050_ndvi)[0]

print("Predicted crop yield in 2050 based on NDVI:", crop_yield_2050)

 # Calculate the R-squared (R2) score for the crop yield prediction

y_pred = model.predict(X)

r2 = r2_score(crop_yield, y_pred)

print("R-squared (R2) score for the crop yield prediction:", r

7.4. Research Matrix

Research objectives	Research questions	Data needed and sources	Data analysis approach	Expected results
To analyses spatial-temporal greenness of maize landscape.	How does the greenness of maize evolve throughout the agriculture season?	Landsat 7 and 8 images. https://earthexplorer.usgs.gov/	Band combination and NDVI calculation in ArcGIS using the formula: NDVI = (NIR - Red) / (NIR + Red)	NDVI indices representing the spatial-temporal changes in maize greenness over the agriculture season.
To identify the indicators for monitoring maize phenology	What are the indicators of a healthy maize plant/maize plantation?	Field survey questionnaire	Descriptive statistics and data visualization	A set of indicators that characterize a healthy maize plant and the factors affecting phenology.
To analyze the correlation between maize health indices and production	Which maize health indices are significantly correlated with potential yield in the prediction of crop yields using time series data analytics?	Field survey questionnaire	regression analysis (linear regression)	Identification of key maize health indices influencing crop yield and their correlation with production potential.

To predict maize yield production using time series remote sensed data	What is the level of agreement between predicted maize yield and measured yield for the last 3 decades?	Maize yield collected data from survey.	• Processing linear regression model using the training subset, with maize yield as the dependent variable and selected remote sensing features as independent variables. We employed evaluation metrics such as R-squared (R2) to quantify the model's accuracy and goodness of fit. Interpret the coefficients of the linear regression model to understand the individual contributions of different remote sensing features in predicting maize yield. • Extract insights into how changes in NDVI and other variables impact maize yield.	Maize yield predicted.