Development of an Integrated Farming Information System for Smallholder Farmers in Developing Countries

Thesis by

Babatunde David Aremu

Supervised by

Prof. Benjamin Risse, (ifgi, WWU)

Co-Supervised by

Dr. Torsten Prinz, (ifgi, WWU)

Prof. Dr. Marco Painho (NOVA IMS, UNL)

In Partial Fulfillment of the Requirements for the Degree of Master of Science in Geospatial Technologies

University of Münster,

Universidade Nova de Lisboa (UNL),

Universitat Jaume I (UJI)

Münster, Germany

2024

DECLARATION OF ORIGINALITY

I declare that the work described in this document is my own and not from someone else. All the assistance I have received from other people is duly acknowledged and all the sources (published or not published) are referenced.

____

Babatunde David Aremu

Muenster Germany

28 February 2024

ACKNOWLEDGMENTS

I extend my heartfelt appreciation to all my lecturers over the past 18 months; their impactful guidance has been instrumental in my academic journey. Special gratitude is reserved for my esteemed supervisors: Prof. Risse Benjamin, Dr. Torsten Prinz, and Prof. Dr. Marco Painho, whose unwavering support significantly contributed to the successful completion of my thesis.

To my parents, whose boundless love has been my anchor, and my sister, to whom I am deeply indebted for her unwavering support, I express sincere gratitude. Additionally, I am grateful for the care and support of my friends, whose presence has played a crucial role in maintaining my mental stability throughout this endeavor.

ABSTRACT

Smallholder farmers play a pivotal role in bolstering food security within developing nations. Yet, they face a myriad of challenges to agricultural productivity in tropical regions, including pest and disease outbreaks, extreme weather events, and market instabilities, all of which pose threats to food security and stability. In this context, technological advancements have emerged as a transformative force in promoting sustainable agriculture globally.

However, there exists a notable dearth of literature on monitoring crop phenology using web applications, which is essential for fortifying farmers' resilience to climate-related factors and facilitating informed decision-making among stakeholders. Addressing this gap, this study delves into past research and integrates features—such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), weather forecasts, and others—that were previously conceptualized but remained confined to academic discourse and papers, into an application designed to empower smallholder farmers and stakeholders with the tools needed to make informed decisions about farm-related activities, such as irrigation scheduling, fertilizer application, pest management, crop health and land use patterns, which play a crucial role in maximizing crop productivity and ensuring sustainable farming practices.

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

1.1 Overview

Smallholder farmers in developing countries indeed encounter numerous obstacles when it comes to improving their agricultural practices. These challenges include a lack of access to advanced tools and information necessary for making informed decisions about crop health, irrigation, and nutrient management. To address these pressing issues, the development of a Decision Support Web Platform for Farm-Related Activities (DSWPF) is imperative. This platform can serve as a comprehensive resource, providing smallholder farmers with essential data and guidance on crop management, irrigation scheduling, and even fertilizer application practices based on scientific knowledge. By empowering farmers with this information, they can optimize their agricultural processes, increase productivity, reduce resource wastage, and ultimately achieve more sustainable and profitable farming practices. This chapter provides a detailed background of study, statement problem, significance of study including its aims and objective.

1.2 Background

Agriculture stands as a pivotal force in combating poverty, inequality, and hunger, particularly in countries where a significant portion of the population engages in farming activities (Justina, Robert, Edward, & Felix, 2023). Poverty can be directly addressed through agricultural development, as a substantial proportion of the rural poor depend on agricultural activities for their livelihoods (FAO, 2012). It also plays a crucial role in global economic growth, contributing 4% to the world's gross domestic product (GDP). In many least-developed countries, agriculture's contribution to GDP exceeds 25%, underscoring its significance (World Bank, 2023).

However, global agriculture will need to significantly alter in the ensuing decades in order to meet the future food needs of a growing and increasingly affluent and urbanized population. Globally, smallholders in developing countries are crucial to the equation of food security (Fan, 2020). Over 80% (475 million) of the world's farms operate on less than two hectares of land. According to Lowder *et al.*, these farms produce 80% of the food produced in Asia and sub-Saharan Africa (SSA), although making up only 12% of all farmlands worldwide (Lowder, 2014; Hoang, 2020). Smallholder farmers are indispensable in ensuring food security in

Nigeria and contribute significantly to the global food system (Chiaka, et al., 2022; Daniel & John, 2022).

Smallholder farmers already confront multiple risks to their agricultural productivity in the tropics, such as pest and disease outbreaks, extreme weather, and market shocks, among others, which frequently jeopardise the security of their household's food supply and income (Karen O'Brien, 2004). Smallholder farmers are projected to be disproportionately impacted by climate change, which will make their risks even worse. The primary cereal crops grown by smallholder farmers, rice, maize, and wheat, will be negatively impacted by even mild temperature changes, according to recent studies utilising regional and global simulation models (Morton, 2007).

Agriculture, when combined with digital innovation and integrated approaches, not only alleviates poverty but also propels inclusive growth, reduces disparities, and addresses global food security concerns (Gassner, et al., 2019). Technological advancements have become a catalyst for revolutionizing sustainable agriculture on a global scale (Khan, 2021). These breakthroughs encompass a broad spectrum of methods, such as precision agriculture, remote sensing, sensor technology, digital platforms, and data analytics. They possess significant potential to revolutionize conventional farming methods, enhance resource efficiency, reduce environmental footprint, and enhance overall agricultural sustainability (Triantafyllou A, 2019). The COVID-19 pandemic has showcased the importance of digital agriculture in maintaining food production and supply chains in developing countries by offering remote access to information and resources, digital agriculture proves to be a resilient solution. (Willy, et al., 2020). The remarkable accessibility of high-resolution satellite imagery, encompassing spatial, spectral, and temporal resolutions, has spurred the adoption of remote sensing in various precision agriculture applications. These include tasks such as crop monitoring, irrigation control, nutrient application, disease and pest management, as well as yield forecasting (Sishodia RP, 2020).

While smart, digital, and precision technologies are revolutionizing agriculture worldwide, it's essential to emphasize their potential for smallholder farmers in low-income countries. These smallholders, despite representing just 12% of global farmland, produce an estimated 80% of the food in regions like Asia and sub-Saharan Africa (Sarah, Lowder, Skoet, & Raney, 2016) which signifies substantial opportunities for them to harness these technologies for increased productivity and income.

Smallholder farmers often have limited knowledge about the boundaries of their plots, which can lead to inefficiencies in land use. Image segmentation techniques can be employed to delineate land boundaries using remote sensing data and satellite imagery. Such a system can assist farmers in better organizing and utilizing their land resources. Previous studies, such as those by T. Tiemann (2023), have explored the use of integrated farming options in Southeast Asia, highlighting the importance of precise land delineation (Tiemann & Douxchamps, 2023).

Vegetative indices like the Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI), and Enhanced Vegetation Index (EVI) are valuable tools for assessing crop health and water stress. These indices can be calculated using satellite imagery and drone technology, providing smallholder farmers with essential data for crop monitoring and decision-making. Digital farming systems can offer a number of benefits to smallholder farmers, including increased productivity, reduced costs, and better market linkages (Xie, Luo, & Zhong, 2021). Accurate weather information plays a critical role in determining the appropriate timing for fertilizer application. By integrating near real-time weather data into the web platform, smallholder farmers can make informed decisions about when and how much fertilizer to apply (Dhanaraju, et al., 2022). Notably, the United Nations has acknowledged the significance of frontier technologies in alleviating information-related obstacles encountered by smallholder farmers. These technologies are instrumental in delivering invaluable information that empowers farmers to make well-informed decisions (United Nations, 2021).

This project is going to transform the way smallholder farmers in developing countries manage their farms. It will enable them to make data-driven decisions, enhance crop health, optimize resource utilization, and ultimately improve their overall quality of life. This project aligns with global efforts, as recognized by the United Nations Sustainable Development Goals 2, to achieve zero hunger by 2030 by investing in sustainable agricultural practices to reduce and mitigate the effects of conflict and pandemic on global nutrition and food security.

1.3 Statement of Problem

Smallholder farmers in developing countries, particularly Nigeria, face numerous challenges due to the reliance on rain-fed agriculture, lack of access to crucial agricultural information, and the impacts of climate change due to increased temperatures and more extreme weather events (Commodity Port, 2019; Sharma, 2021; Josephine, 2022). These challenges are compounded by a rapidly increasing population and inefficient production techniques, exacerbating food insecurity (World Bank, 2023; Nmadu & Akinola, 2015).

In response to these challenges, there is an urgent need for innovative solutions to secure sustainable food production and distribution. One promising approach is the development of a web platform that aids smallholder farmers in making informed decisions about farm related activities. This system would leverage geospatial technologies, machine learning, and user-centered design principles to bridge the digital divide and provide near real-time agricultural insights. By empowering farmers with this information, the platform will contribute to the advancement of sustainable farming practices, heightened productivity, and ultimately, improved livelihoods.

1.4 Research Questions

- What are the optimal vegetation indicators that can provide actionable insights to support smallholder farmers in making informed decisions about crop health, irrigation, and nutrient management?
- Which global land cover classification datasets are most effective for accurate land cover classification and image segmentation?
- Which tools and technologies are most suitable for developing a user-friendly and accessible Integrated Farming Information System that seamlessly integrates real-time data for smallholder farmers and decision makers?
- What are the benefits of these technologies to farmers and stakeholders?

1.5 Aims and Objectives

The primary aim of this project is to develop a web platform that aids smallholder farmers in making informed decisions about farm related activities. The platform will provide actionable insights to enhance agricultural productivity, sustainability, and the overall livelihoods of farmers in developing countries.

The specific objectives are to;

a) determine NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), and EVI (Enhanced Vegetation Index) for selected farms in Benue State using satellite imagery to gain insights into crop health and vegetation cover.

b) integrate weather data from Open Weather Map into the platform, enabling farmers to make informed decisions on fertilizer application based on weather conditions.

c) utilize global land cover classification datasets to automatically categorize and map land use types within the AOI.

d) develop an interactive web platform for data visualization which will provide accessible and accurate visual representations of NDVI, NDWI, and EVI data.

1.6 Significance

Nigeria faces a severe hunger crisis, with a Global Hunger Index score of 28.3 in 2023 (Global Hunger Index, 2023). This situation is further intensified by the fact that a substantial portion of the Nigerian population, 63% (133 million people), lives in multidimensional poverty which contributes directly to food insecurity (Utomi, 2023). Despite these challenges, smallholder farmers play a pivotal role in ensuring food security for Nigeria and make significant contributions to the global food system (Daniel & John, 2022). Their resilience and dedication are essential to addressing the country's hunger crisis.

The Smallholder farmers are vulnerable to the effects of climate change and lack access to essential resources, which can affect their agricultural output (Chiaka, et al., 2022). The empowerment of smallholder farmers hinges on the provision of timely and accurate information regarding improved agricultural practices. This entails overcoming challenges in disseminating tailored advice, as traditional methods like in-person meetings or radio programs often fall short (Fabregas, 2022).

Firstly, the platform's capability for integration of vegetative indices such as NDVI, NDWI, and EVI, enables precise monitoring of crop health and water stress. This precision is instrumental in enhancing precision farming practices, optimizing resource use, and ultimately maximizing crop yields (Mitiche & Aggarwal., 1985). Furthermore, the incorporation of weather information into the platform addresses a common challenge among smallholder farmers who often lack access to weather data for decision-making (WMO, 2020). This integration enables timely and data-driven fertilizer application, reducing resource waste and enhancing yield quality.

Landcover classification, another objective of the platform, provides critical insights into land use. It empowers farmers to optimize land resources efficiently, supporting sustainable land management and conservation practices, which are especially crucial in developing regions (Phan, Kuch, & Lehnert, 2020). In addition, the platform's provision of real-time weather forecasts and climate data equips smallholder farmers with the tools to better adapt to climate variability and extreme weather conditions. This resilience is essential for farmers vulnerable to the impacts of climate change (Roudier, et al., 2014).

By equipping smallholder farmers with the tools and information needed for improved agricultural practices, this thesis contributes to the broader goal of ensuring a stable and sufficient food supply, particularly in regions where food security is a pressing concern.

2. LITERATURE REVIEW

2.1 Smallholder Farmers

Smallholder farmers, managing plots under 24 acres (Bread for the World, 2023), play a crucial role in global food production, contributing over 50% of the world's agricultural gross product (Ricciardi, Ramankutty, Mehrabi, Jarvis, & Chookolingo, 2018). In Ghana, they account for 90% of local food production, constituting 28.3% of GDP and engaging over 50% of the labor force (Emmanuel, 2016). In Nigeria, smallholders cultivate 70% of arable land, generating 90% of the country's food output, vital for food security (FAO, 2012; Adeite, 2022). Over 80% of Nigerian farmers are smallholders, efficiently cultivating diverse crops like maize and rice (Chiaka, et al., 2022). Despite focusing on specific crops due to external support, smallholders contribute to biodiversity preservation, often outperforming larger enterprises (Chiaka, et al., 2022).

Chicka et al., (2022) investigates the potential of smallholder farmers in Nigeria to steer the country towards self-sufficiency and ensure ample household food consumption through local production. Their examination focuses on food production, yield outcomes based on crop production and harvested areas, and the proportion of crops allocated for food or other purposes. Their findings reveal a concerning trend of low production and declining yields for essential crops such as rice, sorghum, soybean, cassava, and yam, with maize being the exception, despite an increase in harvested areas from 2015 to 2018. This indicates an insufficient per capita food supply, particularly for cereals. They propose strategies to address this, including closing the yield gap for cereals, minimizing post-harvest losses, and establishing a sustainable equilibrium in the utilization of major food crops for animal feed to alleviate pressure on land resources. The regional variations in production performance underscore the need for tailored approaches to harness the agricultural potential of each geopolitical zone. Lastly, their study advocates for promoting dry-season cultivation through irrigation to enable biannual harvesting, offering valuable insights for policymakers, stakeholders, and the international community seeking to collaborate and invest in the agricultural sector (Chiaka, et al., 2022).

Smallholder farmers in Nigeria grapple with various challenges affecting their livelihoods and agricultural productivity. These include limited capital, insufficient labor, market access issues, post-harvest losses, mechanization constraints, and information gaps (Adeite, 2022; Chiaka, et al., 2022; Mgbenka & Mbah, 2016). External factors like global economic crises and inadequate access to essential agrochemicals exacerbate the hardships faced by these farmers. Addressing these issues is crucial for improving the well-being and food security of smallholder farmers in Nigeria (Commodity Port, 2019; FAO, 2012; Fan, 2020).

Africa is currently grappling with an escalating food security crisis due to a projected population surge, doubling by 2050, leading to a corresponding doubling of food demand. Smallholder farmers, responsible for 80% of crop production in Sub-Saharan Africa, face challenges such as climate change effects and limited access to finance, hindering their ability to invest in necessary technologies. Access to finance could enable them to procure improved inputs, potentially doubling yields and incomes, thus addressing the growing demand for food. Financial institutions interested in lending to agribusinesses and smallholder farmers encounter risks like seasonality, irregular cash flows, and systemic issues. To effectively analyze and monitor credit portfolio risk, these institutions require operational data on farmers and farmlands. Recognizing the data and information gap between farms and financial institutions, satellite and remote sensing technology aid financiers in managing their agriculture lending operations, encompassing pre-loan assessments and ag-portfolio monitoring at scale. This not only enables financiers to save time and costs but also facilitates market expansion while concurrently granting millions of smallholder farmers access to a broader range of financial services (*Disrupt Africa*, 2021).

2.2 Remote Sensing for Agriculture

Plants interact uniquely with sunlight, spanning the full electromagnetic spectrum emitted by the sun, based on the observed wavelength. This interaction leads to three pathways for incident solar radiation: transmission, reflection, or absorption. Notably, the information regarding the biophysical composition and physiological state of plants is encoded in the reflected electromagnetic radiation, a phenomenon measurable through satellite sensors (Segarra, 2020).

Remote sensing methodologies aim to deduce the characteristics of objects by analyzing alterations in the properties of electromagnetic energy caused by interactions with these objects. Nevertheless, it is essential to note that the spectral behavior of vegetation primarily hinges on the spectral attributes of its leaves (Teresa Calvão, 2015). In vegetation, the way different light wavelengths are absorbed or reflected is directly tied to the leaf's cellular structure, illustrated in Figure 2.1. Healthy green vegetation exhibits significant electromagnetic responses in the 'green' visible and near-infrared (NIR) wavelengths. Specifically, healthy leaves absorb a substantial portion, around 70–90%, of visible radiation, notably in the blue (around 450 nm) and red (around 670 nm) wavelengths, while reflecting a majority of green light (around 533 nm), hence appearing green to human eyes due to this reflection by chlorophyll pigments within chloroplasts in the palisade cells. Near-infrared (NIR) wavelengths are mainly reflected and transmitted through leaves. This information, derived from the work of Roman and Ursu (Anamaria Roman, 2016). Figure 2.2 illustrates how the spectral signature of healthy vegetation can be used to interpret its spectral characteristics.

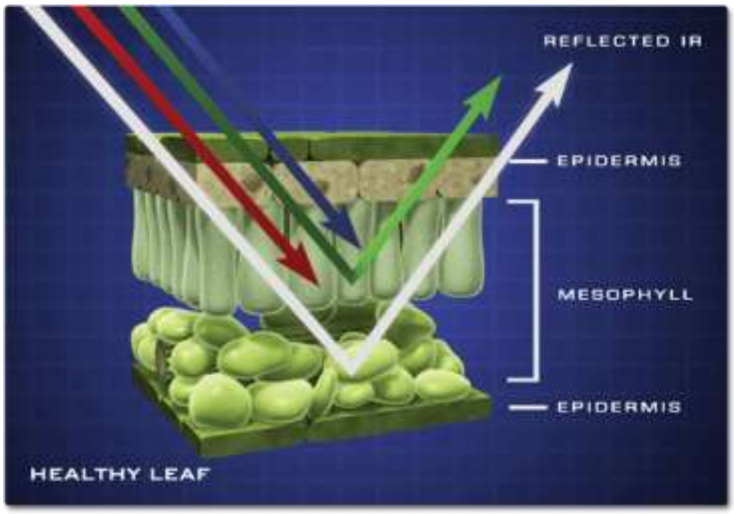

Figure 2.1 - Absorption and Reflection of wavelength of healthy leaf

Light wavelengths absorption or reflection is directly tied to the leaf's cellular structure. Image sourced from (Fisher & Lippincott, n.d.)

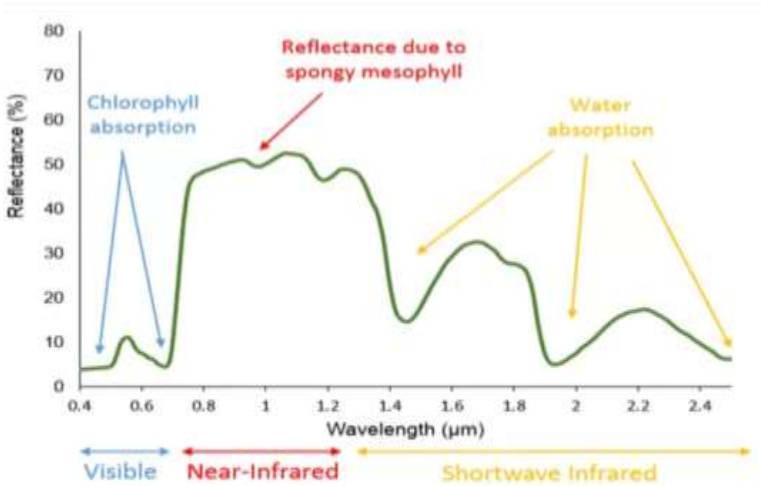

Figure 2.2 - Vegetation Spectral Signature

Healthy green vegetation exhibits significant electromagnetic responses in the 'green' visible and near-infrared (NIR) wavelengths. Image sourced from (Remote sensing in action , 2018)

2.3 Vegetative Indices and Agricultural Insights.

The introduction of Earth observation satellites in 1972 marked the onset of a groundbreaking period for worldwide examination and analysis of vegetation. This significant development also gave rise to the creation of vegetation indices (VIs). These indices portray the condition of vegetation using simple mathematical combinations of reflectance captured across multiple spectral channels, while mitigating the influence of various factors like soil backdrop, atmospheric conditions, and sun–target–sensor geometry (Zeng, 2022).

Since the early 1970s, many VIs have been created (Table 1). More and more of them are being used to tackle intricate ecological issues like vegetation response to long-term climate change because many of them are easily estimated using publicly available remote-sensing data (Xingwang Fan, 2016). VIs also serves as effective tools for both quantitative and qualitative assessments of vegetation cover, health, growth patterns, and various other applications (Xue, 2017).

Vegetative indices (VIs) are mathematical combinations of two or more spectral bands that are used to quantify the amount and condition of vegetation. VI is calculated from remotely sensed data, such as satellite imagery, and can be used to monitor crop growth, detect stress, and assess crop yields (Zubler & Yoon, 2020). It is a crucial tool in precision agriculture, providing valuable insights for monitoring plant growth, health, and environmental impacts. These indices assess various aspects, including crop growth, vigor, biomass, and chlorophyll content, aiding farmers in making informed decisions to improve yields and optimize crop management practices (Radočaj, Šiljeg, Marinović, & Jurišić, 2023). Beyond traditional uses, modern applications include physicochemical monitoring, real-time data analysis, and farm activity planning, providing several advantages in precision farming. Significant vegetation indices derived from remote sensing offer insights into the growth, vigor, and dynamics of terrestrial vegetation, further enhancing the understanding of agricultural landscapes (Jinru & Baofeng, 2017). One of the most used and implemented indices calculated from multispectral information as a normalized ratio between the red and near infrared bands is the Normalized Difference Vegetation Index (NDVI) (Karnieli, Agam, & Pinker, 2010).

The work by Ranga B. Myneni *at el.* (1995) reviews empirical findings demonstrating strong connections between spectral vegetation indexes and vital vegetation parameters like leaf area, biomass, and physiological functions. Of particular importance are the widely used broad-band red and near-infrared indexes, serving as reliable indicators of chlorophyll levels and energy absorption in dense vegetation. Their study emphasizes the practical application of spectral vegetation indices in remote sensing, enabling estimation and monitoring of vegetation parameters, health assessments, and dynamic changes. These indexes also facilitate the identification and mapping of various vegetation types and land cover classes, offering valuable insights for land use studies.

2.3.1 NDVI - Normalized Difference Vegetation Index

NDVI quantifies vegetation health by comparing the reflectance of near-infrared light, which is reflected by healthy vegetation, and red light, which is absorbed by vegetation (GISGeography, 2023; Wikipedia, 2023). The earliest reported use of NDVI in the Great Plains study was by Rouse *et al.*, 1973 (Rouse, Jr, A., & and Deering, 1978). NDVI is calculated from the visible and near-infrared light reflected by vegetation. Healthy vegetation absorbs most of the visible light and reflects a large portion of the near-infrared light, resulting in a high NDVI value. Barren areas or non-vegetated surfaces, on the other hand, have lower NDVI values. NDVI values range from -1 to 1, where higher values indicate healthier and denser vegetation. The use of the Normalized Difference Vegetation Index (NDVI) faces limitations that affect its application. Atmospheric conditions can impact accuracy, especially in situations sensitive to varying weather. Saturation issues, particularly in dense vegetation areas, pose challenges in data interpretation (Huang, Tang, & Hupy, 2021). Sensor quality is pivotal, introducing variability and affecting the reliability of NDVI results. Calculating NDVI is complex due to atmospheric conditions, limited usable bands, and a reliance on sunlight, leading to potential inaccuracies (Qiang, et al., 2022).

Komal Choudhary *et al.* (2019) focused on utilizing NDVI time series derived from Landsat 8 and Sentinel-2 satellite data to monitor agricultural phenology in Guangdong, China. Their research involved a series of steps, including data pre-processing, signal filtering, and interpolation to construct monthly NDVI time series representing a full crop phenological cycle. Using NDVI values ranging from -1 to +1, they categorized the agricultural areas into five segments based on NDVI levels, delineating regions as no agriculture, low, medium, high, and very high agriculture areas. The paper underscores the efficacy of NDVI in identifying surface features and its significant potential for supporting sustainable agricultural development and decision-making processes. This work provides valuable insights into the practical application of NDVI time series derived from satellite data for monitoring agricultural phenology, contributing to the advancement of remote sensing techniques in agricultural studies and sustainable land management.

In their 2020 research, Mukesh Singh, Boori, Komal Choudhary, and Alexander Kupriyanov demonstrated the effectiveness of NDVI time series from Sentinel and Landsat data in monitoring and mapping crop growth stages aligned with the crop calendar. They highlight NDVI's responsiveness to weather conditions and its correlation with crop phenology, establishing satellite remote sensing as a robust and traceable method for crop mapping compared to traditional approaches. The study emphasizes the practical applications of NDVI-derived growth stages—like active tillering, jointing, and maturity—for precise agricultural management decisions related to irrigation, fertilization, and harvest timing. Additionally, their findings support the use of Sentinel-2B and Landsat OLI time series to create accurate crop phenology maps, offering valuable insights for enhanced crop growth simulations and informed agricultural practices.

2.3.2 NDWI - Normalized Difference Water Index

The Normalized Difference Water Index (NDWI), developed by Gao in 1996, is a satellite-derived metric crucial for assessing vegetation water content and the spongy mesophyll structure in vegetation canopies. Bo-Cai Gao (1996), focus revolved around introducing the Normalized Difference Water Index (NDWI) as a tool for remotely sensing liquid water in vegetation from satellite platforms. This index, formulated as $(\rho(0.86\ \mu m) - \rho(1.24\ \mu m))/(\rho(0.86\ \mu m) + \rho(1.24\ \mu m))$, where ρ denotes radiance in reflectance units, is designed to detect liquid water content in vegetation. The study employs laboratory-measured reflectance spectra of stacked green leaves and Airborne Visible Infrared Imaging Spectrometer (AVIRIS) data collected over specific regions like Jasper Ridge in California and the High Plains in northern Colorado. This demonstration showcases NDWI's efficacy in capturing and characterizing liquid water content within vegetation, drawing comparisons with the widely used Normalized Difference Vegetation Index (NDVI). Gao's work emphasizes NDWI's advantage over NDVI, showing its reduced sensitivity to atmospheric effects and its capacity to measure liquid water molecules interacting with solar radiation in vegetation. However, it notes that NDWI, like NDVI, doesn't completely eliminate soil background effects.

Stuart and McFeeters' in 1996 introduced the Normalized Difference Water Index (NDWI) as an approach for assessing water resources. Their study primarily focuses on showcasing

NDWI's utility in delineating open water features within remotely-sensed digital imagery. Their research demonstrates the effectiveness of NDWI in isolating open water features while minimizing the influence of soil and terrestrial vegetation. This capability enables detailed analysis and extraction of information specifically related to open water bodies. Additionally, Stuart and McFeeters suggest that NDWI holds promise in estimating water turbidity—a significant aspect of water quality—using remotely-sensed digital data.

2.3.3 EVI - Enhanced Vegetation Index

The Enhanced Vegetation Index (EVI) stands out as an optimized metric designed to enhance vegetation monitoring by reducing atmospheric influences and isolating the vegetation signal more effectively, especially in regions with high biomass. Unlike the Normalized Difference Vegetation Index (NDVI), the EVI accounts for factors like airborne particles and ground cover beneath the vegetation, making it a valuable tool for quantifying vegetation greenness. EVI excels in sensitivity to high biomass regions, mitigating atmospheric influences, adjusting for canopy signals, and responding more dynamically to changes in plant canopy conditions compared to NDVI (Krishna, 2022).

Wardlow and Egbert's 2010 research compared MODIS 250-m EVI and NDVI data for crop mapping in southwest Kansas. Their findings showcased that both EVI and NDVI data yielded comparable classification outcomes across general crop types, summer crops, and irrigated/non-irrigated areas, achieving high thematic accuracies ranging from 85% to 90%. The study's classified cropping patterns aligned closely with reported data for the area, demonstrating a strong correlation of over 0.95 with USDA-reported crop areas. Although there were minor discrepancies, primarily in transitional zones between cover types, the differences in thematic accuracy and classified crop areas between EVI and NDVI-derived maps were negligible. Moreover, the research revealed that both EVI and NDVI performed equally well when specific growing season phases were used to generate crop maps. Notably, the overall accuracy of EVI and NDVI-derived irrigated/non-irrigated crop maps stood at 94.7% and 94.2%, respectively.

Matsushita, *et al.* (2007) paper explored the impact of topographic effects on the Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI) within a high-density cypress forest. Both indices, offering comprehensive global vegetation insights, are susceptible to errors from atmospheric conditions, soil backgrounds, and topographic influences. Their research underscored the necessity of removing topographic effects from reflectance data before computing the EVI, as it is notably more sensitive to such conditions compared to the NDVI. This recommendation extends to other vegetation indices with non-band ratio formats, like PVI and SAVI. Even in regions with rough terrain where topographic effects on indices like NDVI are typically disregarded, the paper advocates for the removal of these effects in indices such as EVI.

Table 1 - Vegetation Indices Formulas (GISGeography, 2023; Zubler & Yoon, 2020)

Index	Formulae	Purpose
NDVI	$\frac{(NIR - Red)}{(NIR + Red)}$	Quantifies vegetation health by comparing near-infrared and red-light reflectance
NDWI	$\frac{(NIR - SWIR)}{(NIR + SWIR)}$	Assesses vegetation water content using Near-Infrared (NIR) and Short-Wave Infrared (SWIR)
EVI	$\frac{2.5\ (NIR\ -\ Red)}{(NIR\ +\ 6\ \times\ Red\ -\ 7.5\ \times\ Blue\ +\ 1)}$	Monitors vegetation dynamics with enhanced sensitivity

2.3.4 Importance of Incorporating Vegetative Indices for Crop Health Monitoring

Incorporating vegetation indices in agriculture enhances crop health monitoring by offering quantitative data on crop growth, health, and environmental conditions. These indices contribute to informed decision-making, ultimately optimizing agricultural productivity.

2.3.4.1 Yield Estimates

Vegetation indices, such as the Normalized Difference Vegetation Index (NDVI) and Enhanced Vegetation Index (EVI), can be utilized to analyze yield estimates. These indices offer a quantitative assessment of crop health, aiding in predicting and optimizing yield outcomes (Vibhute & Gawali, 2013).

2.3.4.2 Soil Conditions

By assessing the spectral characteristics of crops, vegetation indices contribute to the analysis of soil conditions. This information is vital for understanding the overall health of the agricultural landscape and implementing targeted soil management practices (Panda, Ames, & Panigrahi, 2010).

2.3.4.3 Decision Support

Precision agriculture relies on accurate and timely information for decision-making. Vegetation indices serve as a decision support tool, providing farmers with actionable insights into crop growth, health, and potential issues that may require intervention (Radočaj, Šiljeg, Marinović, & Jurišić, 2023)

2.3.4.4 Monitoring Changes

Remote sensing images, analyzed using vegetation indices, enable the high spatial and cloud-free monitoring of crops. This technology aids in the detection of changes in vegetation over time, allowing for timely adjustments in agricultural practices (Panda, Ames, & Panigrahi, 2010).

2.4 Role of Weather Data in Farming

Weather data plays a vital role in agriculture, influencing a range of agronomic decisions and practices. Accurate weather information is essential for farmers in planning and executing key tasks in farming, including organizing farm operations, determining crop selection and sowing timing, making decisions for risk mitigation, and optimizing fertilizer application (Frisvold & Murugesan, 2013; Agyekum, Antwi-Agyei, & Dougill, 2022).

In their study, Yegbemey *et al.* (2021) investigated the impact of weather forecasts delivered to smallholder maize farmers through mobile phone Short Message Service (SMS) on self-reported labor costs, crop yield, and income. Conducting a pilot field experiment involving 331 randomly selected eligible farmers across six villages, with randomization at the village level, the researchers utilized three regression models—Ordinary Least Squares (OLS), Generalized Estimating Equations (GEE) with a small sample correction, and Randomization Inference (RI)—to estimate impacts. The results revealed a well-balanced treatment and control group, with the treatment group experiencing lower labor costs, higher crop yield, and increased income levels. Consistent impact estimates were observed across regression models, with significance in the Randomization Inference (RI) model for labor costs and yield, or the RI and GEE models for income (Yegbemey, Aloukoutou, & Aïhounton, 2021). These findings also support the potential of weather forecasts to positively influence smallholder farmers' resilience to climate variability.

Table 2 - Weather Information and Their Impact on Agricultural Decisions ((Venkata, et al., 2020; Frisvold & Murugesan, 2013; Siloko, et al., 2021)

Weather Variables	Agricultural Decisions
Temperature	Planting, harvesting, defoliation, crop modeling, disease risk assessment, shelter for animals, pest control, sheep shearing
Precipitation	Planting, harvesting, fertilizer applications, cultivation, spraying, irrigation, disease risk assessment, livestock and poultry protection
Soil Moisture	Planting, harvesting, fertilizing, transplants, spraying, irrigation, monitoring of growing conditions, measuring plant stress
Soil Temperature	Planting, pest overwintering conditions, transplanting, fertilizing
Frost	Pest overwintering conditions, protecting crops from damage, animal sheltering, irrigation to avert crop damage
Degree Days	Planting, irrigation, pest control
Relative Humidity	Harvesting, pollination, spraying, drying conditions, assessing crop stress potential
Wind Speed	Defoliation, harvesting, freeze potential/protection, animal sheltering, shelter construction, pest control, pruning, spraying or dusting, pollination, dust drift, pesticide drift
Wind Direction	Freeze potential/protection, assessing cold or warm air advection over crop areas, pesticide drift, dust drift

2.5 Land Cover Classification

Land cover classification is a fundamental process in geospatial analysis that involves the categorization of Earth's surface into different types, including vegetation, soil, and water. Employing image processing techniques, particularly supervised classification methods, is crucial for generating accurate land cover maps. This process not only provides a comprehensive view of the landscape but also facilitates the analysis of changes over time (Rajinder, 2011).

Digital Image Classification, as an automated extraction process, plays a pivotal role in Land Use Land Cover Assessment (LULC). It allows for the systematic categorization of land cover types, contributing to a detailed understanding of the land's utilization patterns. This information is instrumental in various fields, particularly in urban development planning, where decisions about infrastructure and land use allocation are heavily dependent on accurate land cover maps (Yousefi, et al., 2022).

However, the reliability of land use/cover maps generated through image classification relies heavily on the accuracy of the classification process. Therefore, accuracy assessment becomes a vital component in ensuring the credibility and precision of the generated maps (Sophia & Ndambuki, 2017).

Zander, *et al*. (2022) evaluated three global Land Use Land Cover (LULC) maps: Google's Dynamic World (DW), ESA's World Cover (WC), and Esri's Land Cover (Esri) for the year 2020. Their analysis revealed strong spatial agreement among these maps for water, built areas, trees, and crops. Esri demonstrated the highest overall accuracy (75%) compared to DW (72%) and WC (65%) when employing global ground truth data at a minimum mapping unit of 250 m^2. Water was the most accurately mapped class (92%), followed by built areas (83%), tree cover (81%), and crops (78%). Using European ground truth data from LUCAS with a smaller mapping unit (<100 m^2), WC exhibited the highest accuracy (71%) compared to DW (66%) and Esri (63%). However, certain classes, like shrub and scrub, grass, bare ground, and flooded vegetation, had notably lower accuracies. The study emphasizes the importance of critically assessing global LULC products based on their intended application, thematic resolution, global versus local accuracy, specific class biases, and the necessity for change analysis.

Ding, *et al.* (2022) compared three global land cover products—FROM-GLC10, ESRI2020, and ESA2020—at a 10-meter resolution in Southeast Asia. They assessed their accuracy using field and manual densification points, revealing varied overall accuracies of 75.43%, 79.99%, and 81.11%, respectively. While all three products performed well in croplands, forests, and built-up areas, ESRI2020 and ESA2020 excelled in water, and ESA2020 stood out in grasslands. However, shrublands, wetlands, and bare land showed poor performance across all products, with both producers and user's accuracy below 50%. The study recommends ESA2020 as the primary choice for land cover mapping in Southeast Asia due to its high overall accuracy. Yet, FROM-GLC10 showcased advantages in specific classes like croplands, water, and built-up areas in terms of accuracy measures.

2.5.1 The Importance of Land Cover Classification in Agriculture

Land cover classification in agriculture is a valuable tool that enhances precision farming, aids decision-making, facilitates thematic mapping, supports change detection analysis, and contributes to environmental impact assessments (LaGroJr, 2005; Chenghu, et al., 2018; SATPALDA, 2023).

a. **Precision Farming and Decision – Making:** Accurate land cover maps aid in implementing precision farming techniques. Farmers also can make decisions related to crop selection, planting times, and harvesting based on the prevailing land cover types. Farmers can optimize resource allocation, including water, fertilizers, and pesticides, based on the specific land cover types, leading to increased efficiency and reduced environmental impact. Understanding land cover patterns supports informed decision-making in agricultural practices (LaGroJr, 2005).

b. **Thematic Mapping:** Land cover classification establishes baseline information for thematic mapping. This is crucial for monitoring changes over time, detecting land use shifts, and assessing the impact of various interventions (SATPALDA, 2023).

c. **Change Detection Analysis**: By identifying land cover changes, farmers and policymakers can analyze trends and patterns, allowing for proactive measures to address emerging challenges like land degradation or urbanization (SATPALDA, 2023)

d. **Environmental Impact Assessment:** Land cover classification contributes to understanding the environmental impact of agricultural activities. It helps in assessing factors such as soil stability, water movement, and overall ecosystem health.

2.6 Decision Support Web Platform for Farm-Related Activities (DSWPF).

Agriculture 4.0 represents the cutting-edge evolution of farming technology, aiming to boost productivity, optimize resource allocation, enhance climate resilience, and reduce food waste. This transformation involves leveraging advanced information systems and internet technologies to collect, analyze, and process extensive agricultural data. This enables farmers to make well-informed decisions, maximizing profits and sustainability (Zhaoyu, José Fernán, Victoria, & Néstor Lucas, 2020).

Decision Support Systems (DSS) play a pivotal role in Agriculture 4.0, serving as interactive software tools assisting decision-makers in compiling information and making optimal choices. DSS architectures typically include a database or knowledge base, a decision model, and a user interface (Michele & Zhenli, 2014). In the agricultural and environmental management context, DSS has rapidly expanded, enabling swift assessments at both farm and district levels. Water management is a significant application of DSS in agriculture, addressing the challenges of water scarcity and pollution, particularly in developing countries. Precision irrigation, considering factors like water availability, crop requirements, and land characteristics, is crucial for enhancing crop yields (Iffat, et al., 2021).

Several studies contribute to the understanding and implementation of DSS in agriculture. Borrero and Jesús's (2022) case study introduces "FARMDATA" a digital data platform empowering smallholders in the Andalusian fruit and vegetable sector. This platform aggregates data from various sources, providing farmers with decision-making tools and emphasizing security and transparency (Borrero & Jesús, 2022). Cembor's study focuses on creating a barley yield prediction model as part of an Advisory Support platform for Polish agriculture. Utilizing Multiple Linear Regression, the model demonstrates high precision in simulating barley yields under various conditions (Czembor, Kaczmarek, Pilarczyk, Mańkowski, & Czembor, 2022).

Htun *et al.* (2022) contributes with web-based visual-assisted DSSs for agricultural use cases, demonstrating ease of use and high performance. Weckesser, Beck, Hülsbergen, & Peisl’s work (2022) emphasizes a digital knowledge base integrated with a DSS, specifically addressing nutrient supply for winter wheat. The Crop Portal, developed through participatory methods, showcases the potential of rule-based DSS in practical agricultural scenarios (Weckesser, Beck, Hülsbergen, & Peisl, 2022; Htun, et al., 2022).

Roslin, *et al.* (2021) paper delved into the creation and deployment of the smartphone agricultural management app, Padi2U, tailored for rice field management. It emphasizes the utilization of multispectral imagery and the Normalised Difference Vegetation Index (NDVI) for evaluating crop health status. The app offers practical recommendations aligned with the Department of Agriculture's guidelines, covering aspects such as rice check, pest and disease control, and weed management. User Acceptance Test (UAT) results indicated high satisfaction levels, affirming the app's efficacy and user-friendly nature. Additionally, the paper sheds light on challenges encountered by rice farmers in crop monitoring, soil testing, and equipment maintenance, highlighting how technology like Padi2U could address these issues. The app's potential lies in its capability to facilitate real-time information dissemination and function as a comprehensive database for field-related data in paddy management.

Nojozi, *et al*. (2020) study focused on developing mobile and web applications aimed at disseminating agricultural information to rural subsistence farmers in the Eastern Cape. The research encompassed both qualitative and quantitative phases to comprehensively understand participant perspectives and identify suitable instruments. Qualitative inquiry delved into participant views, while the quantitative phase determined appropriate tools for data collection. Farmers expressed a strong desire for various information, including available bursaries in agriculture, a platform for inquiries and responses, access to agriculture department details, sponsor visibility, product advertising, disease insights, new fertilizers, and workshop information. The mobile application demonstrated notable utility, usability, and accessibility among farmers, proving effective in meeting their information needs. This study emphasizes the importance of technology as a tool for empowering agricultural communities by providing targeted and accessible information.

Many studies focus on developing vegetation indices and analytical techniques without necessarily considering the practical implementation and real-world utility of these findings for farmers and decision-makers. This proposed solution of developing a web application that integrates various components, including vegetation indices, weather data, and land cover classification, into a user-friendly platform is innovative and addresses this gap effectively. By creating an all-in-one solution, to provide stakeholders with a practical tool that can facilitate informed decision-making processes in agriculture and land management. This integrated approach not only streamlines access to critical information but also enhances the usability and applicability of research findings in real-world contexts. By bridging the gap between research and practice, this project has the potential to significantly impact agricultural management strategies, resource allocation, and policy development at both the farm and government levels.

3. IMPLEMENTATION

3.1 Study Area

Benue State, renowned as the nation's acclaimed food basket due to its abundant agricultural produce, including yams, rice, beans, cassava, potatoes, maize, soya beans, sorghum, millet, and cocoyam. Notably, the state contributes over 70% to Nigeria's soya bean production. Situated within the lower river Benue trough in Nigeria's middle belt region, Benue State's geographic coordinates range from longitude 7° 47’ to 10° 0’ East and latitude 6° 25’ to 8° 8’ North. It shares borders with five states: Nasarawa to the north, Taraba to the east, Cross-River to the south, Enugu to the south-west, and Kogi to the west. Additionally, Benue State shares a boundary with the Republic of Cameroon to the south-east. With a population of 4,780,389 (2006 census) and covering a landmass of 32,518 square kilometers, Benue State is a significant area of focus for this study (*Showcasing the Culture of the Good People of Benue State Nigeria North-Central*, n.d.).

Figure 3.0: Study area

Benue State's slogan is "Food basket of the nation", and the major occupation in the state is farming. Image sourced from (National boundary commission)

3.1.1 Implementation Chart

The diagram illustrates the implementation workflow of this study. Initially, the process began with data collection, followed by data processing to rectify anomalies and enhance data quality.

Subsequently, comprehensive analysis was conducted on the processed data. Finally, all findings and insights were integrated into a web platform for accessibility and utilization.

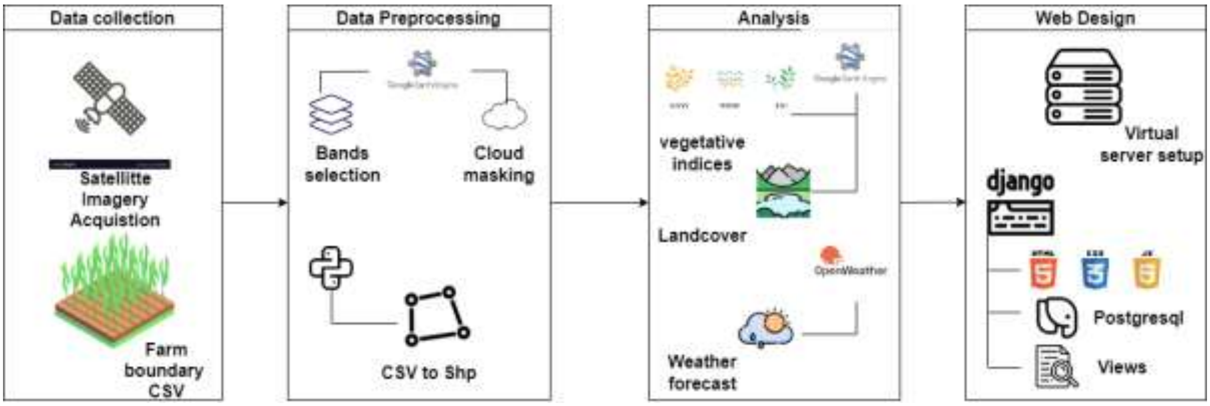

Figure 3.1: Process workflow

The chart above illustrates the major stages involved in implementation of this study

3.2 Data Collection

3.2.1 Satellite Imagery Acquisition

In this study, the acquisition of satellite imagery was a crucial step in obtaining accurate and timely information for the calculation of vegetative indices. The Sentinel-2 MultiSpectral Instrument (MSI) Level-1C data was selected as the primary source of satellite imagery due to its suitability for agricultural monitoring and its availability on Google Earth Engine. Sentinel-2 MSI was chosen for its multispectral capabilities, providing imagery in the visible, near-infrared, and short-wave infrared bands. This enables a comprehensive analysis of vegetation health and land cover types within the study area. The selected bands for this study were bands 2 (Blue), 3 (Green), 4 (Red), 8 (NIR - Near-Infrared), and 11 (SWIR - Short-Wave Infrared). Each band had a spatial resolution of 10 meters, except for band 11 which had a resolution of 20 meters. The choice of these bands was based on their relevance to vegetative indices calculation, ensuring a balance between spatial detail and spectral information.

The selected Sentinel-2 MSI imagery was obtained through the Google Earth Engine platform. This platform facilitated efficient and timely access to a large volume of satellite data, allowing for the retrieval of cloud-free scenes essential for accurate analysis.

3.2.2 Farm Boundary Information

To delineate the study area accurately, the boundary of the farms was provided in CSV format by Tradebuza, an agro startup based in Nigeria. This dataset not only defined the geographical extent of the farms but also highlighted the collaborative effort with local entities, ensuring that the study area was representative of smallholder farms in Benue State, Nigeria.

3.3 Data Preprocessing

Data preprocessing is a critical step to ensure the accuracy and reliability of the analysis. In this study, preprocessing involved the removal of clouds from Sentinel-2 images and the conversion of farm boundary information from CSV format to a shapefile with the appropriate spatial reference.

3.3.1 Cloud Masking for Sentinel-2 Images

To mitigate the impact of clouds on the analysis, a cloud masking function was applied to the Sentinel-2 images using the Google Earth Engine (GEE) platform. The following JavaScript code illustrates the function used:

code sequence 1: *Javascript code delineating cloud masking function*

```
// Function to mask clouds using the Sentinel-2 QA band.
function maskS2clouds(image) {
  var qa = image.select('QA60')
  // Bits 10 and 11 are clouds and cirrus, respectively.
  var cloudBitMask = 1 << 10;
  var cirrusBitMask = 1 << 11;
  // Both flags should be set to zero, indicating clear conditions.
  var mask = qa.bitwiseAnd(cloudBitMask).eq(0).and(
             qa.bitwiseAnd(cirrusBitMask).eq(0))
  // Return the masked and scaled data, without the QA bands.
  return image.updateMask(mask).divide(10000)
      .select("B.*")
      .copyProperties(image, ["system:time_start"])
}
```

This function utilized the Sentinel-2 QA band to identify and mask out cloud and cirrus pixels. The resulting images were then scaled and selected bands retained for further analysis.

3.3.2 Conversion of Farm Boundary Information

The farm boundary information, initially provided in CSV (Comma-separated values) format, was converted to a shapefile with the corresponding spatial reference using Python. The code below demonstrates this conversion process:

code sequence 2: *Python code converting CSV to Shapefiles*

```
import geopandas as gpd
from shapely.geometry import Point
# Read CSV file into a Pandas DataFrame
import pandas as pd
csv_path = '/content/Benue.csv'
df = pd.read_csv(csv_path)
# Creating a GeoDataFrame with Point geometries from the lat and long columns
geometry = [Point(xy) for xy in zip(df['lng'], df['lat'])]
gdf = gpd.GeoDataFrame(df, geometry=geometry)
# Group by farm_id and create convex hulls for each group
grouped_gdf = gdf.groupby('farm_id')['geometry'].apply(lambda x: x.unary_union.convex_hull).reset_index()
# Creating a new GeoDataFrame with the convex hulls
final_gdf = gpd.GeoDataFrame(grouped_gdf, geometry='geometry')
# Set the coordinate reference system (CRS) to WGS 84
final_gdf.crs = 'EPSG:4326'  # EPSG code for WGS 84
output_polygon_shapefile = 'Benue.shp'
final_gdf.to_file(output_polygon_shapefile, driver='ESRI Shapefile', crs='EPSG:4326')
```

This Python code utilized the GeoPandas library to create a GeoDataFrame with point geometries representing farm locations. Convex hulls were then generated for each farm_id, creating the final GeoDataFrame. The spatial reference was set to EPSG:4326 (WGS 84), and the resulting shapefile was stored for subsequent spatial analysis.

These preprocessing steps ensure that the satellite imagery is free of cloud interference, and the farm boundary information is in a suitable format for accurate spatial analysis within the study area.

3.4 Vegetative Index Calculation

The calculation of Vegetative Indices, including NDVI (Normalized Difference Vegetation Index), NDWI (Normalized Difference Water Index), and EVI (Enhanced Vegetation Index), is a fundamental step in assessing crop health and vegetation cover. In this study, the calculation of these indices was performed using GEE with specific functions tailored to each index.

3.4.1 NDVI Calculation

For NDVI, the normalized difference function was applied using the Sentinel-2 imagery on GEE. The following Python code illustrates the function used:

code sequence 3: *Python function for calculating NDVI*

```
def addNDVI(image):
    ndvi = image.normalizedDifference(['B8', 'B4']).rename('ndvi')
    return image.addBands(ndvi)
```

This function computed the NDVI by taking the normalized difference between the Near-Infrared (NIR) band (B8) and the Red band (B4).

3.4.2 NDWI Calculation

The NDWI, focusing on water content, was computed using a similar normalized difference function. The following Python code demonstrates the NDWI calculation function:

code sequence 4: *Python function for calculating NDWI*

```
def addNDWI(image):
    ndwi = image.normalizedDifference(['B3', 'B11']).rename('ndwi')
    return image.addBands(ndwi)
```

This function computed the NDWI by taking the normalized difference between the Green band (B3) and the Short-Wave Infrared band (B11).

3.4.3 EVI Calculation

For EVI, a specific expression was utilized to calculate the index. The following Python code illustrates the EVI calculation function:

code sequence 5: *Python function for calculating EVI*

```
def addEVI(image):

    EVI = image.expression(
```

```
'2.5 * ((NIR - RED) / (NIR + 6 * RED - 7.5 * BLUE + 1))', {
    'NIR': image.select('B8').divide(10000),
    'RED': image.select('B4').divide(10000),
    'BLUE': image.select('B2').divide(10000)
}).rename("EVI")
image = image.addBands(EVI)
return image
```

This function computed the EVI using the specified expression, taking into account the Near-Infrared (NIR), Red, and Blue bands.

These custom functions tailored to each vegetative index ensured accurate calculations based on the chosen Sentinel-2 bands. The resulting index bands were integrated into the image stack for further analysis, providing valuable insights into crop health and vegetation cover within the study area.

3.5 Integration of Weather Data

The integration of weather data into the study was a pivotal step to enable informed decision-making for farmers. This process involved retrieving farm location information from a database, extracting midpoints, and subsequently fetching real-time and forecasted weather data using the OpenWeatherMap API. The acquired weather data was then seamlessly incorporated into user-friendly templates developed with HTML, CSS, and JavaScript for effective visualization on the web platform.

3.5.1 Retrieval of Farm Location Data

The initial step in integrating weather data was retrieving farm location information from a database. An endpoint was created to access the shapefile stored in the database, allowing for the extraction of pertinent geographical details such as latitude and longitude. The midpoint coordinates, representing the central location of each farm, were extracted as JSON data. These coordinates served as the basis for querying weather information specific to each farm.

3.5.2 Weather Data Retrieval from OpenWeatherMap API

The OpenWeatherMap API was utilized to obtain comprehensive weather data for each farm location. The API was queried with the midpoint coordinates, enabling the retrieval of key weather parameters including humidity, pressure, sunrise, sunset, wind speed, and forecasted future days' temperatures.

3.5.3 Data Insertion into Front-End Templates

To enhance user accessibility, the acquired weather data was seamlessly inserted into user-friendly templates designed using HTML, CSS, and JavaScript. These templates formed the basis of the front-end interface, allowing users to interact with and visualize the weather information in a clear and concise manner.

3.6 Land Cover Classification

The process of land cover classification involved integrating the ESRI 10m land cover classification for 2022, available on GEE, with Django application. The results of the classification were visualized on the front end of the application, providing valuable insights into different land cover types within the study area.

3.6.1 Class Definitions

The land cover classification included several distinct classes, each with its own unique characteristics. Brief summaries of some key class definitions are as follows:

- Water: Areas predominantly covered by water throughout the year, such as rivers, ponds, lakes, and oceans.
- Trees: Significant clusters of tall, dense vegetation with a closed or dense canopy, including wooded vegetation, plantations, and swamp/mangrove areas.
- Flooded Vegetation: Areas with obvious intermixing of water throughout a majority of the year, often a mix of grass, shrubs, trees, and bare ground.
- Crops: Areas of human-planted cereals, grasses, and crops not at tree height, including examples like corn, wheat, and fallow plots.
- Built Area: Human-made structures, major road and rail networks, and large homogeneous impervious surfaces, such as houses, villages, roads, and asphalt.
- Bare Ground: Areas with very sparse to no vegetation, including exposed rock or soil, deserts, sand dunes, and dry salt flats.
- Snow/Ice: Large homogeneous areas of permanent snow or ice, typically found in mountain areas or at the highest latitudes.
- Clouds: No land cover information due to persistent cloud cover (Awesome GEE, n.d.).

3.7 Web Platform Design

The development of the web platform was a systematic process aimed at creating an interactive and user-friendly interface for visualizing and analyzing agricultural and environmental data. This involved the establishment of a virtual server, installation of essential libraries, development of the Django project, creation of templates for the frontend, connection to a PostgreSQL database for shapefile management, and implementation of various views for different aspects of the analysis.

3.7.1 Setting Up the Virtual Server and Installing Libraries

The initial step in creating the web platform was setting up a virtual server named "env" on the local computer. This server served as the development environment for the project. Crucial libraries were installed on this server, including Django for web development, google-api-python-client for authentication, earthengine-api for accessing Google Earth Engine with Python, folium and leaflet for GIS capabilities, GDAL for geospatial data processing, among others.

3.7.2 Creation of Django Project and App

The Django framework was employed to structure the web application. A Django project and app were created to organize the code and functionalities effectively. Templates, developed using HTML, CSS, and JavaScript, were designed for the frontend. A static folder was established to store CSS files, images, and JavaScript scripts, ensuring a clean and organized structure.

3.7.3 Database Connection and Shapefile Loading

To manage geographical data efficiently, the web platform was connected to a PostgreSQL database. A model was created to facilitate the loading of shapefiles into the database, ensuring that spatial data was readily accessible for analysis.

3.7.4 Implementation of Views and URL Patterns

Several views were developed to cater to different aspects of the analysis. These included views to display all farm lands, the homepage, vegetative index, weather information, and land cover. Appropriate URL patterns were established to link these views, creating a coherent and navigable structure for users.

3.7.4.1 Farm Lands View

The Farm Lands view was designed to dynamically load shapefiles stored in the PostgreSQL database onto the frontend. This allowed users to visually explore the spatial distribution of farm lands within the study area.

3.7.4.2 Homepage View

Functioning as the central hub of the web platform, the Homepage view served as the gateway for users to navigate through different sections seamlessly. By connecting to templates and leveraging forms.py, the Homepage view facilitated user interactions, allowing them to select start and end dates for subsequent analysis in the Vegetative Index view. It provided an entry point and presented a concise overview of the available features.

3.7.4.3 Vegetative Index View

The Vegetative Index view provided users with rich visualizations of essential indices, including NDVI, NDWI, and EVI. Users were empowered to make informed decisions by interacting with charts and vegetative index graphics. This view, supported by a connection to templates and forms.py, allowed users to specify start and end dates for the vegetative index analysis, enhancing the temporal granularity of the insights.

3.7.4.4 Weather Information View

In the Weather Information view, the web platform seamlessly connects to the OpenWeatherMap API to retrieve real-time and forecasted weather data. Users gained access to critical information such as humidity, pressure, wind speed, and temperature forecasts. The incorporation of live weather data enriched the platform's functionality and provided users with up-to-date insights.

3.7.4.5 Land Cover View

The Land Cover view harnessed the power of Google Earth Engine (GEE) to load the ESRI 10m land cover classification for 2022. This view allowed users to explore and analyze different land cover types within the study area. The integration of GEE facilitated the dynamic loading of complex spatial datasets, offering users a comprehensive understanding of the environmental landscape.

This comprehensive approach ensured the seamless integration of diverse functionalities, providing users with a robust and intuitive platform for agricultural and environmental data exploration.

4. Methods and Results

4.1 Django

Django, an open-source web application framework written in Python, employs the Model-View-Template (MVT) design pattern. Its rapid development capabilities have made it highly sought-after in the current market, allowing for the swift creation of various applications. The MVT structure entails models serving as the database, views controlling functionality, and templates facilitating user-side interaction. In Django, the model manages the database, with commands like "python manage.py makemigrations" detecting changes in the models.py file and preparing data for storage in the specified database, such as sqlite3. Subsequently, "python manage.py migrate" saves these changes in the database. Finally, executing "python manage.py runserver" launches the project locally, providing a localhost address. The views.py file handles requests and API calls, managing template interactions through Python functions.

The diagram depicted below delineates the procedural sequence initiated when a user intends to utilize the application. Initially, the user engages with the Django project through a designated URL, whereby this URL subsequently directs to the views for the analysis conducted on platforms such as Google Earth Engine or Open Weather Map. Subsequently, employing templates, the analysis outcomes are presented on the frontend, contingent upon the selection of the farm from the database, which stores the pertinent shapefiles. Such integration is facilitated by the Django models, thereby enabling seamless interaction and data retrieval for user-driven analyses (*Gore et al*., 2021).

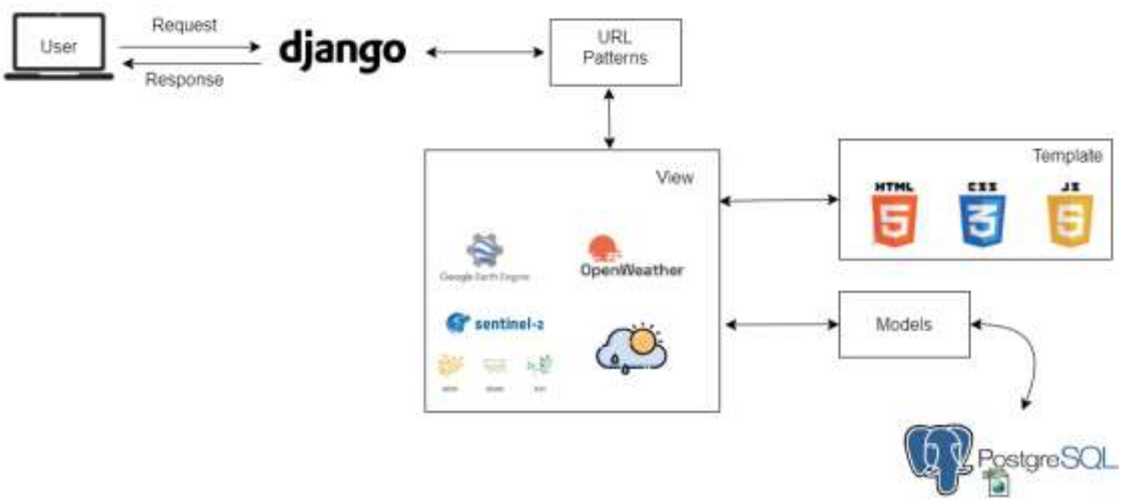

Figure 4.0: Application procedural sequence

This sequence depicts what happens within the application when a user makes a request and the flow of processes to get a response

4.1.1 Django Model

Within the MVC architecture, this component serves as an intermediary for storing user data in the database. It is tasked with managing the logical aspects of the web application and determining the storage mechanism for the data within the database (Gore *et al*., 2021). The Farm model serves as a fundamental component within the Django project, encapsulating essential attributes and functionalities pertaining to agricultural entities. The model definition is outlined below:

code sequence 6: *Python code creating django models which is then used to create tables in the database*

```
from django.contrib.gis.db import models
class Farm(models.Model):
    farm_id = models.BigIntegerField(null=True)
    crop = models.CharField(max_length=10, null=True)
    size = models.FloatField(null=True)
    geom = models.MultiPolygonField(srid=4326)
    def __str__(self):
        return str(self.farm_id)
    class Meta:
        ordering = ['farm_id']
```

Model Attributes:

- farm_id: A unique identifier assigned to each farm within the system. This field is of type BigIntegerField allowing for large integer values.
- crop: Denotes the type of crop cultivated within the farm. This attribute is of type CharField with a maximum length of 10 characters.
- size: Represents the size of the farm in a floating-point format. This field is of type FloatField.
- geom: Defines the geometric shape of the farm using a MultiPolygonField from Django's spatial database functionalities. The spatial reference identifier (SRID) is set

to 4326, indicating the use of the WGS 84 coordinate system for geographic information.

Additional Functionalities:

The __str__ method is overridden to provide a human-readable representation of the Farm model instance. It returns the farm_id converted to a string. The Meta class specifies the default ordering of Farm instances based on their farm_id.

4.1.1.1 Database Connection

To inform Django about the utilization of PostgreSQL as the database backend, adjustments were made to the settings.py file as follows:

code sequence 7: *Python code connecting django project to postgresql*

```
DATABASES = {
    'default': {
        'ENGINE': 'django.contrib.gis.db.backends.postgis',
        'NAME': 'FIS',
        'USER': 'postgres',
        'PASSWORD': 'postgres',
        'HOST': 'localhost',
        'PORT': '5432',
    }
}
```

This configuration specifies PostgreSQL as the database engine and provides the necessary credentials and connection details. Subsequently, a load.py file was created to populate the shapefiles into the database. The code is outlined below:

code sequence 8: *Python code used to load the shapefiles of the farm lands to postgresql*

```
from pathlib import Path
from django.contrib.gis.utils import LayerMapping
from .models import Farm


farm_mapping = {
    'farm_id': 'farm_id',
    'crop': 'crop',
```

```
    'size': 'Size',
    'geom': 'MULTIPOLYGON',
}

benue_farm_shp = Path(__file__).resolve().parent / 'shapefile' / 'aoi' / 'Benue.shp'

def run(verbose=True):
    lm = LayerMapping(Farm, benue_farm_shp, farm_mapping, transform=False)
    lm.save(strict=True, verbose=verbose)
```

This script utilizes Django's LayerMapping utility to map the fields from the shapefile to the corresponding fields in the Farm model. The run function executes the mapping and saves the data into the database, with verbosity options for logging purposes.

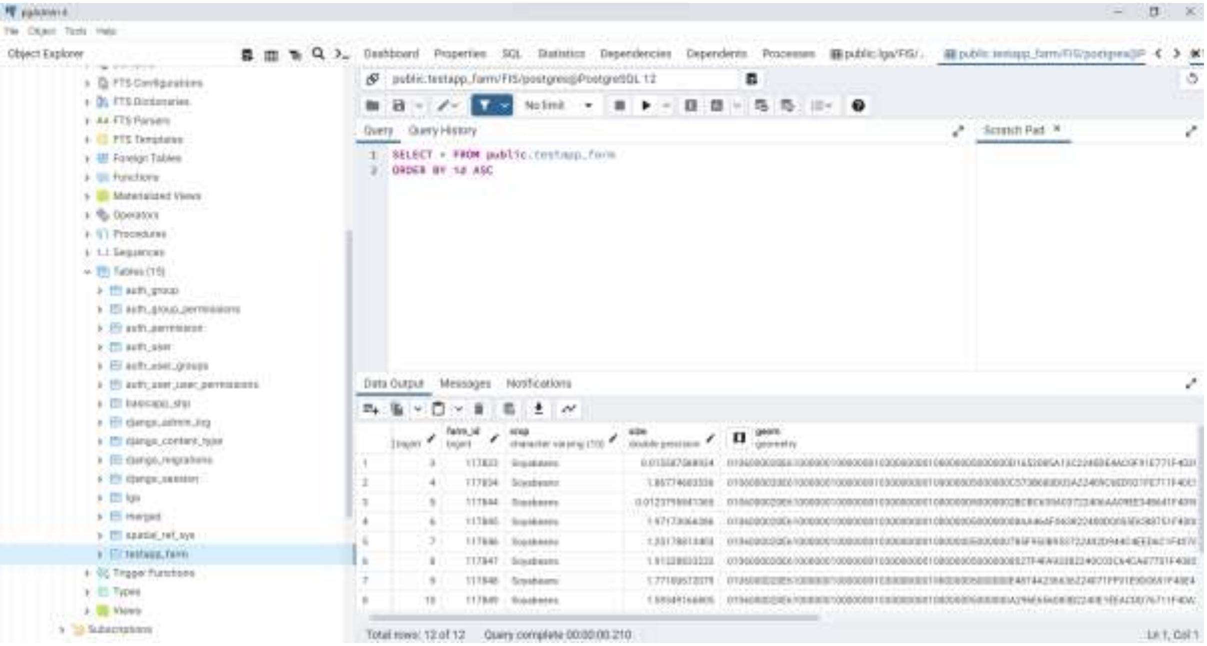

Figure 4.1: Showing successful database connection

Illustration of the successful connection of the django model with postgresql showing the uploaded shapefiles

4.1.2 Django Views

Django views encompass a collection of functions and classes, all housed within the views.py file located in the app directory. These views represent the user interface visible in a web browser when rendering a website (Gore *et al*., 2021). In Django, views are categorized into two types: Function-based views and Class-based views. In this project, function-based views were employed. These views are essentially Python functions that receive a request and produce a response. For the purpose of this project, several views was implemented. Firstly, the base view was created to list all the farmlands available. Subsequently, the dashboard view was developed to facilitate the analysis process. Furthermore, additional views were established to present the outcomes of the analysis, including the vegetative index view, weather forecast view, and landcover view.

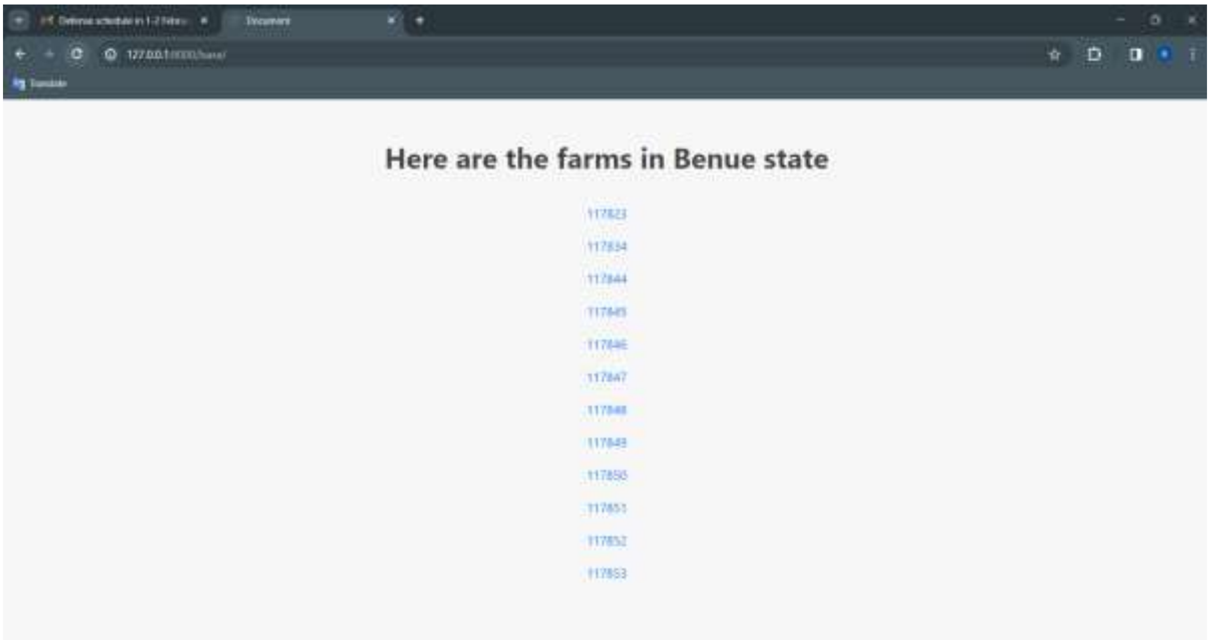

Figure 4.2: Base view showing the list of farm lands

This is the landing page which shows a list of farm lands in this study

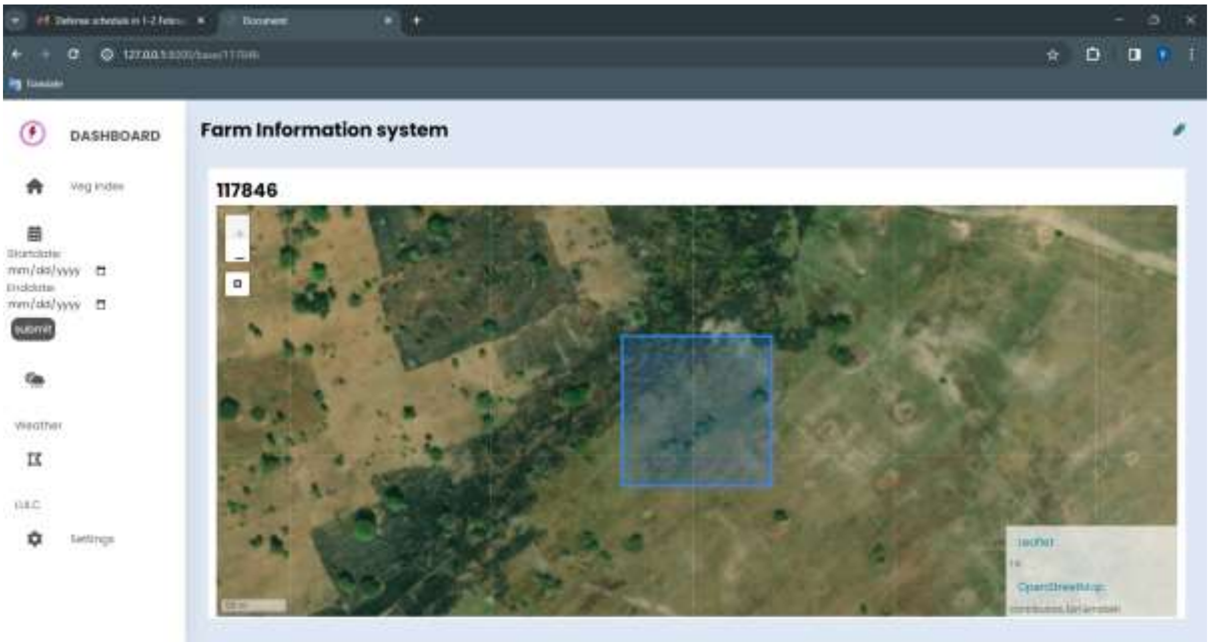

Figure 4.3: Dashboard View

When a random farm is selected the dashboard view is loaded with a polygon shapefile of the farm overlaid on a basemap provided by leaflet. The dashboard offer 3 different analysis on the selected farm

4.1.3 Django Templates

Django offers a straightforward method for generating dynamic HTML content through its templating system. Templates in Django are typically crafted using a combination of HTML, CSS, and JavaScript. The Django template engine effectively organizes and generates HTML pages that are presented to end-users. Django primarily operates in the background, and templates are instrumental in providing the structural layout of websites (Gore *et al*., 2021). Foundational templates were established to serve as the basis for all views within the application. This template was customized as required to accommodate the specific rendering needs of each page.

4.1.4 Django Forms

HTML forms represent a fundamental element of contemporary websites, serving as the primary means to gather information from visitors and users. Django incorporates a Form class designed explicitly for generating HTML forms. While it's possible to accomplish similar tasks with advanced HTML, Django streamlines the process, particularly in terms of form validation. Once users become accustomed to Django forms, the conventional HTML forms may fade into obscurity. Django manages three key aspects regarding forms: preparing and organizing data for rendering, generating HTML forms from data, and handling the submission and processing of forms and customer data (Gore *et al*., 2021). Below is the form developed to capture user input:

code sequence 9: *Python code used to create a form to accept users input*

```
from django import forms
# Custom widget creation
class DateInput(forms.DateInput):
    input_type = 'date'
class DateForm(forms.Form):
    StartDate = forms.DateField(widget=DateInput)
    EndDate = forms.DateField(widget=DateInput)
```

This form utilizes Django's forms module and includes two fields: StartDate and EndDate. Each field is associated with the DateField class, and incorporates a custom widget, DateInput, to enhance the user experience by providing a date picker input.

4.2 Analysis of Vegetative Indices

To obtain the vegetative indices, users initially designate a specific farm, following which the application loads the dashboard view. Subsequently, users proceed to complete a Django form, which encompasses the input of the intended investigation's date range. Upon form submission, the view.py file is invoked, establishing a connection with Google Earth Engine APIs to execute the requisite calculations on Google's servers. The fundamental calculations conducted are detailed in the implementation chapter. Subsequently, the calculated vegetative indices view is returned, allowing for the loading and toggling of indices on and off via the layer pane interface.

4.2.1 Normalized Difference Vegetation Index (NDVI)

Monitoring the phenology of crops and identifying disruptions to their growth are essential for empowering farmers to effectively manage production risks (Hufkens *et al*., 2019). Numerous techniques exist for identifying crop phenology, with the Normalized Difference Vegetation Index (NDVI) threshold being the most widely employed method, as documented by numerous researchers. Over an extended period, numerous national and international agencies across various countries have relied on NDVI as a key indicator of crop condition (Boori *et al*., 2020).

The Normalized Difference Vegetation Index (NDVI) is a widely utilized vegetation index that ranges from +1.0 to -1.0. It serves as a valuable indicator of vegetation health, with low NDVI values indicating barren areas and high values indicating dense vegetation. By averaging NDVI values over time, typical growing conditions for a specific region and time of year can be established, enabling comparisons of vegetation health. NDVI analysis over time can identify areas of thriving vegetation, stress, and changes due to human activities or natural disturbances like wildfires or changes in plants' phenological stage (*U.S. Geological Survey*, 2018).

The Vegetative Indices View presents NDVI values for the year 2023, alongside a comprehensive chart illustrating the time series data depicting the phenological progression of crops over the specified timeframe. The values indicated fluctuations in vegetation density and growth patterns, providing insights into crop health and phenological changes. Additionally, a legend area is incorporated to provide clarity on the representation of different colors within the chart.

This view holds significant relevance in precision agriculture, offering users the capability to drop pin markers on areas exhibiting stressed vegetation. Furthermore, it facilitates the extraction of latitude and longitude coordinates for on-site physical inspection of the identified portions of the land. This functionality proves particularly advantageous in the context of vast agricultural landscapes, where such analysis provides an overarching assessment of crop health and enables precise identification of stressed crops.

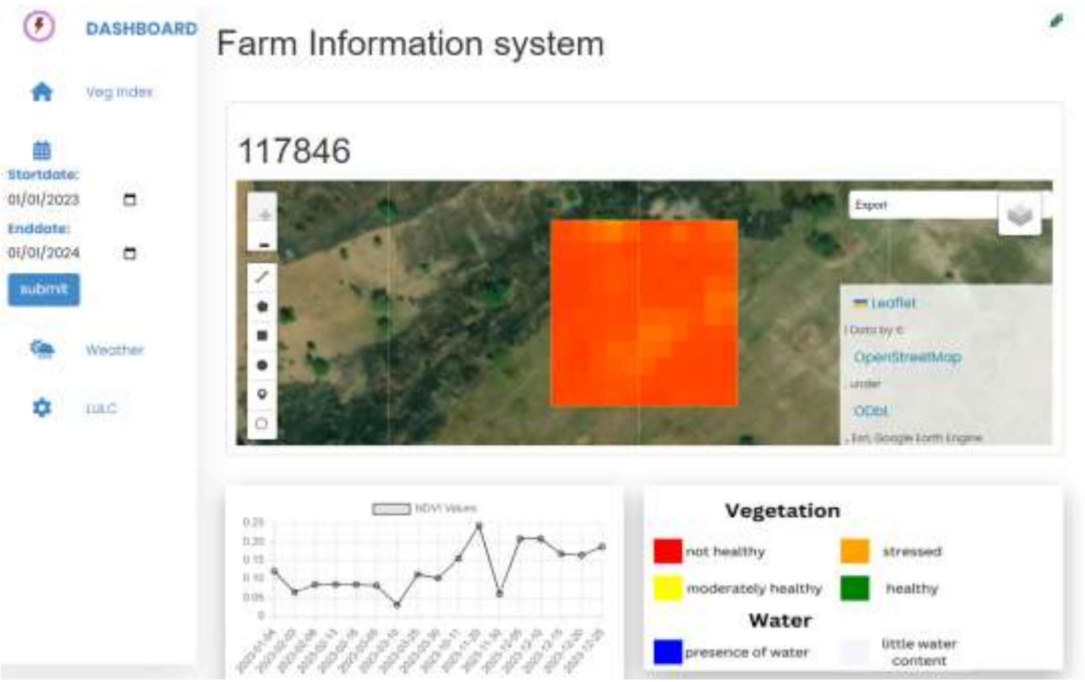

Figure 4.4: Vegetative indices view for NDVI

A raster retrieved from Google's API (Application Programming Interface) portrays the aggregated values of NDVI across a specific time frame. Additionally, a chart is generated to provide quantitative insights into the data.

4.2.2 Normalized Difference Water Index (NDWI)

During drought events, vegetation canopy is susceptible to water stress, which can significantly impede plant development and lead to crop failure or reduced agricultural yields. Early detection of plant water stress is pivotal in mitigating such outcomes. Furnishing stakeholders with near-real-time data on plant water stress can markedly enhance water and agricultural management practices, particularly by facilitating targeted irrigation in areas where plant water requirements are unmet (European Drought Observatory, 2011).

The Normalized Difference Water Index (NDWI) serves as a robust indicator of plant water content and is closely associated with plant water stress. Consequently, it serves as an effective proxy for assessing plant water stress levels. The image below presents NDWI values for the year 2023. Additionally, a legend area is incorporated to provide clarity on the representation of different colors within the chart. NDWI in the diagram below highlighted areas with abundant water content, crucial for assessing irrigation needs and hydrological dynamics.

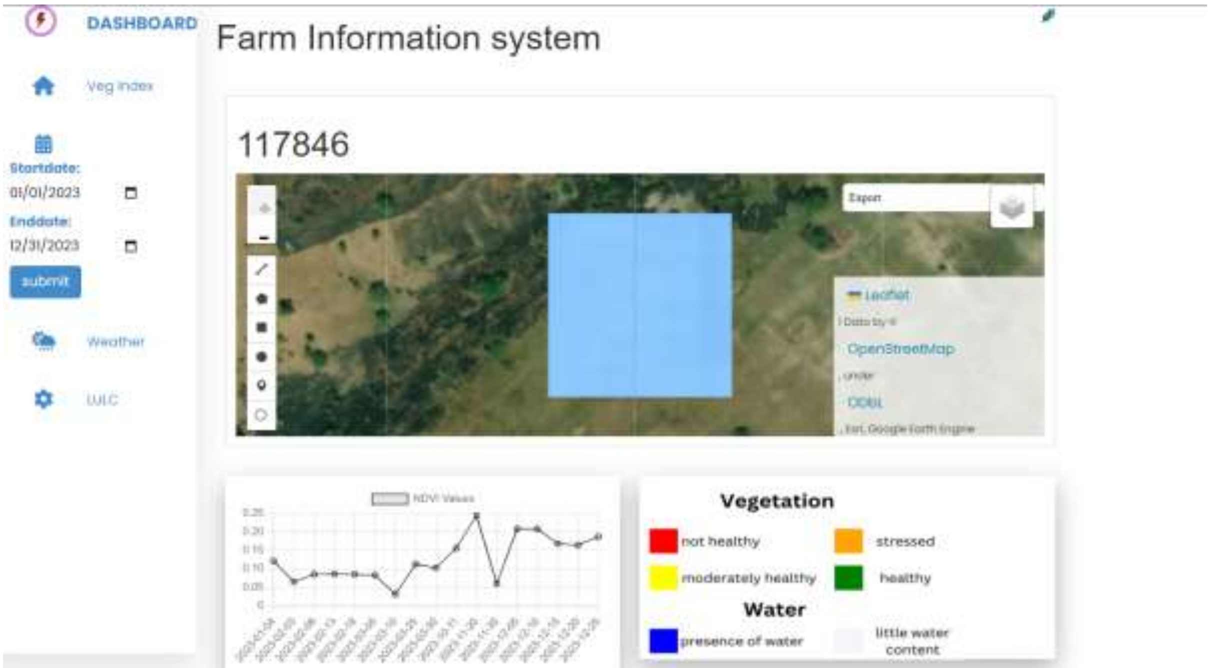

Figure 4.5: Vegetative indices view for NDWI

A raster retrieved from Google's API (Application Programming Interface) portrays the aggregated values of NDWI across a specific time frame.

4.2.3 Enhanced Vegetation Index (EVI)

The Enhanced Vegetation Index (EVI) mirrors the Normalized Difference Vegetation Index (NDVI) in its ability to gauge vegetation greenness. However, EVI offers corrections for certain atmospheric conditions and canopy background noise, rendering it more adept in regions characterized by dense vegetation. This adjustment involves the incorporation of an "L" value to accommodate canopy background, "C" coefficients for atmospheric resistance, and values derived from the blue band (B). By integrating these refinements, the EVI facilitates index calculation as a ratio between the red (R) and near-infrared (NIR) values, thereby mitigating background noise, atmospheric interference, and saturation under most circumstances (*Landsat Enhanced Vegetation Index | U.S. Geological Survey*, n.d.).

The EVI formula is represented as follows:

EVI = G * ((NIR - R) / (NIR + C1 * R – C2 * B + L))

The incorporation of additional corrections by EVI elucidates why the results portray moderately healthy vegetation growth throughout 2023, in contrast to NDVI, which depicts the vegetation as stressed, as illustrated in the image below.

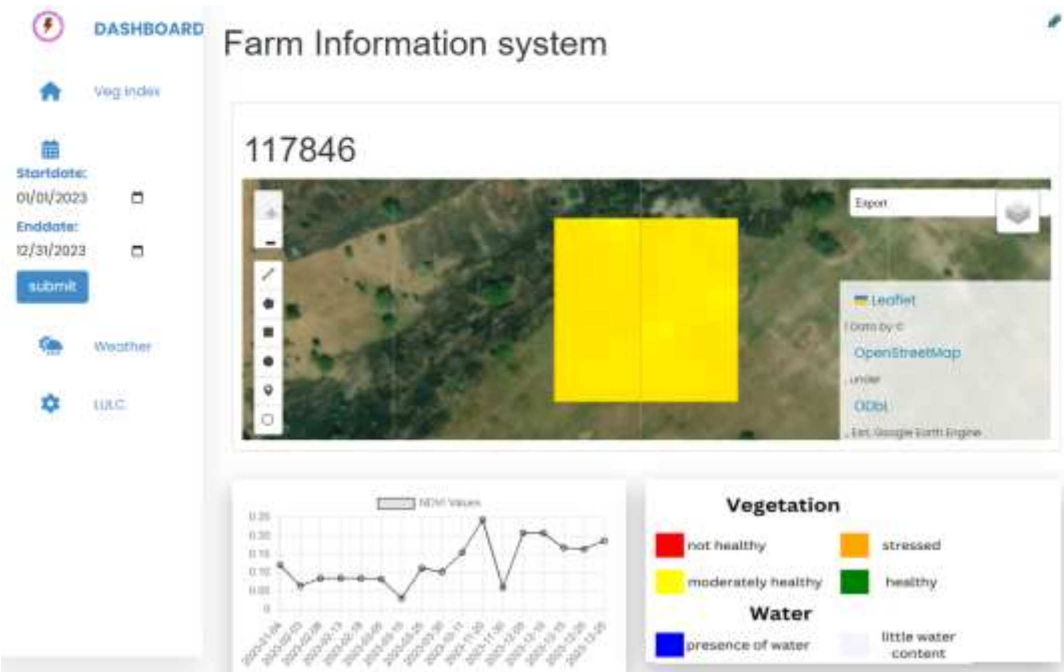

Figure 4.6: Vegetative indices view for EVI

A raster retrieved from Google's API (Application Programming Interface) portrays the aggregated values of EVI across a specific time frame.

4.3 Weather Data Integration

Weather forecasting plays a vital role in facilitating effective planning of farm operations, encompassing tasks like planting, irrigation, fertilizer application, pruning/weeding, harvesting, or livestock mating, as agriculture heavily relies on seasonal patterns and weather conditions. Traditionally, farmers depended on intuition, past experiences, and keen observation to forecast weather, often leading to substantial losses due to inaccurate predictions. The unreliability of these methods is exacerbated by the increasingly frequent and unpredictable weather changes attributed to climate change (*Role of Weather Forecasting in Farming*, 2023).

To integrate weather data into the application, a JavaScript function was developed to establish a connection with the HTML template, enabling the rendering of data on the frontend. Within the weather.js file, a function was implemented. This function accepts the coordinates corresponding to the midpoint of the farmland. Subsequently, it utilizes the latitude and longitude coordinates to retrieve data from the Open Weather API. The function extracts both current and future weather data, which are then presented on the frontend of the application as illustrated in the diagram below.

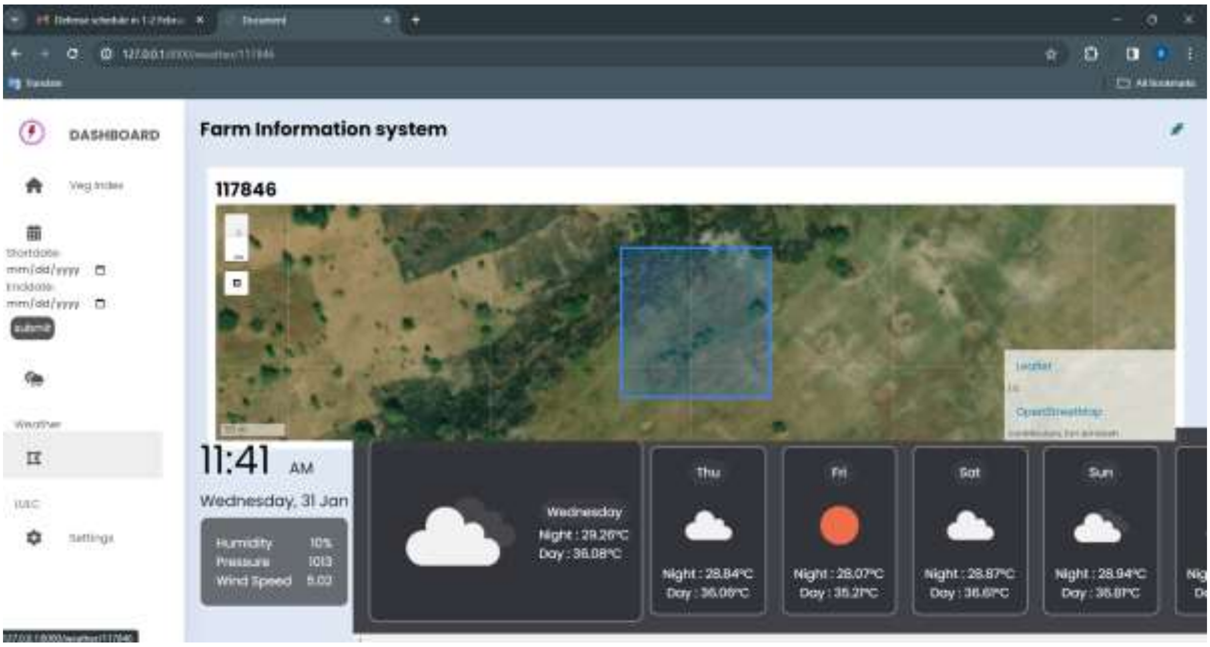

Figure 4.7: Weather View

The diagram illustrates the current weather conditions and provides a forecast for the upcoming seven days.

4.4 Land Cover Classification

A time series consisting of annual global maps depicting land use and land cover (LULC) is available, encompassing data from 2017 to 2021. These maps are derived from ESA Sentinel-2 imagery with a resolution of 10 meters. Each map represents a composite of LULC predictions spanning nine classes throughout the year, providing a comprehensive snapshot for each annual period. The dataset was curated by Impact Observatory, utilizing billions of human-labeled pixels provided by the National Geographic Society to train a deep learning model for land classification. The global map was generated by deploying this model to the Sentinel-2 annual scene collections accessible on the Planetary Computer platform. The accuracy assessment for each map exceeds 75% (Krishna *et al*., 2021).

According to the literature review, ESRI global land cover outperformed other global land cover datasets, leading to its selection for integration into the application. To incorporate ESRI land cover data into the app, the API was utilized to access the image collection, which was subsequently filtered for the year 2022 and the relevant farm lands. Visualization techniques were then applied to accurately represent the corresponding land cover classes before rendering the data to the frontend template. Additionally, a designated div element was created on the frontend to house the legend, illustrating the classes depicted on the map.

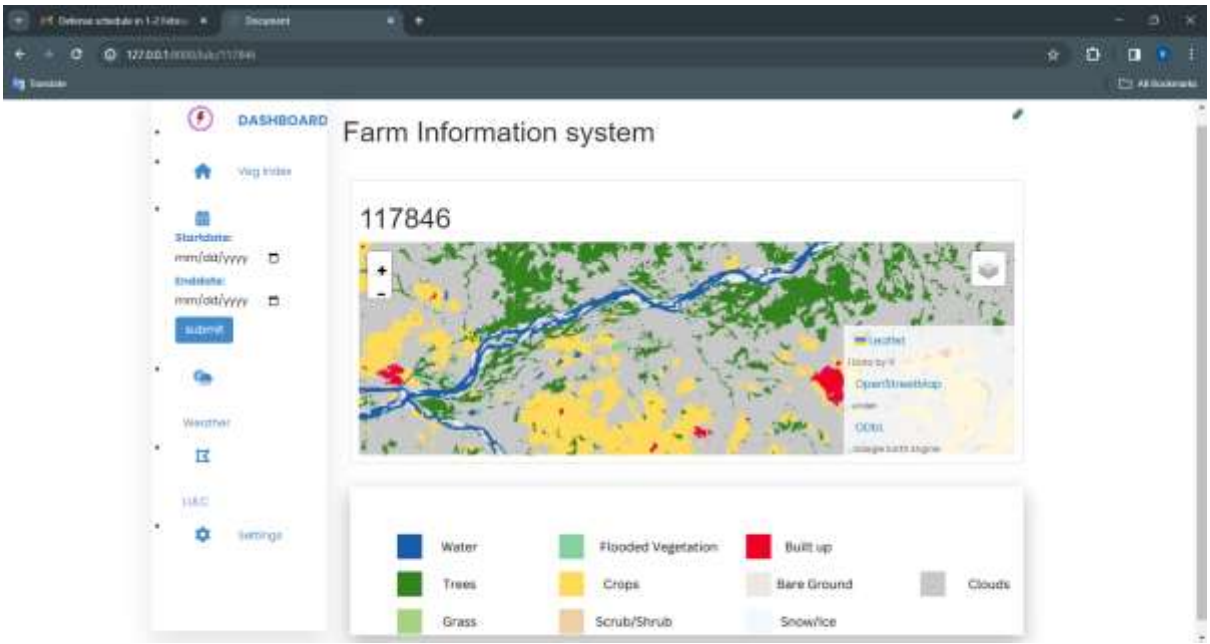

Figure 4.8: Landcover view

The diagram illustrates the 2022 land cover with the different classes within the area of interest.

4.5 Code Implementation

The GitHub repository associated with this thesis project serves as a centralized location for storing and managing the codes developed throughout the research endeavor. It encapsulates the practical implementation of the methodologies discussed in this study and facilitates access to the underlying software resources.

The code repository can be accessed at the following URL:

https://github.com/daveveed/farmInformationSystem.git

The repository contains scripts, modules, and other code artifacts essential for the implementation of various aspects of the research project. These codes encompass functionalities related to data collection, preprocessing, analysis, visualization, and web application development.

To access the codes and utilize them for further exploration or replication of the study findings, follow these steps:

- Navigate to the repository URL provided above.
- Clone the repository to your local machine using Git or download the code files directly from the repository.
- Refer to the Requirements.txt file for detailed instructions on setting up and running the code modules.

The views.py file, located within the testapp folder, is a critical component of this application. It facilitates integration with the Google API, enabling the generation of indices and the seamless integration of various parts of the application, such as user forms and models. Due to its extensive nature, including the entire code section in this document would elongate it significantly. Therefore, access the views.py file through the following link: https://github.com/daveveed/farmInformationSystem/blob/master/testapp/views.py

4.6 License Information

The codes stored in this repository are shared under the Massachusetts Institute of Technology (MIT) License. Refer to the LICENSE.md file within the repository for detailed information regarding the terms and conditions of use.

5. Discussion & Conclusions

This study extends beyond conventional research, as there have been numerous studies aligned with my objectives. However, a noticeable gap exists, wherein there is a scarcity of tangible products or tools accessible to end users, based on my research findings. The primary goal of this research is to address this gap by developing a web platform aimed at assisting smallholder farmers and decision-makers in making informed decisions regarding farm-related activities. Unlike traditional literature-based approaches, this research endeavors to create a practical tool that potential end users can actively engage with. For instance, farmers are less likely to delve into literature on how NDVI can aid in farm monitoring, but a user-friendly tool providing real-time updates on their farming activities can significantly enhance their ability to optimize farm operations. Furthermore, such a tool, through notifications, can increase farmers' resilience to the impacts of climate change by keeping them informed about weather-related updates. This thesis underscores the significance of employing remote sensing technologies and web-based tools in enhancing agricultural productivity, environmental sustainability, and informed decision-making within agricultural landscapes.

5.1 Summary of Key Findings

5.1.1 Vegetative Indices Analysis

The analysis of NDVI, NDWI, and EVI revealed significant variations in vegetative health and crop vitality over time NDVI values indicated fluctuations in vegetation density and growth patterns, providing insights into crop health and phenological changes. NDWI measurements highlighted areas with abundant water content, crucial for assessing irrigation needs and hydrological dynamics. EVI assessments demonstrated the vegetation's response to environmental stressors, aiding in the identification of areas susceptible to drought or other adverse conditions.

5.1.2 Weather Data Integration

The integration of real-time and forecasted weather data from the OpenWeatherMap API facilitates informed decision-making for farmers about when to apply fertilizers, pesticides etc. Weather information on humidity, pressure, wind speed, and temperature provides valuable insights into weather patterns and trends, enabling proactive agricultural management practices.

5.1.3 Land Cover Classification

The classification of land cover types using the ESRI 10m land cover dataset showcased the spatial distribution of diverse land cover categories. Identification of water bodies, vegetation clusters, built areas, and bare ground enhanced understanding of the environmental landscape and land use patterns. The analysis of land cover changes over time highlighted areas of ecological significance and potential areas for conservation efforts.

Overall, the answers to the research questions are the following:

What are the optimal vegetation indicators that can provide actionable insights to support smallholder farmers in making informed decisions about crop health, irrigation, and nutrient management?

The methodology highlights that the most commonly utilized vegetation indicators include NDVI, NDWI, where EVI is employed to substantiate and validate the outcomes derived from NDVI analysis.

Which global land cover classification datasets are most effective for accurate land cover classification and image segmentation?

This research examined the endeavors of previous researchers, which served as the foundation for selecting the land cover provider for this study. Among the available options, three global Land Use Land Cover (LULC) maps were considered: Google's Dynamic World (DW), ESA's World Cover (WC), and Esri's Land Cover (Esri). The study determined that Esri's land cover exhibited the highest overall accuracy. Consequently, the dataset from Esri was chosen for use in the analysis.

Which tools and technologies are most suitable for developing a user-friendly and accessible Integrated Farming Information System that seamlessly integrates real-time data for smallholder farmers and decision makers?

Given the time constraints of this study, the selection of tools and technologies was guided by the need for simplicity and effectiveness. For cloud computation, Google Earth Engine (GEE) was chosen due to its user-friendliness and efficient processing capabilities. As a cloud-based platform for geospatial analysis, GEE harnesses Google's computational resources, thereby reducing processing time. Moreover, GEE hosts satellite imagery and offers free access for academic purposes. In conjunction with GEE, Django was employed as the web framework for its ease of use and seamless integration with GEE. This choice facilitated the development of the web platform, enabling smooth interaction between the backend processing powered by GEE and the frontend interface provided by Django.

What are the benefits of these technologies to farmers and stakeholders?

The integration of technologies such as remote sensing, web-based platforms, and data analytics offers several benefits to farmers and stakeholders in the agricultural sector. However, it also comes with certain limitations.

Benefits:

- Improved Decision-Making: Farmers can make more informed decisions regarding crop management, irrigation scheduling, and resource allocation based on real-time data and insights provided by these technologies.
- Enhanced Productivity: Remote sensing technologies enable farmers to monitor crop health, detect diseases and pests early, and optimize inputs such as fertilizers and pesticides, leading to improved crop yields and productivity.
- Resource Efficiency: By precisely targeting inputs such as water, fertilizers, and pesticides based on data-driven recommendations, farmers can minimize waste and reduce environmental impact, promoting sustainable agricultural practices.
- Risk Management: Weather forecasting and analysis tools help farmers mitigate risks associated with adverse weather conditions, allowing for timely adjustments in farming practices and crop management strategies.
- Cost Savings: By optimizing resource usage and reducing input costs, farmers can realize significant cost savings over time, improving their overall profitability and financial sustainability.

Limitations:

- Technological Barriers: The adoption of advanced technologies may be hindered by factors such as limited access to internet connectivity, inadequate infrastructure, particularly in rural and remote areas.
- Data Interpretation Challenges: Farmers may struggle to interpret complex data generated by remote sensing and weather forecasting tools, requiring training and support to effectively utilize the available information for decision-making.

- Digital Divide: Disparities in access to technology and digital literacy skills among farmers and stakeholders may exacerbate inequalities and limit the equitable distribution of benefits from technological advancements in agriculture.

Despite these limitations, the continued advancement and integration of technologies in agriculture hold immense potential to drive innovation, improve sustainability, and enhance livelihoods for farmers and stakeholders.

5.2 Research Limitations

The research encountered several limitations that warrant acknowledgment. Firstly, Nigeria's tropical climate results in frequent cloud cover, posing challenges in acquiring cloud-free satellite images consistently throughout the year. Therefore, the study's reliability is contingent upon the availability of satellite imagery across different seasons. Additionally, the research relies on open and freely available resources, such as open weather map, which imposed limitations on the frequency and extent of forecasts due to account constraints. Moreover, the study is in its beta stage, and due to time constraints, it was not feasible to engage real-world users for evaluating user interactions and obtaining feedback. Consequently, the effectiveness of the web application in facilitating data exploration and decision-making processes for farmers and stakeholders remains unassessed. These limitations underscore the need for further research and refinement to enhance the robustness and applicability of the study's findings and outcomes.

5.3 Future Research Directions

Expanding upon this tool presents significant potential, as it could evolve into a comprehensive platform for decision-making in farm-related activities. There are several features that could be integrated into the platform for future research and development, including:

- Land Surface Temperature (LST): Incorporating LST data would enhance the platform's capability to monitor temperature variations and their impact on agricultural productivity.
- Yield Prediction Algorithm: Developing an algorithm for yield prediction would provide valuable insights into crop performance and help farmers make informed decisions regarding planting and harvesting.

- Integration of Multiple Satellite Images: Enhancing the system's robustness by incorporating data from multiple satellite providers ensures continuity in data availability, even in scenarios where certain providers may experience limitations.
- User Feedback Evaluation: Conducting user feedback evaluations would enable refinement and improvement of the platform's usability and functionality based on user experiences and preferences.
- Comparison with Field Results: Comparing the platform's outputs, such as vegetative indices, with actual field data would validate the accuracy and reliability of the data and analyses generated by the platform.
- Mobile Compatibility: Developing a mobile-compatible version of the app would enhance accessibility and usability, allowing potential users to access and interact with the platform conveniently on mobile devices.

These enhancements would contribute to the platform's effectiveness in supporting farmers and stakeholders in making informed decisions and optimizing agricultural practices.

References

Adeite, A. (2022). *UNCOMMON FACTS ABOUT SMALLHOLDER FARMERS IN NIGERIA*. Retrieved from babangona: https://babbangona.com/uncommon-facts-about-smallholder-farmers-in-nigeria/#:~:text=Farmers%20in%20Nigeria-,There%20are%20about%2038%20million%20smallholder%20farmers%20in%20Nigeria,%25%20of%20the%20country's%20population

Agyekum, T., Antwi-Agyei, P., & Dougill, A. J. (2022). The contribution of weather forecast information to agriculture, water, and energy sectors in East and West Africa: A systematic review. *Front. Environ. Sci.*, 935 - 696. doi:doi: 10.3389/fenvs.2022.935696

Augustine, L. (2020). Smallholder Farmers' Access to Inputs and Finance in Africa. *The Role of Smallholder Farms in Food and Nutrition Security*. doi:https://doi.org/10.1007/978-3-030-42148-9_7

Awesome GEE. (n.d.). *ESRI 10m Annual Land Use Land Cover (2017-2022)*. awesome-gee-community-catalog. Retrieved January 23, 2024, from https://gee-community-catalog.org/projects/S2TSLULC/

Balana, B. B., & Oyeyemi., M. A. (2022). Agricultural credit constraints in smallholder farming in developing countries: Evidence from Nigeria. *World Development Sustainability, 1*. doi:https://doi.org/10.1016/j.wds.2022.100012

Boori, M. S., Choudhary, K., & Kupriyanov, A. (2020). Crop growth monitoring through Sentinel and Landsat data based NDVI time-series. *Computer Optics*, *44*, 409-419. 10.18287/2412-6179-CO-635

Borrero, J. D., & Jesús, M. (2022). A Case Study of a Digital Data Platform for the Agricultural Sector: A Valuable Decision Support System for Small Farmers. *Agriculture, 12*(6). Retrieved from https://doi.org/10.3390/agriculture12060767

Bread for the World. (2023). *What Are the Challenges of Smallholder Farmers Around the World?* Retrieved November 1, 2023, from Bread for the World: https://www.bread.org/article/challenges-of-smallholder-farmers/

Chenghu, Z., Tao, P., Jun, X., Ting, M., Zide, F., & Jianghao, W. (2018). Urban Dynamics and GIScience. *Comprehensive Geographic Information Systems*, 297 - 312.

Chiaka, J. C., Zhen, L., Yunfeng, H., Xiao, Y., Muhirwa, F., & Lang, T. (2022). Smallholder Farmers Contribution to Food Production in Nigeria. *Frontiers in Nutrition, 9*. doi:10.3389/fnut.2022.916678

Churi, A., Mlozi, P., Mahoo, H., Tumbo, S., & Casmir, R. (2013). A Decision Support System for Enhancing Crop Productivity of Smallholder Farmers in Semi-Arid Agriculture. 3.

Commodity Port. (2019, January 28). *Five Major Problems Facing*. Retrieved from Commodity Port: https://www.commodity-port.com/2019/01/28/five-major-problems-facing-agriculture-in-nigeria/

Czembor, E., Kaczmarek, Z., Pilarczyk, W., Mańkowski, D., & Czembor, J. (2022). Simulating Spring Barley Yield under Moderate Input Management System in Poland. *Agriculture, 12*, 1091. doi:https://doi.org/10.3390/agriculture12081091

Daniel, M., & John, N. (2022). Challenges Smallholder Farmers Face in Extracting Value from Agricultural information. *The African Journal of Information Systems, 14*(1). Retrieved from https://digitalcommons.kennesaw.edu/ajis/vol14/iss1/1

Dhanaraju, M., Chenniappan, P., Ramalingam, K., Pazhanivelan, S., Kaliaperumal, & Ragunath. (2022). Smart Farming: Internet of Things (IoT)-Based Sustainable Agriculture. *Agriculture*(12). doi: https://doi.org/10.3390/agriculture12101745

Ding, Y., Yang, X., Wang, Z., Fu, D., Li, H., Meng, D., Zeng, X.-P., & Zhang, J. (n.d.). A Field-Data-Aided Comparison of Three 10 m Land Cover Products in Southeast Asia. Remote sensing. *Remote Sensing*, *14*(19), 5053-5053. 10.3390/rs14195053

Emmanuel, A.-A. (2016). An Evaluation of Challenges Facing Smallholders in Ghana: A Case study for the Aowin Suaman District. *Journal of Biology, Agriculture and Healthcare, 2*(6).

Ephraim, F. P. (2017). Farm Labour Problems of Small Scale Farmers: A Case Study of Some Farming Communities in Plateau State Nigeria. *Journal of Agriculture and Sustainability, 10*(2), 187 - 197. Retrieved from https://infinitypress.info/index.php/jas/article/download/1615/655

European Drought Observatory. (2011). *NDWI: Normalized Difference Water Index*. https://edo.jrc.ec.europa.eu/documents/factsheets/factsheet_ndwi.pdf

Ezekiel, O. (2018). *MECHANIZATION FOR SMALLHOLDER FARMING: AN INDISPENSABLE TOOL FOR ECONOMIC DIVERSIFICATION.*

Fabregas, R. (2022). *Digital Agricultural Extension for Development.* . Springer eBooks.

Fan, S. (2020). The Role of Smallholder Farmers in Food and Futrition Security.

FAO. (2012). *State of Food and Agriculture 2012: Investing in Agriculture for a Better Future.* FOOD AND AGRICULTURE ORGANIZATION.

Fisher, A., & Lippincott, M. (n.d.). Public Lab: Public Lab Lesson 3: Photography in a New Light. Retrieved February 28, 2024, from https://publiclab.org/wiki/public-lab-lesson-3-photography-in-a-new-light

Frisvold, G., & Murugesan, A. (2013). Use of Weather Information for Agricultural Decision Making. *Weather, Climate, and Society., 5*, 55-69. doi:10.1175/WCAS-D-12-00022.1.

García-Pedrero, A., Gonzalo-Martín, C., & Lillo-Saavedra. (2017). A machine learning approach for agricultural parcel delineation through agglomerative segmentation. *International Journal of Remote Sensing,, 38*(7), 1809-1819. doi:10.1080/01431161.2016.127831

Gassner, A., Harris, D., Mausch, K., Terheggen, A., Lopes, C., Finlayson, R., & Dobie, P. (2019). Poverty eradication and food security through agriculture in Africa: Rethinking objectives and entry points. *Outlook on Agriculture, 48*(4), 309-315. doi:https://doi.org/10.1177/0030727019888513

GISGeography. (2023, October 14). *What is NDVI (Normalized Difference Vegetation Index)?* Retrieved from GISGeography: https://gisgeography.com/ndvi-normalized-difference-vegetation-index/

Global Hunger Index. (2023). *Nigeria - Global Hunger Index*. Retrieved from https://www.globalhungerindex.org/nigeria.html

Gore, H., Singh, R. K., Singh, A., & Singh, A. P. (2021). Django: Web Development Simple & Fast. *Annals of R.S.C.B, 25*(6), 4576-4585.

Hiroyuki, T., & Sheu, S. (2010). *Agricultural Mechanization and the Smallholder Farmers in Nigeria.* Abuja: NIGERIA STRATEGY SUPPORT PROGRAM.

Hoang, H. G. (2020). Determinants of the adoption of mobile phones for fruit marketing by Vietnamese farmers. *World Development Perspectives, 17*, 100 - 178. doi:https://doi.org/10.1016/j.wdp.2020.100178

Htun, N.-N., Rojo, D., Ooge, J., De Croon, R., Kasimati, A., & Verbert, K. (2022). Developing Visual-Assisted Decision Support Systems across Diverse Agricultural Use Cases. *Agriculture, 12*, 10 - 27. doi:https://doi.org/10.3390/agriculture12071027

Huang, S., Tang, L., & Hupy, J. (2021). A commentary review on the use of normalized difference vegetation index (NDVI) in the era of popular remote sensing. *J. For. Res., 32*, 1-6. Retrieved from https://doi.org/10.1007/s11676-020-01155-1

Huanxue, Z., Mingxu, L., Yuji, W., Jiali, S., Xiangliang, L., Bin, L., . . . Qiangzi, L. (2021). Automated delineation of agricultural field boundaries from Sentinel-2 images using recurrent residual U-Net. *International Journal of Applied Earth Observation and Geoinformation, 105*. doi:https://doi.org/10.1016/j.jag.2021.102557

Hufkens, K., Melaas, E. K., Mann, M. L., & Foster, T. (2019). Monitoring crop phenology using a smartphone based near-surface remote sensing approach. *Agricultural and Forest Meteorology, 265*, 327-337. https://doi.org/10.1016/j.agrformet.2018.11.002

Iffat, A., Lydia, T., Matthew, T. H., Marta, M., Peter, d., & Daniel, R. (2021). Application, adoption and opportunities for improving decision support systems in irrigated agriculture: A review. *Agricultural Water Management, 257*, 107 - 161. doi:https://doi.org/10.1016/j.agwat.2021.107161

Isola, M. (2022, October). *Small-scale farmers facing myriad of challenges hampering productivity*. Retrieved from tribuneonlineng.com: https://tribuneonlineng.com/small-scale-farmers-facing-myriad-of-challenges-hampering-productivity-%E2%80%95-assapin/

Jin, Z., Azzari, G., You, C., Di Tommaso, S., Aston, S., Burke, M., & Lobell, D. (2019). Smallholder maize area and yield mapping at national scales with Google Earth Engine. *Remote Sensing of Environment., 288*, 115-128.

Jinru, X., & Baofeng, S. (2017). Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. *Journal of Sensors*, 17. Retrieved from https://doi.org/10.1155/2017/1353691

Josephine, O. (2022, January 6). *Five challenges that will impact Nigeria's 2022 agric output*. Retrieved from Businessday.ng: https://businessday.ng/agriculture/article/five-challenges-that-will-impact-nigerias-2022-agric-output/

Justina, A. O., Robert, D. O., Edward, M., & Felix, A. A. (2023). Welfare dynamics of innovations among agricultural households in Ghana: Implication for poverty reduction. *Heliyon, 9*(7). doi:https://doi.org/10.1016/j.heliyon.2023.e18066

Karen O'Brien, R. L. (2004). Mapping vulnerability to multiple stressors: climate change and globalization in India. . *Global Environmental Change*, 303-313. Retrieved from https://doi.org/10.1016/j.gloenvcha.2004.01.001

Karnieli, A., Agam, N., & Pinker, R. (2010). Use of NDVI and land surface temperature for drought assessment: merits and limitations. *Journal of Climate, 23*(3), 618–633.

Kaur, A. (2023). Field Boundary Delineation. doi:10.13140/RG.2.2.19642.57282.

Khan, N. R. (2021). Potential Role of Technology Innovation in Transformation of Sustainable Food Systems: A Review. Retrieved from https://doi.org/10.3390/agriculture11100984

Krishna, K., Caitlin, K., & Zoe, S.-W. (2021). Global land use / land cover with Sentinel 2 and deep learning. *IEEE International Geoscience and Remote Sensing Symposium IGARSS*, 4707-4707. 10.1109/IGARSS47720.2021.9553499

LaGroJr, J. A. (2005). Land Use Classification. *Encyclopedia of Soils in the Environment*, 321-328. doi:https://doi.org/10.1016/B0-12-348530-4/00530-0

Landsat Enhanced Vegetation Index | U.S. Geological Survey. (n.d.). USGS.gov. Retrieved February 17, 2024, from https://www.usgs.gov/landsat-missions/landsat-enhanced-vegetation-index

Lowder, S. K. (2014). What do we really know about the number and distribution of farms and family farms in the world? . *Background paper for The State of Food and Agriculture 2014.* doi:10.22004/ag.econ.288983

Mgbenka, R. N., & Mbah, E. (2016). A Review Of Smallholder Farming In Nigeria: Need For Transformation. *European - American journals*. doi:https://doi.org/10.37745/ijaerds.15

Michele, R., & Zhenli, H. (2014). Chapter Six - Decision Support Systems to Manage Irrigation in Agriculture*Present address: Consiglio per la Ricerca e la Sperimentazione in Agricoltura, Cereal Research Centre, S.S. 673km 25,200, 71122 Foggia, Italy,. *Advances in Agronomy, 123*, 229-279. doi:https://www.sciencedirect.com/science/article/pii/B9780124202252000066

Mitiche, A., & Aggarwal., J. (1985). Image segmentation by conventional and information-integrating techniques: a synopsis. *Image and Vision Computing, 3*(2), 50-62. doi:https://doi.org/10.1016/0262-8856(85)90013-7.

Morton, J. (2007). The impact of climate change on smallholder and subsistence agriculture: Natural Resources Institute . *University of Greenwich, UK.*

NDVI, the Foundation for Remote Sensing Phenology | U.S. Geological Survey. (2018, November 27). USGS.gov. Retrieved February 13, 2024, from https://www.usgs.gov/special-topics/remote-sensing-phenology/science/ndvi-foundation-remote-sensing-phenology

Nmadu, J. N., & Akinola, A. (2015). Farm Labor Supply and Utilization for Food Crop Production in Nigeria. *Proceedings of INTCESS15- 2nd International Conference on Education and Social Sciences*, (pp. 311 - 315). Istanbul, Turkey.

Nojozi, N., Scott, M. S., & Nomnga, P. (2016). An m-agric application for broadcasting agricultural information for subsistence farmers in rural areas of the eastern cape. 10.1109/ISTAFRICA.2016.7530645

Olanrewaju, A. (2020). Analysis of the challenges of small - scale farmers' access to labor in North central Nigeria. *Joournal of Scientific Agriculture, 4*(15), 15 - 20.

Panda, S., Ames, D., & Panigrahi, S. (2010). Application of Vegetation Indices for Agricultural Crop Yield Prediction Using Neural Network Techniques. *Remote Sensing, 2*(3), 673-696. Retrieved from https://doi.org/10.3390/rs2030673

Phan, T., Kuch, V., & Lehnert, L. (2020). Land Cover Classification using Google Earth Engine and Random Forest Classifier—The Role of Image Composition. *Remote Sens, 12*(15). doi:https://doi.org/10.3390/rs12152411

Qiang, W., Álvaro, M.-M., Jordi, M.-M., Manuel, C.-T., Gustavo, & Camps-Valls. (2022). Estimation of vegetation traits with kernel NDVI. *Isprs Journal of Photogrammetry and Remote Sensing, 195*, 408-417. doi:doi: 10.1016/j.isprsjprs

Radočaj, D., Šiljeg, A., Marinović, R., & Jurišić, M. (2023). State of Major Vegetation Indices in Precision Agriculture Studies Indexed in Web of Science: A Review. *Agriculture*, *13*(3), 707. Retrieved from http://dx.doi.org/10.3390/agriculture

Rajinder, N. (2011). *Classifying Landsat image services to make a land cover map*. Retrieved from ESRI: https://www.esri.com/arcgis-blog/products/product/imagery/classifying-landsat-image-services-to-make-a-land-cover-map/#:~:text=Using%20the%20supervised%20classification%20method,cover%20types%20to%20be%20classified

Ricciardi, V., Ramankutty, N., Mehrabi, Z., Jarvis, L., & Chookolingo, B. (2018). How much of the world's food do smallholders produce? *Global Food Security, 17*. doi:10.1016/j.gfs.2018.05.002.

Role of Weather Forecasting in Farming. (2023, January 27). Jiva. Retrieved February 17, 2024, from https://www.jiva.ag/blog/role-of-weather-forecasting-in-farming

Roudier, P., Muller, B., d'Aquino, P., Roncoli, C., Soumaré, M., Batté, L., & Sultan., B. (2014). The role of climate forecasts in smallholder agriculture: Lessons from participatory research in two communities in Senegal. *Climate Risk Management, 2*, 42-55. doi:https://doi.org/10.1016/j.crm.2014.02.001.

Rouse, J., Jr, R. H., A., S. J., & and Deering, D. W. (1978). *Monitoring the vernal advancement and retrogradation (green wave effect) of natural vegetation.* Texas : Remote Sensing Center, Texas A&M Univ., College Station.

Roslin, N. A., Che'ya, N. N., Rosle, R., & Ismail, M. R. (2021). Smartphone application development for rice field management through aerial imagery and Normalised Difference Vegetation Index (NDVI) Analysis. *pertanika journal of science and technology*, *29*(2). 10.47836/PJST.29.2.07

Sabo, B., Isah, S., Chamo, A., & Rabiu, M. (2017). Role of Smallholder Farmers in Nigeria's Food Security. *Scholarly Journal of Agricultural Science*. Retrieved from http:// www.scholarly-journals.com/SJAS

Sandeep, K. M., & Prabhu, J. (2021). Delineation of field boundary from multispectral satellite images through U-Net segmentation and template matching. *Ecological Informatics, 64*. doi:https://doi.org/10.1016/j.ecoinf.2021.101370

Sarah, K., Lowder, Skoet, J., & Raney, T. (2016). The Number, Size, and Distribution of Farms, Smallholder Farms, and Family Farms Worldwide. *World Development, 8*, 16-29. doi:https://doi.org/10.1016/j.worlddev.2015.10.041

SATPALDA. (2023, September). *Significance of Land Use / Land Cover (LULC) Maps*. Retrieved from Satpalda: https://satpalda.com/blogs/significance-of-land-use-land-cover-lulc-maps/

Sharma, A. A. (2021). Machine Learning Applications for Precision Agriculture: A Comprehensive review. *IEEE Access, 9*, 4843-4873. doi:doi:10.1109/ACCESS.2020.3048415

Showcasing the Culture of the Good People of Benue State Nigeria North-Central. (n.d.). Scouts for SDGs. Retrieved January 21, 2024, from https://sdgs.scout.org/post/showcasing-culture-good-people-benue-state-nigeria-north-central

Siloko, I., K.E., U., A, S. E., Enoyoze, E., Bobadoye, A., Ishiekwene, C., . . . Nwankwo., W. (2021). Effects of some meteorological variables on cassava production in Edo State, Nigeria via density estimation. *Scientific African, 13*. doi:https://doi.org/10.1016/j.sciaf.2021.e00852

Sishodia RP, R. R. (2020). Applications of Remote Sensing in Precision Agriculture: A Review. *Remote Sensing, 12*. Retrieved from https://doi.org/10.3390/rs12193136

Sodiq, J. (2023, April 05). *Top 10 Highest Agricultural Producing States in Nigeria*. Retrieved Oct 2023, from Onlineworld.ng: https://www.onlineworld.ng/2023/02/agricultural-producing-states-nigeria.html

Sophia, S. R., & Ndambuki, J. M. (2017). Accuracy Assessment of Land Use/Land Cover Classification Using Remote Sensing and GIS. *International Journal of Geosciences*.

Spectral properties and unique spectral signatures – Remote Sensing in Action 9841384. (2018, January 18). Remote Sensing in Action 9841384. Retrieved February 28, 2024, from https://remotesensinginactionreflectivelearningblog.wordpress.com/2018/01/18/spectral-properties-and-unique-spectral-signatures/

Tao, C., Xusheng, J., Gaoxiang, Y., Hengbiao, Z., Jifeng, M., Xia, Y., . . . Weixing, C. (2020). DESTIN: A new method for delineating the boundaries of crop fields by fusing spatial and temporal information from WorldView and Planet satellite imagery. *Computers and Electronics in Agriculture, 178*. doi:https://doi.org/10.1016/j.compag.2020.105787.

The National Aeronautics and Space Administration. (2010, August 10). *Reflected Near-Infrared Waves*. Retrieved January 7, 2024, from https://science.nasa.gov/ems/08_nearinfraredwaves/

Tiemann, T., & Douxchamps, S. (2023). Opportunities and challenges for integrated smallholder farming systems to improve soil nutrient management in Southeast Asia,. *World Development Sustainability*. doi:https://doi.org/10.1016/j.wds.2023.100080.

Triantafyllou A, S. P. (2019). Precision Agriculture: A Remote Sensing Monitoring System Architecture. Retrieved from https://doi.org/10.3390/info10110348

Tsao, A., Ikenna, N., Ayodeji, J., Uzoma, A., & David, B. L. (2023). Canopy Height Mapping for Plantations in Nigeria Using GEDI, Landsat, and Sentinel-2. *Remote Sensing, 15*(21), 51 - 62. Retrieved from https://doi.org/10.3390/rs15215162

United Nations. (2021, November). *United Nations.* Retrieved from https://www.un.org/development/desa/dpad/publication/frontier-technology-issues-frontier-technologies-for-smallholder-farmers-addressing-information-asymmetries-and-deficiencies/

Utomi, J.-M. (2023, October 18). *Food crisis and Nigeria's multi-dimensional poverty*. Retrieved from Vanguard: https://www.vanguardngr.com/2023/10/food-crisis-and-nigerias-multi-dimensional-poverty/

Venter, Z. S., Barton, D. N., Chakraborty, T., Simensen, T., & Singh, G. (2022). *Global 10 m Land Use Land Cover Datasets: A Comparison of Dynamic World, World Cover and Esri Land Cover. Remote sensing*. Remote Sensing. 10.3390/rs14164101

Venkata, S., Konduri, T. J., Vandal, S., Ganguly, R, A., & Ganguly. (2020). Data Science for Weather Impacts on Crop Yield. *Frontiers in Sustainable Food Systems*. doi:https://doi.org/10.3389/fsufs.2020.00052

Vibhute, A., & Gawali, B. (2013). Analysis and modeling of agricultural land use using remote sensing and geographic information system: a review. *International Journal of Engineering Research and Applications. , 3*, 81-91.

Vlachopoulos, O., Brigitte, L., Jinfei, W., Ataollah, H., Armand, LaRocque, & Greg, P. (2020). Delineation of Crop Field Areas and Boundaries from UAS Imagery Using PBIA and GEOBIA with Random Forest Classification. *Remote Sensing, 12*, 26 - 40.

Watkins, B., & Van Niekerk, A. (2019). Automating field boundary delineation with multi-temporal Sentinel-2 imagery. *Computers and Electronics in Agriculture., 167*. doi:10.1016/j.compag.2019.105078.

Weckesser, F., Beck, M., Hülsbergen, K.-J., & Peisl, S. A. (2022). Digital Advisor Twin for Crop Nitrogen Management. *Agriculture, 12*. Retrieved from https://doi.org/10.3390/agriculture12020302

Wikipedia. (2023, Oct). *Normalized difference vegetation index*. Retrieved from Wikipedia: https://en.wikipedia.org/wiki/Normalized_difference_vegetation_index

Willy, D. K., Yacouba, D., Hippolyte, A., Francis, N., Michael, W., & Tesfamicheal, W. (2020). *COVID-19 Pandemic in Africa: Impacts on Agriculture and Emerging Policy Responses for Adaptation and Resilience Building.* Retrieved from Technologies for African Agricultural Transformation: https://www.farm-d.org/app/uploads/2020/06/TAAT-Policy-Working-Paper-on-COVID19_FINAL-for-Dissemination_May-2020.pdf

WMO. (2020). *WORLD METEOROLOGICAL ORGANIZATION*. Retrieved from https://worldweather.wmo.int/en/home.html

World Bank. (2023, SEPTEMBER). *THE WORLD BANK*. Retrieved from AGRICULTURE OVERVIEW: https://www.worldbank.org/en/topic/agriculture/overview#1

Xie, L., Luo, B., & Zhong, W. (2021). How Are Smallholder Farmers Involved in Digital Agriculture in Developing Countries: A Case Study from China. *Land, 10*(245). doi:https://doi.org/10.3390/land10030245

Yegbemey, R. N., Aloukoutou, A. M., & Aïhounton, G. B. (2021). The Impact of Short Message Services (SMS) Weather Forecasts on Cost, Yield and Income in Maize Production: Evidence from a Pilot Randomised Controlled Trial in Bembèrèkè, North Benin. Afri. *Africa Development / Afrique et Développement,, 46*(1), 163–188. Retrieved from https://www.jstor.org/stable/48618359

Yousefi, S., Mirzaee, S., Almohamad, H., Al Dughairi, A., Gomez, C., Siamian, N., . . . Abdo, H. (2022). Image Classification and Land Cover Mapping Using Sentinel-2 Imagery: Optimization of SVM Parameters. *Land, 11,*, 993. doi: https://doi.org/10.339

Zhaoyu, Z., José Fernán, M., Victoria, B., & Néstor Lucas, M. (2020). Decision support systems for agriculture 4.0: Survey and challenges. *Computers and Electronics in Agriculture, 170*, 105 - 256. doi:https://doi.org/10.1016/j.compag.2020.105256

Zubler, A. V., & Yoon, J. Y. (2020). Proximal Methods for Plant Stress Detection Using Optical Sensors and Machine Learning. *Biosensors (Basel)., 10*(12). doi:10.3390/bios10120193.

Zubler, A., & Yoon, J. (2020). Proximal Methods for Plant Stress Detection Using Optical Sensors and Machine Learning. *Biosensors (Basel), 10*(12), 193. doi:10.3390/bios10120193