# EXPLORING THE USE OF UNMANNED AERIAL VEHICLE RGB DATA FOR CROP MONITORING AND MAPPING WITHIN A SMALLHOLDER SETTING: A CASE STUDY IN SWAYIMANE

**by**

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# PREFACE

The research contained in this thesis was completed by the candidate while based in the Discipline of Hydrology, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg, South Africa. The research was financially supported by the Water Research Commission (WRC).

The contents of this work have not been submitted in any form to another university and, except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

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## DECLARATION 1: PLAGIARISM

I, Evania Chetty, declare that:

(i) the research reported in this thesis, except where otherwise indicated or acknowledged, is my original work;

(ii) this thesis has not been submitted in full or in part for any degree or examination to any other university;

(iii) this thesis does not contain other persons' data, pictures, graphs or other information, unless specifically acknowledged as being sourced from other persons;

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## DECLARATION 2: PUBLICATIONS

My role in each paper and presentation is indicated. The * indicates the corresponding author. The details are also provided of the contributions of each author to the research and writing of each publication.

**Publication 1 (Chapter 3)** is in preparation for submission to the *International Journal of Remote Sensing* with authors:

Chetty, E*, Gokool, S, Mahomed, M. 2024. A Comparative Analysis of Multi-spectral and RGB-acquired UAV data for Cropland Mapping in Smallholder Farms.

The research reported on is based on the data collected by E Chetty from areas in and around the study site in Swayimane. E Chetty undertook the design experiment, data collection and analysis. Advice on the methodologies and structure of the paper was sought from S, Gokool and M, Mahomed. Subsequently, the review of relevant literature, data analysis as well as all figures and tables have been produced by E Chetty.

**Publication 2 (Chapter 4)** is in preparation for submission to the *Journal of Agronomy* with authors:

Chetty, E*, Gokool, S, Mahomed, M. 2024. Assessing the potential of UAV-RGB data for LAI estimation in a Smallholder Farm.

This paper is an analysis of data collected at a sugarcane field in Swayimane. The experiment was designed by E Chetty and the data was collected by E, Chetty, S, Gokool and M, Mahomed provided advice and supervision on data interpretation as well as on the paper structure. The data was analysed by E, Chetty and written by the same.

**Presentations:**

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Chetty E*, Gokool S, and Mahomed M. 2023. Exploring the use of unmanned aerial vehicle data for crop mapping and monitoring within a smallholder farm setting: A case study in Swayimane. *7th Annual Fountain Hill Research Symposium.* Fountain Hill Estate, Wartburg, South Africa, 18-19 October 2023.

Chetty E*, Gokool S, and Mahomed M. 2024. A Comparative Analysis of Multi-spectral and RGB Acquired UAV Data for Cropland Mapping in Smallholder Farms. *South African Hydrological Society Conference*. Protea Breakwater Lodge, Cape Town, South Africa, 2-4 October 2024.

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ABSTRACT

Smallholder farms within Sub-Saharan Africa (SSA) are the backbone of agricultural systems due to their significant contribution to food production, thus rendering them essential for enhancing food security across the region. Despite this, their limited financial capacity, lack of resources and access to technology and information pose significant challenges for optimal agricultural production. The detrimental consequences of climate change and population expansion further impede their capacity to keep up with food demands. Advancements in precision agriculture (PA) such as the use of unmanned aerial vehicles (UAVs) can provide, near real-time data collection and adequate spatiotemporal resolution for smallholder heterogeneous farms thereby enabling informed and customised agriculture management to optimise agricultural productivity and resource use.

This study investigates the potential of UAV-RGB data as a reliable and cost-effective solution to facilitate PA in smallholder farms. Specifically, it assessed UAV RGB data for land use classification and evaluated its effectiveness in estimating Leaf Area Index (LAI). While various sensors such as multi-spectral and hyperspectral sensors, offer significant spectral depth, their high costs limit the applicability for smallholder farmers. In contrast, UAV-RGB sensors are more affordable, promoting wider adoption. These sensors coupled with machine learning algorithms within cloud computing environments are more commonly appearing as accurate alternatives, particularly for processing large complex agricultural remote sensing datasets. Subsequently, this study utilizes machine learning classification approaches, comparing the two commonly used UAV multi-spectral and RGB sensor data for cropland mapping and crop monitoring. The Random Forest (RF) classifier effectively classified agricultural land with UAV-RGB data, achieving an area under the curve receiver operating characteristic (AUC-ROC) value of 0.75, while the UAV multi-spectral data yielded a marginally higher AUC-ROC of 0.77. For crop monitoring, we assessed LAI as a key growth metric, where the RF ensemble produced UAV-RGB LAI predictions with a root mean square error (RMSE), mean absolute error (MAE) and R-squared ($R^2$) of 0.45, 0.31 and 0.73 respectively, which was less accurate but still reliable when compared to the UAV multi-spectral predictions (RMSE = 0.37, R2 = 0.81 and MAE = 0.24)

The findings underscore the effectiveness of UAV-RGB data as a low-cost alternative that enhances the accessibility for smallholder farms, promoting the widespread adoption of precision agriculture practices. By enabling the accurate classification of agricultural land and monitoring of crop growth through reliable LAI predictions, this technology facilitates tailored solutions, improved decision-making and resource management, ultimately optimising agricultural practices and productivity. These advancements hold significant implications for developing nations such as SSA where smallholder farming systems are vital for sustaining food production which strengthens food security thereby resulting in a domino effect on various socio-economic factors.

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## LIST OF SYMBOLS

| | |
|---|---|
| $^{o}C$ | Degree Celsius |
| % | Percentage |
| $km^2$ | Kilometres squared |
| m | Meters |
| mm | millimetres |
| m/s | Meter per second |
| nm | nanometres |
| $R^2$ | R-squared |

## LIST OF ABBREVIATIONS

| | |
|---|---|
| AGL | Above Ground Level |
| AI | Artificial Intelligence |
| API | Application Programming Interface |
| AUC-ROC | Area Under the Curve Receiver Operating Characteristic |
| BBTD | Banana Bunch Top Disease |
| BPNN | Backpropagation Neural Network |
| Caret | Classification and Regression Tree |
| CC | Canopy Coverage |
| CHM | Canopy Height Model |
| CPU | Central Processing Unit |
| CRP | Calibrated Reflection Panel |
| CSV | Comma Separated Value |
| DL | Deep Learning |
| DLS | Downloading Light Sensor |
| DT | Decision Tree |
| EMLM | Ensemble Machine Learning Model |
| FPR | False Positive Rate |
| GCPs | Ground Control Points |
| GEE | Google Earth Engine |
| GIS | Geographic Information System |
| GLM | Generalized Linear Model |
| GPS | Global Position Systems |
| GPU | Graphics Processing Unit |
| GSD | Ground Sampling Distance |
| GTB | Gradient Tree Boost |
| HPC | High Performing Computing |
| ICT | Improvement Communication and Technologies |
| IoT | Internet of things |
| ISPA | International Society of Precision Agriculture |
| kml | Keyhole Markup Language |
| kNN | k Nearest Neighbor |

| | |
|---|---|
| LAI | Leaf Area Index |
| LightGRM | Light Gradient Boosting Machine |
| Linear Regression | LR |
| LULC | Land Use Land Cover |
| MAE | Mean Absolute Error |
| ML | Maximum Likelihood |
| MLM | Multiple Linear Regression |
| N | Nitrogen |
| NNI | Nitrogen Nutrition Index |
| NDVI | Normalized Difference Vegetation Index |
| OA | Overall Accuracy |
| OBIA | Object-Based Image Analysis |
| OOB | Out Of Bag |
| PA | Precision Agriculture |
| RR | Ridge Regression |
| RGB | Red-Green-Blue |
| RGBVI | Red-Green-Blue Vegetation Index |
| RF | Random Forest |
| RMSE | Root Mean Square Error |
| SDGs | Sustainable Development Goals |
| SSA | Sub-Saharan Africa |
| SVM | Support Vector Machine |
| svmRadial | Support Vector Machine with Radial Kernel |
| SWIR | Shortwave Infra-red |
| TPR | True Positive Rate |
| UA | User Accuracy |
| UAS | Unmanned Aircrafts Systems |
| sUAS | small Unmanned Aerial Systems |
| UAVs | Unmanned Aerial Vehicles |
| VARI | Visible Atmospherically Resistant Index |
| VHR | Very High Resolution |
| VIs | Vegetation Indices |
| VIF | Variance Inflation Factor |

| | |
|---|---|
| VNIR | Visible Near Infra-red |
| VTOL | Vertical Takeoff and Landing |
| xgbTree | Xtreme Gradient Boosting |

# CHAPTER 1: INTRODUCTION

## 1.1 Rationale for the research (nature and scope)

When considering the role of agriculture in feeding 7.2 billion people worldwide, the prevailing view is often tied to large-scale, industrial efficient systems that produce significant quantities of food which are then distributed globally (Fanzo, 2017). Whilst these systems are crucial, it is a one-dimensional approach to what constitutes agriculture and who feeds us (Fanzo, 2017). However, agricultural systems in Sub-Saharan Africa (SSA) predominantly revolve around smallholder farms which are approximately two hectares or less in size (Kim *et al.*, 2021). Recent estimates reveal that around 33 million smallholder farms within SSA contribute to 90 % of the agricultural production within some countries in this region (Kim *et al.*, 2021). This is indicative of the vital role of smallholder farms in SSA when it comes to supplying large quantities of the region's food, enhancing food security and promoting improved nutrition, amongst other factors such as poverty and livelihood status (McCarthy *et al.*, 2023).

Whilst there are African countries that have provided some resources to catalyze agricultural productivity, smallholder farms continue to face ongoing challenges which have adverse effects on their agricultural productivity (Nyambo *et al.*, 2022). A significant number of smallholder farms face a severe shortage of essential input resources, financial assistance along with suboptimal productivity which ultimately constrains the potential of these farmers to enhance food production. Additionally, the impacts of climate change and population growth have intensified the pressure on agricultural food systems. Collectively, these challenges have caused smallholder farms to fall short of their capacity to potentially address food security (Gokool *et al.*, 2023). To mitigate the issue, smallholder farms require economically viable, context-specific information to guide and inform their decisions, thereby ultimately enhancing agricultural productivity while efficiently utilizing their critical resources (Nhamo *et al.*, 2020).

Within smallholder farms, precision in resource use are often lacking and advanced methods for improving them are not always feasible (Onyango *et al.*, 2021). In addition, government recommendations made within SSA have not effectively acknowledged the variability in farmlands, hence, blanket recommendations are adopted by agricultural production regions resulting in low efficiencies of applied input resources (Soropa *et al.*, 2019). However, it is crucial to recognize that the precise use of resources and management practices for many of these farms can significantly boost agricultural productivity (Onyango *et al.*, 2021).

The aforementioned is particularly true for SSA regions, where Precision Agriculture (PA) is targeted at the needs of the farmers and existing constraints which are all aimed at enhancing agricultural productivity (Brisco, 1998; Onyango *et al.*, 2021). PA has emerged as a transformative approach, enabling a shift away from conventional farming practices towards data-driven agricultural management which emphasize appropriate farming techniques through site-specific information (Khose *et al*., 2016). Each field is treated as a distinct entity, enabling recognition of variability in crop health, soil composition and climatic conditions amongst other variables which would require customized solutions (Navalgund *et al*., 2007; Khose *et al*., 2016). Through this approach, crops are cultivated with enhanced precision, the use of critical resources is optimized, and sustainable agricultural systems are promoted. Overall, the intended purpose of PA is to bridge the gap between growing food demands and the pressing necessity for ecological, environmental and natural resource conservation (Padmavathy and Poyyamoli, 2011).

Presently, the agricultural sector is embracing the fourth industrial revolution which is being facilitated by advancements in information and communication technologies (Boursianis *et al.*, 2022). Advanced technologies such as global positioning systems (GPS), geographic information systems (GIS) and remote sensing are just some of the tools which have great promise in being utilized to improve agricultural systems and optimize input resources that are aimed at enhancing agricultural production, reducing inputs and minimizing yield losses (Andreo, 2013; Sishodia *et al.*, 2020). In more recent times, artificial intelligence (AI) techniques including machine learning have been utilized for various PA tasks (Mollick *et al*., 2023). Through leveraging sophisticated data analytics and machine learning algorithms, vast amounts of data can be processed and interpreted in a succinct yet rigorous manner which enables an automated and precise use of critical input resources (Boursianis *et al.*, 2022). Collectively, these tools provide the means to refine decision-making processes, thus providing actional insight to augment crop management practices (Aubert *et al.*, 2012, Alaieri, 2024). Various approaches have been employed to collect rapid, high-density data suitable for monitoring applications in agriculture, however, remote sensing has proven to be the most appropriate. The techniques implemented to acquire such data are through proximal remote sensing, satellite systems, manned aerial vehicles and unmanned aerial vehicles (UAVs) attached with various remote sensing sensors (Pinter *et al*., 2003; Mulla, 2013; Toth and Jóźków, 2016; Fakhar and Khalid 2023; Kganyago *et al*., 2024).

Amongst the proximal sensors, satellites have been widely utilized for PA applications such as crop monitoring, disease detection and soil analysis, amongst various other applications, with satellite sensors providing information that allows for the assessment of crop vigor, identification of stressed plants, yield estimation and information on soil moisture, temperature and composition, among others (Yang *et al*., 2009; Yang *et al*., 2018). These sensors vary in spatial, spectral and temporal resolution; however, open-access satellite products often have a coarse spatial resolution (>20 m), thereby constraining their applicability in smallholder farms. This is attributed to the inherent small-scale nature of these farms which are characterized by intercropping thereby creating a highly heterogenous mosaic of vegetation which necessitates higher spatial resolution to accurately capture complex dynamics within the smallholder farms (Yonah *et al*., 2018; Cucho-Padin *et al*., 2020).

Whilst advanced satellite products may offer unprecedented spatial resolution, the associated costs are prohibitive for widespread adoption (Cucho-Padin *et al*., 2020). Additionally, satellite imagery with a higher spatial resolution is accompanied by a decreased temporal resolution with lengthy revisit times (Landsat: 16 days, Sentinel-2: 5 to 10 days), resulting in significant data gaps within crop growing seasons which on occasion, are impacted by cloud cover haze and other unfavorable atmospheric conditions (Hall *et al*, 2018). In contrast, images captured by manned aerial vehicles yield a superior spatial resolution (meter to sub-meter) compared to open-source satellite images, however, their operational expenditure exceeds feasible thresholds for prolonged use, which thereby renders these techniques uneconomical particularly for resource-poor and financially scarce smallholder farms (Gokool *et al*., 2023).

Considering the limitations in spatial resolution and cost of the aforementioned platforms, UAV-based remote sensing has emerged as a viable solution. This approach has shown immense potential in the agricultural sector, particularly within the context of smallholder farms. With the declining cost of accessing digital technology, UAVs have become more economically feasible and accessible (McCarthy, 2023). This presents an opportunity for farms in SSA to bridge the digital gap and enable transformation within the struggling agricultural sector (Deichmann *et al.*, 2016). The advent of UAV-based remote sensing systems has advanced the field of remote sensing and PA (Tsouros *et al.*, 2019). The adoption of UAVs for

PA applications offers a practical and cost-effective way to acquire data in comparison to previous methods (Loures *et al.*, 2020).

One of the crucial advantages of leveraging UAVs is the provision of centimeter-scale spatial resolution data which results in ultra-high-definition maps thus enabling the precise representation of smallholder heterogenous farms (Lu and He, 2018; Bochtis *et al*., 2023). This is vital for comprehensive knowledge and identification of crop distribution and health dynamics of vegetation (Tsouros *et al.*, 2019). This significantly improves the performance of the monitoring systems. Furthermore, the high temporal resolution of UAV-based systems is reflected in their flexible flying times which are user-defined (Varela *et al.*, 2021). The high temporal frequency allows for the comprehensive coverage of crop growth cycles without omitting the critical development stages (Burkart *et al.*, 2018). Equipped with specialized sensors, UAVs have evolved into powerful sensing systems which are complementary to the Internet of Things (IoT) techniques (Salima *et al*., 2019; Tsouros *et al.*, 2019). Depending on the PA task at hand, there are a variety of sensors onboard agricultural UAVs which can be utilized (Mogili and Deepak, 2018).

The selection of these sensors is limited due to low payload capacity, low weight and compact size of onboard sensors. In this instance, commonly leveraged sensors within PA that fit the criteria mentioned are hyperspectral, multi-spectral and Red-Green-Blue (RGB) (Tsouros *et al.*, 2019). While there are additional types of sensors, their increased cost has limited their use for data acquisition (Zhao *et al.*, 2018). Hyperspectral sensors whilst extremely capable, are met with accessibility constraints which counterbalance their inherent capabilities (Yao *et al.*, 2019; Mishra *et al.*, 2020). Hyperspectral remote sensing is conceptualized as the simultaneous acquisition of images in numerous (tens to hundreds), narrow (<20 nm) and contiguous spectral bands thereby providing detailed information on observed objects (Goetz *et al*., 1985; Teke *et al*., 2013). Characteristically, these sensors capture light within the 400–2500 nm range which is inclusive of the visible, near-infrared (NIR) shortwave infrared (SWIR) frequency bands (Teke *et al*., 2013). The spatial resolution of these sensors differs in accordance with the platform in which it is utilized for instance, hyperspectral sensors for satellite systems tend to have a reduced spatial resolution ranging from 30-150 m when compared to the airborne counterparts which are characterized by higher spatial resolution which ranges from (35 cm-4 m) (Thenkebail *et al*., 2018).

On the other hand, commonly used multi-spectral sensors which are lower in cost in comparison to hyperspectral sensors capture approximately five to twelve channels which also require complex preprocessing methods to be able to extract meaningful information from the data. These sensors can acquire high spatial resolution, multiband remotely sensed data ranging from the visible to NIR bands therefore striking a balance between attainability and functionality (Deng *et al*., 2018). Contrary to the reduced number of bands of multi-spectral sensors, recent studies have indicated the frequent use of these sensors in comparison to hyperspectral sensors based on their lower cost (Tsouros *et al*., 2019).

Regardless of the continuous improvement of hyperspectral sensors over the years, there is still a lack of ubiquitous feasibility when applied in real-time applications in comparison to other sensors like RGB (Yao *et al.*, 2019). Additionally, the impractical characteristics of utilizing hyperspectral data stem from the data size which is highly dimensional as well as the exorbitant labor costs associated with data acquisition and use, as subject specialists are required to do exhaustive data processing (Yao *et al.*, 2019). Similarly, commonly used multi-spectral sensors also require complex preprocessing methods to be able to extract meaningful information from the acquired images (Tsouros *et al*., 2019). The interplay between the spectral resolution of the above-mentioned sensors and their technological feasibility, compounded by their associated complexities, has constrained their widespread adoption among smallholder farms (Amarasingam *et al*., 2022). However, with growing research exploring the capabilities of RGB sensors, it is understood that to some extent, RGB sensors can pose a counterintuitive solution which challenges the notion that high-performance imaging must come at the expense of feasibility and practicality. UAVs equipped with commercial RGB sensors have been utilized to characterize and monitor various features, particularly in agricultural research and environmental applications (Yuan *et al.*, 2019). They are characterized as economically feasible and user-friendly sensors in comparison to the costly and complex sensors that have been previously mentioned (Panday *et al.*, 2020). This is particularly advantageous for smallholder farms that lack the financial resources to invest in costly sensors. UAV-RGB sensors have emerged as pivotal tools in PA, offering a cost-effective and accessible means to capture high-resolution data for various applications. Their integration with advanced machine learning algorithms has revolutionized tasks such as but not limited to crop classification, crop monitoring disease identification, and yield estimation (Hasan *et al.*, 2019; Maimaittijiang *et al*., 2020;  Ahmed and Yadav, 2023).

Despite limitations in pixel-wise differentiation, the incorporation of texture and shape data enhances their utility in agricultural and environmental monitoring. Noteworthy studies have showcased the efficacy of UAV-RGB data for common PA applications such as cropland classification and crop monitoring among others (Norasma *et al*., 2018; Ballesteros *et al*., 2018; Oide *et al*., 2022). By leveraging machine learning techniques, UAV-RGB imagery enables data-driven agricultural practices that allow for tailored, site-specific interventions resulting in optimized crop management, resource efficiency, and agricultural productivity. This technology not only benefits large-scale agricultural operations but also holds immense potential for smallholder farms, bridging the gap between traditional and PA to enhance food supply and sustainability.

While it is understood that UAVs have emerged as transformative tools which can revolutionize agricultural practices, with a potentially far-reaching beneficial impact within SSA agricultural systems, their uptake in SSA smallholder farms has been severely lagged (McCarthy *et al*., 2023). This is owing to perceived high costs, lack of access and support associated with the use of this cutting-edge technology to advance agricultural practices within smallholder farms (Tsouros *et al*., 2019; Gokool *et al*., 2023). To address these challenges, there is a necessity to utilize cost-effective and practical approaches to implement cutting-edge technology in smallholder farms to revolutionize their agricultural farming systems.

In the context of resource scarce and financially insecure demographics such as smallholder farms, the selection of UAV onboard sensors for PA applications is met with a trade-off between spectral depth and cost. Specifically, multi-spectral sensors that capture spectral information beyond the visible spectrum that offer valuable information for common PA applications such as, crop monitoring and classification. However, they are often associated with substantial investment costs which are higher than RGB sensors, but still less costly in comparison to hyperspectral sensors which could potentially reduce the widespread adoption of this technology among financially constrained smallholder farms in SSA. Conversely, UAV-RGB sensors provide high spatial resolution data at a reduced cost but with a restricted spectral resolution which can potentially limit their applicability to certain PA applications. Consequently, it is essential to evaluate the trade-off between the cost and spectral richness of these UAV onboard sensors to gain insight into a suitable sensor to be utilized for smallholder farms, based on their unique characteristics and challenges. Extensive research has been conducted on the application of these sensors for PA. However, a gap persists in directly comparing the performance of UAV multispectral and RGB data, particularly in the context of smallholder farms within SSA. This gap centres on assessing the reliability of a low-cost approach to support PA applications in such environments. Hence, this study seeks to explore the reliability of utilizing UAV-RGB data as a cost-effective alternative to guide and implement PA within smallholder farm settings in SSA. Through this approach, the study aims to provide an accessible and practical approach to adopting UAVs to guide and inform PA in smallholder farms.

### 1.2 Research Questions

1. What is the most appropriate way to facilitate PA within a smallholder farm setting?
2. What is the classification accuracy of UAV-RGB data relative to multi-spectral data for cropland mapping within a smallholder farm context?
3. Can UAV-RGB-derived data produce reliable estimates of crop growth parameters such as LAI?
4. Does UAV-RGB data serve as a cost-effective and reliable alternative to multi-spectral data for the facilitation of PA within resource-scarce and constrained financial capacity smallholder farms?

### 1.3 Aim

Based on the trade-off between cost and spectral richness that exists between UAV multi-spectral and RGB sensors, this study aims to directly compare the use of UAV multi-spectral data and RGB data for PA applications within a smallholder farm setting. Consequently, this would determine the reliability of UAV-RGB data to be leveraged as a low-cost alternative to costly approaches to facilitate PA within a smallholder farm context.

### 1.4 Objectives

Considering the overall aim of the study, this thesis is divided into three parts, which are intended to fulfil the following specific objectives:

i. To undertake a comprehensive and critical analysis of literature, in order to evaluate the potential of UAVs to facilitate PA applications, with particular focus being given to the socio-economic circumstances of smallholder farms in SSA.
ii. To identify and accurately map croplands within a smallholder farm setting.
iii. To monitor and evaluate crop growth and development within a smallholder farm.

### 1.5 Outline of dissertation/thesis structure

Figure 1.1 displays an overview of the structure of the thesis and is repeated at the beginning of each chapter, with the relevant parts of the figure addressed in the following chapter, highlighted in grey. Additionally, this thesis adheres to a publication style (which have been published, are in press, submitted or are intended for submission, following the approach that has been accepted by the University of KwaZulu-Natal) where each chapter is mostly self-contained.

In total, there are five chapters, with Chapter 1 being a general introduction of this thesis containing the background of the study, the main aim of the study, the objectives as well as research questions. Chapter 2 undertakes a comprehensive and critical analysis of the literature to evaluate the potential of UAVs to facilitate PA applications, with a particular focus being given to the socio-economic circumstances of smallholder farms in SSA. Chapters 3 and 4 are regarded as standalone papers containing their own introduction, methodology, results and discussion as well as conclusion sections. It is important to note that similarities may exist between these two chapters as they both contribute to the overarching aim of this study. Chapter 3 focuses on identifying and accurately mapping croplands within a smallholder farm setting. Whereas Chapter 4 is devoted to monitoring and evaluating crop growth and development within a smallholder farm. The final concluding chapter, Chapter 5, presents a comprehensive summary of the key findings from each of the chapters, thereafter synthesizing conclusions and contributions of the research. Additionally, this chapter mentions the limitations of the study and recommendations for future study.

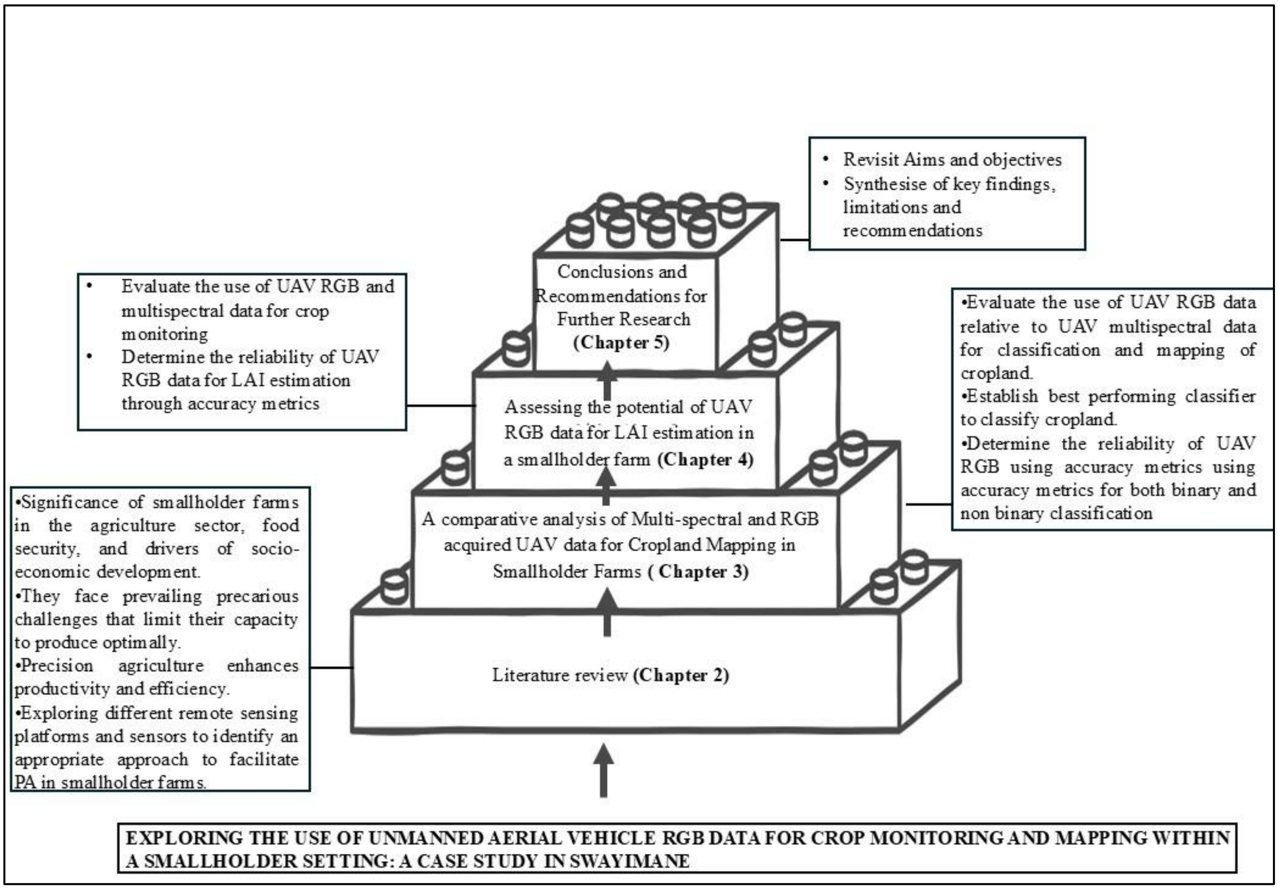


**Figure 1.1 Schematic overview of the research study**

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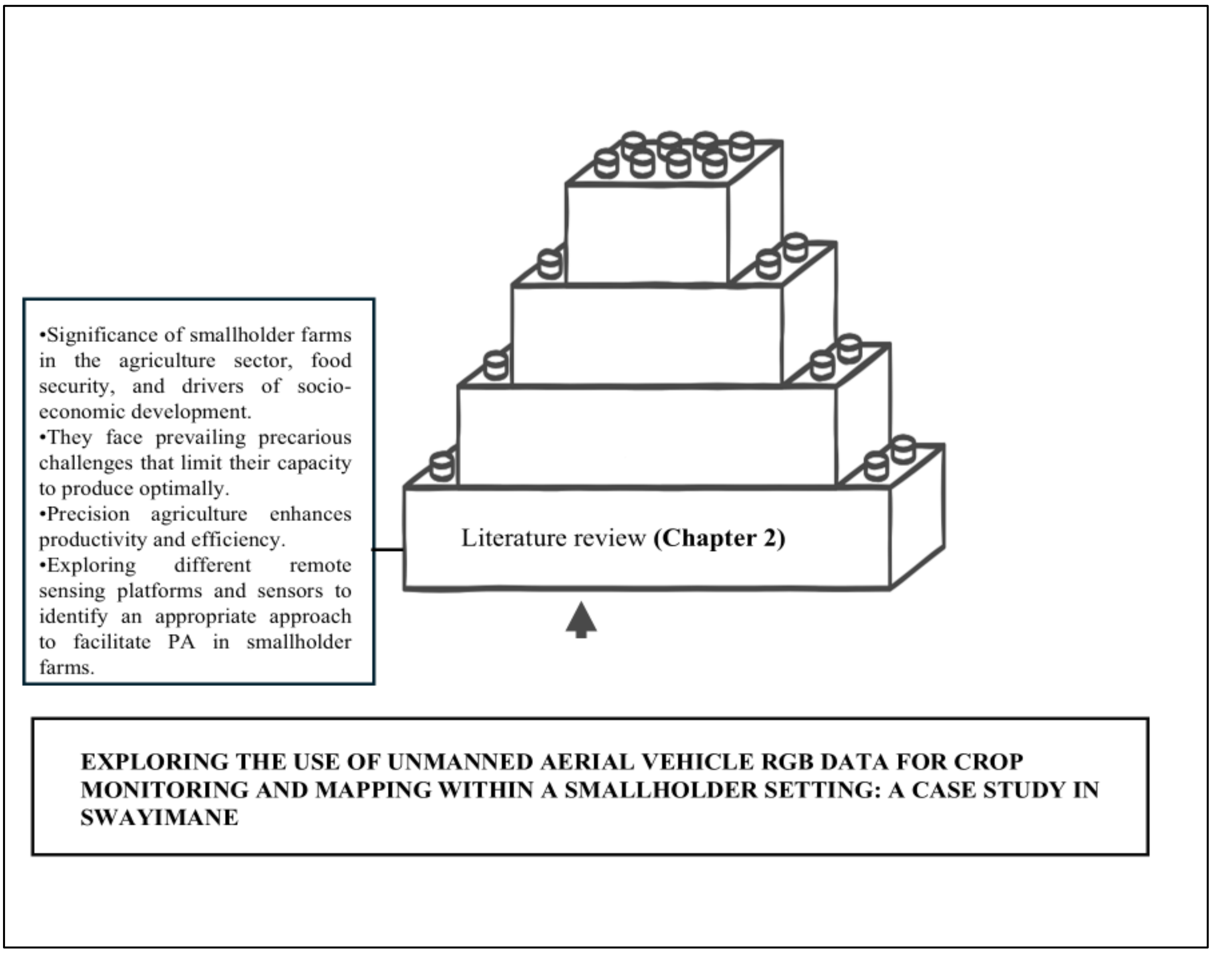
**Lead into Chapter 2**: Concluding Chapter 1, the study set out to assess the potential of UAV-RGB data for cropland mapping and monitoring within a smallholder farm setting. To build a strong foundation in addressing these objectives, Chapter 2 presents a literature review consisting of several components which begin by establishing the pivotal role of smallholder farms in food security amongst other things, followed by exploring the unique challenges they encounter. In response to this, studies on the use of PA are explored as a potential solution to bolster agricultural productivity and enhance resource efficiency within such settings. To explore fitting solutions to facilitate PA within a smallholder farm setting, this chapter reviews remote sensing platforms namely satellite, manned aerial vehicles and UAVs assessing their applicability, accessibility and feasibility in the context of smallholder farms. Further focus is placed on common onboard sensors such as RGB, multi-spectral and hyperspectral assessing their strengths and weaknesses within the context of smallholder farms. Through this structured review, Chapter 2 aims to identify the use of a feasible cost-effective solution for facilitating PA within smallholder farms.



# CHAPTER 2: LITERATURE REVIEW

## 2.1 Introduction

The agricultural sector is a fundamental element of the food system particularly in SSA where exponential population growth and climate change impacts have precipitated food demands. Developing countries have a high dependency on agriculture with approximately 50-90 % of its population obtaining employment, income and livelihood from this sector (Sibanda *et al*., 2023). Of this group, an estimated 70–90% are identified as smallholder farmers who are participating in subsistence farming on less than two hectares of land with infertile soils due to conventional farming practices and climate change related shocks (Sibanda *et al*., 2023; Giller *et al* 2021). A sub-national consensus study conducted by Jin *et al*. (2019) was indicative of a 50 % food calorie production by farms measuring five hectares and less in size. Despite the pivotal role smallholder farmers have in contributing to food security, particularly in developing nations, there are a plethora of challenges leading to food insecurities. These challenges primarily include the adoption of rudimentary agricultural practices, financial constraints, inadequacy of input resources and appropriate technological tools that have heavily impacted the optimal agricultural production of smallholder farmers (Giller *et al*., 2021).

Characteristically, the traditional farming practices which dominate smallholder farm systems are rooted in uniform field management along with manual labor. Consequently, this can lead to inefficient resource use, diminishing crop productivity and an inability to adapt to variations in field conditions. As the dual pressure of climate change and population expansion prevails in threatening current food systems, it is imperative to shift away from conventional farming techniques to scale the agricultural production of smallholder farms. Collectively the downfalls associated with conventional farming practices as well as environmental concerns and the urgent need to improve agricultural production, have paved the way for the adoption of PA. Within this approach, the use of remote sensing through traditional platforms such as satellites and manned aerial vehicles and more recent platforms such as UAVs have advanced PA enabling data-driven agricultural practices to augment agricultural productivity. Among these, UAVs fitted with common onboard sensors have been advocated for as an alternative to traditional remote sensing platforms based on their cost effectiveness, high-resolution data acquisition and flexibility which have made it fitting in resource-poor and financially contained settings. Consequently, leveraging UAVs to facilitate PA serves as a critical tool which provides high resolution, timely insight of smallholder farms which require efficient and accurate data for optimizing yield and resource use.

## 2.2 Precision Agriculture

According to a study by Carrer *et al*. (2022), PA, as defined by the International Society for Precision Agriculture (ISPA), is a strategic approach involving state-of-the-art data collection, processing, analysis and communication technologies that result in enhanced yields, reduction in critical input resources, namely water and nutrients, and in the mitigation of harmful environmental impacts. PA enables a reduction in input resource costs by introducing tailored management strategies pertaining to specific field areas, fostering efficient use of critical resources and ultimately reducing input costs (Brisco *et al*., 1998; Finger *et al*., 2019; Loures *et al*., 2020). Additionally, the sophisticated technological tools adopted for PA management permit near real-time data collection enabling farmers to make better, informed decisions pertaining to their current crop status resulting in rapid responses to any changes in crop conditions. Consequently, this reduces crop failure and improves crop quality and yield which enhances food availability which contributes to strengthening food security (Shafi *et al*., 2019). Furthermore, as a result of the above-mentioned benefits, a holistic data-driven approach can be implemented to maximize agricultural output sustainably. In line with the findings of several research studies, PA is characterized as an effective management approach to guide and inform agricultural practices (Schimmelpfennig and Ebel, 2016; Loures *et al*., 2020; Finco *et al*., 2023). By leveraging PA techniques within smallholder farm settings, there is potential to revolutionize the traditional agricultural practices implemented by smallholder farms while fostering profitable and sustainable agricultural development (Onyango *et al*., 2021).

Within the SSA regions, numerous smallholder farms are operating under circumstances that are typified by inadequate access to input resources and management practices which are categorized as suboptimal (Onyango *et al*., 2021). These circumstances are further compounded by the market constraints that smallholder farmers experience. Often, the precise use of input resources is seldomly applied and advanced methods of improving them are not affordable (Soropa *et al*., 2020; Onyango *et al*., 2023). Additionally, government recommendations provided to SSA countries offer minimal assistance in distinguishing the variability that exists amongst the various farming regions.

In numerous instances, smallholder farmers that partake in traditional agricultural practices utilize blanket approaches which lead to the excessive use of applied input resources such as water, fertilizer, herbicides and pesticides that result in the overexploitation of critical resources and the misuse of agrochemicals which have detrimental environmental implications (Onyango *et al*., 2023). The heavy reliance on traditional agricultural techniques impacts their productivity and efficiency thereby resulting in a significant reduction in yield and income of these smallholder farmers (Myeni *et al*., 2019). Furthermore, with the adoption of traditional farming practices, labor and resource-intensive approaches are associated, which can place a further strain on the existing limited capacity of smallholder farms (Mutero *et al*., 2016). Moreover, the continuous use of these techniques may perpetuate cycles of reduced productivity and environmental degradation which presents a substantial threat to the sustainability of smallholder farms (Bienabe and Vermeulen, 2011).

With the integration of remote sensing technologies into modern agricultural techniques, a pathway for smallholder farms to bridge the gap between traditional farming and PA farming exists. Subsequently, through leveraging the power of remote sensing, PA can transform rudimentary farming practices thereby enabling smallholder farms to make precise data-driven decisions which in turn contribute to the overall resilience of agricultural systems in the face of climate change, population growth among other challenges.

## 2.3 Remote Sensing in Agriculture

To date, remote sensing approaches have been the focus for the majority of PA studies and are one of the most important technologies for PA (Lopez-Granados *et al*., 2006; Salima *et al*., 2019). In past decades, manned aerial vehicles and satellites were used for capturing desired images utilized for PA (Huang *et alet al*., 2017). More recent studies indicate the prevalence of UAVs with various onboard sensors being utilized to collect rapid, high-density data for PA (Noguchi and O'Brien, 2003; Toth and Jóźków, 2016).

Remote sensing platforms have been widely applied in agriculture for various purposes, ranging from large-scale surveys to targeted mapping exercises. These applications include crop classification, yield estimation, land use and land cover mapping, crop growth monitoring, soil moisture estimation, and PA. Remote sensing provides valuable data for early detection of crop stress, disease outbreaks, and pest infestations, enabling timely interventions. Additionally, it is instrumental in drought and flood condition monitoring, supporting disaster preparedness and mitigation strategies (Andreo, 2013; Shanmugapriya *et al*., 2019; Sharma, 2023). The integration of remote sensing with GIS and GPS technologies further enhances site-specific management for PA, facilitating improved resource efficiency and decision-making in farming operations (Shanmugapriya *et al*., 2019). These applications enable farmers to monitor spatial and temporal variations in crop growth, detect early signs of stress, and optimize input distribution to improve yield efficiency**.**

Subsequently, data processing and analysis facilitate accurate agricultural decisions. The within-field variability obtained from agricultural remote sensing allows for site-specific management as an alternative to blanket management approaches associated with traditional farming practices that are implemented in many farms. For smallholder farmers within SSA, the implementation of PA can play a pivotal role in enabling efficient applications of scarce input resources along with augmented productivity (Onyanga *et al*., 2021)

Whilst satellite and manned aerial vehicle remote sensing platforms have been the focus of agricultural management research over the last 60 years, their adoption at the farm scale has not been extensive (Colwell, 1956; Jackson, 1984; Pinter *et al.*, 2003). This is a result of infrequent coverage, inadequate pixel resolution, atmospheric disturbance and untimely delivery of data to users (Jackson, 1984; Pinter *et al.*, 2003). Contrastingly, ground-based remote sensing typically has a smaller coverage area, with a dynamic acquisition schedule and high spatial resolution. However, the increase in spatial resolution of these platforms is accompanied by the increments in cost (Noguchi and O'brien, 2003). In the context of PA for smallholder farmers, UAVs are identified as a more economical, and timely solution to acquire high spatial resolution data (Xiang *et al*., 2019; Radoglou-Grammatikis *et al*., 2020). In comparison to traditional remote sensing platforms UAVs demonstrated requisite capabilities on providing high spatial (cm) and temporal (daily) resolution coupled with low altitude operations in small fields resulting in a more precise and timely representation of smallholder heterogenous farms which account for a significant portion of agricultural land globally (Gokool *et al*., 2024). These platforms further possess unique capabilities as well as limitations which are detailed in sub-section 2.3.1.3. For the use of UAV technology, the spectral resolution is constrained based on the onboard sensor which dictates its suitability for various PA applications. Subsequently, sub-section 2.3.2 provides further detail on common UAV onboard sensors with a particular focus on establishing a fitting sensor along with the use of UAVs to facilitate PA within a smallholder farm.

### *2.3.1 Remote Sensing Platforms*

2.3.1.1 Satellites

Since the 1970s, there have been various satellite sensors in existence such as but not limited to Landsat, MODIS and Sentinel being frequently utilized for agricultural applications spanning large geographical locations (Macdonald *et al.*, 1980 Karmakar *et al.*, 2023). Research studies have identified that satellite-derived data with varying spatial and temporal resolutions have been extensively documented in studies which leverage these sensors for an array of PA purposes (Bhatti *et al*., 1991; Gao *et al*., 2014; Ibnelhobyb *et al*., 2016; Palchowdhuri *et al*., 2018; Shakun *et al*., 2021). Advanced satellite sensors such as SPOT 5, 6 and 7 and GeoEye 1 offer unprecedented spatial (5-10 m) and temporal resolution (Yang *et al*., 2018). These satellite sensors have been used for various PA tasks including but not limited to crop monitoring, crop identification as well as classification and mapping (Yang *et al*., 2009; Yang *et al*., 2011, Wagner and Hank, 2013)

Despite significant advances in spatial, spectral, and temporal resolution of satellite sensors, the use of satellite images has limited benefits within a smallholder farm setting. Additionally, the cost associated with recent advanced satellite images has prohibited widespread adoption within the agricultural domain (Cucho-Padin *et al*., 2010). While there are plentiful satellites that produce images characterized by high spatial (<5 m) and temporal (daily) resolutions, as well as made available for public use, they do not possess the appropriate resolution for PA applications within smallholder farm scales (Sishodia *et al*., 2020). For example, a study by Burke and Lobell (2017), noted a limitation of utilizing satellite data within smallholder heterogeneous fields, as low spatial resolution compromised the accuracy of yield estimations. Specifically, this study highlighted the constraints of Landsat imagery, an open-access satellite program by the US Geological Survey and NASA, which collects data at a 30-meter spatial resolution. Therefore, the adoption of satellite platforms is unsuitable to guide and inform PA practices within a smallholder farm setting as high spatial resolution plays a crucial factor for local scales in the case of smallholder farms due to the heterogeneous nature of their land

Similarly, a study conducted by Peter *et al*. (2020), highlighted the prevailing challenges of poor temporal resolution, inadequate spatial resolution and cloud cover which are encountered when commercial or open-source satellite imagery such as Planet (3 m) and Sentinel 2 (20 m) was utilized within a smallholder farm context in southern East Africa. Cloud cover further exacerbates the limitation of low spatial resolution by obstructing clear visibility of the earth's surface, hindering the acquisition of high-resolution imagery necessary for precise identification and management of specific agricultural issues (Bukowiecki *et al*., 2021). Additionally, lengthy revisit periods of satellites delay the acquisition of updated information, affecting the ability to monitor crop conditions in real-time and promptly detect issues pertaining to crops, ultimately hindering the ability to make informed decisions promptly (Katsigiannis *et al.*, 2016).

Given the aforementioned limitations, researchers and practitioners are unable to obtain accurate, timely data that is required to implement PA for effective crop management, thus rendering the data ineffective for the use of smallholder farms. Furthermore, smallholder farms face financial constraints (Chandra and Collis, 2021) which, in turn, hinder the utilization of commercial satellite platforms for data acquisition as it poses negative financial implications thereby leading to a lack of investment in such techniques. Subsequently, within the context of a smallholder farming setting, the use of satellite platforms to guide and implement PA is unbefitting. Despite satellite platforms offering valuable insight for agricultural purposes, their limitations have prompted research on alternative platforms in an attempt to obtain precise and real-time agricultural data (Cucho-Padin *et al*., 2020; Sishodia *et al*., 2020).

2.3.1.2 Manned Aerial Vehicles

In the 1920s, researchers began exploring the use of manned aerial vehicles primarily for agricultural purposes by applying chemicals to crops via aerial platforms (NAVA, 2001). Following this, airplanes were leveraged for capturing analogue aerial imagery and for vegetation mapping with advancements in photographic equipment evolving in the 1950's (Jafarbiglu and Pourreza, 2022). Subsequently, sensors attached to manned aerial vehicles were introduced for agricultural purposes at an altitude of approximately 300 m above ground level (AGL) for tasks such as soil moisture mapping (Schmugge *et al*., 1978). However, limited financial resources restricted the utilization of aircraft for research purposes since capturing images by manned aircraft is a costly affair. Furthermore, the operational complexities in flight planning, limited repeatability as well as the absence of precise autopilot systems like terrain-following limited their use in research avenues (Barnes *et al*., 2018). Nevertheless, a few studies were conducted by private and governmental sectors that produced promising results that piqued other researchers' interest in the field (Jafabiglu and Pourreza, 2022).

Therefore, while manned aerial vehicles are characterized by higher payload capacity, improved spatial resolution and endurance for data collection covering extensive areas of agricultural land, they are often associated with exorbitant operational costs, slow turnaround time for data delivery as well as high operational complexities (Zhang and Kovacs, 2012; Raeva *et al*., 2019). Along with open-source satellite platforms, manned aerial vehicles offer a medium to low spatial resolution ranging from 0.5 to 60 meters that are often inadequate for various PA applications particularly crop classification on smallholder farms (Liaghat and Balasundram, 2010; Lundeen and Gowey, 2021). Additionally, the reduced spatial resolution blurs images furthering the incapacity of the data obtained from these platforms to be utilized for detailed analysis, particularly on small-scale heterogenous plots. Furthermore, while the repeatability of utilizing the manned aircraft is dependent on the operator, the cost of consistent and prolonged usage is exorbitant. Infrequent usage results in data gaps which can be further affected by unfavorable atmospheric conditions such as strong wind, rainfall, and fog limiting flights (Ahmad *et al*., 2021). Therefore, impaired data quality may compromise the reliability and accuracy of crop monitoring systems, resulting in decreased agricultural productivity.

There are also high costs associated with the procurement, and maintenance, along with the technological expertise and trained pilot personnel that are required for the utility of manned aerial vehicles (Ioja *et al*., 2023). In contexts characterized by data scarcity and resource limitations, the use of this platform could be financially burdening and operationally complex, rendering them unsuitable for data acquisition for PA. However, given the challenges that were associated with satellite and manned aerial vehicles and with recent advancements in technologies, UAVs have gained prominence and have begun to largely replace manned aircraft in obtaining remote sensing data (Shishodia *et al*., 2022). Therefore, conclusively, given the drawbacks regarding satellites in (subsection 2.3.1.1) and manned aircraft in this subsection (subsection 2.3.1.2), the use of UAVs is viewed as a more fitting platform to implement PA for smallholder farms and is further detailed below.

#### <u>2.3.1.3 Unmanned Aerial Vehicles</u>

As several research studies have pointed out, agricultural productivity is pivotal for achieving the Sustainable Development Goals (SDGs), in particular, Goal 1 (no poverty) and Goal 2 (zero hunger) (McCarthy *et al*., 2023). Given the recent introduction of UAVs into this sector, transformative potential has been shown particularly for SSA smallholder farms (Haula and Agbozo, 2020).

UAV technologies have revolutionized remote sensing in agriculture through characteristics that promote efficiency and enable improved agricultural management, thereby catalyzing progress towards achieving the SDGs by allowing efficient land monitoring and decision-making processes (Simelli and Tsagaris, 2015; Mogili and Deepak, 2018; Haulua and Agbozo, 2020; McCarthy *et al*., 2023). UAVs high maneuverability allows access to geographically challenging locations, and both manual and autonomous flight modes offer flexibility for various tasks. Unlike satellite imagery, UAVs capture aerial images at user-defined intervals for timely monitoring, thus providing comprehensive information leveraged for informed and site-specific farming practices.

In a study by Nhamo *et al*. (2020), the efficiency of UAVs was emphasized as an effective alternative to traditional farming methods, enhancing water management and crop productivity through the processing and analysis of high-resolution UAV-based crop data. Additionally, McCarthy *et al*. (2023) explored the use of UAVs to enhance agricultural productivity and food security in smallholder farms. Using a DJI Mavic 2 Pro (20 MP, 1-inch CMOS sensor), high-resolution imagery was collected and provided to farmers, who annotated land use and investigated on-farm issues such as soil erosion, pests, diseases, and water stress. These insights, discussed with agricultural extension agents, supported informed decision-making, improved resource efficiency, and reduced costs. The study highlighted both the benefits and limitations of UAV technology in this context. Moreover, the ability of UAVs to gather data at low altitudes along with the high spatial resolution obtained at cm scale, fits the nuanced requirements for PA applications within smallholder farm contexts (Zhang *et al*., 2023).

The early 2000s marked the advent of using small UAVs, weighing less than 25 kilograms for agricultural purposes (Simpson *et al*., 2003). In a bibliometric analysis by Moraes *et al*. (2023), a significant surge in scientific publications related to agricultural UAVs was observed between the period 2000 to 2020. This literature emphasized the growing relevance of UAVs in modern agricultural methodologies within the last decade. In terms of their advancements, UAVs are characterized by their autonomous flying capabilities and advanced software that supports flight planning and deployment based on GPS (Dutta and Goswami, 2020). The advanced software takes into account various parameters, including failsafe modes and geo-fencing, highlighting their strategic value in agricultural management (Dutta and Goswami, 2020). Furthermore, sophisticated onboard cameras such as hyperspectral, multi-spectral as well as RGB in conjunction with computational algorithms work together to compute vegetation indices (VI), which can assist in discriminating plant species (Handique *et al*., 2017), phenotypic monitoring (Burkart *et al*., 2018), and assessing water status (Cornejo-Velazquez *et al*., 2017), along with various other PA practices.

The use of UAVs for crop monitoring offers numerous advantages in terms of obtaining field data in a convenient, cost-effective, and timely manner compared to traditional methods (Tsouros *et al*., 2019). While high-resolution satellite imagery can be costly and not easily accessible for small farms, UAVs present an affordable alternative to manned aerial vehicles and high-resolution satellite products (Sishodia *et al*., 2020). Although there may be initial investment costs involved in adopting UAV technology, advancements in low-cost sensor technologies and potential cost savings are expected to outweigh these expenses in the future (Sishodia *et al*., 2020). Additionally, community-based participation models contribute to enhancing the cost-effectiveness of utilizing UAVs by reducing reliance on specialized personnel (Zhang *et al*., 2012).

A study by Sishodia *et al*. (2021) noted that acquiring frequent satellite scanning for the complete duration of the crop growth cycle is hindered due to cloud cover and/or limitations associated with the sensor platform such as infrequent revisit periods. On the contrary, UAVs can be deployed numerous times throughout the growing season to retrieve information on a cm-scale as required. Moreover, depending on the desired temporal resolution, farmers can monitor their crop fields on a monthly, weekly, daily, and even hourly basis (Zhao, 2018). Thus, UAV's flexible deployment schedule allows for real-time observation of crops at the field scale, thereby prompting the facilitation of timely intervention through the entity of the crop growing cycle. As a result, there is an overall improvement in farm management such as, but not limited to, enhanced crop productivity (Nhamo *et al*., 2020). However, opting to use UAVs instead of satellites for obtaining reflectance data from crops provides flexible temporal resolution and higher spatial resolution which is advantageous in acquiring precise and specific information relevant to the targeted field and crop (Sishodia *et al*., 2020).

The real-time monitoring capabilities of UAVs allow for timely interventions in crop health and growth, enabling farmers to optimize resource allocation and enhance overall agricultural productivity (McCarthy *et al*., 2023). Additionally, the use of UAVs can lead to significant savings on fuel and maintenance costs compared to traditional farm equipment. While the acquisitions of UAVs and related supplementary assets necessitate significant initial capital, it yields superior image resolution in comparison to alternative remote sensing technologies. Moreover, the upfront investment is offset by the ability to conduct repeated flights, leading to a higher frequency of data collection and thereby reducing labor and resource expenses (Gokool *et al*., 2024). Despite the array of advantages, the adoption of UAV technologies by smallholder farmers is encumbered by a number of challenges. These encompass not only financial constraints associated with affordability but also insufficient awareness and digital literacy among farmers (McCarthy *et al*., 2023). Furthermore, there exists a lack of supportive policies and subsidies aimed at promoting their widespread use in agricultural practices (Gokool *et al*., 2024).

### *2.3.2 Sensors*

The success of UAV imaging within the agricultural domain is attributed to the integration of cutting-edge sensors for the purposes of precise agricultural data procurement (Shahi *et al*., 2023). The synergies between the aforementioned UAV characteristics as well as the sensors installed are paramount for an array of agricultural purposes (Alvarez -Vanhard *et al*., 2021). These sensors, ranging from LiDAR for detailed terrain mapping to RGB cameras for visual data procurement which enhance the capabilities of UAVs for mapping and monitoring purposes. While there are numerous sensors for PA applications, hyperspectral, multi-spectral and RGB sensors are selected based on their extensive adoption within PA and the substantial body of literature which supports their utility within this field (Adao *et al*., 2017; Prey *et al*., 2018; Velusamy *et al*., 2021; Zuo *et al*., 2021). As such, these sensors are further detailed in the subsections below.

#### 2.3.2.1 Hyperspectral Sensors

Hyperspectral sensors provide high-quality data sets which are attributable to the ability of these sensors to collect data from numerous bandwidths within the electromagnetic spectrum. Characteristically they acquire more than a hundred contiguous, narrow spectral bands with an approximate bandwidth ranging from 5-10 nm within wavelengths that ranges between 500 - 2500 nm (Khose *et al*., 2022). Hyperspectral sensors integrated with UAVs present distinctive characteristics that delineate their capabilities to capture in various spectral ranges enabling a vast operational scope as it is able to obtain data that is not easily identifiable by other sensors such as multi-spectral or RGB which have fewer bandwidths (Khose *et al*., 2022; Jafarbiglu and Pourreza, 2022). These sensors, as elucidated in the literature, have proven to be invaluable tools in the field of remote sensing, seamlessly integrating imaging and spectroscopy (400 –

2500 nm) (Singh *et al*., 2020). These sophisticated systems typically consist of much finer granularity thus enabling detailed spectral analysis essential for PA tasks such as target detection, anomaly identification, and classification among others. Prominent applications of hyperspectral remote sensing were for geology and mining with more recent applications of agricultural use (Sabins, 1999; Adao *et al*., 2017). Over the last 15 years, hyperspectral sensors onboard rotary and fixed-winged UAVs have primarily been used to estimate VI and band values which were then compared to ground truth variables (Khose *et al*., 2022).

Notwithstanding the considerable advances of hyperspectral sensors through the last decades, there remains a significant limitation which prevails as these sensors still lack the ubiquitous feasibility to be utilized in real-time applications in comparison to more accessible and feasible RGB cameras (Ram *et al*., 2024). In this instance, the data obtained from these sophisticated sensors necessitate the constant supervision of subject specialists (Merfield, 2016). Additionally, an inherent limitation of these sensors is the impracticality of utilizing these sensors which is a result of the high dimensional data size, exorbitant cost and the intense labor that is associated with data procurement and analysis (Ram *et al*., 2024). In view of these shortcomings, there has been limited adaptation of this data in the research community when compared to digital images. For this reason, the analysis of hyperspectral data is confined to research laboratories upon the completion of exhaustive data processing by subject specialists (Ram *et al*., 2024). Furthermore, it is recognized that the application of this technology is not profitable when compared to multi-spectral or RGB sensors as a result of the inherent operational complexity and cost which are compounded by the complex workflows associated with atmospheric and radiometric calibration (Lo´ Pez-Granados, 2011).

#### 2.3.2.2 Multi-spectral Sensors

In contrast to hyperspectral sensors which are often criticized for their associated high costs and complexity, multi-spectral sensors strike a balance between usability and cost (Deng *et al*., 2018). These sensors typically attain data ranging from the visible (400 -700 nm) to the NIR spectrum (700 – 1000 nm) (Lo´ Pez-Granados, 2011). In terms of the bandwidth of multi-spectral sensors, they are divided into two categories namely, narrowband and broadband. The discrepancy between these two lies in the spectrum range with narrowband having a smaller range capturing data in comparison to broadband which has a wider range (Deng *et al*., 2018; Sampson *et al*., 2023). Consequently, providing less detailed spectral coverage when compared to hyperspectral sensors (Shukla and Kot, 2016; Lu *et al*., 2022). While hyperspectral sensors excel due to their detailed spectral capabilities, multi-spectral sensors are a much more attainable option for PA tasks requiring continuous crop monitoring (Morales *et al.*, 2020).

Despite the spectral difference between hyperspectral and multi-spectral sensors, it has been noted in recent works that multi-spectral sensors are utilized more frequently due to their lower cost (Tsouros *et al*., 2019). A study conducted by Barjaktarovic (2024) noted that multi-spectral imaging is a widely adopted method to obtain information pertaining to vegetation status. With the use of multi-spectral data, it is possible to derive numerous VIs with normalized difference vegetation index being extensively utilized as a standard measure of crop condition and health (Barjaktarovic, 2024). The details pertaining to the use of this VI for crop monitoring purposes can be found in various studies conducted by but not limited to Hassan *et al*. (2019), Duan *et al*. (2017) and Guan *et al*. (2019). Beyond crop monitoring, multi-spectral sensors have been extensively used in various PA tasks such as mapping. For instance, Mollick *et al*. (2023) leveraged geo-spatial-based machine learning approaches combined with UAV multi-spectral data for land use mapping. In another study conducted by Chen *et al*. (2020) UAV multi-spectral data was able to accurately classify croplands.

While the use of this sensor has been gaining traction of recent as a result of the greater number of spectral bands in comparison to just three RGB bands, the compulsory radiometric and atmospheric calibration in addition to the slow imaging speed poses limitations in their utility (Mohidem *et al*., 2021; Rosle *et al*., 2021). For instance, while combining UAV and multi-spectral sensors may enhance data collection capabilities, it necessitates complex workflows for processing and analysis which may exceed the technological capacity of local teams (Laliberte *et al*., 2011). Furthermore, while these sensors may have a reduced cost in comparison to hyperspectral sensors, it remains cost-prohibitive in financially constrained settings (Simoneau and Aubé, 2023). These distinct limitations primarily lie in the financial implications and complexities that are affiliated with these advanced sensor technologies, in the context of resource-poor and finically constrained frameworks, the procurement and operational expense of hyperspectral and multi-spectral sensors present as a limiting factor. Consequently, this impedes access to these advanced technological tools, reducing the adoption of PA practices particularly amongst smallholder farms that require innovative and low-cost solutions to bolster agricultural productivity (Mapanje *et al*., 2023). Consequently, this underscores the need for economical and practical approaches to enhance the applicability of modern technology in small-scale farming contexts to facilitate PA strategies within their farming operations.

2.3.2.2 Red Green and Blue (RGB) Sensor

By assessment of the strengths and limitations of the above-mentioned sensors, RGB sensors stand (400 – 700 nm ) out as the predominant and commercially accessible sensor integrated into UAVs equipped with cameras, delivering high-resolution quality images while meeting cost-effective operational requirements (Esposito *et al*., 2021; Mohidem *et al*., 2021). Additionally, these sensors obviate the need for radiometric and atmospheric calibration which presents an added advantage over costly and complex multi-spectral and hyperspectral sensors (Rosle *et al*., 2021). Despite these advantages, RGB sensors are met with a spectral limitation due to their broad spectral bandwidths, which hinder the pixel-wise differentiation between similar spectral signatures. However, this limitation can be mitigated by incorporating additional information related to texture, leaf shape, and size into the classification process (Mohidem *et al*., 2021). This approach enhances the discriminatory power of RGB sensors in distinguishing between different vegetation types, thereby improving their utility in agricultural and environmental monitoring applications. Over the years, these sensors have garnered significant attention in research and are increasingly integrated into advanced machine-learning algorithms for tasks such as weed and crop recognition, disease identification, phenology analysis, pathology assessment, and various other applications (Rosle *et al*., 2021).

For instance, Gruner *et al*. (2019) carried out a study on an experimental farm in Germany that adopted the use of UAV-RGB imaging in order to predict biomass within a heterogeneous grassland. The results indicated that in particularly harsh weather conditions, there is improved robustness in yield estimation. In a similar instance, Niu *et al*. (2019) established a high correlation between the plant height derived from UAV-RGB imagery and in situ data collected from the 1.3-hectare maize field in Zhaoujun, China. The authors noted that the high correlation is indicative of the efficacy of this method in enabling the estimation of above-ground biomass (Niu *et al*., 2029).

Further research highlighted the potential of UAV-RGB imagery to estimate leaf area index (LAI) in a study conducted by Hasan *et al*. (2019). The results indicated that UAV-RGB imagery can accurately estimate the LAI of winter wheat which is a vital indicator of crop health. This serves as an option that enables farmers to make informed decisions regarding their crop management. Whereas a study that focused on UAV-RGB imagery to monitor corn found that UAV-RGB imagery was able to accurately identify the different growth stages of the corn which can facilitate the precise use of resources for irrigation and fertilization purposes (Andrade *et al.*, 2019). Additionally, a study by Choros *et al*. (2020) that focused on monitoring crop conditions within a potato field found that UAV-RGB images successfully detected crop stress and disease which can allow farmers to take timely action to prevent yield losses. Similarly, Selvaraj *et al*. (2020) developed an early warning system for banana bunchy top disease (BBTD) in Africa using UAV-RGB imagery and a RF classifier, demonstrating the potential of UAV-based approaches for disease monitoring.

To enhance the capabilities of UAV-RGB imagery for data-driven agricultural practices, there is a growing number of studies that have incorporated the use of machine learning techniques (Bouguettaya *et al.*, 2022). This is a result of the ability of machine learning to handle complex and multidimensional data, which is essential for PA, as data is utilized from diverse sources with differing formats that require to be analyzed to facilitate optimal agricultural practices and informed decision-making (Mahmood *et al.*, 2020). In addition, machine learning is advantageous for PA due to its ability to identify trends and patterns in large agricultural datasets which is crucial for uncovering insights that enable optimal crop management, improved resource efficiency and enhanced crop productivity (Sumarsono *et al.*, 2024). For instance, Randelovic *et al*. (2020) leveraged UAVs equipped with an RGB sensor and Random Forest (RF) machine learning approach to assess the density of soybeans in Serbia in a non-destructive and digital manner across 266 experimental fields over a period of twelve months. The machine learning model yielded validation results of a correlation coefficient (r) = 0.87, mean absolute error (MAE) = 6. 24 and a root mean square error (RMSE) = 7.47. These results were indicative of the potential of utilizing a machine learning model which was constructed on simple VI values that enabled the prediction of plant density whilst minimizing the use of human labor (Randelovic *et al.*, 2020).

Additionally, a study carried out by Qiu *et al*. (2021) incorporated machine learning with UAV-RGB imagery to estimate the nitrogen nutrition index (NNI) for rice plants in Pukou district in China. The RF classifier had the highest performance in estimating rice NNI, with r-squared ($R^2$) values ranging between 0.88-0.96 and RMSE ranging from 0.03 to 0.07. Therefore, the authors concluded that the combination of UAV-RGB images with machine learning algorithms is an inexpensive, practical, and scalable approach to rapidly qualify rice NNI, which can effectively improve nitrogen use efficiency and provide precise guidance in fertilization. Another significant application of UAV-RGB imagery for PA practices is yield estimation as this was evident in a case study conducted by Naik *et al*. (2023) which employed UAV-RGB imagery and advanced machine learning techniques to develop a methodology to predict wheat. Various digital variables which reflected the growth trend of the respective crops were utilized for the purposes of yield prediction. The results indicated that amongst the various machine learning models employed within the study, support vector machine (SVM) most accurately estimated yield prior to harvest.

Beyond the extensive use of UAV-RGB data for various crop monitoring tasks, it has also been widely adopted for cropland mapping and LULC mapping, for example, a study conducted by Ozturk and Colkesen (2021), explored the integration of RGB-derived indices such as green leaf index and triangular green index along with ensemble modelling for land cover classification highlighting the potential of VIs incorporated and UAV imagery for accurate LULC classification. Similarly, Xu *et al*. (2019) employed an object-based approach along with VI's (visible-band difference, excess green, normalized green-red difference index and red-green ratio index) and texture information to accurately classify cultivated lands utilizing visible light imagery. The findings of this study emphasize the spatial detail of UAV imagery which enables precise cropland delineation. Furthermore, Andrade *et al*. (2024) demonstrated the efficacy of UAV-RGB-derived data, including RGB bands and visible-band difference VI, in conjunction with RF, k-nearest neighbor, and Gaussian mixture model classifiers for classifying crops, exposed soil, and mulch cover within an intercropped forage cactus system. These findings reinforced the viability of UAV-RGB data as a remote sensing approach for indirect crop.

Collectively, the above-mentioned case studies showcase the profound potential of employing UAV-RGB imagery for crop monitoring and cropland mapping. The success of this approach for various applications underscores the potential of utilizing UAV-RGB to enhance agricultural practices for smallholder farms. These farms may be able to gain valuable insight pertaining to their crop conditions through leveraging the capabilities of UAV-RGB data thus enabling data-driven decisions which can enhance crop yield, maximize resource use and reduce waste. Additionally, this technology serves as a feasible alternative to sophisticated and costly remote sensing tools making it more suitable for financially constrained and resource scarce contexts. Furthermore, leveraging UAV-RGB data for agricultural operations in smallholder farms could potentially bridge the gap between conventional farming and PA, ultimately leading to improved agricultural practices, enhanced productivity and therefore an improved food supply.

## 2.4 Synthesis of Literature

The dual pressures of climate change and exponential population growth, as well as the precarious circumstances among smallholder farms pose a significant threat to current food systems, exacerbating the prevailing issues of food security, malnutrition and socio-economic instability particularly within developing nations. To address these pressing issues, it is imperative to assist smallholder farmers in achieving higher agricultural productivity with their limited resources. PA emerges as a promising approach when compared to conventional techniques, offering a more systematic and strategic method to aid smallholder farmers in optimizing their agricultural productivity.

Amongst the many components of PA, the utilization of remote sensing technology serves a pivotal purpose in providing critical data for informed decision-making and resource management. Within the various remote sensing platforms (satellites, manned aerial vehicles and UAVs), UAVs have been identified to be well-suited for smallholder farming contexts. Their high spatial resolution, user-defined intervals, low flight altitude, and cost-effectiveness set them apart from satellites and manned aircraft, making them a viable option for acquiring high-resolution data in near real-time, thereby enabling them to guide and implement PA practices on smallholder heterogenous farms. In an attempt to identify both the potential and limitations of utilizing UAVs for PA within smallholder farms, a critical evaluation of the literature was undertaken. A key finding of this evaluation revealed that the success of UAV imaging depends on the sensor, and while hyperspectral and multi-spectral sensors provide intricate spatial detail, their applicability within the context of smallholder farmers is constrained by several factors, primarily the exorbitant costs.

The literature underscored the unsuitability of these advanced sensors for small-scale agricultural operations, prompting research into RGB sensors as a more practical option for smallholder farmers. Further research highlighted that RGB sensors are a more suitable option that smallholder farmers can utilize to guide and implement PA practices. While literature acknowledges the inherent limitations associated with these sensors, the integration of machine learning techniques has emerged as an effective tool to further enhance the capabilities and accuracies of RGB data.

While the application of UAV-RGB data was demonstrated successfully in various applications within the domain of PA, the adoption of these technologies to guide and implement PA within a smallholder farm setting in a developing nation such as SSA has not been comprehensively accounted for in past research studies. As such, there remains a paucity of research which directly compares the accuracy and functional capacity of a cost-effective sensor, as in the case of UAV-RGB data to that of data obtained from a costlier and more complex sensor. Such comparative analysis is critical in ascertaining the use of UAV-RGB data as a cost-effective alternative capable of meeting the demands of precision and reliability that are required to facilitate PA within a smallholder farm setting. The limited application of this approach in smallholder farm settings represents a missed opportunity to implement data-driven decisions enabling enhanced agricultural productivity, efficient use of critical resources and sustainable farming practices.

In an attempt to narrow this gap, this study aims to evaluate the reliability of UAV-RGB data by comparing it to that of UAV multi-spectral data to facilitate PA within a smallholder farm context. Through this, the study seeks to provide a reliable, accessible low-cost alternative to implement PA, particularly for data-scarce and resource-constrained scenarios such as a smallholder farm. Ultimately, by attempting to address this research gap, this research could serve as a potential eye-opener for smallholder farms to adopt technologies to facilitate PA practices which provide them with innovative evidence-based approaches to bolster their agricultural productivity, enhance sustainability and optimize resource use. These advancements can thereby contribute significantly to strengthening food security, decreasing the prevalence of malnutrition and enhancing livelihoods as well as fortifying resilience within resource-constrained and financially underserved smallholder farms agricultural productivity, enhancing sustainability and optimizing resource use. These advancements can therefore contribute significantly to strengthening food security, decreasing the prevalence of malnutrition and enhancing livelihoods, as well as fortifying resilience within resource-constrained and financially underserved smallholder farms.

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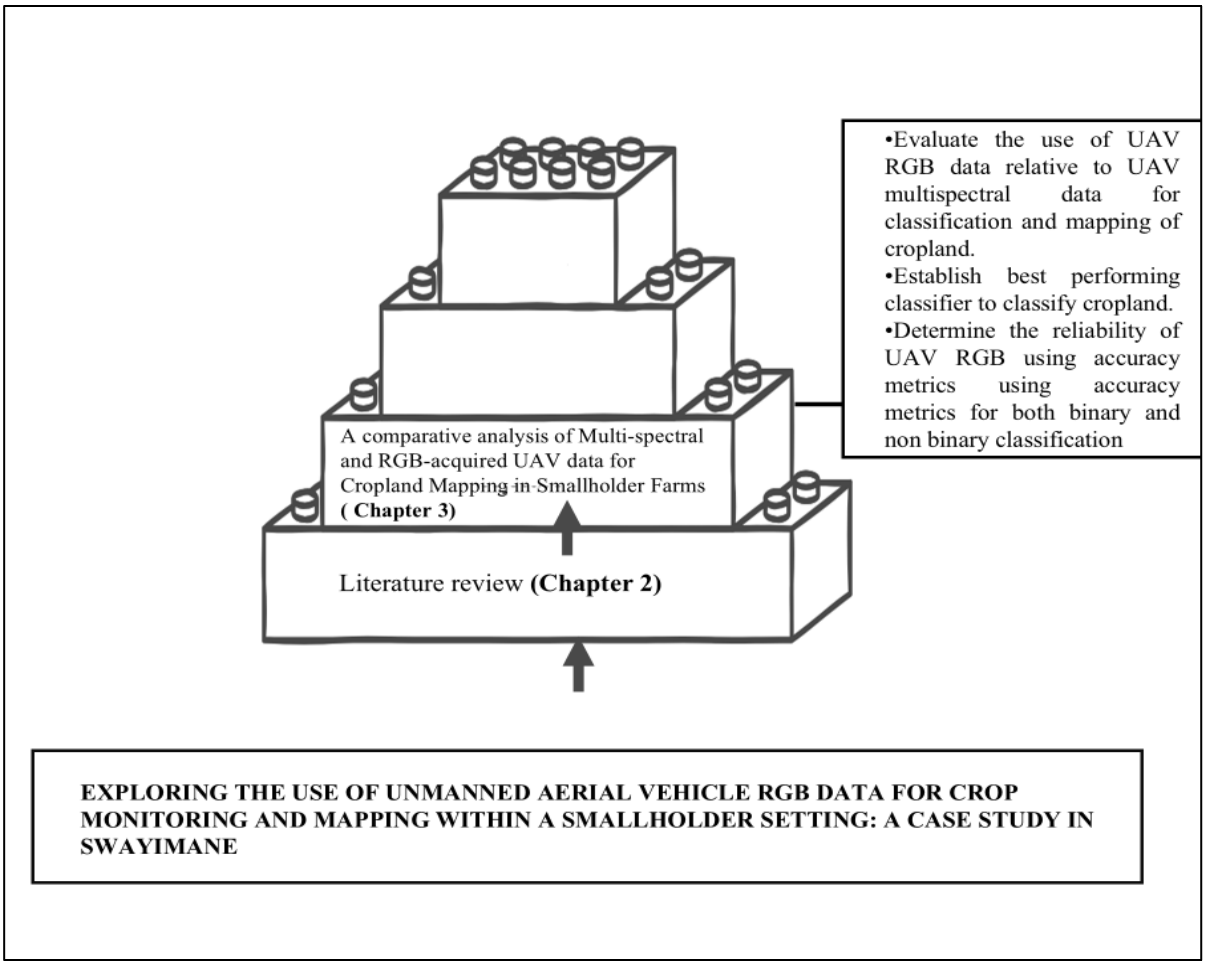
**Lead into Chapter 3**: Having established that UAVs along with RGB sensors are a suitable approach for PA within a smallholder farm context, Chapter 2 also identified a research gap within the literature pertaining to limited empirical evidence comparing UAV-RGB data with more advanced and costly sensors such as multi-spectral sensors for PA within a smallholder farm context. Such comparison is necessary in validating the reliability of UAV-RGB data as a low-cost alternative which potentially could democratize the access of advanced technology tools for PA within smallholder farms. Chapter 3 addresses this gap by comparing UAV-RGB and multispectral data for cropland mapping, a key PA application. This comparison evaluates the reliability of UAV-RGB as a cost-effective alternative to multispectral data and assesses its potential to support data-driven, site-specific management in resource-constrained smallholder farms. By enabling more efficient resource use and improving decision-making, this approach ultimately enhances productivity, strengthens food security, and promotes sustainability.



# CHAPTER 3: A COMPARATIVE ANALYSIS OF MULTI-SPECTRAL AND RGB ACQUIRED UAV DATA FOR CROPLAND MAPPING IN SMALLHOLDER FARMS (PAPER 1)


## 3.1 Abstract

Smallholder farms are pivotal in ensuring food security, particularly in developing nations. However, they generally encounter challenges that impede their capacity to produce optimally. The adoption of precision agriculture (PA) practices demonstrates the potential to improve the sustainability and productivity of smallholder farms. Within the PA paradigm, unmanned aerial vehicles (UAVs) are being advocated as a suitable tool to facilitate this process, hence, in this study, we aimed to explore the potential of adopting a relatively cost-effective UAV-based approach to classify and map agricultural land within a smallholder farm. For this purpose, the Google Earth Engine (GEE) open-source cloud-computing platform was leveraged to process and analyze the UAV-acquired imagery over a smallholder farm in the KwaZulu Natal province of South Africa. Several machine learning-based classification approaches were also utilized in the study, given its benefits in efficiency and accuracy in handling voluminous and complex data, hence, in this study, it was used to map croplands using Red-green-blue (RGB) and multi-bands and vegetation indices (VI). The results of this investigation demonstrated that the random forest (RF) machine learning algorithm achieved marginally higher classification accuracies which indicated an overall accuracy (OA) of 68 % (RGB) and 75 % (multi-spectral) for non-binary classification. For the binary classification, the RGB data obtained an area under the receiver operating characteristic curve (AUC - ROC) of 0.75 compared to a 0.77 achieved by multi-spectral data. Despite the reduced classification accuracy with RGB data, the results demonstrated the reliability of leveraging a low-cost alternative for cropland mapping in smallholder farms, presenting a viable opportunity to resource-poor and data-scarce farming systems to facilitate PA practices, which in turn can transform their agricultural practices, optimize resource use and enhance agricultural productivity.



**Keywords:** *Food security, Precision agriculture, Agricultural productivity, Drones, Machine learning*

### 3.2 Introduction

With a burgeoning world population and the detrimental impacts of climate change threatening agri-food systems, the agriculture sector requires significant transformation to fulfil future food demands. Smallholder farms which typically occupy less than two hectares in size play a pivotal role in contributing to agricultural production, food security and in driving the local economies (Nve and Ma, 2018). In many developing nations, smallholder farms are crucial role players in the growth of their socio-economic status contributing to an employment rate of approximately 70% within rural areas and an estimated food production rate of 80% in Sub-Saharan Africa (SSA). Despite their vital role, these smallholder farms face various challenges, namely, limited critical resources, suboptimal management practices, poor infrastructure and market constraints which are all compounded by the lack of finance and government assistance (Dhillon and Moncur, 2023; Gokool *et al*., 2024). Furthermore, their traditional farming practices have proven to be timeous, laborious and lack spatial representation and targeted crop management which has led to reduced productivity and high crop failure. Consequently, their agricultural productivity lags following an ineffective contribution to food security and in addressing socio-economic adversities (Kamara *et al*., 2019).

Subsequently, to address the aforementioned challenges including the food insecurity concerns, context-specific and economically feasible solutions are required by agricultural researchers, policymakers and local government to aid in devising bespoke management practices for smallholder farms to enhance their agricultural productivity. Thus, it will assist in addressing the needs of feeding a projected growing population which are also facing a climate crisis that is threatening current food systems To this end, integrating remote sensing technologies and precision agriculture (PA) for cropland mapping of smallholder farms is a transition away from traditional farming practices towards modernized data-driven techniques which are potentially a key component for specific site-specific management thereby resulting in allocative resource efficiency and optimal agricultural management. Leveraging remote sensing technologies, such as satellites or UAVs to capture spatial data that is utilized to accurately classify agricultural land is primarily beneficial in its capacity to inform tailored interventions that target specific agricultural challenges and conditions thereby mitigating blanket approaches to ensure optimized and customized intervention strategies. As a result, this approach assists with increasing productivity as it enables transformation in agricultural monitoring of crops, careful water stewardship, sustainable land use management as well as enhancement of climate change mitigation through real-time informed management decisions (Näschen *et al*., 2019; Munthali *et al*., 2022; Gokool *et al*., 2023; Mengesha *et al*., 2024).

In recent years, various remote sensing platforms such as satellites, manned aerial vehicles and unmanned aerial vehicles (UAVs) have all been employed to collect rapid, high-density data suitable for PA applications (Sishodia *et al*., 2020). While satellite and manned aerial vehicle remote sensing platforms have been the focus of agricultural management research over the last 60 years, their adoption at the farm scale has not been extensive (Colwell,1956; Jackson, 1984; Pinter *et al*., 2003). This is a result of infrequent coverage, inadequate pixel resolution to capture the level of heterogeneity found at a farm scale and atmospheric disturbance which impacts data quality and the untimely delivery of data to users (Jackson, 1984; Pinter *et al*., 2003; Mulla, 2013). Additionally, the financial expenditures associated with the procurement of advanced satellite data as well as the maintenance of manned aerial vehicles are exorbitant when implemented for widespread long-term agricultural use (Norasma *et al*., 2019). Moreover, satellite revisit periods and unstable atmospheric conditions impede the capacity of satellite platforms to acquire timely and consistent data during the entirety of the agricultural cultivation period, negatively impacting the reliability and efficacy of satellite-based monitoring for agricultural purposes in the context of smallholder farms (Bergstrom *et al*., 2022; Pandey and Jain, 2022).

UAVs on the other hand have advanced PA and remote sensing techniques (Shishodia *et al*., 2020; Delavarpour *et al*., 2021), offering a more timely and accurate representation of smallholder farms which are often characterized by landscapes with mixed crops, trees and livestock which traditional satellite imagery may not accurately represent (Jin *et al*., 2017; Gokool *et al*., 2024). UAVs offer distinctive attributes that have been showcased in a plethora of PA practices (Norasma *et al*., 2019; Tsouros *et al*., 2019; Shishodia *et al*., 2020). UAVs can be deployed at user-defined intervals throughout a crop's growing season to retrieve information on a centimeter scale which is minimally impacted by cloud cover (Zhao, 2018). Also, unlike satellite platforms, UAVs have low flight altitudes which possess the potential to provide high spatial resolution data that is dependent on the optical properties of on-board cameras (Gokool *et al*., 2024). Based on these two characteristics, UAVs have been identified as more advantageous than traditional remote sensing platforms as the high spatial resolution results in an accurate representation of smallholder heterogeneous farmland while the high temporal resolution prompts accurate and timely responses in producing actionable information pertaining to crop status (Elarab *et al*., 2015; Huang *et al*., 2021). This low-cost alternative to attain high-resolution data holds great transformative potential through facilitating PA within smallholder farms possibly catalyzing progress towards precise and efficient decision-making for agricultural monitoring (McCarthy *et al*., 2023).

Furthermore, UAVs can be equipped with a diverse array of sensors, including the commonly utilized sensors which namely are, hyperspectral, multi-spectral, and RGB (Tsouros *et al*., 2019; Yao *et al*., 2019; Olson and Anderson, 2021). These sensors play a crucial role in capturing high-resolution images that provide intricate spatial details essential for monitoring vegetation characteristics and evaluating crop parameters. While hyperspectral and multi-spectral sensors offer valuable insights into various crop parameters through distinct vegetation indices, their high costs and complex data processing requirements present challenges in seeking access to this vital information required for guiding PA practices within resource-scarce smallholder farm settings (Hasan *et al.*, 2019; Yamaguchi *et al.*, 2020). Conversely, recent research has indicated that commercial RGB sensors which are more cost-effective than hyperspectral and multi-spectral sensors can provide valuable insights that can contribute to precise agricultural practices, optimal resource allocation, and sustainable farming techniques, thereby enhancing agricultural output efficiency (Raj *et al*., 2020; Velez *et al*., 2022; Kazemi and Ghanbari Parmehr, 2023).

In addition, a growing number of studies have been conducted on the implementation of UAV-RGB for PA, highlighting its potential to revolutionize traditional farming practices into modernized, site-specific, and cost-effective methods while promoting environmental sustainability. For example, a study conducted by Hall *et al*. (2018) noted the satisfactory quantitative and visual evaluation of UAV-RGB data for the delineation and classification of a maize field within a smallholder farm in Ghana. In another study, Bohler *et al*. (2018) established that within the context of their study, very fine spatial resolution UAV data (0.05 m resampled to 0.5 m resolution) which consisted of spectrally poor uncalibrated RGB bands provided sufficient information to distinguish between agricultural crops within a small heterogeneous field. Furthermore, Radocaj *et al*. (2023), found that a low-cost UAV equipped with a commercial RGB sensor was utilized to successfully produce a vegetation mask using supervised classification and machine learning as part of a two-step method for identifying cropland suitability in micro-scale farms. Consequently, the study observed that agricultural production can be improved by effectively managing crops and soil properties, particularly in unsuitable growing areas (Radocaj *et al*., 2023).

In recent years, machine learning has undergone significant transformation as artificial intelligence (AI) has evolved and developed, making its own technological leaps thereby transforming PA tasks such as but not limited to land use land cover (LULC) and cropland mapping (Detsikas *et al*., 2024). The synergy of these technologies has expanded the options relative to image classification that have been extensively applied for UAV-based LULC or cropland mapping (Lee *et al*., 2021; Bouguettaya *et al*., 2022). Furthermore, the development of cloud computing platforms has complemented machine learning within the context of PA through the provision of necessary infrastructure required for the processing, analysis and storage of data sets (Zhang *et al*., 2020). The scalability and flexibility offered by cloud computing services enable the efficient management of large and complex data obtained by various remote sensing technologies. Moreover, cloud computing platforms offer a suite of complex machine-learning algorithms which enable timely data analysis and decision-making (Jindal, 2023). The integration of machine learning and cloud computing offers dual advantages of operational efficiency as well as the reduced cost associated with computational resources required for data management and storage which is beneficial in resource-scarce and financially constrained contexts (Li *et al*., 2022).

While there have been various research initiatives that focused on UAV-RGB for PA applications, there remain limited studies being conducted on investigating its efficacy in comparison to multi-spectral sensors, particularly within a smallholder farm context. Subsequently, this study places emphasis on the comparison between these specific sensors, as it allows one to determine the trade-offs between multi-spectral sensors which are less expensive than hyperspectral and an RGB which is low cost and widely accessible. In this instance, whilst advocating for the utilization of a relatively low-cost UAV-RGB sensor it is essential to determine if it provides a comparable functionality and accuracy to that of their multi-spectral counterparts. Hence, further investigation into this knowledge gap is crucial for understanding the viability and practicality of utilizing UAV-RGB imagery for smallholder farms to guide and inform precise agricultural management practices. As such, the scope of this study is to evaluate the accuracy of UAV-RGB cropland maps against UAV multi-spectral to determine the potential of utilizing UAV-RGB data as a low-cost and reliable solution to classify and map agricultural land within a smallholder farm setting.

### 3.3 Materials and Methods

#### *3.3.1 Study site description*

This study was conducted in the area of Swayimane, which is a rural community located approximately 13 km outside of Wartburg under the uMshwathi local municipality, in the province of KwaZulu-Natal (Figure 3.1). Swayimane is the largest of four rural communities spanning approximately 32 $km^2$ of land (Basdew *et al*., 2017). The moist midlands mist belt in which Swayimane is located in, experiences average temperatures which fall within the ranges of 11.80 ℃ and 24.00 ℃ (Dlamini, 2024). The seasonal climatic conditions within the area are dry winters and fairly hot wet summers with annual precipitation varying between 600 and 1100 mm (Dlamini, 2024).

There are an estimated 9329 agricultural households within this region, actively partaking in farming which has been identified as the main economic activity in this area (Basdew *et al*., 2017). Many of the community members in Swayimane rely on subsistence agricultural farming for sustenance (Archer *et al.*, 2010). The majority of the farming systems within this area are dominated by crop production with small-scale farmers primarily growing, beans, amadumbe (taro), sweet potato, and sugarcane (Ndlovu *et al*., 2022). Additionally, smallholder maize farmers dominate Swayimane, hence, it is recognized as a staple food by the local community (Ndlovu *et al*., 2021).

However, it is important to note that the small-scale farmers in this area are often faced with numerous challenges, including a lack of water and irrigation systems, increased land degradation, and financial constraints that prevent them from producing optimal agricultural outputs (Mkhize 2016). Moreover, these subsistence farmers are highly dependent on rain-fed, traditional farming practices and manual labor which leads to an overuse of critical resources, unsustainable practices as well as limited yield productivity (Jangid *et al*., 2012; Ndlovu *et al*., 2021). Overall, the socio-economic characteristics of the community coupled with the biophysical attributes of the area provide the ideal opportunity to demonstrate how UAVs can be adopted as a cost-effective approach in providing suitable spatiotemporal information which can aid smallholder farmers in guiding and informing their decisions about agricultural practices to boost crop productivity, minimize crop failure and reduce input costs at a localized level.


**Figure 3.1 Location of the study site at Swayimane within the Umswathi Local Municipality in Kwa-Zulu-Natal, South Africa**

### *3.3.2 Data acquisition and processing*

As part of step one (Figure 3.2), aerial images of the study site were obtained utilizing a DJI Matrice 300 (M-300) UAV fitted with a MicaSense Altum multi-spectral sensor and a Downwelling Light Sensor (DLS-2) (Figure 3.3). The novel characteristics of the DJI M-300 platform are its 15 km transmission range, 7000 m maximum altitude, obstacle avoidance, flightpath planning and locational position tracker. The DJI M-300 excluding the payload, has an optimal flight time of 55 minutes with a maximum flight speed of 27m/s, transcending a vast majority of UAV platforms available on the market (Brewer *et al.*, 2022). Additionally, the MicaSense Altum camera is a multi-spectral imaging sensor encompassing five high-resolution spectral bands which are blue (475 nm center, 32 nm bandwidth), green (560 nm center, 27 nm bandwidth), red (668 nm center, 14 nm bandwidth), red-edge(717 nm center, 12 nm bandwidth), and near-infrared (842 nm center, 57 nm bandwidth) that are integrated with a radiometric longwave infrared thermal imaging sensor (8000–14,000 nm) (Figure 3.3). The high-performance camera allows for a synchronized capture of multi-spectral and thermal images whilst utilizing the global shutter to produce precise and aligned imagery through its one-second capture rate (Hutton *et al*., 2020).

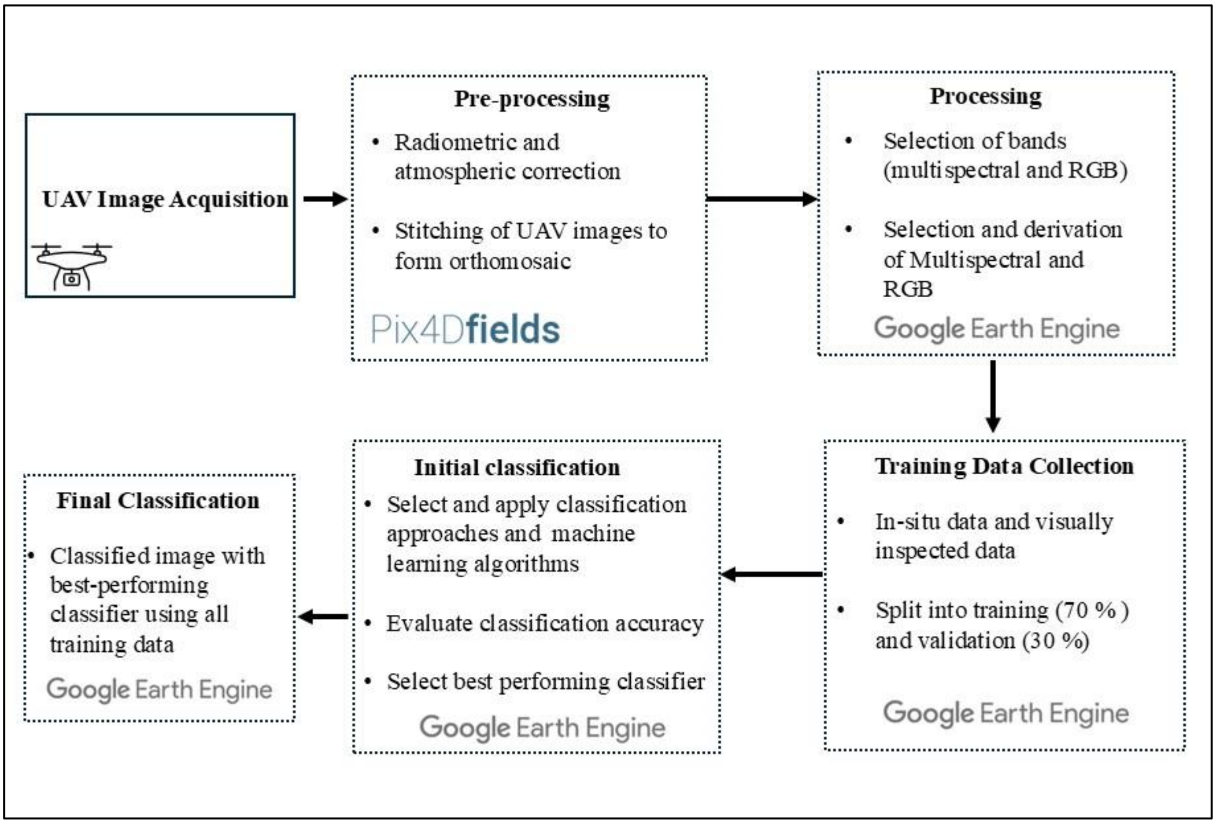



**Figure 3.2 Conceptual flow diagram depicting the methodology**

Furthermore, to assist with accurate surveying results, the Altum sensor includes a DLS 2 with embedded geographical position system (GPS) and a compact CRP (Calibrated Reflectance Panel) for accurate light calibration. The configuration of the Altum imaging sensor allowed for images that consist of an 80% overlap to be captured across the study site. Moreover, the DJI M-300 UAV platform comprises four rotating wings and is equipped with vertical landing and take-off (VLOT) technology which makes it well-suited for conducting flights in a rural setting within close proximity to settlements (Brewer *et al.*, 2022).

**Figure 3.3 DJI Matrice 300 UAV platform and MicaSense Altum Multi-spectral camera**

In Google Earth Pro, the perimeter of the study area which spanned approximately 339.557 $km^2$ was digitized and imported as a Keyhole Markup Language file (kml) into the DJI M-300 smart controller. Furthermore, an optimal flight path that captured images covering the entirety of the study site was designed through the utilization of the kml file. The DJI M-300 was configured to fly at an altitude of 100 m which was sufficient to capture data at 0.07 m pixel resolution for the entire study area. In terms of the calibration of the imaging sensor, this was conducted before and after every flight mission to consider light intensity fluctuations over the course of the day. This process was carried out by utilizing the MicaSense Altum CRP. The UAV image was captured between 10:00 and 12:00 am UTC on the 3rd of August 2023. As part of step two (Figure 3.2) the acquired UAV image was then pre-processed utilizing Pix4D fields software (version 1.8) before further analysis. The preprocessing of the UAV image entailed atmospheric and radiometric corrections performed in Pix4D fields in which the corrected images had then been mosaicked to create a single georeferenced orthomosaic. As per step 3 (Figure 3.2), in saving the orthomosaic, a GeoTIFF file format was chosen as it is the required format for the image to be uploaded and imported into the cloud computing GEE platform for further processing.

In the context of this research, two distinct data sets had to be collated to facilitate the application of non-binary and binary classification techniques (APPENDIX A). Non-binary classification involves categorizing data into multiple categories, for this study, 950 points were identified through visual inspection of the orthomosaic whilst 50 GCPs were acquired in situ from the respective study site. Subsequently, a total of 1000 points were equally selected for five broad land cover classes namely: ‘buildings and infrastructure’, ‘bare soil’, ‘agriculture’, ‘grassland’ and 'trees and shrubs’ (Table 3.1). In contrast, Binary classification entails the assignment of data samples to one of two exclusive categories (Kumari and Srivastava, 2017). The objective within this framework is to ascertain the classification of land cover as either 'agriculture' or 'other'. The dataset utilized for this technique integrated 50 ground control points (GCPs) alongside 550 visually inspected points obtained from the orthomosaic image in GEE, with a total of 600 points earmarked for the specified classifications (Table 3.2)

**Table 3.1 Non-Binary classes**

| **Id** | **Class** | **Description** | **Image** |
|---|---|---|---|
| **0** | Buildings and Infrastructure | Areas of land occupied by human settlements of various sizes, roads/streets, solar panels |  |

| | | | |
|---|---|---|---|
| **1** | Bare soil | Areas of baren soil, dirt roads, no buildings and harvested crop. |  |
| **2** | Croplands | Areas of land cultivated with taro, sweet potato, sugar cane and maize |  |
| **3** | Grassland | Area dominated by continuous cover of grass. |  |
| **4** | Trees and Shrubs | Woods plants higher than 5m and shorter than 5m |  |

**Table 3.2 Binary classes**

| ID | Class | Description |
|---|---|---|
| **0** | Other | Areas of land identifying buildings and infrastructure, bare soil, grassland and trees and shrubs. |
| **1** | Cropland | Areas of land cultivated with crops such as taro, sweet potato, sugar cane and maize |

For both binary and non-binary classification techniques, the dataset was split into a training subset, which consisted of 70 % of the data, utilized for predictive model development, while the remaining 30 % formed a validation set, used to evaluate the accuracy of the classification model (Masiza *et al*., 2020; Pech-May *et al*., 2022; Zhao *et al*., 2024). For the RGB dataset, the red, green and blue bands of the multi-spectral sensor along with RGB-derived vegetation indices (VIs) (Table 3.3) were extracted from each training and validation point. Similarly, the respective bands of the multi-spectral sensor and multi-spectral derived VI's (Table 3.4) were also extracted from the training and validation points which forms part of step 3 and 4 depicted in the conceptual diagram of the methodology (Figure 3.2). For the prediction of the selected land cover classes, the GEE platform offers a suite of machine learning classification algorithms such as Random Forest (RF), Support Vector Machine (SVM), Maximum Likelihood (ML), Gradient Tree Boost (GTB), Decision Tree (DT), and Classification and Regression Tree (CART) as noted in step 5 (Figure 3.2).

However, within this study, the RF and GTB algorithms with a specified number of decision trees ($n$ = 200) were selected for modelling and predicting the chosen land cover classes. As part of step 6 (Figure 3.2), the model that exhibited superior performancewas evaluated based on commonly used accuracy metrics such as Overall Accuracy (OA), User Accuracy (UA), Producer Accuracy (PA), Kappa coefficient, Area Under the Receiver Operating Characteristic Curve (AUC-ROC), and Out-Of-Bag (OOB) error. These metrics are standard in land use classification studies, and their calculations and interpretations have been well-documented in the literature for similar methodologies (Smits *et al*., 1999; Liu *et al*., 2002; Islami *et al*., 2022 Gokool *et al*., 2024).

**Table 3.3 RGB-derived VIs**

| Vegetation Index | Equation | Reference |
|---|---|---|
| Excessive Green Index | 2 (Green - Red - Blue) | Woebbecke *et al*., 1995 |
| Triangular Greenness Index | Green (0.39 × Red) - (0.61 × Blue) | Fuentes Peailillo *et al*., 2018 |
| Excess Red Vegetation Index | (1.4 × Red - Green) / (Green + Red + Blue) | Meyer and Neto, 2008 |
| Visible Atmospheric Resistance Index | (Green - Red)/ (Green+ Red - Blue) | Eng *et al*., 2019 |
| Excess Blue Vegetation Index | (1.4 × Blue - Green) / (Green + Red + Blue) | Meyer and Neto, 2008 |

**Table 3.4 Multi-spectral-derived VIs**

| Vegetation Index | Equation | Reference |
|---|---|---|
| Normalized Difference Vegetation Index | (NIR - Red) / (NIR + Red) | Xue and Su, 2017 |
| Green Normalized Difference Vegetation Index | (NIR - Green) / (NIR + Green) | Moges *et al.*, 2005 |
| Normalized Difference Vegetation Index Red-Edge Index | (NIR - $Red_{edge}$) / (NIR + $Red_{edge}$) | Dalla Marta *et al.*, 2015 |
| Enhanced Vegetation Index | 2.5× (NIR - Red) / ((NIR + 6 × Red7.5 × Blue) +1) | Roy, 2021 |
| Soil Adjusted Vegetation Index | ((NIR - $Red_{edge}$) / (NIR + $Red_{edge}$+1)) × (1+0.5) | Xue and Su, 2017 |
| Simple Near Infrared Ratio | NIR / Red | Amarsaikhan *et al.*, 2023 |
| Simple Blue and Red-Edge Ratio | (($Red_{edge}$ + Red + 0.5) / Blue) × 1.5 | Gokool *et al.*, 2024 |
| Simple NIR and Red-Edge Ratio | NIR/$Red_{edge}$ | Gokool *et al.*, 2024 |
| Green Chlorophyll Index | (NIR/Green) - 1 | Gitelson *et al.*, 2003 |

## 3.4 Results

### *3.4.1 Classifier Performance*

3.4.1.1 Non -Binary Classification

The results highlighted in Table 3.5 indicate the outcome of non-binary classification utilizing RF and GTB for multi-spectral and RGB data. With the use of multi-spectral data, the RF excelled with a 75 % OA, surpassing GTB by 2 %. Additionally, RF obtained a higher Kappa coefficient in comparison to GTB with a substantial agreement of 0.69. In a contrary scenario with the use of RGB data, the RF classifier and GTB achieved an OA of 68 %. Notably, RF demonstrated a moderate agreement by achieving a 0.61 kappa coefficient which was marginally higher than that of GTB. Whilst the RF classifier may have marginally outperformed the GTB, it also produced the highest mean misclassification rate of 45 % and 55 % for UAV multi-spectral and RGB data respectively when attempting to classify agricultural land.

**Table 3.5 The outcome of non-binary classification using RF and GTB**

| Accuracy Assessment<br>Non-Binary Classification | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Multi-spectral | | | | RGB | | | |
| Classification Algorithm | RF | | GTB | | RF | | GTB | |
| Overall Accuracy | 75 % | | 73 % | | 68 % | | 68 % | |
| Kappa coefficient | 0,69 | | 0,66 | | 0,61 | | 0,60 | |
| | PA | UA | PA | UA | PA | UA | PA | UA |
| Buildings and Infrastructure | 91 % | 86 % | 93 % | 85 % | 92 % | 91 % | 94 % | 94% |
| Bare soil | 80 % | 90 % | 80 % | 90 % | 85 % | 81 % | 86 % | 82% |
| Cropland | 60 % | 50 % | 53 % | 47 % | 44 % | 56 % | 42 % | 53% |
| Grassland | 69 % | 78 % | 64 % | 70 % | 51 % | 46 % | 45 % | 43% |
| Trees and Shrubs | 74% | 71% | 70 % | 67 % | 70 % | 65 % | 70 % | 62% |

Upon the visual inspection of the non-binary classified maps, it is indicative that the buildings and bare soil were most accurately classified when viewed in correlation with the UAV pre-processed orthomosaic of the study site. This is consistent with the statistical analysis presented in the tabulated results above, suggesting that the RF classification algorithm effectively classified buildings and infrastructure and bare soil. However, the UA and PA when leveraging the RF classifier to classify cropland and grassland exhibited mediocre results. Further analysis through visual inspection of Figure 3.4 also indicated misclassification of these land use types as well as trees and shrubs

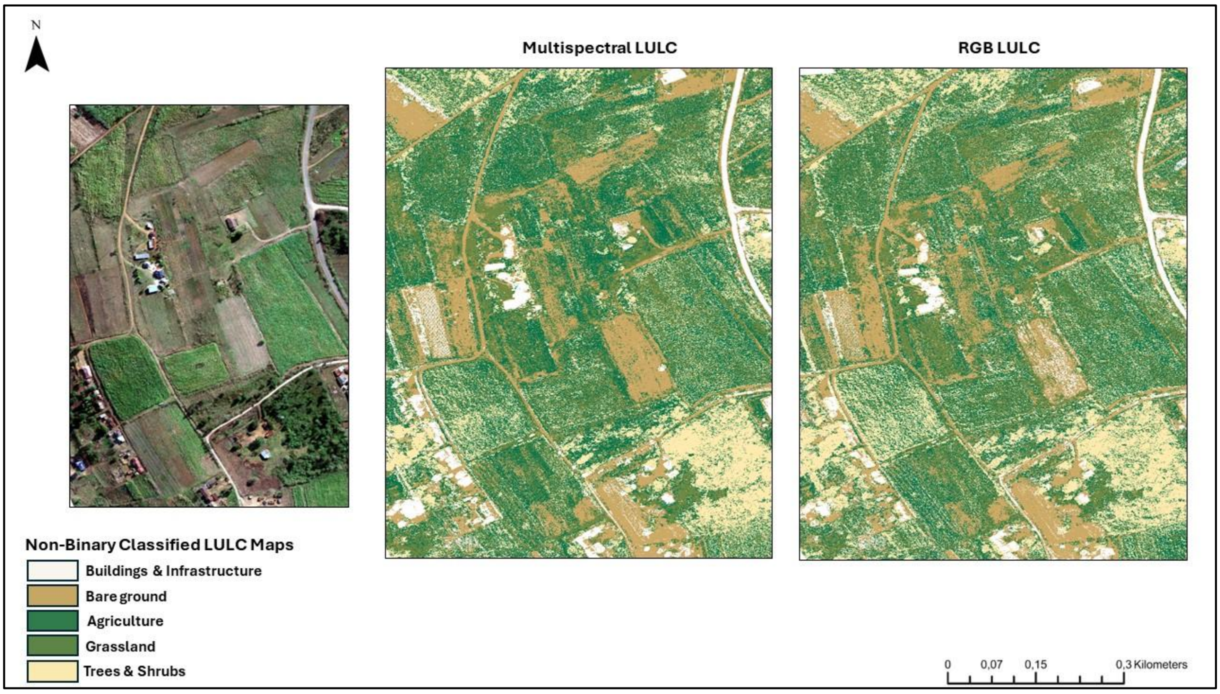



**Figure 3.4 Nonbinary classification using best-performing classifier**

3.4.1.2 Binary Classification – Probability Mode

The results presented in Table 3.6 highlight the outcomes of binary classification using the probability mode for both multi-spectral and RGB data. The analysis reveals that both multispectral and RGB data effectively classified agricultural land, with multispectral data exhibiting slightly superior performance. The AUC-ROC values indicate that models utilizing multispectral data, particularly the RF classifier, outperformed those using RGB data, albeit with only a marginal difference. The RF classifier demonstrated a consistently higher AUC-ROC compared to the GTB classifier for both data types, suggesting that RF provided a more robust model in distinguishing agricultural land from non-agricultural land. Although the AUC-ROC values for RGB data were lower, they remained within an acceptable range, confirming the reliability of RGB data for cropland classification.

In terms of model generalization, the OOB error values further support these findings. The multispectral data yielded a lower OOB error, indicating slightly better model generalization when compared to RGB data. Nevertheless, the disparity between the OOB error values for multispectral and RGB data was minimal, suggesting comparable predictive performance across both data types. Collectively, these results underscore the superior performance of RF in both multispectral and RGB contexts, with only a marginal reduction in performance when RGB data is employed.

**Table 3.6 The outcome of binary classification in probability mode using RF and GTB**

Accuracy Assessment
Binary Classification -Probability mode

Multi-spectral

| Classification Algorithm | **RF** | **GTB** |
|---|---|---|
| AUC-ROC | 77 % | 76 % |
| Out-of-bag error matrix | 0,25 | |

RGB

| Classification Algorithm | **RF** | **GTB** |
|---|---|---|
| AUC-ROC | 75 % | 72 % |
| Out-of-bag error matrix | 0,29 | |

Figure 3.5 and Figure 3.6 showcased the ROC curve using the RF classifier with RGB and multi-spectral data which plotted the True Positive Rate (TPR) against the False Positive Rate (FPR) at various threshold settings. The AUC values of 0.75 and 0.77 measured the area underneath the entire ROC curve and are representative of the probability that a positive instance that is chosen randomly ranks higher than a randomly chosen negative instance. Hence an AUC of 0.77 and 0.75 is indicative that the RF classifier had a strong ability to distinguish between the classes.

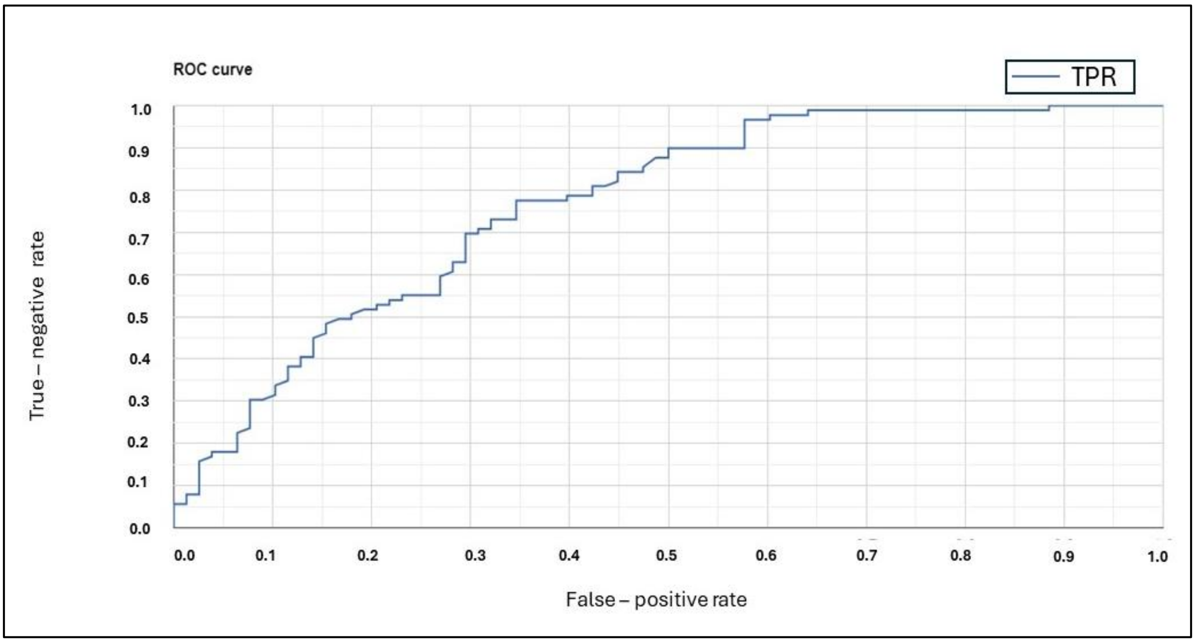



**Figure 3.5 ROC curve plotted using RF with RGB data**

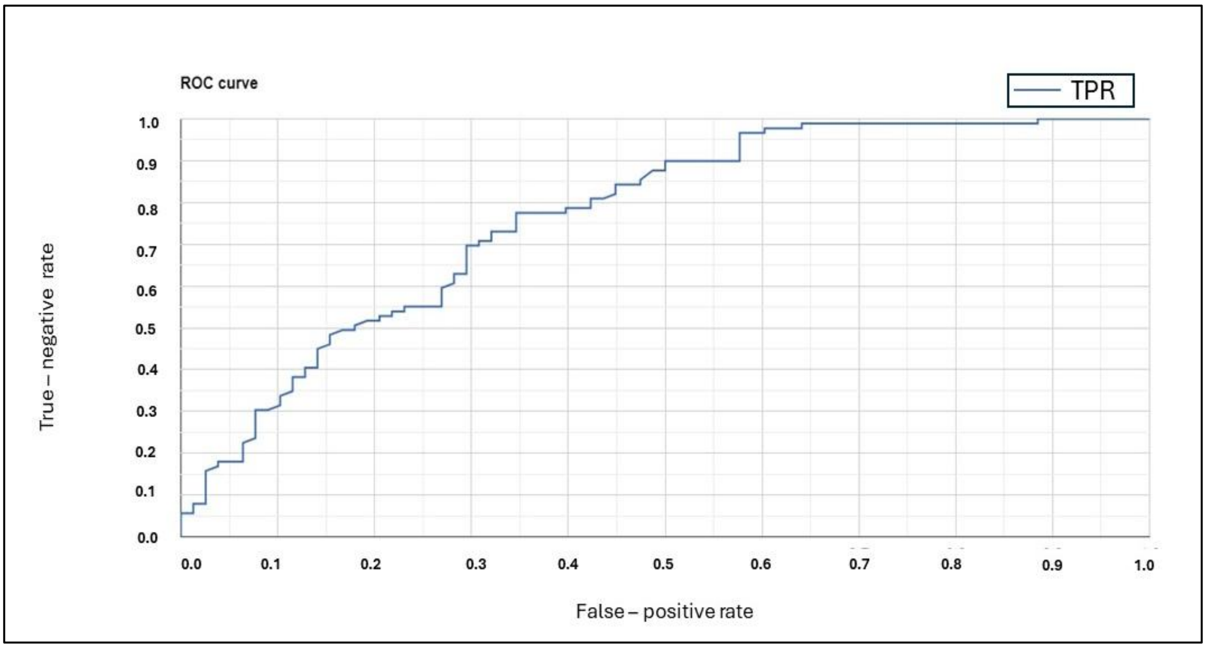



**Figure 3.6 ROC curve plotted using RF with multi-spectral data**

Through the visual inspection of the UAV-RGB and UAV multi-spectral cropland maps (Figure 3.7) a noticeable similarity was revealed, corroborating the statistical analysis which was indicative of a minimal 2% difference in accuracy. The high degree of similarity between the statistical analysis and the visual analysis of the image underscored the reliability of the classification results obtained when utilizing binary classification in conjunction with the RF machine learning algorithm for UAV-RGB and multi-spectral datasets. In addition, the visual comparison between the UAV-RGB cropland map and the orthomosaic image revealed that the agricultural land classified in the UAV-RGB cropland map was accurately classified for the most part. This further highlighted the reliability of utilizing UAV-RGB data to map cropland within smallholder farms.


**Figure 3.7 UAV Multi-spectral cropland map (left) and UAV-RGB cropland map (right)**

### 3.5 Discussion

The binary classification approach, which employed a total of 600 points with 300 points allocated to each class, achieved AUC-ROC scores of 77 % for multi-spectral data and 75 % for RGB data. This indicated a comparable 2 % difference in AUC-ROC values. Despite the marginal loss in accuracy observed utilizing UAV-RGB imagery relative to UAV multi-spectral imagery, the model performed at a satisfactory level to classify cropland. Furthermore, the comparable OOB error estimate of the UAV-RGB and multi-spectral images indicate consistent performance in the classification task, reinforcing the potential of utilizing UAV-RGB imagery for land use classification within smallholder farm settings. According to Swets (1988) and Peterson *et al*. (2008) a threshold of 70 % is a determination of model usefulness, hence, the AUC-ROC values obtained within this study signify a satisfactory level of diagnostic accuracy in the model's ability to distinguish between the two classes (Peterson *et al*., 2008). This suggests that the RF classifier is able to correctly classify 77 % and 75 % of the total area under the ROC curve.

As such, the effectiveness of the RF classifier in this study aligns with previous research demonstrating the strong performance of the RF classifier across various datasets and classification approaches. Prins *et al*. (2019) showed that integrating multiple remote sensing datasets, including LiDAR, Sentinel-2, and aerial imagery, enhanced classification accuracy. Similarly, Lee *et al*. (2021) applied RF with an object-based approach using UAV data, further reinforcing its effectiveness in mapping agricultural land. Böhler *et al*. (2018) also found RF to be highly effective, achieving an accuracy range from 66.7% (pixel-based) to 94.6% (object-based with merged crops), demonstrating the advantages of OBIA over pixel-based methods. The results of this study fall within the accuracy range reported in these studies, with minor discrepancies due to differences in data sources, classification methodologies, and spatial resolutions. Despite these variations, RF consistently demonstrated strong classification performance, highlighting its reliability and adaptability for land cover and crop classification across different agricultural contexts.

The non-binary classification approach which utilized 1000 training points was equally allocated to five land cover classes. The overall accuracy of 75 % and 68 % for UAV multi-spectral and RGB classification suggested that both data types provided valuable insight into land cover classification, however, the higher accuracy of the model employing multi-spectral data for the classification yielded a higher accuracy, indicating its superiority in this context. Despite the satisfactory overall performance, the UA and PA revealed that for the cropland class, there was an average misclassification rate of 45 % and 50 % for the model employing multi-spectral and RGB. Whilst the comparison of these two classification approaches was not explicitly intended for this research, future studies which aim to do so should ensure that the number of training points allocated to each class for both classification approaches remain constant. This has the potential to mitigate bias in the results (Allen *et al*., 2020; Wen *et al*., 2023), thereby enabling an impartial comparison of the two approaches to accurately classify land cover within a smallholder farm.

Further demonstration of the capabilities of the UAV-RGB imagery to accurately classify agricultural land was demonstrated through a visual comparison between a crop mask produced using freely available Copernicus Sentinel 2 satellite images at a 10-meter spatial resolution

(Figure 3.8) and the UAV-RGB crop mask map produced within this study (Figure 3.7) (Roy, 2023). Both the UAV-derived LULC maps demonstrated superior spatial representativeness. The discrepancy in the level of detail is a result of the coarser spatial resolution of freely available satellite imagery whereas the higher spatial resolution of the UAV images provides a more visually detailed image identifying cropland. Considering that RGB imagery is a cost-effective solution with a minimal loss in classification accuracy in comparison to multi-spectral data, it presents a favorable option for smallholder farm settings.

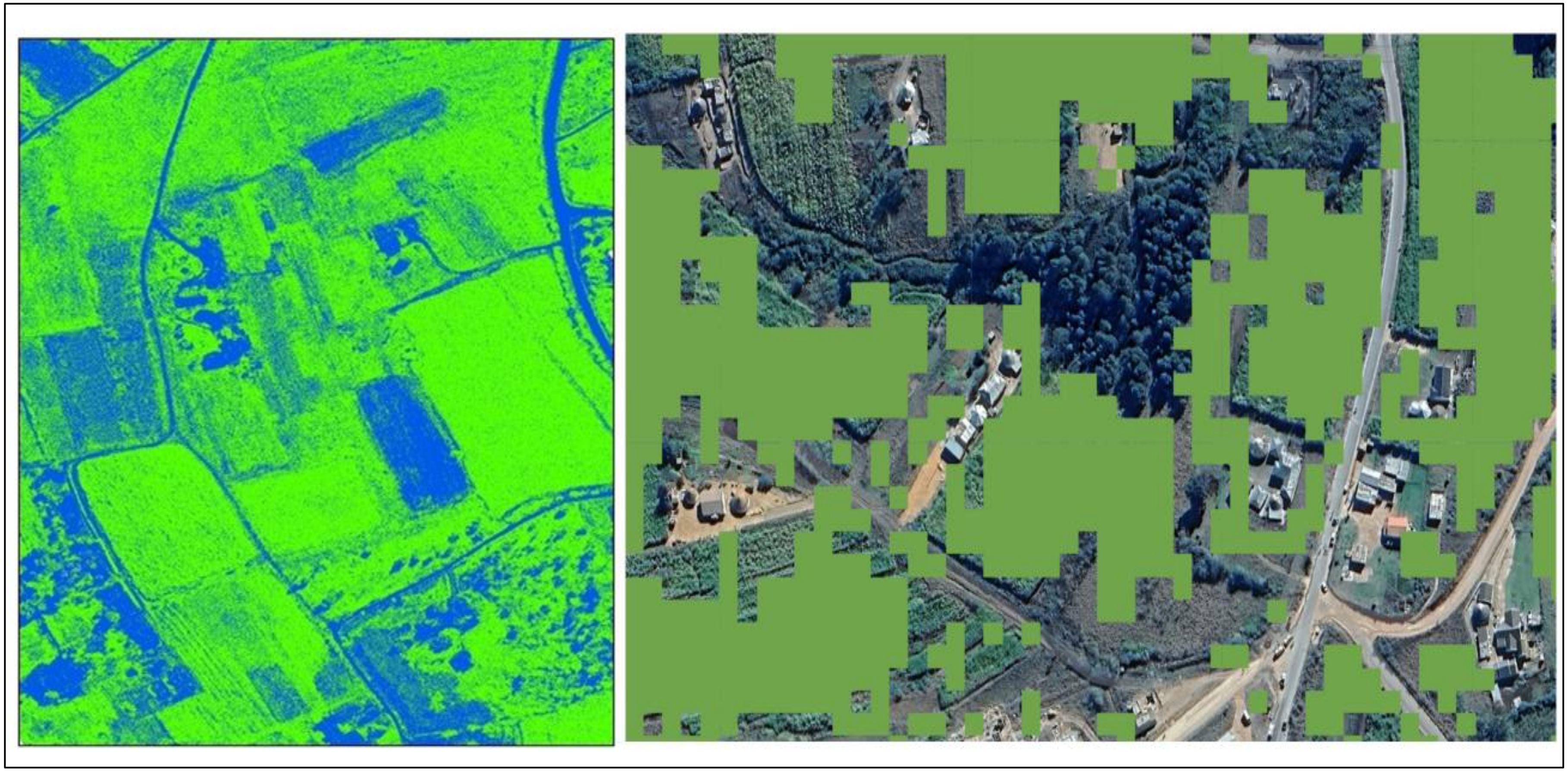


**Figure 3.8 A crop mask produced using UAV-RGB image (right) and Copernicus Sentinel 2 satellite image (left)**

Additionally, the result of this study reflects those of a study by Jonsson (2018) which demonstrated the capabilities of UAV-RGB imagery and machine learning techniques for the general classification of agricultural lands on a large scale. The study utilized the OA metric that achieved 88.00% for RGB and 86.10 % for multi-spectral employing varying spatial resolutions. The minimal 2.1 % difference between the OA values mirrors the marginal 2% difference in accuracy metric values observed within the present study with UAV-RGB performing slightly lower. The consistent findings across both studies suggest that utilizing UAV-RGB imagery in combination with the appropriate machine learning classifier can provide a comparable accuracy to its costlier and complex multi-spectral counterparts. Ultimately, this reinforces the viability of this low-cost approach in classifying croplands at local scales.

The comparison of OOB error value estimates achieved by the model utilizing UAV multi-spectral and RGB data indicated a minimal 3 % variation with RGB data obtaining a marginally higher result of 0.29 compared to 0.25 achieved by utilizing the multi-spectral dataset. The results imply that both models have a prediction error rate of 29 % and 25 % on the data points which are not included in the process of training specific decision trees within the RF model. The misclassification could be owing to insufficient training data which can be seen as a limitation to model performance. In a study by Belgiu and Dragut (2016) it was noted that insufficient information provided to the model to learn the underlying patterns of the land cover classes can adversely affect the OOB error rate, decreasing its reliability. Similarly, the study by Breiman (2001) explained that the OOB error estimate which is an unbiased estimate of the test set error has great variability and unreliability in the instance where the training sample size is limited.

While the accuracy metrics typically reflect the classifier's performance based on the training and validation data, ultimately, ground truthing of the final classified maps is essential for assessing its true accuracy and, therefore, indispensable in ensuring the credibility of the results obtained. The reliability and validity of machine learning models may be impacted by a lack of in-situ data (Sharma *et al*., 2017). Overfitting to the training data may occur as a result of inadequate representation of the real-world agriculture conditions undermining the model's capacity for generalization on unseen data (Ali *et al*., 2022).

Furthermore, remote sensing technologies which are commonly used for cropland mapping require sufficient amounts of reliable in-situ data for calibration and validation (Kalisperakis *et al*., 2015). Without this, the insights derived from these models may be flawed thereby leading to erroneous interpretations and misguided agricultural interventions (Sanches *et al*., 2020). In light of this, future studies should focus on enhancing the quantity and quality of in-situ data available for machine learning model testing and validation. This could be carried out through utilising synthetic data generation to augment existing datasets as well as collaborative efforts between local stakeholders, practitioners and researchers can facilitate the of more comprehensive and equitable in-situ data which could better equip machine learning models to address the complexities associated with agricultural systems (Klemmer, 2020; Wang *et al*., 2021).

Building on this, it is also essential to consider the difference in data distribution when comparing the two classification approaches. While the training data of non-binary classification comprises a large dataset with multiple classes, the training points per class are relatively lower. Subsequently, there are fewer training points for the cropland class which may have contributed to the poor performance for this particular class in comparison to the binary classification. The latter classification approach aggregates the data into two broader classes, namely agriculture and others with a more concentrated dataset for each category. As a result, this approach was able to classify agricultural land more accurately. The disparity in results not only underscores the importance of data distribution across classes, but it also highlights the trade-off between model complexity and accuracy. These findings suggest that while non-binary classification offers a more accurate classification of cropland, it may require a substantially larger dataset across all classes to achieve a reliable classification of agricultural land. Given these findings, future studies should ensure an adequate amount of data is utilized for model training and development regardless of the classification approach implemented. Hence, adequate data may result in more accurate results, enhancing the precision of the classification predictions which is essential to PA, particularly in instances of limited resources where precision is of paramount importance.

Along with ensuring sufficient data, effective hyperparameter tuning of the selected classifier is another factor to consider when achieving accurate results. If hyperparameters, such as maximum depth of trees, number of features at each split, and minimum samples per leaf, are not fine-tuned, the RF model may not effectively capture the complexity of the relationships within the land cover data, hence, negatively impacting the OOB error estimate (Probst, 2019). While this process was not incorporated into the model development for binary and non-binary classification approaches, both could have improved their reliability and accuracy through hyperparameter tuning. Hence, future studies should consider fine-tuning hyperparameters which could potentially enhance the accuracy of the classification outcomes.

Several other studies have utilized UAV-RGB imagery for various PA tasks, benefiting from its ultra-high spatial resolution and timely data collection, despite its limited spectral resolution. However, in this study, spectral information from the RGB bands of an onboard multi-spectral sensor was used to produce UAV-RGB imagery instead of a distinct RGB camera. This could also have negative implications on the spatial resolution compared to using a dedicated RGB camera as multi-spectral sensors generally have lower spatial resolution. For example, Herzig *et al*. (2021) conducted a comparison between the performance of RGB and multi-spectral cameras mounted on UAVs for high-throughput phenotyping and yield prediction in barley breeding. The outcome of this study indicated that the UAV-RGB imagery obtained from a DJI Phantom equipped with a X4S default camera provided higher spatial resolution and precision in estimating canopy height and vegetation cover than compared to the multi-spectral imagery obtained from a DJI Matrice 600 Pro. Therefore, future studies should consider using a dedicated RGB sensor for accurate comparisons between these types of sensors.

In addition, the findings of the study conducted by Herzig *et al*. (2021) support the recommendation to employ a dedicated onboard RGB camera for proper comparisons between UAV-RGB and multi-spectral sensors. Moreover, the study by Markham and Townshed (1981) noted that finer spatial resolution increases the spectral-radiometric variation of land cover types which influences classification accuracy. Therefore, a reduced spatial resolution of the UAV-RGB imagery produced from the red, green and blue bands of the multi-spectral sensor could ultimately reduce the classification accuracy.

Additionally, the classification technique employed within this study is a traditional pixel-based approach. A study conducted by Zhang *et al*. (2016) recommended utilizing this technique with RGB imagery in the instance that users lack experience in image processing. Conclusively, this recommendation fits the aim of this study, which is to develop practical and cost-effective approaches to implement PA in resource-scarce smallholder farms. However, the varying degrees of misclassification amongst the two classification approaches in the present study indicate room for improvement in classifier performance. The study conducted by Mollick *et al*. (2022) showcased the superior performance of the object-based image analysis (OBIA) technique for the classification of agricultural regions when compared to the traditional approaches. Hence, it is recommended that future studies should explore the use of this technique to assist with improving classifier performance.

Contrary to the implementation of machine learning for classification purposes, deep learning (DL) approaches present opportunities for enhanced accuracy (Pandey and Jain, 2022; Gokool *et al*., 2024). For instance, a study conducted by Yang *et al*. (2022) showcased the robust performance of DL, which was utilized to classify the lodging extent of maize with UAV-RGB classifying non-lodging and achieved over 90 % accuracy. The study further identifies that while the classification utilizing multi-spectral imagery achieved the most accurate results, the use of low-cost UAV-RGB imagery provided comparable accuracies, therefore, it presents itself as an approach to which smallholder farms can leverage to detect crop lodging (Yang *et al*., 2022). While it's recommended to explore the potential of this approach for classification purposes, it is further important to note that DL approaches are complex and computationally intensive (Thompson *et al*., 2020; Hu *et al*., 2021). Hence, it is essential to explore the trade-offs between model complexity and performance to ensure optimal results are achieved in future studies.

In addition, the cloud computing platform, GEE that was utilized to carry out the objective of this study, is an open-source service which does not require data to be downloaded and managed locally (Amani *et al*.,2020). All operations are handled by Google's central processing unit (CPUs) and graphics processing unit (GPUs), hence, it makes a great tool for processing and analyzing with large geographical and temporal scales (Gorelick *et al*., 2017; Ravanelli *et al*., 2018). It further possesses capabilities for remote sensing data to be shared automated or semi-automatedly and for processing, as well as for analysis procedures to be developed either by experts or non-experts. This platform features a powerful web-based application programming interface (API) enabling users to easily access archived remote sensing data through the use of Javascript and Python (Loukili *et al*., 2022). Collectively these fosters improved access, reduced cost and enhanced efficiency when executing tasks. Some of the familiar constraints experienced when leveraging the GEE platform are that image analysis is restricted to the tools availed within this platform. Additionally, there is a limited selection of ML classifiers as well as computational restrictions which prohibit complex machine learning algorithms with excessively large data sets and lengthy training periods to be run within the platform (Amani *et al*., 2020). Nevertheless, these are minor limitations in comparison to the freely available processing power and rapid dissemination of comprehendible results that can easily be made available to various users (Zhao *et al*., 2024).

Beyond the above-mentioned points, this study utilized a single UAV image to classify croplands which demonstrated that UAV-RGB data produced a reliable classification accuracy compared to that of UAV multi-spectral data. While this study has achieved satisfactory results, it remains limited to this specific context. The performance of UAV-RGB data for cropland mapping may differ across various spatial, temporal and geographical contexts. Therefore, it is recommended that future studies should expand this methodology by utilizing multiple images, possibly across different time periods, seasonal conditions, growth stages and management practices. Additionally, this approach should be applied across differing geographical regions with varying agricultural contexts to acquire comprehensive insight into its broader applicability and effectiveness. Collectively this will serve not only as validation for these findings but also prompt further investigation into the consistent performance of UAV-RGB data in varying scenarios ensuring its reliability to produce reputable results which can be leveraged to facilitate PA practices.

### 3.6 Conclusion

Smallholder farmers are vital contributors to food security in SSA by producing a significant portion of the food supply within this region, often through implementing traditional farming practices. However, they encounter various challenges that limit their capacity to maintain food security, especially in the light of climate change and rapid population expansion and its associated impacts to the agriculture sector. Subsequently, within the different remote sensing tools, UAVs serve as a valuable tool to facilitate PA by leveraging cutting-edge capabilities to overcome the limitations of conventional farming practices and enabling more precise, data-driven, and bespoke management practices. Accurate cropland maps are essential for targeted interventions that can enhance recourse efficiency, agricultural productivity and sustainability. This is particularly beneficial for smallholder farms which require tailored approaches which can minimize resource wastage and reduce costs associated with the over-application of essential input resources. Additionally, accurately classifying croplands can enable timely and tailored interventions, which can have a far more-reaching impact on crop resilience, resource management and yield potential.

As such, the outcome of this study proposed the use of UAV-RGB imagery as a cost-effective option as compared to other sensors for cropland mapping of smallholder farmlands, facilitated by leveraging the GEE platform and machine learning algorithms. RGB imagery has emerged as a promising alternative to utilizing multi-spectral imagery, particularly in scenarios where multi-spectral data is inaccessible or economically unfeasible. This is especially crucial for stakeholders who may encounter challenges in utilizing multi-spectral data as well as allocating resources for its acquisition. While UAV multi-spectral imagery remains a more accurate approach for cropland classification, the comparable results of UAV-RGB imagery along with the appropriate machine learning classifier hold great potential for the classification of croplands within a smallholder farm setting. However, it is important to note that the use of UAV-RGB data for cropland mapping is not without its limitations. For instance, the limited number of spectral bands associated with an RGB sensor may not be as effective as a multi-spectral sensor when distinguishing between numerous classes with similar spectral signatures. Hence, further research is required to overcome this limitation, enabling UAV-RGB data to accurately classify multiclass within smallholder farm settings in the absence of a multi-spectral sensor.

Lastly, despite the limitations of this study, it is evident that this approach offers a reliable alternative to multi-spectral imagery in the instance that resources are inaccessible or economically unfeasible. Furthermore, this study has underscored the potential of utilizing a lower-cost sensor with restricted spectral resolution without significantly compromising the accuracy of the classified maps. Consequently, this cost-effective approach can be adopted in data-scarce and resource-poor SSA regions to guide and inform PA applications, particularly within smallholder farms, potentially optimizing resource use and significantly enhancing agricultural production.

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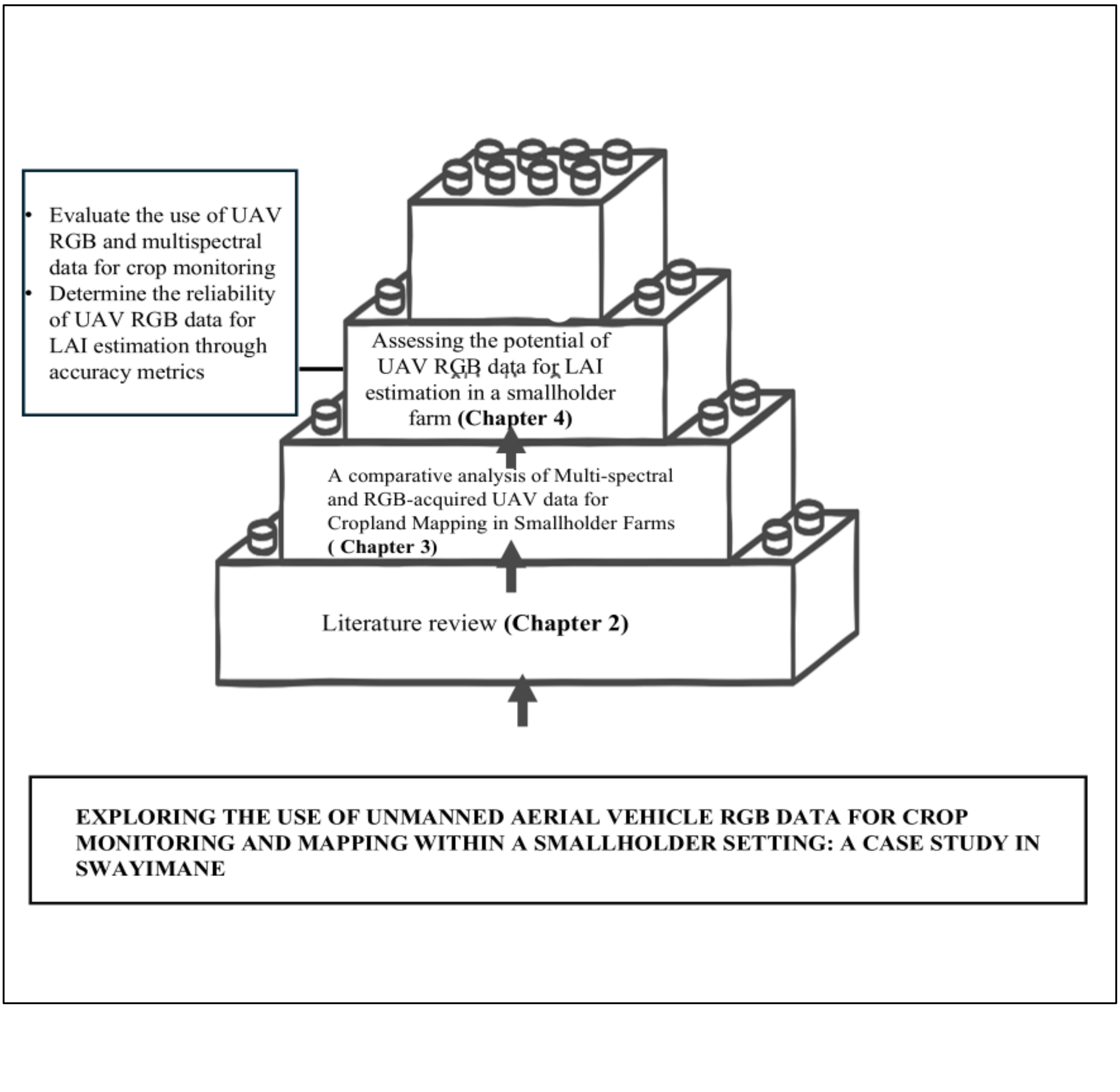
**Lead into Chapter 4**: Following the successful application of UAV-RGB data for cropland classification and mapping in smallholder farms, Chapter 4 extends this investigation to another common and critical PA task being crop monitoring. This chapter addresses the second objective, examining the use of UAV-RGB data for crop monitoring within a smallholder farm setting. This study employs UAV-RGB data and multi-spectral data to estimate LAI which is an extensively utilized indicator of crop growth, development and productivity. This chapter aims to further validate the use of UAV-RGB data as a low-cost reliable alternative through evaluating its performance relative to multi-spectral data for LAI estimation.



# CHAPTER 4: ASSESSING THE POTENTIAL OF UAV-RGB DATA FOR LAI ESTIMATION IN A SMALLHOLDER FARM SETTING (PAPER 2)

## 4.1 Abstract

Smallholder farms are of paramount significance in bolstering food security, particularly in developing nations where they form an integral part of the agricultural production systems. Hence, it is crucial for them to produce quality crops in sufficient quantities. Through the advancements in precision agriculture (PA), the use of unmanned aerial vehicles (UAVs) has become a popular agricultural management tool, offering high spatial resolution and near real-time data required for monitoring crop dynamics at farm scale. Considering this, the study proposed a low-cost method utilizing UAV Red-Green-Blue (RGB) spectral bands and vegetation indices (VI) compared to UAV multi-spectral spectral bands and VI's for estimating leaf area index (LAI) which is often used to monitor crop growth and development. UAV data in combination with machine learning-based approaches was utilized to estimate LAI as these approaches are known to bolster the power of attaining relevant insight from complex and voluminous UAV-based remote sensing data. To evaluate the reliability and accuracy of utilizing this approach, UAV-derived LAI estimates were compared against ground-based LAI measurements that were obtained from a sugarcane field in Swayimane, KwaZulu-Natal, South Africa. The results indicated that the use of UAV multi-spectral data produced the most accurate LAI estimates with root mean square error (RMSE), mean absolute error (MAE) and R-squared ($R^2$) values of 0.36, 0.24 and 0.81 respectively. While the use of UAV-RGB data provided less accurate LAI estimates (RMSE = 0.45, MAE = 0.31 and $R^2$ = 0.73), it still offered reliable results for estimating LAI. This cost-effective yet reliable approach prompts wider adoption of advanced remote sensing techniques in resource-constrained data-scarce farming regions, permitting tailored and informed agricultural interventions that prompt improved resource efficiency and enhanced agricultural output, particularly for smallholder farmers.

***Keywords:*** *Precision agriculture; Crop monitoring; Drones; Remote sensing; Machine learning*

## 4.2 Introduction

The rural economy of the Sub-Saharan Africa (SSA) regions is noted to be deeply rooted in agriculture (Livingston *et al*., 2011). A substantial component of these agricultural production systems comprises of smallholder farms representing 80 % of all farms in SSA, with an estimated production contribution of 90 % in some SSA countries (Wiggins, 2009). Unprecedented pollution expansion amongst developing nations consequently leads to the growing demand for food supply among other resources such as but not limited to land, water, herbicides and pesticides (Grzelak and Sapa., 2018). Combined with the consequences of climate change, this has exacerbated the pressure on the current food systems thereby threatening food security in SSA (Livingston *et al*., 2021). However, smallholder farms with limited resources and a heavy reliance on conventional farming techniques continue to struggle to satisfy these food demands.

Additionally, the great dependency of smallholder farmers on rainfed agriculture poses a significant threat to crop health, physical development and overall crop productivity when considering the impacts of climate change and the overall availability of our water resources (Brewer *et al*., 2022). Considering the contribution of smallholder farms to food security and thereby, in improving farmer's income, advancement of farmer's livelihoods, boosting economic growth, combating climate change and balancing biodiversity within SSA, it is imperative to establish economical, practical and effective solutions to ensure their optimal production of healthy crops (Nhamo *et al*., 2020). As such, current agricultural interventions require modern technology that would effectuate the monitoring of crop conditions and farming activities which can pave the way for more effective, informed and tailored management practices (De Ocampo and Montablo, 2024). Consequently, this has the potential to assist smallholder farms in observing the growth and development of their crops, allowing them to implement remedies when necessary, prompting optimal resource utilization, minimal wastage and enhanced crop production.

Several published research articles have identified a variety of crop growth and development indicators (Ni *et al*., 2017; Cuaran and Leon, 2021; Zhu *et al*., 2020) for example, crop height and biomass are identified to be the critical components in monitoring crop health and growth (Tumlisan, 2017; Nhamo *et al*., 2020). In other studies, soil quality and nitrogen levels have been utilized to monitor crop health and productivity (Spiertz, 2009; Sahu *et al*., 2020).

Amongst these variables, the majority of studies have utilized leaf area index (LAI) estimates to gain further insight into the health status, canopy composition and nutritional supply of crops (Li and Chen, 2011; Yonah *et al*., 2018; Hasan *et al*., 2019). LAI as defined by Du *et al*. (2022) refers to the total area of leaves per unit ground area which is a key parameter for canopy structure which directly relates to crop photosynthetic activity, respiration and evapotranspiration (Du *et al*., 2022). Additionally, LAI estimates have frequently been utilized to gain a comprehensive understanding of crop biomass characteristics (Dong *et al*., 2019). This was further reiterated in a study by Gitelson *et al*. (2014), noting that the total accumulation of LAI has a strong correlation to crop biomass and yield.

Additionally, there is a known strong association between LAI and plant physiological processes which in turn is directly related to the productivity of a crop (Buthelezi *et al*., 2023). The ability of LAI to reflect crop productivity, growth status, water stress and pest and disease identification has made it a valuable indicator of crop deficiencies which severely impact crop growth, development and yield (Teruel *et al*., 1997; Zhang *et al*., 2022; Barbouchi *et al*., 2016; Tewes *et al*., 2020; Liu *et al*., 2023) Subsequently, extensive research has been conducted on utilizing LAI to monitor crop growth and development which could be highly beneficial for smallholder farms, enabling informed decisions pertaining to agricultural management and resource allocation, optimizing crop productivity and quality, as well as ultimately combating food insecurity concerns (Wu *et al*., 2007; Goswami *et al*., 2015; Tunca *et al*., 2018; Ma *et al*., 2018; Perez *et al*., 2022; Buthelezi *et al*., 2023).

The conventional techniques for quantifying and estimating LAI are typically found to comprise of field surveys and point sample techniques which are generally associated with high accuracy (Tunca *et al*., 2018). However, these traditional methods are laborious, time-consuming and lack spatial representation (Nie *et al*., 2016 Martinez-Guanter *et al*., 2019). Contrastingly, remote sensing technology has become a vital tool within the agricultural research domain, as it offers timeous, non-destructive methods of monitoring and estimating various crop productivity parameters over large and small scales (Hasan *et al*., 2019). For example, satellite sensors have played a key role in estimating LAI in agricultural fields by capturing reflected and emitted radiation from the Earth's surface, providing valuable data for monitoring crop dynamics (Doraiswamy, 2004; Wittamperuma *et al*. 2012).

While remote sensing data obtained through satellites and manned aerial vehicle platforms have proven to be useful, they are also possessed by limitations such as high operational costs, inadequate spatiotemporal resolution and reduced reliability in adverse weather conditions (Swain *et al*., 2012; Hunt *et al*., 2014; Hussain *et al*., 2020). Additionally, the inadequate spatial and temporal resolution of freely available imagery from commonly utilized satellite sensors such as Landsat and Sentinel 2 has constrained their effectiveness at capturing crop dynamics within smallholder heterogeneous fields (Hilker *et al*., 2009; Yang *et al*., 2015; Nguyen *et al*., 2020). Furthermore, the associated cost of utilizing high-resolution satellite imagery may be prohibitive for financially constrained smallholder farms. As such, during the last decade, unmanned aerial vehicle (UAV) technology within the remote sensing sphere has represented a true paradigm shift, overcoming the deficiencies of conventional remote sensing platforms, particularly for PA practices (Salami *et al*., 2014; Yao *et al*., 2017; Simic Milas *et al*., 2018). This is owing to the maximum flexibility of UAVs which can be operated at user-defined intervals as well as acquiring high spatial resolution data through low flight altitude (Calderón *et al*., 2013; von Bueren *et al*., 2014; Lu and He, 2017). These spatiotemporal characteristics coupled with their relatively low costs, represent a potentially well-suited approach for smallholder farm applications (Cobo *et al*.,2010; Zhang and Kovacs, 2012).

Numerous studies have showcased the potential of very high-resolution (VHR) UAV imagery for monitoring crop growth and development (Schirrmann *et al*., 2016; Tumlisan, 2017; Heidarian Dehkordi *et al*., 2020; Nhamo *et al*., 2020). These included. hyperspectral and multispectral sensors onboard UAV platforms that have been extensively utilized for crop monitoring applications. For instance, Cheng *et al*. (2022), employed UAV multispectral imagery acquired using a RedEdge-MX sensor mounted on a DJI M210 UAV. This sensor captured data across five spectral bands—blue (475 nm), green (560 nm), red (668 nm), red edge (717 nm), and near-infrared (840 nm). The acquired imagery was utilized to accurately estimate LAI in maize crops under varying water and fertilizer stress conditions, highlighting the efficacy of UAV-based multispectral sensing for precision crop monitoring.Additionally, Poudyal *et al*. (2023) utilized a UAV DJI Matrice 600 Pro and a Pika-L 2.4 hyperspectral imaging sensor (450 to 1100 nm) to obtain hyperspectral imagery to predict morpho-physiological traits in sugarcane and used machine learning algorithms that resulted in estimated LAI producing a prediction accuracy of 81%. However, the exorbitant cost and complex processing of these sophisticated sensors coupled with the size and weight limitation of sensors attached to UAVs have limited their implementation for agricultural observation, particularly in resource-scarce developing nations and for smallholder farms.

Consequently, UAVs equipped with consumer-grade Red-Green-Blue (RGB) sensors have been gaining popularity for various PA applications and especially given the low costs associated with these sensors (Hassan *et al*., 2019; Du *et al*., 2022). UAV-RGB provides high-resolution imagery at a low cost compared to the aforementioned sensors and can be utilized to discern agronomic and crop conditions, aid in appropriate management practices and improve yields within smallholder farms (Yonah *et al*., 2018). Research studies have also demonstrated the potential of UAV-RGB image data in predicting LAI, for example, the study by Gao *et al*. (2016) showed that winter wheat LAI was accurately estimated using UAV-acquired RGB imagery with R-squared ($R^2$) = 0.71, root mean square error (RMSE) = 0.80, and $p < 0.01$.

Concurrently with the recent advancements in UAVs and computer processing capacity, machine learning has bolstered the power of attaining pertinent agricultural information from UAV-based remote sensing data (Due *et al*., 2022). This is a result of the unprecedented advantage in non-linear and complex data filling and recognition as well as the modelling of these non-linearity and heteroscedasticity relationships between crop growth parameters such as LAI and the large amount of data which is contained in UAV-based images (Du *et al*., 2022; Illniyaz *et al*., 2022). Resultantly, the synergy between UAV and machine learning has been classified as an effective approach for crop growth and development monitoring (Du *et al*., 2022).

This improvement in the data mining ability particularly with sensors that have limited spectral bands provides an effective way to enhance the prediction of LAI (Illinyaz *et al*., 2022). A study conducted by Yu (2023) demonstrated the effectiveness of combining UAV-RGB data with machine learning models which resulted in significant improvements in the accuracy of LAI estimation. In another study, linear regression (LR) backpropagation neural network (BPNN) and random forest (RF) models were compared for LAI estimation which displayed the robust performance of the RF model ($R^2$ = 0.71-0.88, RMSE = 0.12-0.25) in estimating maize LAI (Du *et al*., 2022). Further demonstration of the robust performance capabilities of machine learning approaches by the RF model was also demonstrated for estimating LAI among other variables for monitoring rice growth by Qiu *et al*. (2021).

While UAV-RGB data is becoming more frequently utilized for crop monitoring, limited studies have actually explored their application within a smallholder farm context, particularly in SSA. In addition, the comparative accuracy of spectrally limited, low-cost UAV-RGB data versus the costlier and complex multi-spectral data remains underexamined at local scales. This signifies a gap within the research arena, as smallholder farms, which often operate under financially constrained and resource-poor circumstances, could benefit from leveraging these relatively low-cost technologies to obtain reliable data for crop monitoring and in improving their crop yields.

As such, this study intends to fill this gap by comparing the predictive accuracy of UAV-RGB and multi-spectral data in estimating LAI in a sugarcane field within a smallholder farm, in an attempt to evaluate the potential of UAV-RGB data to serve as a reliable low-cost alternative for local scales. These datasets comprise of their respective spectral bands and VI's and will hereafter be referred to as UAV RGB data and UAV multispectral data, respectively.While there are three commonly utilized sensors (namely, hyperspectral, multi-spectral and RGB sensors) onboard UAVs, this study focuses specifically on multi-spectral and RGB, as multi-spectral sensors strike a balance between cost and spectral detail rendering them more accessible than hyperspectral whereas, RGB sensors exemplify a low-cost alternative with reduced spectral bands. As such, through this comparison, it will be determined if UAV-RGB data can be adopted as a reliable cost-effective alternative to predict LAI which then can be utilized as an indicator of crop growth, potentially fostering precise, data-driven agricultural management and development. Subsequently, these findings are crucial for facilitating PA within resource-constrained smallholder farms to enhance their crop productivity and optimize their resource use. By optimizing crop productivity through the adoption of accessible and reliable PA technologies, this study has broader implications for improving the livelihood and economic status of smallholder farms as well as in enhancing food security.

## 4.3 Materials and Methods

### *4.3.1 Study site*

This study was conducted in a sugarcane field which was 7500 $m^2$ in the community of Swayimane, which is located approximately 55 km northeast of Pietermaritzburg, within the province of Kwa-Zulu-Natal, in South Africa (Figure 4.1). This is a densely populated area and lies within the uMshwathi local municipality. Swayimane is situated in the moist midlands mist belt, with average temperatures ranging between 11.80 °C to 24.00 °C (Dlamini, 2024). The seasonal climatic conditions within this area are mainly dry winters and hot, humid summers with an annual precipitation varying from 600–1200 mm (Brewer *et al*., 2022).

An estimated 9329 households in Swayimane are engaged in agricultural farming which has also been recognized as their primary economic activity (Basdew *et al*., 2017). For sustenance, a large portion of the Swayimane community relies on subsistence agricultural production, underscoring the major role it plays within this community (Archer *et al*., 2010). Amongst the smallholder farms in the community, the farming systems are mainly dominated by crop production, with maize, beans, amadumbe (taro), sweet potatoes and sugarcane being the commonly grown crops (Kruger *et al*., 2018).

Despite the moderate to high rainfall and deep soils which characterizes this area, there is also a deficiency in minerals which are essential for the sustainability of crop production (Gokool *et al*., 2024). Further compounding this situation is the adverse effects of extreme weather events. It was evidenced in a study conducted by Brewer *et al*. (2022), that the occurrence of hailstorms had damaged the crop in the adjacent field from the delineated area in Figure 4.1. The projected increase in these extreme weather events poses a further threat to food security and the livelihoods of the Swayimane community and its surrounding areas. Overall, the community's socioeconomic traits, together with the region's biophysical features, present an ideal opportunity to showcase how UAVs can serve as an economical and practical approach for crop monitoring and mapping within smallholder farms.

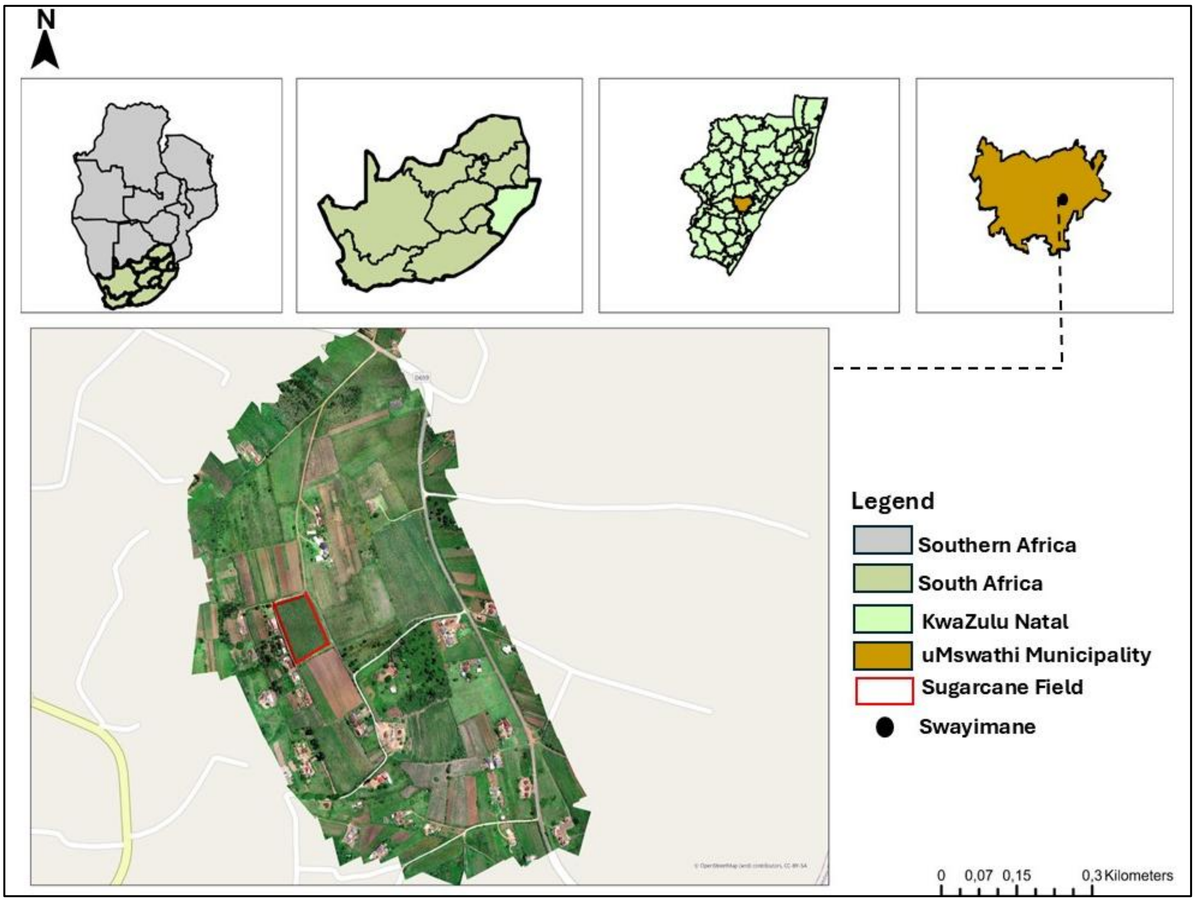



**Figure 4.1 Study site map of Swayimane, located within the uMshwathi municipality in KwaZulu-Natal province, South Africa**

### *4.3.2 Data collection and processing*

Within Google Earth Pro, the selected sugarcane field as depicted in Figure 4.1 was digitized to produce polygons outlining the boundaries of the study site, spanning approximately 7500 $m^2$. Thereafter, the digitized polygon was uploaded into ArcGIS Pro (version 3.3.0) software to identify sampling points within the field. A grid-based sampling approach was utilized, with sampling points established at a 10 m distance between rows and a 16 m difference between each of the sampling points (Figure 4.2). The coordinates of 36 sampling points were then uploaded to a handheld global positioning unit (GPS) unit with a 3.16 m planimetric accuracy (Fator and Zomrawi, 2015), which was then used to navigate to the predetermined points within the fields. Each sampling point was numerically tagged for easier identification during the collection of LAI measurements, which were conducted over a significant portion of the grand growth phase of the crop cycle, with an average crop height of 2.43 m during this period.

The plant canopy analyzer (LiCOR 2200C) was employed to quantify the LAI in the field (APPENDIX C). This sophisticated device is fitted with a fisheye optical sensor which consists of five concentric rings centered at 7º, 22º,38º, 52º and 68º zenith angles which measure radiation both above and below the canopy. For this study, the procedure for obtaining LAI measurements involved capturing four measurements below the crop, one above the crop, another measurement above the crop, and finally four below the crop. Thereafter, an LAI estimate was recorded for each sampling point within the field. Concurrently, UAV images were captured between 10:00 and 12:00 am UTC over the study site for the data collection period. A Keyhole Markup Language file (kml) comprising of the digitized boundary of the study site was imported to the UAV smart controller. Through this kml file, an optimal flight path was designed to ensure images of the entire study site were captured.

The UAV platform employed to capture the aerial images of the study site was the DJI Matrice 300 (M-300), fitted with a MicaSense Altum multi-spectral camera and a Downwelling Light sensor (DLS-2) (Figure 4.2). Among the unique features of the UAV platform are its 15 km transmission range, 7000 m maximum flying height, flight route planning, and obstacle avoidance. In contrast to other UAVs on the market, the M-300 boasts unique features including an optimal flying endurance of 55 minutes and a maximum flight speed of 27 m/s. Due to its four rotating wings and vertical landing and take-off (VTOL) capability, the UAV (M-300) is a great choice for performing flights in rural areas. The high-resolution multi-spectral and thermal imaging sensor utilized in this study comprised of five narrow bands (blue, green, red, red-edge and near-infrared) and a radiometric longwave infrared thermal imaging sensor. The multi-spectral bands of the MicaSense Altum sensor offer a resolution of 2064 x 1544 (3.2 megapixels per band) at a 120 m height and a 5.2 cm per pixel ground sampling distance (GSD), at a height of 120 m. The sensor resolution of the thermal infrared camera is 160 × 120 and a GSD of 81 cm per pixel at 120 m. For the purpose of this study, the DJI M-300 was configured to fly at an altitude of 100 m, considering the battery life of the platform while also covering the total area of the study site.

Prior to and following each flight mission, the MicaSense Altum calibrated reflectance panel (CRP) (Figure 4.2) was utilized to calibrate the sensor to account for variations in light intensity throughout the day. Before conducting additional investigations, the obtained UAV images were pre-processed using the Pix4D fields software (version 1.8). The atmospheric and radiometric corrections of the UAV photos were carried out in Pix4D fields, and these images were then mosaicked to produce a single georeferenced orthomosaic. A GeoTIFF file format was selected to save the orthomosaic since it is the required format for images to be uploaded onto the Google Earth Engine (GEE) cloud computing platform for further processing and analysis. This cloud computing platform offers an open-source, high-performing computing power for geospatial analysis (Gorelick *et al*., 2017, Zhao *et al*., 2021). Additionally, users have easy access to built-in algorithms and the programming interface which can be utilized to create, customize and run algorithms automatically for data manipulation and analysis (Gokool *et al*., 2022). GEE also allows users to ingest and process their data utilizing the various features availed within this platform (Gokool *et al*., 2022).

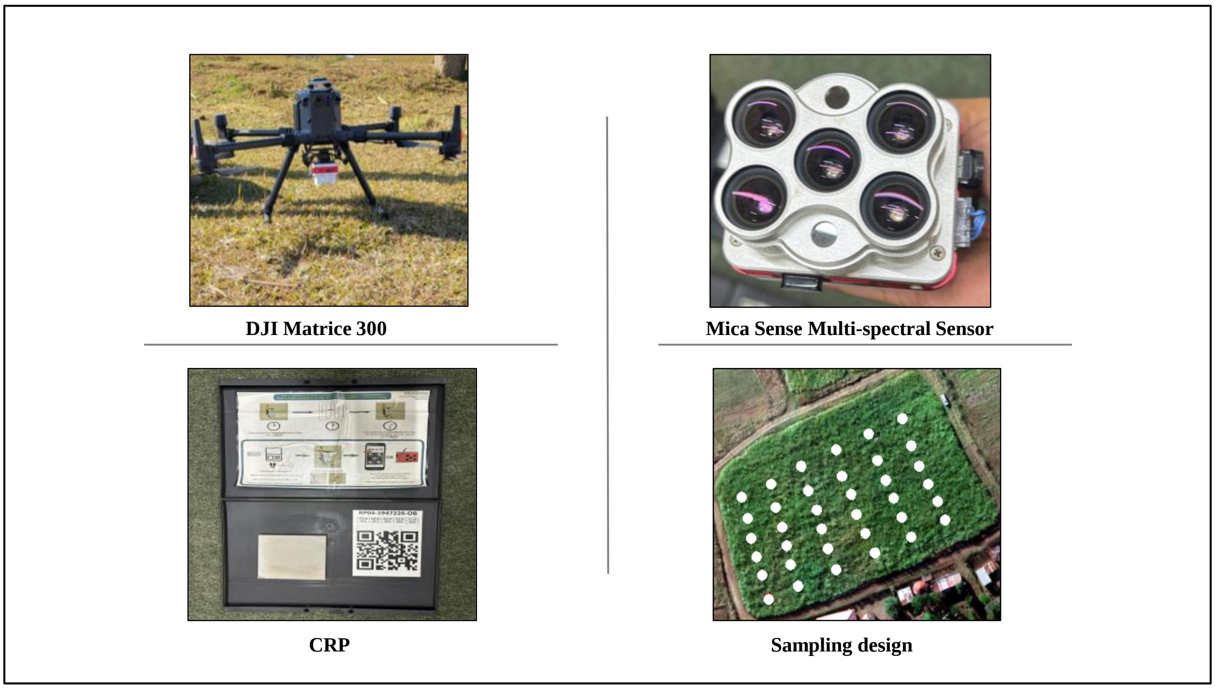



**Figure 4.2 The DJI Matrice (Top left) and MicaSense Altum multi-spectral camera (Top right, CRP (Bottom left) and sampling design for data collection (Bottom right)**

For this study, an image collection was created to store and manage the UAV images that were uploaded to the GEE platform. This image collection contained a series of multi-spectral images that were captured over the study period (2023-2024). The RGB images utilized in the study were derived from the red, green and blue bands of the multi-spectral sensor. The various multi-spectral and RGB vegetation indices (VIs) (Table 4.1) were calculated for 36 points for each of the selected images within the collection, totaling 360 points used for model training and development. Subsequently, the mean values for the indices along with the band values for each geographic coordinate point, date and point identifier were then exported as a comma-separated value (CSV) file for further analysis.

**Table 4.1 Multi-spectral and RGB-derived VIs**

| Vegetation Index | Equation | Reference |
|---|---|---|
| **Multi-spectral VI** | | |
| Normalized Difference Vegetation Index | (NIR - Red) / (NIR + Red) | Xue and Su, 2017 |
| Green Normalized Difference Vegetation Index | (NIR - Green) / (NIR + Green) | Moges *et al*., 2005 |
| Normalized Difference Vegetation Index Red-Edge Index | (NIR - $Red_{edge}$) / (NIR + $Red_{edge}$) | Dalla Marta *et al*., 2015 |
| Enhanced Vegetation Index | 2.5× (NIR - Red) / ((NIR + 6 × Red7.5 × Blue) +1) | Roy *et al*., 2023 |
| Soil Adjusted Vegetation Index | ((NIR - $Red_{edge}$) / (NIR + $Red_{edge}$+1)) × (1+0.5) | Xue and Su, 2017 |
| Shortwave Near Infrared | NIR / Red | Amarsaikhan *et al*., 2023 |
| Simple Blue and Red-Edge Ratio | (($Red_{edge}$ + Red + 0.5) / Blue) × 1.5 | Gokool *et al*., 2024 |
| Simple NIR and Red-Edge Ratio | NIR/$Red_{edge}$ | Gokool *et al*., 2024 |
| Green Chlorophyll Index | (NIR/Green) – 1 | Gitelson *et al*., 2003 |
| RGB VI | | |

| | | |
|---|---|---|
| Modified Green Red Vegetation Index | ($Green^2$ - $Red^2$) / ($Green^2$ + $Red^2$) | Bendig *et al*., 2015 |
| Red-Green-Blue Vegetation Index | ($Green^2$ - Red × Blue) / ($Green^2$ + Red × Blue)) | Zhang *et al*., 2022 |
| Visible Atmospherically Resistant Index | (Green - Red)/ (Green+ Red - Blue) | Eng *et al*., 2019 |
| Triangular Greenness Index | Green (0.39 × Red) - (0.61 × Blue) | De Magalhães and Rossi, 2024 |

Upon acquiring the necessary UAV data within the GEE cloud computing platform, this data required further cleaning and processing before the development of machine learning models could be utilized to estimate LAI from multi-spectral and RGB-derived VIs. Thus, the R statistical software (version 4.4.0) was employed, and the data was inspected, with any irrelevant columns being removed which in the context of this study were the date column, sample point identifier and co-ordinate points columns, as well as the columns comprising of the mean band values which were not required for LAI estimation. Mean values were used to infill missing data for particular variables. Thereafter, the relationship between variables was examined through a correlation matrix, and the variance inflation factor (VIF) was used to assess the multicollinearity between the different predictor variables, thereby prompting the removal of strongly correlated variables from the training data set. Thereafter, add-in packages in R, namely classification and regression training (Caret) (Kuhn, 2008) and caretEnsemble (Mayer, 2013) packages were leveraged to build and evaluate the machine learning models. These selected packages integrate essential tools required to carry out simple and complex machine learning functions, thereby facilitating efficient model training and development (Gokool *et al*., 2022).

A range of widely adopted machine learning algorithms from the caret application such as generalized linear model (GLM), support vector machine with Radial Kernel (svmRadial), xtreme gradient boosting (xgbTree), ranger and k nearest neighbour (kNN) were selected for application in this study. These algorithms represented a combination of both simple and complex machine-learning approaches. Additionally, GLM (ensemble 1) and RF (ensemble 2) were utilized to develop two ensemble machine learning models (EMLM) by stacking the above-mentioned base algorithms and combining their predictions (Gokool *et al*., 2024). Given the sampling size, k-fold cross-validation with 10 folds and 10 repeats was chosen over the traditional approach of utilizing training and testing subsets for model training and evaluation. Ultimately, the model performance was assessed through frequently employed machine learning accuracy metrics such as RMSE, mean absolute error (MAE) and $R^2$ to evaluate the predictive accuracy and robustness (APPENDIX B). Figure 4.3 provides a conceptual overview of the methodology implemented in this study, illustrating sequential steps involved in data collection and processing. The subsequent discussion elaborates on these sequential steps by attempting to provide a comprehensive understanding of the methodology.

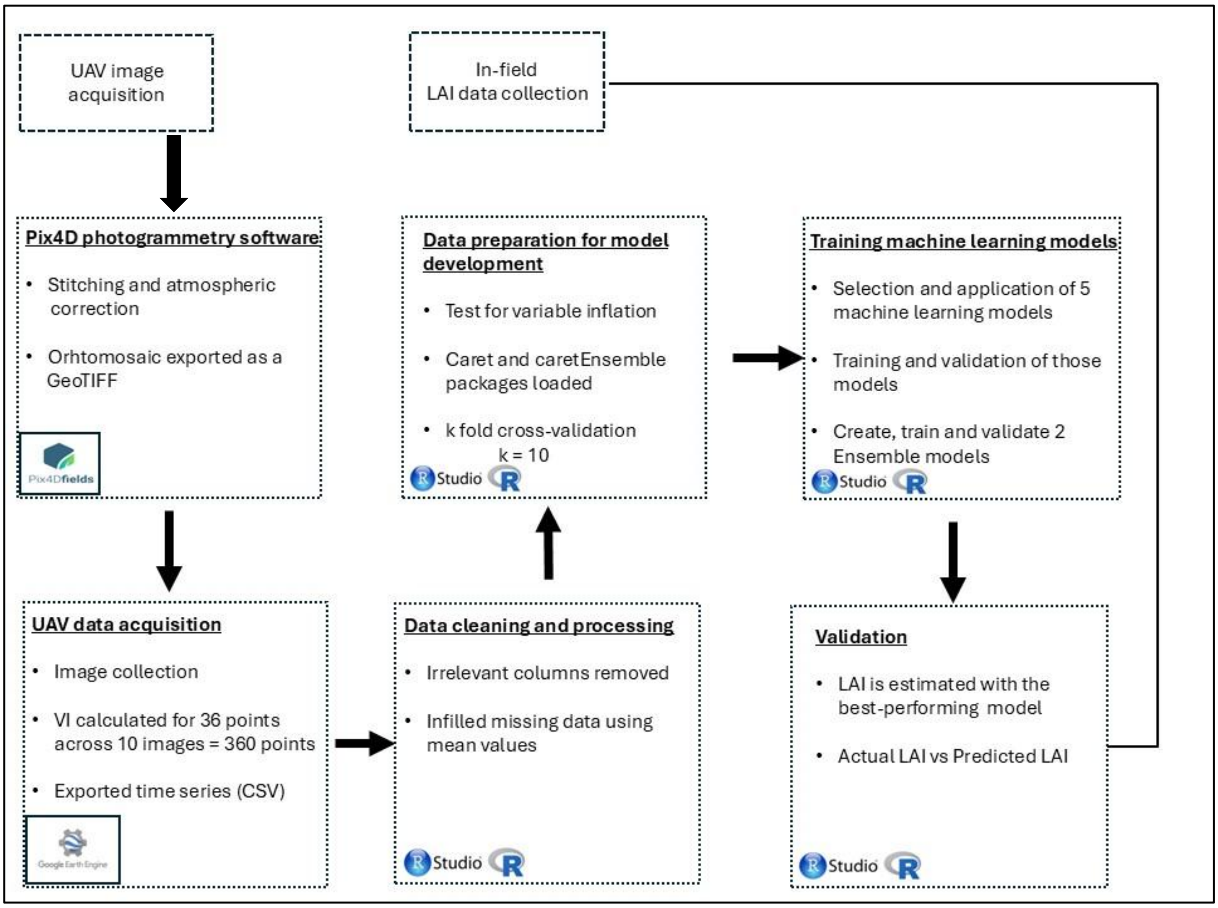



**Figure 4.3 A conceptual representation of the workflow utilised to produce the predictive models**

## 4.4 Results

### *4.4.1 Descriptive Statistics of Ground-based Measured LAI*

Insight into the descriptive statistics of ground-based measured LAI for the data collection period is provided in Table 4.2. In August, LAI values ranged from 2.95 to a maximum of 6.43 with a mean LAI value of 3.84. Contrastingly in February 2024, LAI values had gradually increased with a minimum value of 4.07 and a maximum of 6.78. The mean LAI was substantially higher at the end of the data collection period with a value of 4.97. Between these dates, there had been fluctuations in LAI values indicating periods of variability in crop growth. These fluctuations could stem from a range of factors including but not limited to seasonal transitions, growth stages and management practices (Roy and Chakravarty, 2002; Villa *et al*., 2017; Buthelezi *et al*., 2022). Additionally, potential device errors or management inaccuracies may have contributed to the notable variability in the obtained LAI values.

**Table 4.2 Statistics of sugarcane LAI throughout the data collection period**

| Date in the growth cycle | Min | Max | Med | Mean | Standard Deviation |
|---|---|---|---|---|---|
| | | | LAI | | |
| 2023-08-10 | 3.47 | 6.43 | 4.16 | 4.36 | 0.78 |
| 2023-08-16 | 2.95 | 5.29 | 3.56 | 3.62 | 0.60 |
| 2023-08-31 | 3.29 | 4.00 | 3.51 | 3.54 | 0.18 |
| 2023-09-14 | 3.00 | 3.97 | 3.20 | 3.29 | 0.27 |
| 2023-09-28 | 3.51 | 4.89 | 3.60 | 3.70 | 0.27 |
| 2023-10-11 | 3.23 | 3.86 | 3.72 | 3.08 | 0.15 |
| 2023-10-26 | 2.01 | 3.32 | 3.13 | 2.96 | 0.41 |
| 2023-11-22 | 3.71 | 4.04 | 4.00 | 4.10 | 0.86 |
| 2024-02-06 | 4.07 | 4.72 | 4.61 | 4.55 | 0.16 |
| 2024-02-21 | 5.06 | 6.78 | 5.37 | 5.40 | 0.32 |

### *4.4.2 Estimation of LAI*

The tabulated results present the accuracy metrics of the machine learning models and the ensemble models with the best-performing model indicated in bold within Table 4.3. The RF ensemble model achieved an RMSE of 0.36 and an $R^2$ value of 0.81 when UAV multi-spectral data was utilized to predict LAI. This indicated that the predicted values deviated from the actual values by 0.36 on average, underscoring the high accuracy of estimated LAI values. Additionally, a strong correlation between the actual and predicted LAI values is observed based on the 81% variation captured in the actual data by the model. Furthermore, the MAE of 0.24 reflects a minimal average prediction error. In comparison, the RGB dataset yielded a higher RMSE of 0.45 and MAE of 0.31 and a lower $R^2$ value of 0.74. This suggests the RF ensemble model employing UAV-RGB data for predicting LAI has a reduced accuracy in comparison to UAV multi-spectral data. Despite this, the model has provided reliable results for estimating LAI.

**Table 4.3 Accuracy metrics of the machine learning and EMLM in predicting LAI using UAV multi-spectral and RGB data**

| **Predictor Variable: LAI** | | | | | | |
|---|---|---|---|---|---|---|
| **Accuracy metrics of machine learning models** | | | | | | |
| | **UAV Multi-spectral Data** | | | **UAV-RGB Data** | | |
| | **RMSE** | **$R^2$** | **MAE** | **RMSE** | **$R^2$** | **MAE** |
| glm | 0.70 | 0.28 | 0.52 | 0.78 | 0.20 | 0.59 |
| knn | 0.62 | 0.44 | 0.41 | 0.74 | 0.27 | 0.56 |
| rpart | 0.66 | 0.35 | 0.46 | 0.79 | 0.18 | 0.59 |
| ranger | 0.60 | 0.48 | 0.41 | 0.70 | 0.33 | 0.53 |
| xgbTree | 0.62 | 0.44 | 0.44 | 0.74 | 0.26 | 0.56 |
| svmRadial | 0.60 | 0.48 | 0.41 | 0.73 | 0.31 | 0.52 |
| Ensemble 1 | 0.61 | 0.46 | 0.40 | 0.71 | 0.32 | 0.52 |
| **Ensemble 2** | **0.37** | **0.81** | **0.24** | **0.45** | **0.74** | **0.32** |

### *4.4.3 Ground-based measured LAI and Estimated LAI*

Figure 4.4 illustrates the comparison between the ground-based measured LAI, the UAV multi-spectral and the RGB-predicted LAI across various dates within the growing season of sugarcane. It is noted that in the earlier months of the data collection period, there was a reduced LAI which could have resulted from the cooler temperatures and reduced rainfall during the winter season. Thereafter, there is a gradual increase in LAI which is followed through until February. This observed increase may be attributed to the warmer temperatures, increased sunlight and precipitation associated with the spring and summer seasons (September – February).

Throughout the data collection period, the UAV-RGB and multi-spectral data captured the seasonal variability of LAI, with UAV multi-spectral predictions obtaining a closer alignment with actual LAI measurements. Despite the greater deviations of the UAV-RGB predictions in comparison to UAV multi-spectral LAI, it remained well aligned with the observed seasonal variation in ground-based LAI. While the overall trend showcased an increase in LAI values as the seasons transitioned, there are factors beyond seasonality such as but not limited to tillage practices, nutrient availability and as well as pest and disease infestation that may result in variations in LAI highlighting the complexity of factors that influence crop growth and development (Hashimoto *et al*., 2019; Alchemi and Jamin, 2022).

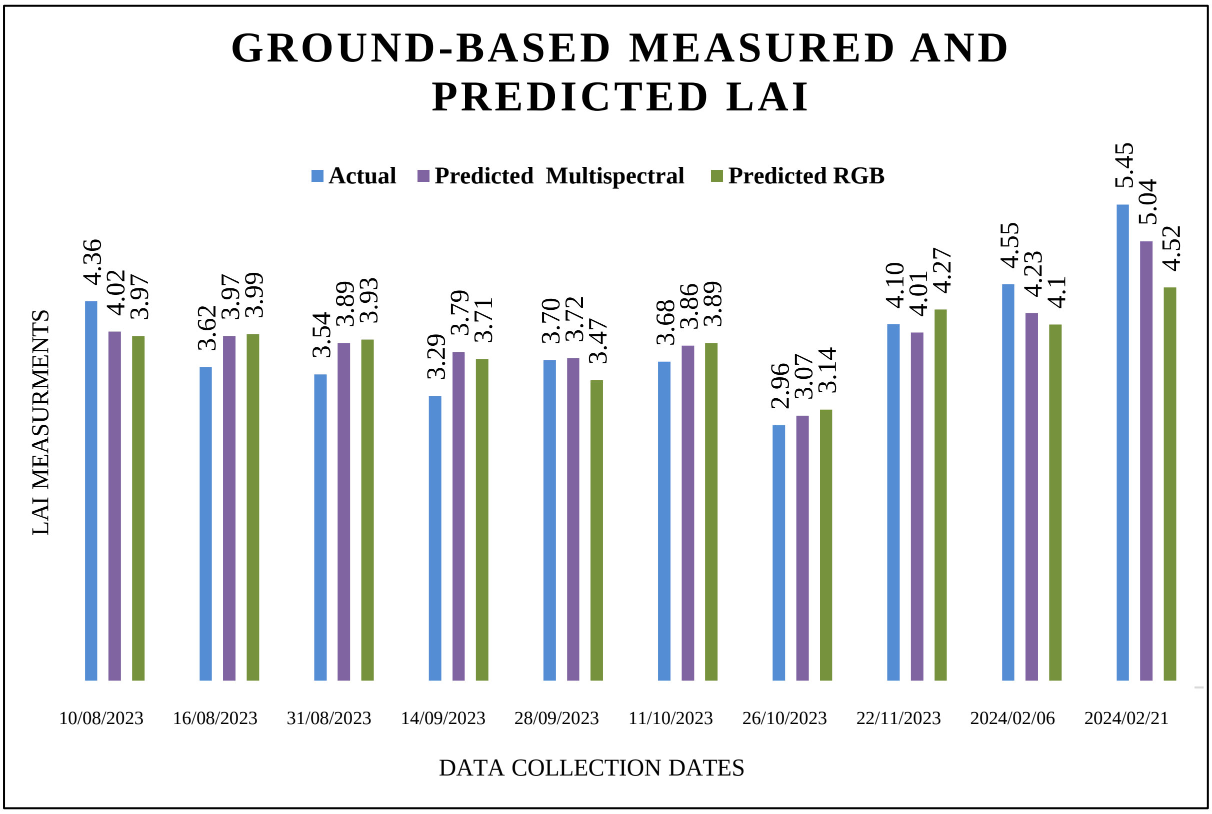



**Figure 4.4 Ground-based measured LAI vs Multi-spectral and RGB Estimated LAI**

### *4.4.4 Mapping the Spatial Distribution of the Estimated LAI*

The predicted LAI ranged from 2.28 to 7.54 for the multi-spectral data and 2.2 to 6.76 for the RGB data (Figure 4.5 and Figure 4.6). At the initial stages of the collection period, both maps indicated moderate LAI values. Thereafter, LAI values increased as both maps displayed a transition from yellow to red, indicating higher LAI values. However, the multi-spectral map displayed more extensive red areas in comparison to the RGB maps which highlight the finer differentiation in LAI. Through the latter months of the collection periods, both maps depicted high LAI values as red shades represent the majority of the area. This progression is representative of the healthy growth and development of the sugarcane crop. While the multi-spectral maps provided a more precise and detailed spatial differentiation of the predicted LAI, the RGB maps are in close alignment with the spatial distribution patterns captured by multi-spectral predicted LAI maps.


**Figure 4.5 Spatial distribution of LAI using UAV-RGB data**

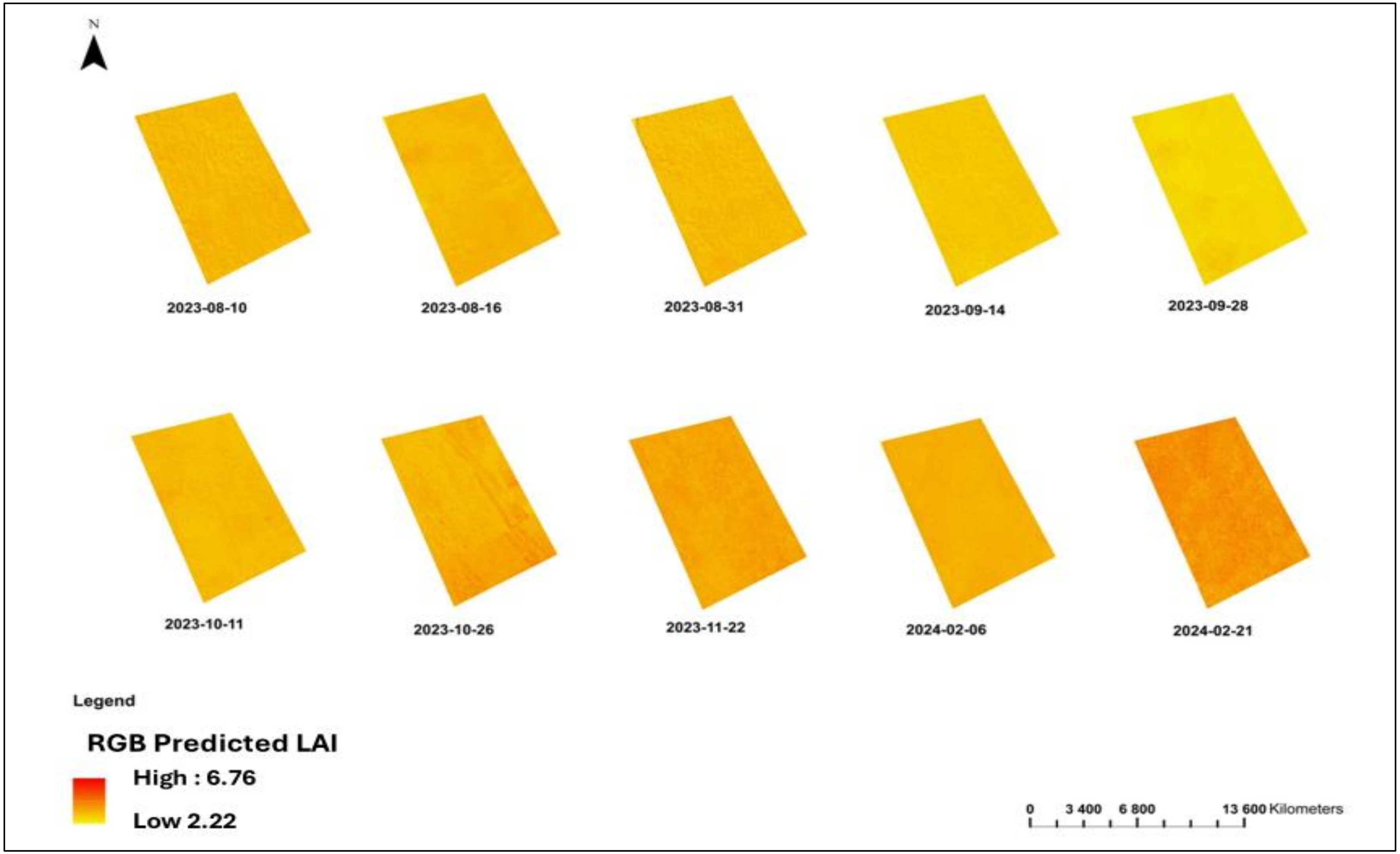



**Figure 4.6 Spatial distribution of LAI using UAV-RGB data**

## 4.5 Discussion

This study intended to undertake a comparative analysis of the predictive capabilities of UAV multi-spectral and UAV-RGB data for estimating LAI within a smallholder farm context. Subsequently, it sought to determine the reliability and viability of estimating LAI using the low-cost UAV-RGB approach for monitoring crop growth and development in smallholder farms.

The observed trend in ground-based LAI across the data collection period reflects the typical growth dynamics that are associated with seasonal conditions. The latter winter season (August) is characterized by lower temperatures and no precipitation which limits plant photosynthetic activity as well as growth and development. Hence, a reduced LAI was noted. As the season transitioned into spring and summer (September – February), there was a gradual increase in LAI. This increase can be attributed to warmer temperatures and increased precipitation which are essential for crop growth and development. Optimal temperatures and ample water availability in the summer season stimulate photosynthetic activity and leaf growth, hence, an increased LAI (Silva *et al*., 2020; Ramezani *et al*., 2020). Adequate soil moisture due to increased precipitation not only bolsters crop photosynthetic activity but also improves nutrient uptake which is essential for leaf expansion (Silva *et al*., 2020). However, there are a multitude of factors beyond seasonality that influence the LAI of crops. For instance, agronomic practices such as tillage and cropping systems significantly impact LAI (Oga *et al*., 2015; Mogale *et al*., 2022). Additionally, various studies have highlighted the significance of integrating nutrient management practices which improved leaf area development (Hashimoto *et al*., 2019). Ultimately, understanding the multiple factors that may impact LAI could prompt effective and informed decision strategies to optimize LAI, thereby enhancing crop growth and yield.

The RF ensemble model most accurately captured the seasonal variation, demonstrating a close correspondence between the trends shown by predicted and ground-based LAI values, as evidenced in Figure 4.4. The superior performance of the RF ensemble model concurs with the findings established within the literature which have demonstrated the strong predictive capabilities of ensemble models. The augmented performance is a result of the combination of multiple base models which allowed for more accurate predictive results (Li *et al*., 2023).

This approach leverages a multi-model level structure which combines and integrates the predictions of the machine learning base models, thereby reducing errors and increasing the accuracy of the estimated results. The strong adaptability and generalization ability of ensemble models which utilize a stacking approach effectively leverages the complementarity between the different base models to further accentuate the robustness and accuracy of the estimations (Taghizadeh-Mehrjardi *et al*., 2020; Li *et al*., 2021; Gu *et al*., 2022). Similar results were obtained in a study by Chen *et al*. (2022) which demonstrated the robust and accurate capabilities of employing ensemble models, utilizing a RF stacking approach compared to traditional machine learning models for LAI estimation. Another study conducted by Zhai *et al*. (2023), achieved the highest estimation accuracy for chlorophyll content utilizing a stacking ensemble method which surpassed the results achieved by machine learning models, such as ridge regression (RR) and light gradient boosting machine (LightGRM). In addition to these studies, various other studies have shown the superiority of EMLM utilizing a stacking approach for retrieving various vegetation parameters (Breiman, 1996; Schwenker, 2024; Alebele *et al*., 2020).

The model employing UAV-RGB data for predicting LAI yielded an $R^2$ value of 0.74, implying that the RF model accounts for 74.00 % of the variability in LAI. With an RMSE of 0.45 and MAE of 0.32, these predictions suggest reasonable accuracy, approximating the actual LAI values with a deviation of 0.45 and 0.32 respectively. When the model leveraged UAV multi-spectral data to predict LAI, it showcased an improved performance with an $R^2$ value of 0.81, and RMSE and MAE values of 0.37 and 0.24 respectively. These findings conclusively reveal that while the multi-spectral data provides a marginally higher accuracy when compared to RGB data, the latter provides reliable predictive results for LAI. Subsequently, the results obtained concerning the LAI predictions agree with previous studies that utilized UAV-RGB data to monitor crop growth and development. For instance, a study employing UAV digital images and RGB-derived VIs achieved $R^2$ values ranging from 0.71 – 0.88 on the test datasets for predicting the LAI of maize throughout its growth stages (Du *et al*., 2022).

Additionally, the findings in this study are analogous to the findings in a study by IIniyaz *et al*. (2022) which achieved 0.825 for UAV-RGB data and 0.89 for UAV multi-spectral data when estimating LAI in pergola-trained vineyards, as both studies demonstrated the superior performance of multi-spectral data while validating the reliability of UAV-RGB data. The results of this study further coincide with the findings of the present study by demonstrating the superior performance of ensemble models for LAI prediction (IIniyaz *et al*., 2022). The results from the above-mentioned studies reinforce the reliability of utilizing UAV-RGB data to predict LAI across different crop species and environments.

UAVs equipped with RGB sensors have demonstrated significant efficacy in predicting several crop parameters that extend beyond estimating LAI. Various studies indicated that UAV-RGB-derived data can effectively monitor crop growth and development by accurately predicting critical crop parameters such as nitrogen status, crop biomass, plant height and chlorophyll content. For instance, UAV-RGB data in conjunction with machine learning algorithms were utilized to predict the nitrogen nutrition index (NNI) in rice, achieving high accuracies in $R^2$ values ranging from 0.88-0.96 which resulted in improved efficiency in nitrogen applications and guidance for targeted fertilization in rice production (Qiu *et al*., 2021).

Additionally, a study on sugar beet leaves demonstrated the potential of UAV-RGB-derived vegetation indices to accurately estimate chlorophyll content as indicated by a strong correlation to traditionally obtained chlorophyll measurements (Sanchez-Sastre *et al*., 2021). Subsequently, it was established that RGB-derived indices utilized for chlorophyll content estimation potentially hold great promise to indirectly measure nitrogen (N) status and sucrose content estimations prior to harvest which is a decisive factor in leaf growth rate and root storage (Sanchez-Sastre *et al*., 2021). Lastly, UAV-RGB imagery effectively estimated crop height and above-ground biomass of maize when utilizing VI's, as the $R^2$ values for both crop parameters ranged from 0.82 to 0.90 (Niu *et al*., 2019). Consequently, the results of this study highlight the feasibility of this approach to monitor canopy height and above-ground biomass. Collectively, these studies demonstrate the wide adoption of UAV-RGB data for monitoring different crop species using various crop parameters, highlighting the feasibility and the efficacy of leveraging the UAV-RGB data for crop monitoring.

Smallholder farms are beset by various challenges that have contributed to suboptimal agricultural productivity and adversely impacted food security, particularly in developing nations. Therefore, cost-effective and practical solutions are crucial for enhancing agricultural productivity within this context. This study's findings have demonstrated the potential of UAV-RGB data to estimate LAI to monitor crop growth and development in a smallholder farm context. While the use of multi-spectral data for LAI estimation has provided more accurate results, UAV-RGB LAI estimates were found to be reliable for monitoring crop growth and development in a smallholder farm context.

Given the financial endemic which characterizes smallholder farms, UAV-RGB data provides a cost-effective alternative to their multi-spectral counterparts. The feasibility of UAV-RGB sensors may catalyze its widespread adoption, permitting the implementation of advanced PA monitoring techniques without substantial investment. The affordability coupled with the accessibility of user-friendly RGB sensors presents an opportunity to democratize the implementation of advanced technological applications for a plethora of PA tasks. Integrating this information into farming practices can facilitate data-driven agricultural practices which can result in informed and targeted agricultural management practices. This is advantageous for data-scarce and resource-constrained smallholder farms, as it enables the application of input resources more judiciously, thereby enhancing resource efficiency whilst reducing wastage.

With the detrimental impacts of climate change on agricultural productivity, leveraging this information can lead to adopting climate-smart agricultural practices which will equip smallholder farms to better manage the risks associated with climate variability. Regular monitoring of LAI could potentially enable the early detection of crop stress, hence leveraging this information may enable informed, targeted and swift responses to changes in crop conditions ensuring healthier and higher yields with minimal crop loss, thereby enhancing the capabilities of smallholder farms to upkeep food demands as a result of improved agricultural productivity.

While this study successfully achieved its objective and demonstrated success in its findings, it also acknowledges possible limitations, thereby providing insight for future research within a similar scope. These may include potential factors, such as limited in-situ data which can restrict the model's abilities to capture the temporal and spatial variability associated with agricultural systems. Since LAI is affected by a myriad of factors, it is therefore essential to ensure comprehensive in-situ data to account for the variability to avoid over-simplified model predictions (Sun *et al*., 2023). In this instance, future studies should aim to increase the sampling size, as larger datasets align with real-world conditions could assist in capturing greater variability and enhance the robustness of the model (Settibathini *et al*., 2024).

Building on this recommendation, a critical limitation of this study was the heavy dependence on the quantity and quality of in-situ data for predicting LAI. Consequently, this raises concern regarding the broader applicability, particularly in instances characterized by data scarcity and financial constraints, thereby limiting the data availability. Furthermore, inconsistencies and inaccuracies in the LAI measurements can propagate through the modelling process, thereby compromising the precision and accuracy of the predicted LAI values. To overcome these limitations, future studies should focus on dependency reduction of in-situ data, for example the study by Hassan *et al*. (2019) solely relied on UAV-RGB indices such as the visible atmospherically resistant index (VARI) and red green blue vegetation index (RGBVI) as well the digital number of the blue channel to predict LAI of winter wheat, resulting in accurate and reliable data for PA applications, such as crop monitoring. Future research should further systematically evaluate in-situ data to ensure optimal quality as the "garbage in, garbage out" analogy summaries the relationship between in-situ data and model performance, thereby necessitating high quality in-situ data (Chen, 2021).

Additionally, the model is missing key features such as, but not limited to, morphological features being crop height and canopy coverage which could be vital for predicting LAI (Lee and Lee, 2011; Jia *et al*., 2014). While the consensus points to the more accurate performance of multi-spectral data in comparison to RGB data, this was not the case for a study conducted by Lu *et al*. (2022) as results obtained indicated that UAV-RGB images marginally outperformed UAV multi-spectral images for predicting LAI. The results achieved within the study could be attributed to the use of the canopy height model (CHM) which was utilized to compensate for the absence of structural information in LAI estimation. Additionally, canopy coverage (CC) was also employed to serve as a correction parameter to alleviate the overestimation of LAI. Consequently, Lu *et al*. (2022) noted a significant improvement in accuracy of 22.6 % and 43.6 % for multi-spectral and RGB LAI estimation respectively. Collectively, this study showcased a simple and practical method, particularly for the use of low-cost UAV-RGB sensors to predict LAI. Building on this, it is recommended that future studies exploring LAI prediction models should strongly consider including CHM and CC as key input variables, as it has the potential to enhance the accuracy of LAI predictions.

While various studies, including the current one, have demonstrated the success of machine learning techniques for crop monitoring, recent advancements have led to the emergence of deep learning (DL) techniques which may have the potential to provide more reliable and accurate results. Despite the reliable results achieved in this study, the predictive accuracy could be enhanced by utilizing DL models as an alternative to machine learning techniques. This is evidenced in a feasibility study that employed a DL model in conjunction with UAV-RGB images to estimate the LAI of rice and obtained an $R^2$ value of 0.96 which is significantly higher than the accuracy achieved in the current study (Yamaguchi *et al*., 2020). It is therefore recommended that future studies exploring LAI prediction models consider integrating UAV-RGB images and DL techniques to attain more accurate LAI predictions. Ultimately, improved accuracy in results significantly impacts PA tasks and crop management. While this approach has the potential to enhance model accuracy, its complex and data-intensive nature may reduce its efficiency in smallholder farms (Arsenovic *et al*., 2019). Therefore, it is vital to consider carefully balancing model complexity and accuracy to ensure suitability for the context of smallholder farms.

Overall, the results of this study demonstrated the reliability of UAV-RGB data, showing a strong correlation between ground-measured LAI and predicted LAI of sugarcane within the specific site of investigation. Future studies can consider replicating and scaling this methodology across different geographical regions with differing agronomic conditions and crop species to enhance the reliability generalizability and applicability of the results. Additionally, while the findings of this study have the potential to benefit smallholder farms, they currently represent a proof-of-concept technique which requires the development and integration of decision support systems as well as extension services to achieve practical impact within smallholder farms. Future research should explore various methodologies for knowledge dissemination to transform the results into actionable information that smallholder farms could adopt to improve their agricultural productivity, for instance, a study conducted by Thar *et al*. (2021), highlighted the improvement in communication and technologies (ITCs) has improved the access to useful communication tools to assist in information delivery. Mobile phones and agricultural apps have the potential to inform farmers about crop quality, pest and disease identification enabling them to apply effective fertilization and water management strategies (Gichamba and Lukandu, 2012; Qiang *et al*., 2012; Woodill and Udell, 2012; Romani *et al*., 2015).

A further limitation of the study is the computational power required to perform model development and evaluation. This is because computationally intensive tasks require high-performing computing resources (HPC) to necessitate robust performance and reduce the performance of bottlenecks (Li, 2020; Hair *et al*., 2021). This limitation prompts the use of cloud-based solutions for future studies which could overcome the inherent challenges of utilizing traditional desktop computing methods when processing remote sensing data (Habibie, 2022). Nevertheless, UAV-derived multi-spectral and RGB data provided satisfactory results in predicting LAI, with UAV-RGB data obtaining reliable LAI estimates. Therefore, enabling the use of this low-cost approach to monitor crop growth and development.

### 4.6 Conclusion

Smallholder farms are often riddled with numerous challenges that hinder their agricultural productivity. These include but are not limited to, inefficient resource utilization, limited access to critical input resources, insufficient finance and a heavy reliance on conventional farming practices. Consequently, smallholder farms require cost-effective and innovative solutions to maximize their crop production and produce healthy yields. Thus, such findings showcase the need for PA practices facilitated by remote sensing technologies, in particular UAVs which possess the capabilities to improve crop management and agricultural productivity through efficient and effective crop monitoring of smallholder farms. This could potentially improve the growth and development of crops, ultimately enhancing agricultural productivity.

The findings of this study suggest that UAV-RGB data can provide reliable LAI estimates with comparable accuracy to UAV multi-spectral predicted LAI. The utilization of low-cost RGB data presents itself as a viable alternative to the costly and more complex multi-spectral data, thus enabling accessibility to modernized and effective crop monitoring techniques. By leveraging UAV-RGB data for LAI estimation, smallholder farms can utilize data-driven agricultural practices which are tailored to their specific fields. Through this guided and informed approach, smallholder farms can effectively monitor crop growth and development, thereby optimizing agricultural productivity and resource use.

While utilizing LAI for monitoring crop growth and development may be extremely beneficial for smallholder farms, this study may also have benefited from exploring the use of UAV-RGB data beyond LAI to gain a more holistic understanding of crop status. Nevertheless, this approach reduces the financial barrier to accessing advanced tools and methods for applying PA applications amongst resource-constrained, data-scarce regions. Ultimately, implementing such innovative and cost-effective approaches may assist in improving agricultural production amongst smallholder farms which is crucial for sustaining food supply, ensuring food security and improving their livelihoods.

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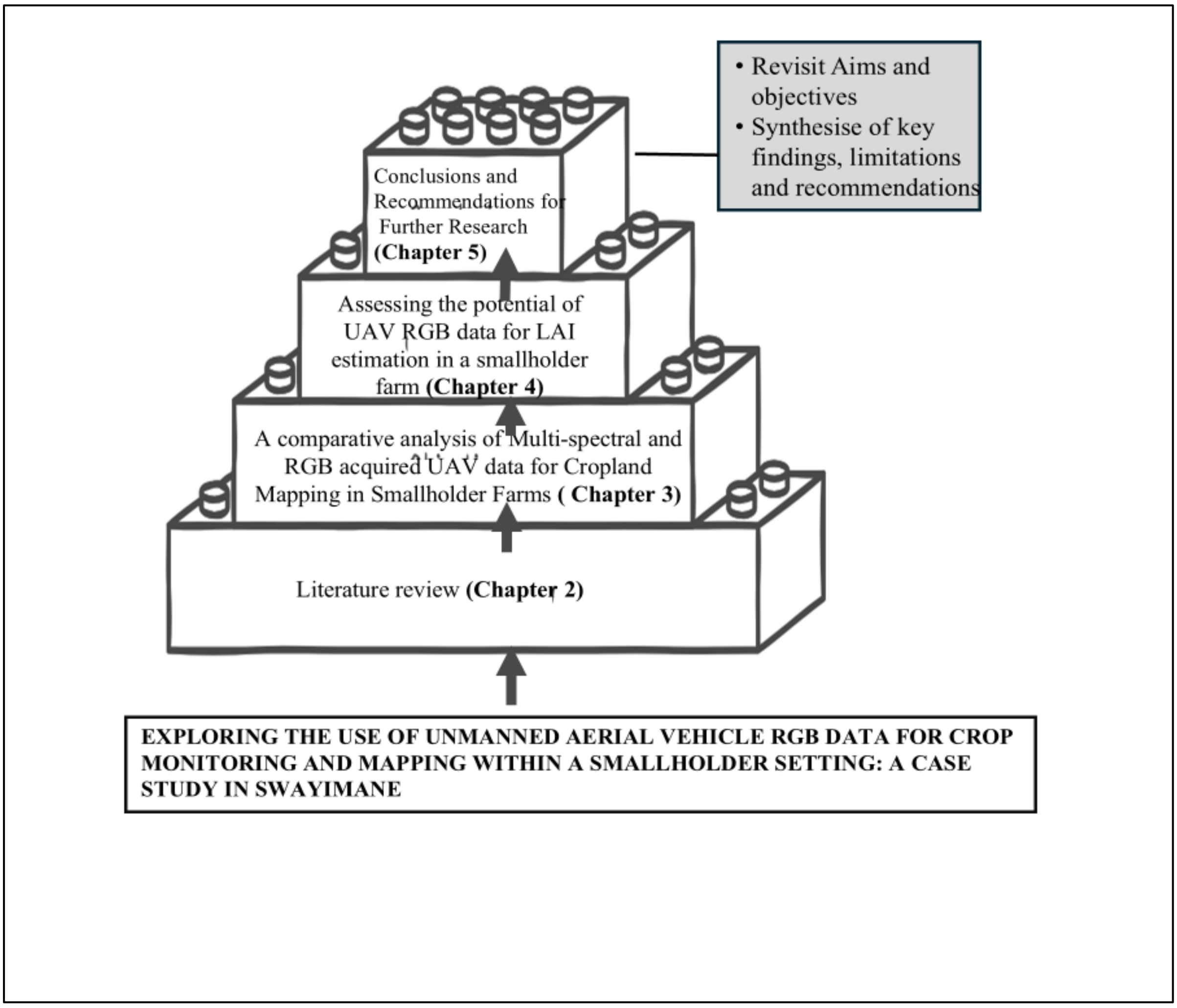
**Lead into Chapter 5**: serves as the concluding chapter in this study, revisiting the aims and objectives as well as synthesizing the key findings. Additionally, this chapter consolidates the study's limitations. Thereafter, this chapter concludes with recommendations for future research outlining potential advancements in the use of UAV applications thereby further supporting the use of modern technology for PA within a smallholder farm setting.



# CHAPTER 5: CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

## 5.1 Introduction

Smallholder farms play a pivotal role in food security, subsequently in alleviating poverty, improving their livelihoods and holding the potential to increase economic growth. This is due to their significant contribution towards agricultural production which stems from numerous SSA countries. However, despite their significance, their conventional farming practices, financial constraints and limited resources collectively impede their capacity to produce and operate optimally, consequently threatening food security (Livingston *et al*., 2021, Hlophe-Ginindza and Mpandeli, 2021). Additionally, the dual pressures of climate change and rapid population expansion have compounded these challenges (Touch *et al*., 2024). Hence, small-scale farms require low-cost, context-specific agricultural solutions to improve their productivity.

Considering the aforementioned challenges, in recent years, PA practices have begun to display the potential to improve the sustainability and productivity of these farms (Erickson and Fausti, 2021; Gokool *et al*., 2023). Among the remote sensing tools, namely, satellites, manned aerial vehicles and UAVs, UAVs have been advocated more frequently to facilitate PA applications due to their compelling advantages, such as their low operational cost, high-resolution imaging capabilities and temporal flexibility which enhances the reliability and effectiveness of data collection (Tsouros *et al*., 2019; Radoglou-Grammatikis *et al*., 2020; Velusamy *et al*., 2021). The use of UAVs has also enabled the attainment of detailed information that surpasses what traditional space-borne open-source remote sensing platforms may provide, and more so for local scales, rendering them suitable for smallholder heterogenous farming initiatives (Onyango *et al*., 2021; Gokool *et al*., 2023; McCarthy *et al*., 2023).

The data collection capabilities of UAVs are further enhanced by onboard sensors such as the commonly utilized hyperspectral, multi-spectral and RGB sensors (Tsouros *et al*., 2019). While hyperspectral sensors offer highly detailed analysis for various PA applications, the exorbitant cost and complexity of both data acquisition and processing, pose a barrier to widespread adoption (Tsouros *et al*., 2019). On the other hand, multi-spectral sensors that capture fewer bands than hyperspectral sensors have been extensively utilized for PA applications, particularly land cover mapping and crop monitoring. While they have a reduced cost compared to hyperspectral sensors, they remain costly and require sophisticated data processing (Cucho-Padin *et al*., 2020). Contrastingly RGB sensors offer a low-cost alternative to facilitate PA. They are more accessible, require less processing and provide high-resolution imagery making them a practical and cost-effective option for resource-constrained smallholder farms (Acorsi *et al*., 2019; Hassan *et al*., 2019; Du *et al*., 2022).

While RGB sensors may have a reduced cost in comparison to hyperspectral and multi-spectral sensors, they are associated with an inherent limitation which is their limited spectral resolution, permitting these sensors to capture information only within the visible spectrum. Conversely, multi-spectral sensors while costlier than RGB sensors, are more affordable when compared to hyperspectral sensors, and can capture information beyond the visible spectrum. The discrepancy in the level of detail captured between these sensors may have a potential impact on the reliability of the data. Through the direct comparison of accuracy between UAV-RGB and UAV-multi-spectral data for cropland mapping and crop monitoring, this study evaluated the potential and reliability of utilizing a low-cost approach to guide and inform PA practices, thereby addressing a critical need to improve agricultural productivity in resource-scarce and financially constrained smallholder farms.

This study sought to compare UAV-RGB data against UAV multi-spectral data to identify any potential loss of accuracy in determining the reliability of UAV-RGB data to be utilized to facilitate PA in a smallholder farm context. It is envisaged that the insights of this research have the potential to democratize the use of advanced and modern agricultural technology in data-scarce and resource-contained agricultural regions. Consequently, this technology may facilitate PA applications, thereby leveraging data-driven agricultural practices which result in informed decisions and tailored management practices that can contribute to enhancing agricultural productivity, prompting resource efficiency and minimizing crop loss as a result of appropriate and timely interventions.

## 5.2 Revisiting the aims and objectives

Based on the trade-offs that exist between the cost and the spectral richness of these sensors, the accuracy and reliability of data collection are influenced, hence, this study aimed to investigate the performance of UAV-RGB data in comparison to UAV multi-spectral data for PA within a smallholder farm context. This study was undertaken specifically with a focus on determining the potential of UAV-RGB data to be utilized as a reliable and cost-effective approach to guide and inform PA for smallholder farms or at local scales. As such, the research objectives for this study were as follows:

- To undertake a comprehensive and critical analysis of the literature to evaluate the potential of UAVs to facilitate PA precision agriculture applications, with a particular focus being given to the socio-economic circumstances of smallholder farms in SSA.
- To identify and accurately map croplands within a smallholder farm setting.
- To monitor and evaluate crop growth and development within a smallholder farm.

The literature review was conducted through a comprehensive search of existing research pertaining to smallholder farms and their contributions to agricultural production, food security as well as socio-economic status, particularly in developing nations.  Emphasis was placed on the plethora of challenges encountered by smallholder frames which have impeded their capacity to produce optimally. To address these challenges extensive research was conducted on leveraging PA with a focus on remote sensing as a key enabling technology. Taking into account the unique characteristics and challenges of smallholder farms, literature was then critically analyzed to identify a suitable remote sensing platform and sensor to facilitate PA on smallholder farms.

To identify and accurately map croplands within a smallholder farm, this study utilized UAV multi-spectral and RGB data with machine learning techniques within the GEE cloud computing platform. The utility of this platform harnessed the processing power of the cloud, along with access to complex machine learning algorithms for efficient and accurate classification of croplands. Once the image was captured by the UAV (DJI Matrice 300) and MicaSense camera, they were pre-processed utilizing the Pix4D fields. The GEE, a geospatial cloud computing platform, facilitated efficient data processing and classification. From the pre-processed images, training location points were combined with GCPs to form the training data set. Subsequently, this training data was split into a subset of training (70 %) and validation (30 %). Both binary and non-binary classification approaches along with different machine learning classifiers namely RF and GTB were explored to evaluate and compare model performance in accurately classifying cropland within a smallholder farm setting. The methodology and results of this objective were detailed in Chapter 3 where the outcomes of the model accuracies and image classification were discussed.

For objective three, ground-based LAI was obtained from 36 equidistant sampling points within a sugarcane field in the community of Swayimane, KwaZulu-Natal, South Africa. This was done using a plant canopy analyzer (LiCOR 2200C) while UAV images were captured of the sugarcane plot in the Swayimane study site, After pre-processing these images it was uploaded to the GEE platform where a comprehensive time series consisting of the date, sample point, latitude and longitudinal coordinates of the 36 points along with mean band values and calculated values for multi-spectral and RGB derived indices were extracted as a CSV file. The measured LAI was then inputted into this CSV file which was imported into R studio for further pre-processing. The data was then cleaned by removing variables not required for model development such as the date, point ID, and information about the sensor bands. Additionally, the VIF technique was utilized to assess multicollinearity among the training data variables which resulted in further removal of unrequired data. Relevant packages were then installed for training and development with a k-fold cross-validation approach (10 folds and 10 repeats were implemented). Common machine learning classifiers along with two ensemble models were evaluated utilizing extensively adopted accuracy metrics such as RMSE, MAE and $R^2$ to determine the model's predictive accuracy. Subsequently, the best-performing model was applied to map the spatial distribution of LAI within the smallholder sugarcane field. An in-depth explanation of the methodology and results is presented in Chapter 4.

**5.3 Key findings**

Several critical insights pertaining to the various remote sensing platforms being adopted for PA were revealed from the comprehensive literature review. It was identified, that within the context of smallholder farms, UAVs are the most appropriate remote sensing platform which could guide and inform PA practices within smallholder farms. This is in stark contrast to the traditional and commonly utilized satellite and manned aircraft platforms, which, despite their advanced capabilities, are often considered prohibitively expensive and pose operational complexities for smallholder farm use. Additionally, the spatiotemporal resolution of freely available satellite platforms is not adequate to capture finer-scale details in smallholder heterogeneous farms.

The literature review further highlighted that UAVs, particularly those that are equipped with RGB sensors offer a low-cost, reliable alternative to costly and complex multi-spectral sensors for facilitating common PA applications such as cropland mapping and crop monitoring, among other applications despite its limited spectral resolution. The resultant synthesis of existing literature also revealed the use of machine learning modalities in conjunction with UAV-RGB data offers enhanced capabilities of leveraging this data to obtain accurate data for PA applications. Through this, essential information can be made available, which can be leveraged to improve crop yield, enhance agricultural production, optimize resource use and in some instances contribute to overall food security.

Ultimately the literature provided cumulative evidence suggesting that UAV-RGB data can be utilized as a cost-effective solution, offering reduced expenditure coupled with superior usability in comparison to traditional remote sensing platforms. This renders the use of UAV-RGB data as an optimal alternative to facilitate PA within resource-scarce and financially restricted contexts which holds the potential to bridge the technological divide which smallholder farms experience. Consequently, this enables a shift away from conventional farming towards data-driven, site-specific and sustainable agricultural practices to improve their agricultural productivity, having a domino effect on various factors such as food security, poverty, malnutrition and livelihoods.

Within chapter 3 of this research, a comparative analysis was undertaken to assess the accuracy of UAV-RGB data against UAV multi-spectral data in producing cropland maps of smallholder farms. The study combined UAV-RGB data and machine learning modalities operated within the GEE platform to produce cropland maps. The findings highlighted the capabilities of UAV-RGB data to accurately classify and map croplands using machine learning classifiers such as the RF which had performed marginally higher than that of GTB. While it was not the focus to compare binary and non-binary classification approaches, classification approaches, The binary classification in probability mode was able to classify croplands which showcased the capabilities of UAV-RGB data which for the most part, accurately classified croplands of smallholder farms with a minimal difference in accuracy when compared to UAV multi-spectral cropland map. While the non-binary classification approach achieved a minimal accuracy differential to that of the binary classification approach, this approach produced the lowest UA and producer accuracy results for the classification of cropland utilizing UAV RGB and multi-spectral data.

Notably, the statistical analysis and the visual analysis coincided with the marginal difference in accuracy which underscored the ability of UAV-RGB data to accurately classify agricultural land within smallholder farms. These findings indicated that in instances where UAV multi-spectral data is inaccessible or financially unattainable, UAV-RGB data can be used as a cost-effective and reliable approach to classify and map croplands of smallholder farms. Furthermore, the utility of the GEE enabled the storage, processing and management of the voluminous UAV data, thereby reducing computational cost and promoting feasibility. Additionally, access to various tools as well as complex machine learning algorithms availed within the open-source cloud computing platform enhances the accessibility of this approach. Smallholder farms may be able to benefit from the use of UAV-RGB data for accurate cropland mapping as it facilitates PA, enabling data-driven agricultural practices for informed decision-making, with tailored management strategies and timely interventions which effectuates improved agricultural management and efficient use of limited resources as well as sustainable agricultural practices.

Building on the classification of agricultural land, the RF ensemble successfully estimated the LAI of sugarcane utilizing UAV multi-spectral and RGB data. The results revealed that the most accurate LAI predictions were obtained utilizing UAV multi-spectral data. However, while less accurate when compared to UAV multi-spectral predicted LAI, the UAV-RGB data produced reliable LAI predictions. These findings further demonstrated the potential of UAV-RGB data to reflect seasonal fluctuations of LAI which for the most part coincided with ground-based measured LAI. Consequently, this showcased the potential of utilizing UAV-RGB data as a low-cost alternative for monitoring crop growth and development. This has significant implications, particularly for smallholder farms that require low-cost accessible and reliable approaches to facilitate PA. The democratization of advanced crop monitoring techniques enables smallholder farms to obtain critical information pertaining to their crop status subsequently enabling informed decision-making, efficient use of critical resources and timely response to changing crop conditions. Ultimately this foster enhanced productivity and resilience of smallholder farms which form an integral component in ensuring food demands are met in the face of climate change and rapid population expansion.

## 5.4 Challenges, Limitations and Recommendations for Future Studies

While this study successfully met its objectives, several challenges and limitations were identified. The study relied on data obtained from a smallholder farm with a specific geographic context. Consequently, the findings of this study are inherently context-specific, hence, it may not be directly applicable in other agricultural settings. Additionally, the accuracy and generalization of machine learning models employed in the study may have also been impacted by data. More specifically, a lack of in-situ data limits generalization and hampers the calibration of remote sensing data. Consequently overfitting, reduced transferability and imprecise decision-making may be a by-product of insufficient data.

Future research may benefit from additional in-situ data through collaborative efforts between researchers and local stakeholders to efficiently obtain enough in-situ data which will augment existing datasets that are utilized for machine learning model development and validation, ensuring enhanced reliability and robustness of model performance. The improvement in results may be attributed to the model's ability to learn from a broader range of data, thereby capturing the inherent complexities and variability of agricultural systems. It is also recommended that future studies should focus on applying these methodologies across diverse agricultural settings to ensure greater generalizability of the results. The study's significant reliance on in-situ data poses a significant limitation, particularly in resource-poor, data-scarce and financially contained contexts. Hence, future research should explore methodologies with a reduced reliance on in-situ data and place more focus on approaches which solely leverage UAV-derived data for predictive analysis of various crop parameters.

An additional limitation of the study could potentially be the use of traditional machine learning techniques. While this technique has proven to be successful in accomplishing the objectives of the study, recent studies have shown that advanced techniques, such as DL, have yielded higher performance for various PA applications. Subsequently, it is recommended that future research explore the application of these advanced techniques to enhance the accuracy of the outcomes. The capacity of DL techniques to handle larger and more complex data sets and capture the relationships within the data enhances the precision of the results required to make informed decisions in agricultural contexts. However, one is cautioned against the high computational demand and complexity of this approach which in the context of resource-constrained smallholder farms may not be effective. Hence, this technique was not considered in this study, to ensure the method aligns with the requirements of implementing practical approaches.

Additionally, while the RF machine learning algorithm marginally outperformed GTB, it did not undergo hyperparameter tuning in order to streamline the modelling process and reduce the computational demand which is in keeping with the practicality of the methods employed. However, this could have constrained model performance, hence through fine-tuning various parameters, the model's ability to capture complex relationships within the data could have been enhanced. As such, future studies should include hyperparameter tuning to enhance classification as well as the prediction outcomes. Additionally, between the different machine learning classification approaches, namely pixel-based image analysis and OBIA, this study utilized a pixel-based approach based on the scope of the research ensuring the practicality of the methods implemented. While this approach was proven to be effective, OBIA techniques are considered more advanced and have shown a greater potential to improve accuracy through integrating spatial context and object features. However, it does require additional computing power, sophisticated software and extensive expertise which one should take into careful consideration when implementing this approach in future studies, to acquire more accurate results for more detailed and precise decision-making for PA applications.

Further limitations of the study included the absence of complementary information, such as soil moisture, plant height, canopy cover as well as climactic and environmental conditions to integrate into the machine learning model. The exclusion of these additional crop parameters and environmental factors may have limited the accuracy of the ensemble model to accurately predict LAI. Overall, evidence suggests that the inclusion of multiple crop variables is beneficial for predicting LAI. Hence, future studies should incorporate additional crop parameters that could likely enhance LAI predictions and possibly provide a more holistic understanding of crop growth and development.

### 5.5 Final comments, summary and conclusions

Smallholder farms form an integral part of agricultural systems, particularly in SSA, however, they face a myriad of challenges which have impeded their capacity to keep pace with food demands in the face of climate change and population growth. In these circumstances, smallholder farms require low-cost, site-specific agricultural solutions to improve their agricultural productivity and optimize resource use. To this end, UAV-RGB data has proven to be a low-cost reliable approach to facilitate PA in a smallholder farm setting. This approach democratizes the adoption of modernized and technological solutions, permitting data-driven agricultural practices which have significant implications for data-scarce resource-poor farming regions. Through the adoption of this approach, smallholder farmers can make informed decisions about their crop management, thereby bolstering agricultural productivity, enhancing resource efficiency and promoting sustainable farming practices. Subsequently, this would have broader implications for improving food security, thereby reducing poverty and malnutrition concerns. Beyond this, facilitating PA application within smallholder farms can significantly improve the livelihoods of smallholder farms. Enhanced productivity and reduced input resource-use can increase profitability and reduce farming costs which has the potential to alleviate poverty. Additionally, improved agricultural production stimulates local economies, as smallholder farms can earn more money, invest more in their farms, scale their operations and create further employment. Furthermore, adopting PA applications fosters sustainable agricultural practices that ensure long-term agricultural viability and resilience, especially when facing the dual pressures of climate change and rapid population growth.

Although this study has demonstrated that UAV-RGB data can serve as a reliable low-cost approach for cropland mapping and monitoring crop growth and development within smallholder farms, it is essential to acknowledge that PA encompasses a wider array of practices that were not included in this study. Hence, further testing in this regard is required before we can advocate for the use of UAV-RGB data for a variety of PA applications. Furthermore, there still remains a limitation in how smallholder farms will interpret this data. Therefore, future research initiatives should focus on developing user-friendly methodologies and tools along with training programs and the use of extension services to assist users in accessing and interpreting the data. By simplifying data visualization and providing decision support systems, smallholder farms would be able to translate this information into actionable decisions to improve their agricultural practices, thereby, attempting to bridge the gap that exists between research and practical application.

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# APPENDIX A

This appendix provides examples of the JavaScript code which was utilized to develop the machine learning models within the GEE platform for classification purposes. Figures A1 and A2 illustrate the code utilized for binary and non-binary classification approaches that were implemented in this study. This code was developed within the GEE which is a cloud computing platform that was utilized for its capabilities for machine learning development and earth observation data analysis. These figures support the discussion pertaining to the development and results of machine learning models within Chapter 3.

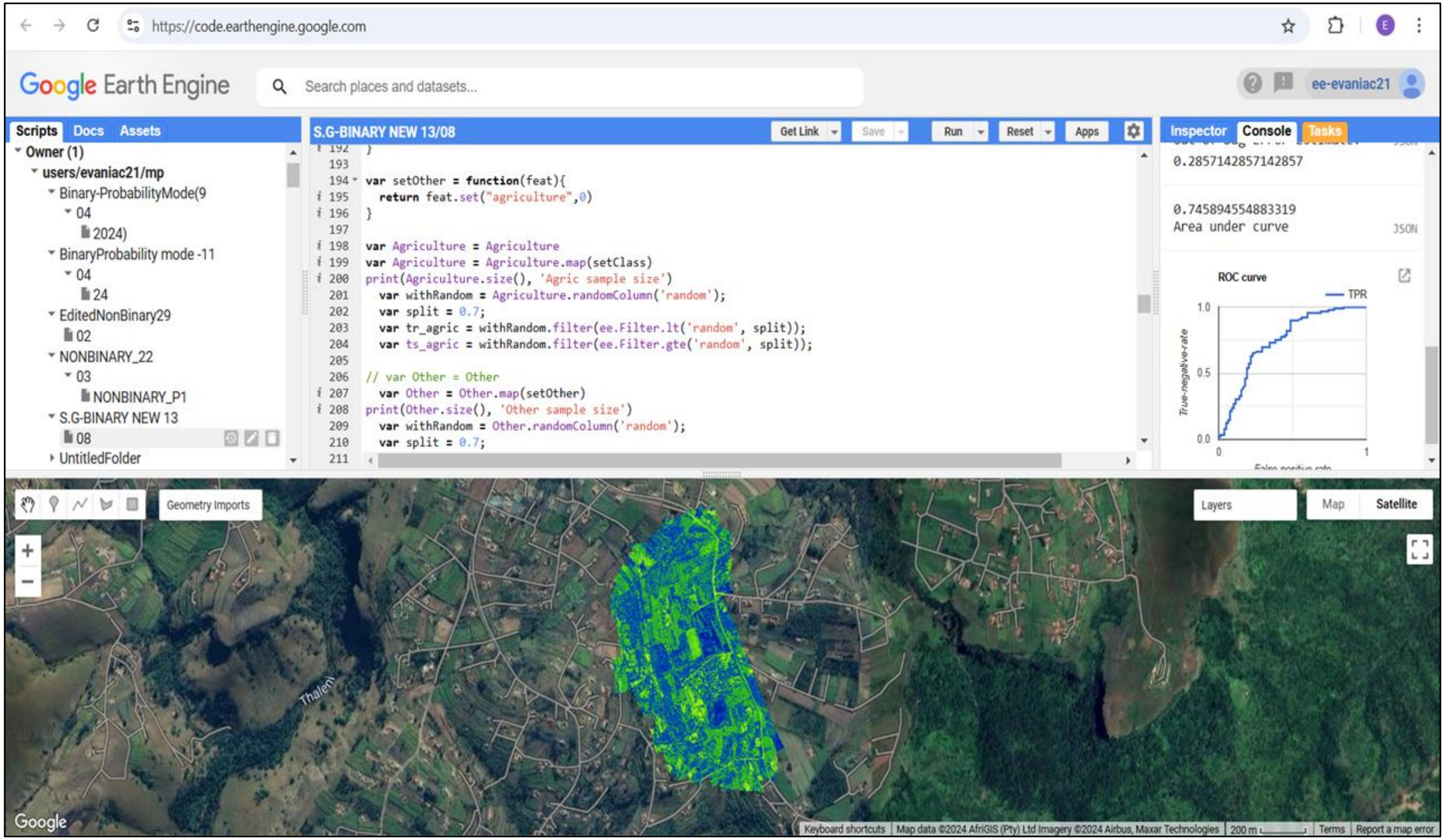


**Figure A1 Example of script for non-binary classification.**

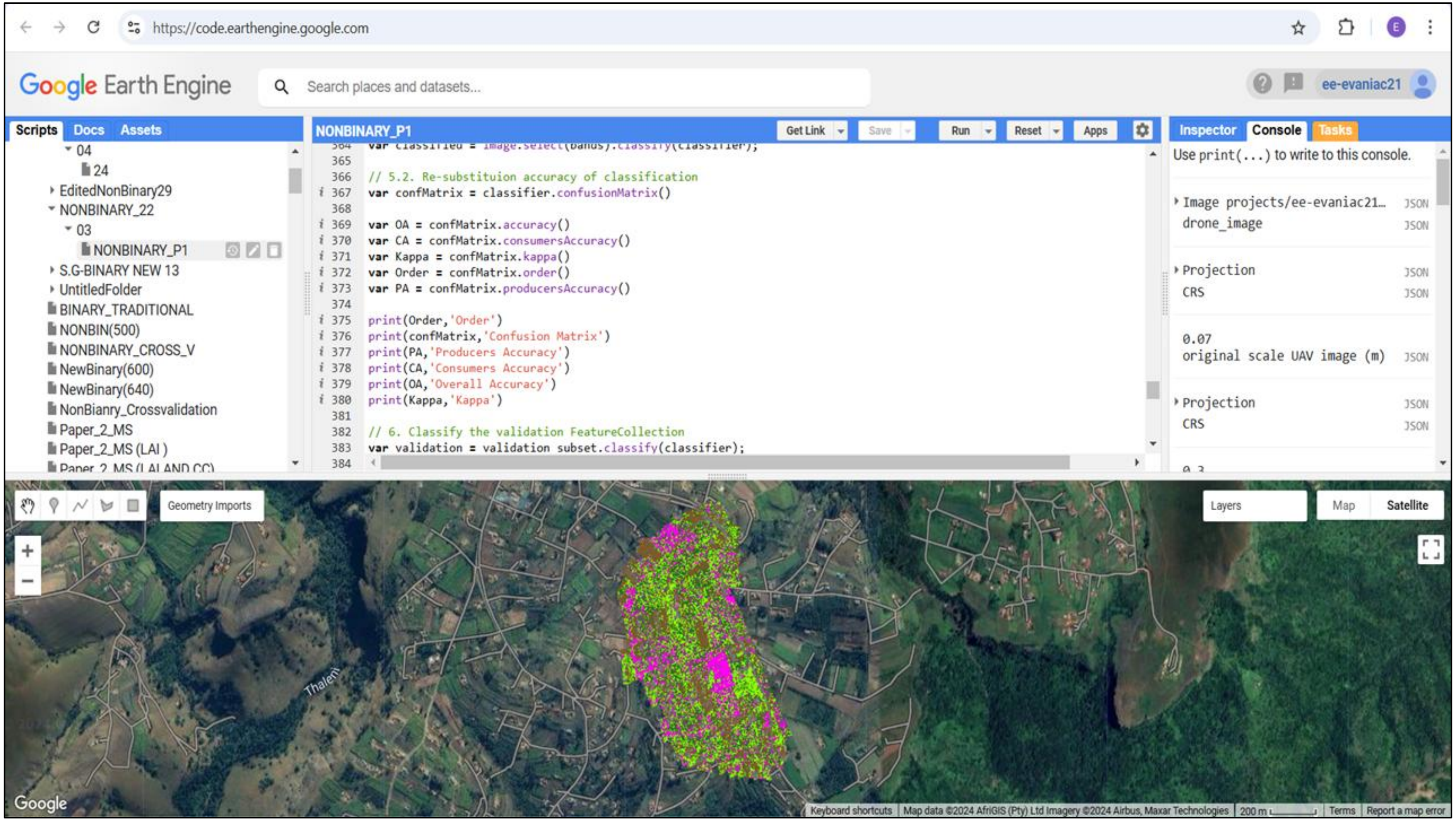


**Figure A2 Example of script for binary classification.**

# APPENDIX B

Figure B1 provides the R code that was utilized to develop and test the machine learning and ensemble models using R studio for the purpose of predicting LAI. The R code utilized various machine learning algorithms to predict LAI based on input variables, namely ground-measured LAI as well as multi-spectral and RGB-derived VI's.

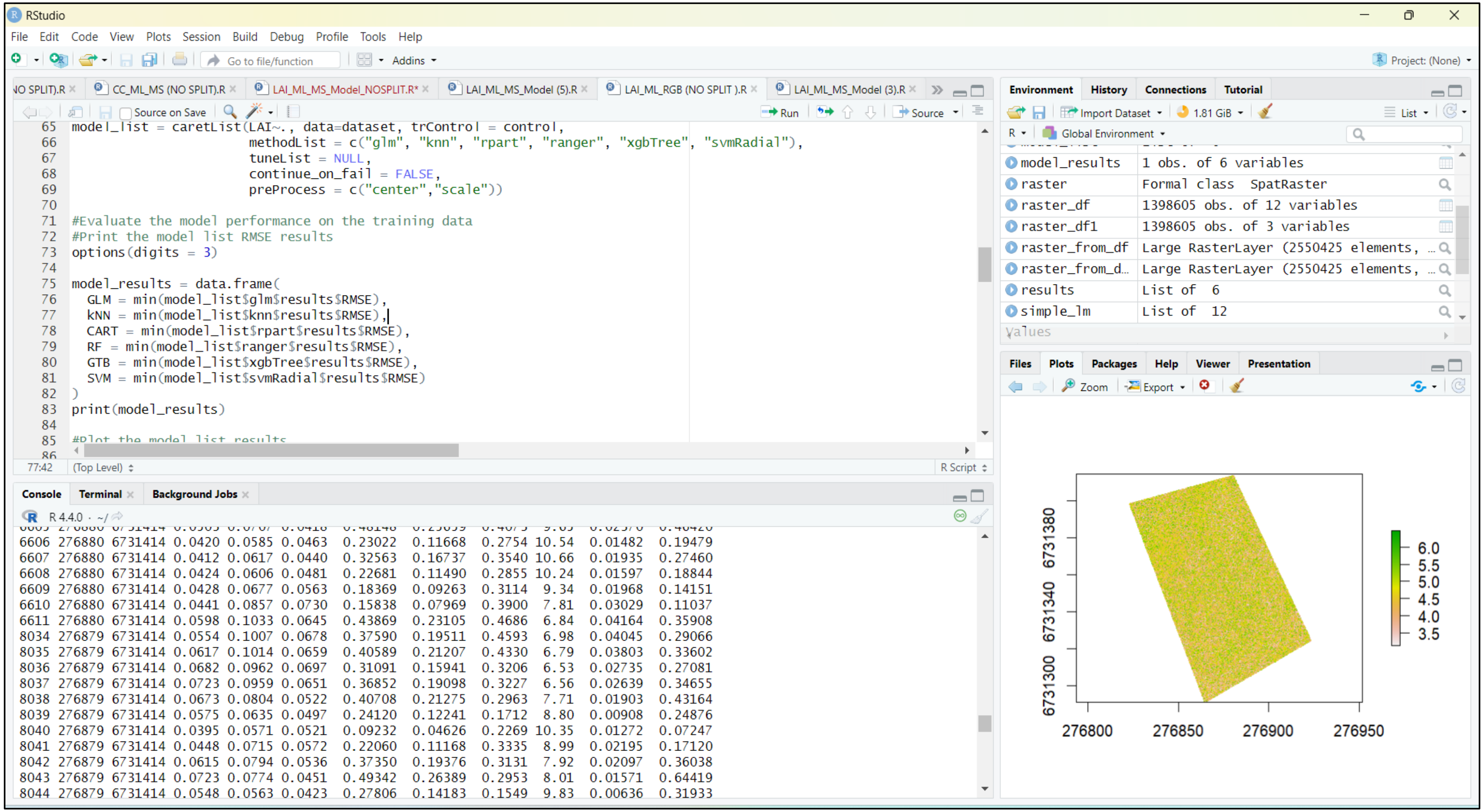


**Figure B1 Example of the script that was used for the LAI prediction.**

# APPENDIX C

This appendix showcased in Table C1, is the raw LAI data using the LiCOR 2200C plant canopy analyzer device that was collected within the demarcated sugarcane field in Swayimane. This data was subsequently compiled into an excel sheet for analysis to attain the descriptive statistics, as reported within the documented (Chapter 4).

**Table C1 Ground-Based measured LAI that was used to calculate the descriptive statistics.**

| 10/08/2023 | 16/08/2023 | 31/08/2023 | 14/09/2023 | 28/09/2023 | 11/10/2023 | 26/10/2023 | 22/11/2023 | 2024/02/06 | 2024/02/21 |
|---|---|---|---|---|---|---|---|---|---|
| 6.43 | 5.29 | 4.00 | 3.64 | 4.89 | 3.24 | 2.03 | 9.04 | 4.07 | 6.78 |
| 4.64 | 3.97 | 3.66 | 3.97 | 4.19 | 3.23 | 2.07 | 3.71 | 4.31 | 5.65 |
| 4.86 | 4.75 | 3.54 | 3.85 | 4.01 | 3.34 | 2.01 | 3.72 | 4.13 | 5.45 |
| 6.41 | 4.12 | 3.66 | 3.57 | 3.84 | 3.47 | 2.19 | 3.81 | 4.23 | 5.62 |
| 5.35 | 4.51 | 3.80 | 3.79 | 4.02 | 3.50 | 2.33 | 3.72 | 4.33 | 5.97 |
| 5.86 | 5.27 | 4.00 | 3.86 | 4.16 | 3.68 | 2.45 | 3.73 | 4.46 | 5.82 |
| 5.66 | 3.68 | 3.35 | 3.30 | 3.57 | 3.73 | 3.13 | 3.81 | 4.56 | 5.33 |
| 5.34 | 3.67 | 3.38 | 3.17 | 3.57 | 3.69 | 3.14 | 3.77 | 4.55 | 5.25 |
| 5.01 | 3.65 | 3.40 | 3.20 | 3.62 | 3.68 | 3.13 | 3.75 | 4.55 | 5.06 |
| 4.65 | 3.65 | 3.51 | 3.29 | 3.67 | 3.68 | 3.11 | 3.75 | 4.52 | 5.22 |
| 4.39 | 3.94 | 3.63 | 3.42 | 3.79 | 3.71 | 3.10 | 3.75 | 4.55 | 5.43 |
| 4.22 | 4.36 | 3.78 | 3.55 | 3.77 | 3.72 | 3.09 | 3.75 | 4.51 | 5.56 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| 4.11 | 3.62 | 3.70 | 3.32 | 3.61 | 3.67 | 2.96 | 3.88 | 4.47 | 5.45 |
| 4.38 | 3.74 | 3.67 | 3.43 | 3.63 | 3.73 | 2.88 | 3.91 | 4.55 | 5.91 |
| 4.24 | 3.67 | 3.62 | 3.39 | 3.62 | 3.76 | 2.81 | 3.92 | 4.57 | 5.33 |
| 4.32 | 3.68 | 3.63 | 3.36 | 3.63 | 3.81 | 2.71 | 3.93 | 4.62 | 5.36 |
| 4.18 | 3.59 | 3.61 | 3.30 | 3.64 | 3.81 | 2.61 | 3.95 | 4.66 | 5.43 |
| 4.21 | 3.60 | 3.70 | 3.38 | 3.65 | 3.86 | 2.58 | 3.97 | 4.71 | 5.37 |
| 4.20 | 3.28 | 3.40 | 3.02 | 3.53 | 3.77 | 3.26 | 4.01 | 4.70 | 5.41 |
| 4.13 | 3.30 | 3.46 | 3.04 | 3.51 | 3.75 | 3.20 | 4.02 | 4.69 | 5.13 |
| 4.07 | 3.34 | 3.50 | 3.10 | 3.52 | 3.78 | 3.18 | 4.05 | 4.70 | 5.41 |
| 4.06 | 3.40 | 3.54 | 3.14 | 3.54 | 3.78 | 3.15 | 4.03 | 4.69 | 5.20 |
| 3.98 | 3.48 | 3.57 | 3.20 | 3.57 | 3.76 | 3.12 | 4.01 | 4.72 | 5.22 |
| 3.89 | 3.53 | 3.63 | 3.26 | 3.60 | 3.82 | 3.09 | 4.07 | 4.68 | 5.25 |
| 3.85 | 3.26 | 3.48 | 3.16 | 3.56 | 3.75 | 3.32 | 4.11 | 4.62 | 5.19 |
| 3.94 | 3.25 | 3.48 | 3.16 | 3.59 | 3.76 | 3.32 | 4.11 | 4.61 | 5.23 |
| 3.89 | 3.25 | 3.51 | 3.20 | 3.62 | 3.77 | 3.32 | 4.15 | 4.62 | 5.27 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 3.79 | 3.16 | 3.45 | 3.15 | 3.59 | 3.75 | 3.30 | 4.14 | 4.62 | 5.28 |
| | 3.73 | 3.12 | 3.41 | 3.11 | 3.59 | 3.73 | 3.29 | 4.15 | 4.62 | 5.95 |
| | 3.67 | 3.07 | 3.37 | 3.07 | 3.57 | 3.71 | 3.29 | 3.99 | 4.63 | 5.30 |
| | 3.49 | 3.08 | 3.33 | 3.02 | 3.59 | 3.69 | 3.24 | 4.16 | 4.58 | 5.33 |
| | 3.47 | 2.95 | 3.30 | 3.00 | 3.57 | 3.66 | 3.23 | 4.17 | 4.61 | 5.83 |
| | 3.86 | 2.98 | 3.29 | 3.01 | 3.56 | 3.65 | 3.23 | 4.17 | 4.61 | 5.41 |
| | 3.56 | 3.00 | 3.32 | 3.02 | 3.56 | 3.66 | 3.24 | 4.17 | 4.62 | 5.37 |
| | 3.60 | 3.03 | 3.34 | 3.05 | 3.58 | 3.68 | 3.27 | 4.11 | 4.63 | 5.32 |
| | 3.62 | 3.03 | 3.34 | 3.07 | 3.57 | 3.68 | 3.25 | 4.17 | 4.62 | 5.27 |
| **Minimum** | 3.47 | 2.95 | 3.29 | 3.00 | 3.51 | 3.23 | 2.01 | 3.71 | 4.07 | 5.06 |
| **Maximum** | 6.43 | 5.29 | 4.00 | 3.97 | 4.89 | 3.86 | 3.32 | 9.04 | 4.72 | 6.78 |
| **Mean** | 4.36 | 3.62 | 3.54 | 3.29 | 3.70 | 3.68 | 2.96 | 4.10 | 4.55 | 5.45 |
| **Median** | 4.16 | 3.56 | 3.51 | 3.20 | 3.60 | 3.72 | 3.13 | 4.00 | 4.61 | 5.37 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Standard deviation** | 0.78 | 0.60 | 0.18 | 0.27 | 0.27 | 0.15 | 0.41 | 0.86 | 0.16 | 0.32 |