The use of Unmanned Aerial Vehicles (UAV) Remotely Sensed Data and Machine Learning Techniques to Predict Maize Yield

By

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Abstract

Given the anticipated growth in the human population, and the challenges posed by climate change, prioritising farming techniques that enhance crop productivity to meet the rising food demand is imperative. The emergence of Unmanned Aerial Vehicles (UAVs) as a new generation of robust remote sensing platforms, mounted with high resolution sensors has facilitated timely and accurate prediction of maize yield in pursuit of sustaining food security. In addition, machine learning techniques have emerged as valuable tools for estimating maize yield over traditional statistical approaches. Therefore, leveraging the new-cutting edge UAV remote sensing technology and machine learning offer great potential to improve the accuracy of maize yield prediction. In this regard, the first objective of this study sought to provide a comprehensive review of studies, seeking to assess the progress and challenges associated with the application of UAV systems and machine learning approaches in estimating maize yield. The review established a discernible gap in literature for studies conducted in the global south, particularly in small-scale farming systems. The review also ascertained a noticeable gap in literature incorporating sophisticated machine learning approaches such as deep learning analytical techniques to precisely predict maize yield. Moreover, the review established that maize Above-Ground Biomass (AGB) is crucial and key indicator for yield potential and crop productivity. Hence, the second objective was to predict maize AGB in small-scale farming systems using UAV-remotely sensed data and deep learning approach. The DJI Matrice 300 UAV mounted with a MicaSense multispectral camera was used to acquire high-resolution images at four maize phenological stages that covered the vegetative (V8 and V12) and reproductive stages (R2 and R5). To account for limitations associated with estimations solely based on UAV-remotely sensed datasets, biophysical measurements and landscape variables were acquired and combined with UAV-derived vegetation indices to model maize AGB using a Deep Neural Network (DNN) model. The V12 maize phenological stage yielded a better overall prediction accuracy (R^2 = 0.74) than the V8 (R^2 = 0.65), R2 (R^2=0.71), and R5 (R^2=0.67) stages. The Deep Neural Network model prediction error was less than 10% across all phenological stages. This study contributes better understanding of precision agriculture facilitated by the cutting-edge UAV-remotely sensed data and machine learning analytical approaches, as a step towards optimising maize production and achieving food security.

Keywords: Maize; Yield; Unmanned Aerial Vehicles; Above-Ground Biomass; Small-Holder Farming; Machine Learning

Preface

This research was conducted at the University of KwaZulu-Natal, Pietermaritzburg Campus, from February 2023 to January 2024 under the supervision of Prof J. Odindi, Prof O. Mutanga, and Dr T.N Matongera.

This document represents the author's original work and has not otherwise been submitted in any form of any qualification fulfilment to any institution. Wherever contributions of others are involved, acknowledgements are clearly indicated by in-text and reference list.

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Dedication

This work is dedicated to my beloved son, Lubanzi Dlamini.

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Acronyms

AGB- Above Ground Biomass

ANN- Artificial Neural Networks

CNN- Convolutional Neural Networks

DEM- Digital Elevation Model

DJI M300- Da-Jiang Innovations Matrice 300

DNN- Deep Neural Networks

FOV- Field of View

GIS- Geographic Information Systems

GNSS- Global Navigation Satellite System

IDB- Index Database

IMU- Inertial Measurement Unit

LAI- Leaf Area Index

LIDAR- Light detection of Ranging

MODIS- Moderate Resolution Imaging Spectroradiometer

NDVI- Normalised Difference Vegetation Index

NIR- Near Infrared

NPK- Nitrogen-Phosphorus-Potassium

PRISMA- Preferred Reporting Items for Systematic Reviews and Meta-Analysis

R- Coefficient of Determination/ Reproductive Stage

ReLu- Rectified Linear Unit

RGB- Red-Green-Blue

RMSE- Root Mean Square Error

RNN- Recurrent Neural Networks

SAGA- System for Automated Geoscientific Analyses

SAVI- Soil Adjusted Vegetation Index

SHAP-SHapley Additive exPlanations

SVM- Support Vector Machine

SWI- Short Wave Infrared

UAV- Unmanned Aerial Vehicle

VTOL-Vertical Take-off and Landing

V-Vegetative Stage

XGBoost- Extreme Gradient Boosting

Chapter One

General Introduction: The use of Unmanned Aerial Vehicles (UAV) Remotely Sensed Data and Machine Learning Techniques to Predict Maize Yield

1.1 Introduction

The proliferating global human population is projected to reach 9.1 billion people by 2050 (Joshi et al., 2023). Currently, more than 820 million people globally are food insecure, and this is expected to increase due to rapid human population growth (Banik, 2019). In Sub-Saharan Africa, one in every four people are subjected to food insecurity (Mabhaudhi et al., 2016). While complete elimination of global food insecurity is unrealistic, literature suggests that increasing food production by 60% yearly can combat this challenge (Muruganantham et al., 2022). Popular staple crops like maize have diverse global applications, including a food source for more than 200 million people, and providing livestock fodder, particularly during dry seasons (Nuss and Tanumihardjo, 2010). Therefore, considering the expected rise in human population and maize's explicit value, enhancing its production is paramount for sustenance. To achieve this, early maize yield prediction plays a vital role in quantifying food availability by the end of the growing season, thereby facilitating informed decisions to optimise the overall yield (Lipovac et al., 2022).

Seed producers and policy makers rely on accurate yield prediction to evaluate hybrids, enhance breeding for subsequent seasons, and employ timely decisions to strengthen food security (Khaki and Wang, 2019). Therefore, timely and accurate maize yield prediction can provide valuable information required to achieve global food security (Lee et al., 2022). Traditional methods such as field surveys, foliar destructive sampling, and visual assessments, often relying on historical data and expert knowledge have been extensively adopted to estimate yield (Chivasa et al., 2017). However, these approaches are outdated, destructive, laborious, subjected to potential sampling errors, and impractical for large spatial extents and repeated observations, hence un-ideal for yield estimation (Rashid et al., 2021). Given the urgent demand to optimise maize production, these approaches are therefore not feasible, necessitating more efficient and timely approaches for precise yield estimations (Schauberger et al., 2020).

Satellite remote sensing has recently shown significant potential to bridge the gap between traditional approaches and accurate yield predictions (Kayad et al., 2019, Li et al., 2022a). Satellite remote sensing provides real time and comprehensive insights to maize crop health and field conditions at various spatio-temporal scales, facilitating precise yield estimations (Medina et al., 2021). Typically, satellite borne sensors capture information by detecting the electromagnetic radiation reflected by maize crops at various wavelengths, thereby facilitating assessment of maize crop health, moisture content, and other key indicators, enabling yield estimations (Kenduiywo et al., 2020, Pede et al., 2019, Omia et al., 2023). For instance, Kayad et al. (2019) used vegetation indices derived from the freely available Sentinel-2 data to predict maize yield with satisfactory results ($R^2 = 0.6$). Despite the success of similar approaches, satellite-borne remote sensing is associated with a number of limitations such as low spatial and temporal resolution, considerably hindering accurate crop information detection at a farm scale (Buthelezi et al., 2023). For instance, the freely available Landsat-8 and Sentinel-2 datasets are limited by the 16 days and 3-5 days revisit frequency, respectively (Arekhi et al., 2019). In addition, Landsat-8 and Sentinel-2 datasets have 30m and 10m spatial resolutions, respectively, providing coarse image data unsuitable for farm scale application (Shao et al., 2019). Moreover, cloud cover often impedes satellite remote sensing by obstructing the transmission of critical electromagnetic wavelengths to maize crops, thereby hindering on board sensors from capturing the desired information (Li et al., 2020b). Considering these limitations, it is imperative to explore and embrace innovative approaches such as Unmanned Aerial Vehicles (UAVs) remotely sensed data to circumvent these limitations and enhance the reliability and precision of maize yield prediction (Zhu et al., 2019a, Wahab et al., 2018, Yang et al., 2022a).

Unmanned Aerial Vehicles have recently emerged as robust new generation of platforms and image acquisition constellations to surmount the challenges associated with satellite based remote sensing (Sishodia et al., 2020). Unmanned Aerial Vehicle-remote sensing has shown potential to bridge the gap between space stations and traditional in-situ field instruments (McCabe et al., 2016, Sishodia et al., 2020). They offer several advantages over satellite remote sensing approach that include easy deployments such as Vertical Take-off and Landing (VTOL), cost-effectiveness, near-real-time imagery acquisition, and ability to overcome weather limitations such as cloud cover (Misra et al., 2022, Saravia et al., 2022, Barzin et al., 2020b). In addition, UAVs are capable of operating with two cameras on a single mission using a dual gimbal connector, thereby collecting two image types in minimal time (Pajares, 2015, Liu et al., 2020). Image sensors are affixed to UAV platforms, enabling them to operate at low altitudes during flight missions, facilitating high spatial resolution image acquisition at different spectral bands (Gaffey and Bhardwaj, 2020). Unmanned Aerial Vehicles-mounted image sensors cover a wide range of the electromagnetic bands including the visible, Red-edge, near-infrared (NIR), and thermal bands, allowing derivation of optimal vegetation indices for estimating maize yield (Istiak et al., 2023, Di Gennaro et al., 2022). However, despite the capabilities of UAV-remotely sensed data, its adoption in predicting maize yield, particularly in marginalised regions such as the global south remains limited (Haula and Agbozo, 2020, Ayamga et al., 2021). Hence, considering the urgent intervention of cutting-edge technology to optimise maize production, more studies need to explore the full potential of UAV–remotely sensed data in the context of yield prediction.

Whereas UAV-derived remotely sensed data offer great potential in estimating yield, the optimal use of this approach alone remains inaccurate, particularly in the context of vertical growing crops like maize (Adewopo et al., 2020a). This is due to the fact that UAVs mounted with Red-Green-Blue (RGB), multispectral, and hyperspectral sensors operate above maize canopy, hence capturing the canopy vegetation index only (Ali et al., 2022). As noted by Barzin et al. (2020a), the canopy vegetation index variation alone cannot provide full variability of maize crops in terms of among others crop height, stalk density, and soil information, thereby restricting precise and accurate yield estimation. In this regard, the incorporation of in-situ biophysical and landscape variables provides comprehensive variability of the maize population, thereby improving maize yield predictions (Franz et al., 2020). Literature has proven the efficacy of incorporating biophysical and landscape variables with UAV-remotely sensed derived vegetation indices on improving maize yield prediction (Adewopo et al., 2020a, Dilmurat et al., 2022b, Sahbeni et al., 2023). Despite the potential valuable insight provided by incorporating various data sources to enhance maize yield prediction, studies exploring this approach remain limited (Adewopo et al., 2020b). Hence, there is need for more studies to explore and embrace the full potential of incorporating various data sources with UAV-remotely sensed derived vegetation indices to strengthen maize yield prediction, and ultimately optimise production.

The combination of multi-source datasets has resulted into comprehensive, highly non-linear and complex datasets, thereby enhancing model calibration and revolutionising the prediction of maize yield (Marques Ramos et al., 2020). Traditional statistical approaches have proven high interpretability and simplicity between maize yield and predictor variables (Kang et al., 2020). Hence, whereas this approach has been fully explored in literature to predict maize yield using linear datasets due to its simplicity, it remains limited to understanding complex and non-linear connections between the predictor variables (Li et al., 2019, Guo et al., 2022). Conversely, deep learning approaches offer great potential by understanding complex and non-linear relationships between predictor variables, hence can be used to achieve precise and comprehensive results in estimating maize yield (Zhai et al., 2023b). Despite the potential contribution of such machine learning techniques in maize yield estimation, this approach remains limited in the field of precision agriculture (Maimaitijiang et al., 2023). Hence, more studies need to explore and embrace the potential of this approach to optimise maize production.

Considering the remarkable role offered by maize for various purposes like human staple food, livestock feed, and processed products such as starch and biofuels (Zhang et al., 2021a, Mohanty and Swain, 2019), it is imperative to recognize the significance of the entire maize crop foliar, including its Above-Ground Biomass (AGB) (Zhu et al., 2019a). In addition, the characterisation and estimation of maize AGB is crucial because it serves as a robust indicator for yield (Naidoo et al., 2021, Cheng et al., 2020, Zhai et al., 2023b). Typically, maize grain yield can be indirectly estimated from the characterisation of maize AGB, on the other hand, livestock fodder can be quantified by predicting the biomass (Yu et al., 2023, Che et al., 2022). Therefore, advancements in precision agriculture, such as the recent development of UAV systems and machine learning techniques offer promising tools to accurately characterize maize AGB for more comprehensive yield estimates (Niu et al., 2019).

The recent advancements in UAV-remote sensing, machine learning techniques, and dynamic approaches to yield estimations such as the characterisations of AGB to forecast productivity is limited in the global south's small-scale farming systems (Wengert et al., 2021, Wan et al., 2020). Since the African continent constitutes more than 18% and 60% of the global population and arable land, respectively, research effort on innovative approaches for enhancing maize production in this region is paramount for addressing food insecurity (Mechiche-Alami et al., 2021, Hossain et al., 2020). South African small-scale farming systems are leading maize produces in Africa, responsible for more than 60% of the country's cropping system, with half of it responsible for securing local food security (Ndlovu et al., 2021b). Hence, capitalising on these settings is paramount for securing global and local food security.

1.2 Aim and objectives

The main aim of this study was to assess the utility and potential of UAV-remotely sensed data and machine learning techniques in predicting maize yield.

1.2.1 Specific objectives

- To review the progress and challenges in the application of UAV-systems and machine learning approaches in estimating maize yield.
- To combine UAV-remotely sensed data with landscape and plant biophysical variables for predicting maize AGB using the deep learning approach.

1.3 Significance of the study

Early prediction of maize yield is paramount in quantifying food availability for the population, thereby reducing hunger and providing insights for the increased production. In this regard, employing high resolution datasets such as UAV-remotely sensed data can immensely contribute towards efficient and precise maize yield prediction. Furthermore, datasets derived from UAV systems, providing high spatial and temporal resolutions, offer an indispensable consideration of including small spatial extents maize crop monitoring requirements. This includes the quick turnover between phenological stages and the short peak photosynthetic activity in maize crops, necessitating the need to employ high temporal UAV-remotely sensed datasets to facilitate precise estimations. Unlike traditional statistical approaches, machine learning techniques offer leveraging capabilities in the context of learning and understanding non-linear and complex patterns within UAV-remote sensing datasets, thereby enhancing maize yield prediction accuracy (Weiss et al., 2020). This innovative approach is not only superior over conventional methods but underscores the need to enhance precision agriculture by offering timely and precise means of efficient maize yield prediction (Pokhariyal et al., 2023).

1.4 Structure of the thesis

This thesis comprises of four chapters. Chapter One provides an introduction, that outlines the aim, main objectives, and the significance of this research. Chapter Two and Three present two standalone research papers that seek to address the proposed objectives. Chapter Two is a systematic review providing a comprehensive analysis of the temporal and spatial distribution of studies and assesses the progress and challenges associated with the application of UAV systems and machine learning approaches in estimating maize yield. Chapter three explores the established gaps and opportunities from the first research paper, thereby combining UAV-remotely sensed data with biophysical and landscape variables to predict maize AGB using deep learning approach in small-scale farming systems of South Africa. Chapter Four presents a synthesis of the whole thesis, outlining significant issues addressed in this study, literature gaps, findings of the research, closing remarks, and recommendations for future research.

Chapter Two

The Integration of Unmanned Aerial Vehicles (UAVs) and Machine Learning Techniques for Predicting Maize Yields for Enhanced Food Security: A Systematic Review

This chapter is based on:

Dlamini, C., Odindi, J., Matongera, T., and Mutanga, O. (Under review). The Integration of Unmanned Aerial Vehicles (UAVs) and Machine Learning Techniques for Predicting Maize Yields for Enhanced Food Security: A Systematic Review. *Scientific African*, Manuscript ID: SCIAF-D-24-00330.

Abstract

The recent developments of Unmanned Aerial Vehicles (UAVs) equipped with smart sensors have demonstrated a remarkable potential to accurately predict maize yield, surpassing existing satellite-based remotely sensed data. In addition, the development of machine learning algorithms, inspired by artificial intelligence, has proven valuable in accurate maize yield estimation than traditional statistical approaches. Using the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) from the Web of science and Scopus scientific databases, this review analyses the temporal and spatial distribution of relevant studies with a focus on evaluating both the progress and challenges in the adoption of UAV systems and machine learning approaches for maize yield prediction. The review identified noticeable gaps in literature for studies conducted in the global south and small-scale farming systems. Despite the remarkable potential provided by advanced deep machine learning approaches for accurate estimations, there is a dearth in literature on maize yield prediction. The progress in yield estimation is further compounded by a comprehensive integration of multi-source datasets with UAV-remotely sensed data to improve the accuracy of maize yield predictions and address limitations associated with estimations solely based on the latter. Moreover, studies on the optimal maize phenological stage for accurate yield estimation remain contradictory. Considering the immense contribution of small-scale farming systems towards food security in the global south, embracing cutting-edge UAV-remote sensing technology and deep learning approaches in this region is necessary. This review provides a better understanding of opportunities provided by UAV-derived data and robust machine learning approaches in predicting maize yield and enhancing food security in the ever-changing climate.

Keywords: Maize Yield; Unmanned Aerial Vehicles; Grain Yield; Above Ground Biomass; Machine Learning; Food Security

2.1 Introduction

The proliferating global human population underscores the need for accelerated food production to sustain and enhance food security (Muruganantham et al., 2022). The global human population is projected to reach 9.1 billion by 2050, hence food production needs to increase by 50% to meet this growing demand (Furukawa et al., 2020). Maize (Zea mays) is one of the most widely produced and consumed cereal crops globally, serving as a staple for the majority of African countries (Abate et al., 2017). The entire maize crop plant has diverse value worldwide, including livestock feed, production of processed products such as starch, ethanol, and bio-fuels (Tollenaar and Lee, 2002, Ngoune Tandzi and Mutengwa, 2019). However, maize production faces significant challenges attributed to edaphic and environmental factors that include climate change, erratic meteorological conditions and degrading soils (Worku, 2018). These variables contribute to the volatility and unpredictability of maize yields, posing substantial risks to global food security (Godde et al., 2021). Hence, in recognition of maize's food and economic value worldwide, adopting robust strategies to optimise its production and address potential production challenges has become paramount (Yang et al., 2021).

Timely yield prediction plays a vital role in sustaining food security by estimating food availability for each season, thereby assisting decision-makers in optimising food distribution, financial management, and adapting cultivation approaches for improved current and future yields (Fathipoor et al., 2019, Naidoo et al., 2021, Joshi et al., 2023). In addition, the foresight enables farmers to evaluate their seed breeds, irrigation patterns and fertilizer application, allowing for timely interventions to address potential shortages, and ensuring a stable and resilient food supply (Rurale, 2021). Literature has proven that yield predictions based on a precise combination of sophisticated technologies and data analytics surpass those from traditional approaches such as field observations and destructive sampling (Barzin et al., 2020b, Quan and Doluschitz, 2021, Teshome et al., 2023). In this regard, the potential of satellite based remotely sensed data and approaches to accurately predict maize yield has been extensively explored recently (Arroyo et al., 2017, Adak et al., 2023). While they have demonstrated remarkable success in providing comprehensive insights for maize yield prediction, they are impeded by among others lengthy revisiting cycles, low spatial resolution, and potential interference by cloud cover (Michez et al., 2018, Chivasa et al., 2017).

The recent emergence of Unmanned Aerial Vehicles (UAVs) systems, mounted with sophisticated sensors, has pioneered a new era for agricultural crop discrimination and accurate maize yield prediction (Feizolahpour et al., 2023, Bao et al., 2023). Unmanned Aerial Vehicles offer promising solutions to limitations associated with traditional satellite derived remotely sensed data and approaches, such as efficacy in incorporating smaller spatial extents by providing high spatial resolutions and cloud-free image data (Arroyo et al., 2017, Chivasa et al., 2021, Teshome et al., 2023). Unmanned Aerial Vehicles systems can be operated a few meters above maize canopy and below cloud cover at user-defined areas of interest and frequency (Ronchetti, 2020). Additionally, UAV systems can be flown any time of the day, thereby encompassing the short photosynthetic active window in maize crops, facilitating precise yield prediction (Abrahams et al., 2023). Unmanned Aerial Vehicles-mounted with sophisticated multispectral, hyperspectral, thermal or Light detection of Ranging (LIDAR) sensors cover a broad spectrum of electromagnetic bands, encompassing the visible, Red-edge, Near-infrared (NIR), and thermal portions, which are crucial for efficient and precise maize yield predictions (Quan and Doluschitz, 2021). Despite the potential success exhibited by UAV-remotely sensed data in timely and feasible maize yield forecasting, these datasets remain largely underexplored (Haghighattalab et al., 2017).

Studies have consistently demonstrated the value of machine learning approaches in harnessing the potential of UAV-remotely sensed data in precise maize yield prediction (Khan et al., 2023, Adak et al., 2021, Nguyen et al., 2023, Han et al., 2019b). Machine learning algorithms are artificial intelligence powered computational models that replicate human intelligence into computer systems (Vong et al., 2021). These algorithms are capable of self-learning from labelled and unsupervised datasets and surpass human-expert results (Vong et al., 2021). Machine learning facilitates the development of robust models capable of interpreting valuable remotely sensed information for feasible and efficient yield prediction (Vong et al., 2021, Yu et al., 2023, Zhai et al., 2023b, Han et al., 2019b). Literature shows that potent machine learning techniques such as deep learning, Extreme Gradient Boosting (XGBoost), and Random Forest are an excellent choice for maize yield prediction (Demir and Sahin, 2023, Mariadass et al., 2022, Oikonomidis et al., 2022, Elavarasan and Vincent, 2020). However, despite their remarkable potential to make accurate yield predictions, studies reviewing their full potential remain limited (Marques Ramos et al., 2020, Guo et al., 2022, Kumar et al., 2023).

Understanding the potential of UAV-remotely derived data, coupled with robust machine learning approaches is paramount in optimising maize yields (Muruganantham et al., 2022). Although various studies have reviewed the potential of remote sensing in crop yield prediction, very few studies have explicitly assessed the prospect of the new cutting edge, UAV-remote sensing technology coupled with robust machine learning approaches to estimate maize yield. For instance, Chivasa et al. (2017) reviewed the use of satellite remote sensing alone in predicting maize yield, specifically in African farming systems. Hussain et al. (2021) also conducted a review analysis of studies focusing on yield prediction for various agricultural crops using UAV remote sensing. To the best of our knowledge, no study has conducted a bibliometric analysis of both UAV-based remotely sensed data and machine learning approaches, specifically for maize yield prediction at a global scale. In this regard, this study seeks to review literature on the progress made in the application of drone-remotely sensed data and machine learning for maize yield predictions, challenges encountered and potential opportunities. In this study, the review seeks to provide insights and potential opportunities for more accurate and efficient methodologies for maize yield predictions, and indeed other field crops.

2.2 Materials and Methods

2.2.1 Criterial for literature search, inclusion, and exclusion approach

The Web of science and Scopus scientific databases were used to retrieve and compile relevant literature on 10th of November 2023. The search was restricted to the publication's tittle, abstract, and keywords using the following string: ("Unmanned Aerial vehicle" OR "Drones" OR "Unmanned Aerial System") AND ("Maize" OR "Corn") AND ("Yield" OR "Above ground biomass" OR "Biomass") AND ("Predicting" OR "Estimation" OR "Modelling"). The selection and structure of keywords was based on previous similar literature reviews and authors experience. "Machine learning" was not included in the search string to account for publications that did not include this term in the title, abstract, and keywords. "Above ground biomass" and "biomass" strings were incorporated to account for publications that characterised them as surrogates to predict maize yield. Despite maize grains being predominantly used as a staple food for the majority of Africa, some regions crush the entire maize foliar for livestock fodder (Dybek et al., 2023). Hence, in this study, the entire above-ground biomass (AGB), including the maize cob, stalk, and grains are considered yield.

The geographic extent and year of publication were not restricted during the literature search, while non-English written articles and systematic reviews were excluded. The literature searches from Scopus and Web of science databases retrieved 152 and 132 publications, respectively (Figure 2.1). The retrieved publications were framed using the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) statement (Figure 2.1). The retrieved publications from both scientific databases were exported to separate Endnote files to screen for eligibility. The first stage involved filtering eligible articles that are exclusively published in peer-reviewed accredited journals and used UAV-remote sensing and machine learning approaches to estimate maize yield. After an extensive filtering, 80 and 23 publications from Scopus and Web of science, respectively, were deemed eligible for screening. Thereafter, 14 duplicates and 11 non-full-text publications were excluded from the bibliometric database. Furthermore, three journal articles were identified through a manual google scholar search and added to the bibliometric database, making a total of 81 publications for meta-analysis. After the screening process, the bibliographic information such as tittle, year of publication, publication type, authors, geographic region, experimental farm type, predictor variables, maize phenological stage, achieved prediction accuracy, keywords, UAV-model, sensor name, sensor type, and machine learning algorithm, were recorded on a Microsoft Excel spreadsheet for quantitative assessment. The recorded information was converted into numerical dataset for analysis.

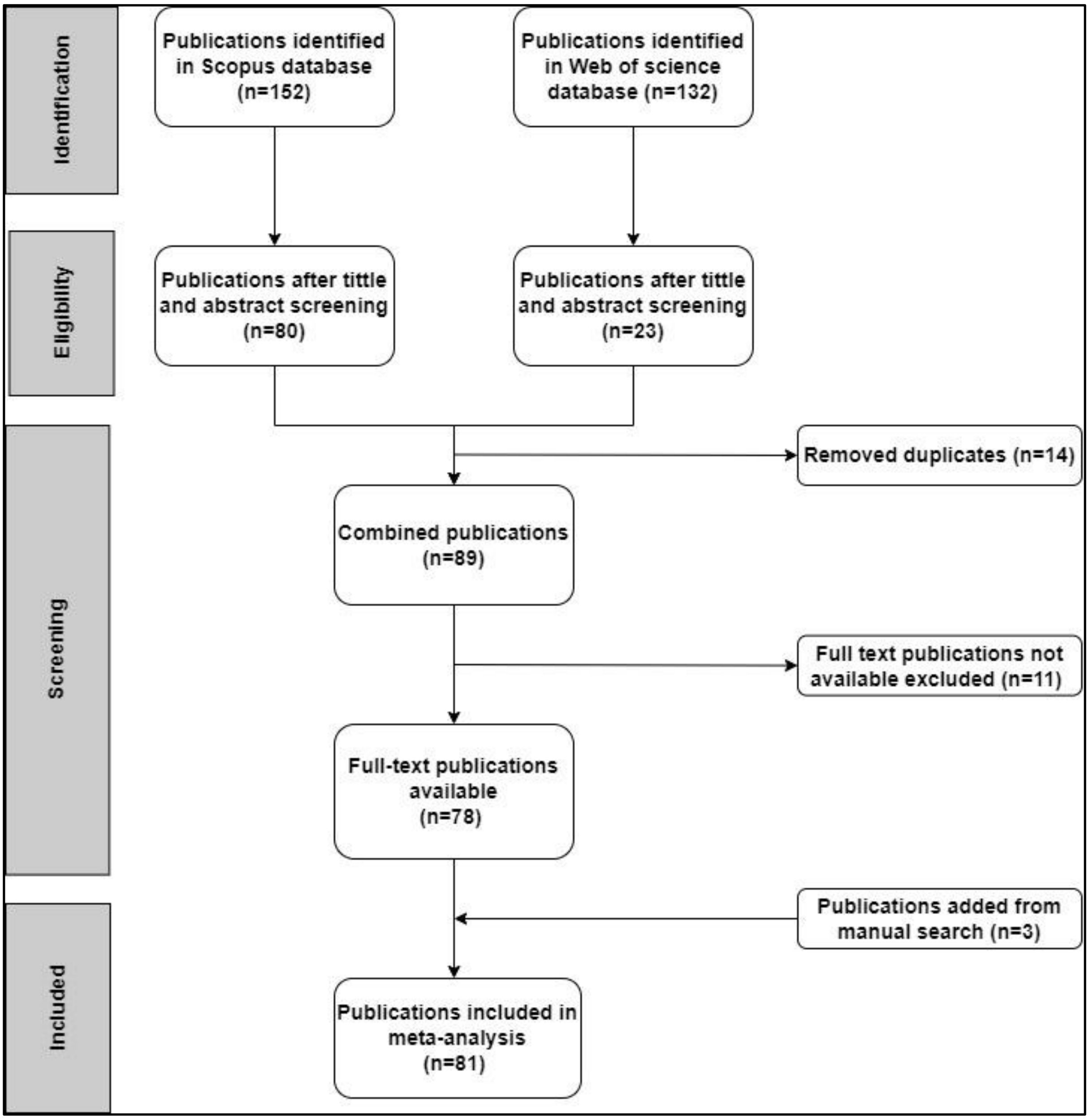

Figure 2.1: PRISMA flow chart showing the publications search process.

2.2.2 Analysis of bibliometric literature

Bibliometric analysis involves quantitative assessment of published articles, essential for evaluating the progress and trends of studies in a research area (Van Raan, 2014). VOSviewer (https://www.vosviewer.com/) software has been extensively used in literature to statistically assess the occurrence and co-occurrence of topical terms used in publications, enabling for assessment of evolutionary trends evaluation (Raparelli and Bajocco, 2019, Videras Rodríguez et al., 2021, Iqbal et al., 2023). The tittle and abstract information of the 81 publications were used in the VOSviewer to assess the evolution of concepts and topics in predicting and mapping maize yield using UAV-remote sensing and machine learning techniques (Figure 2.2 and 2.3).

To account for possible biased reporting, the PRISMA checklist was used to validate the results (http://www.prisma-statement.org/).

2.3 Results

2.3.1 Publications characteristics

The evolution of topical concepts shows a growth of “UAVs” in “forecasting” or “yield prediction”, including “grain (agricultural product)” during the period 2020-2021 (Figure 2.2). Prior to the year 2021, “plant height” was extensively incorporated in predicting maize yield (Figure 2.2). During the year 2021-2022, an extensive incorporation of “machine learning” techniques such as “deep learning” and “support vector machine” alongside “multispectral images”, “infrared devices” and “agricultural robots” is observed (Figure 2.2).

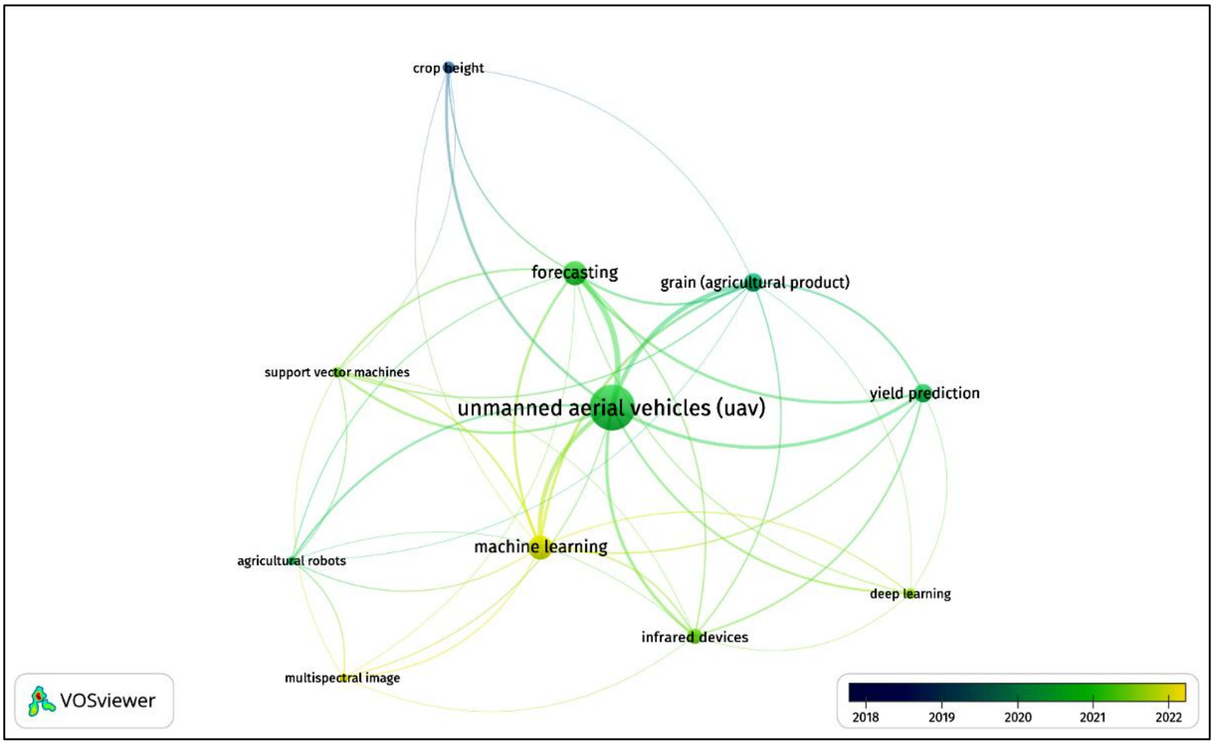

Figure 2.2: The direction and evolution of topical concepts in predicting maize yield.

The VOSviewer diagrammatic output shows different clusters (Red, blue, and green) of the identified keywords, with occurrence and co-occurrence denoted by the same colour (Figure 2.3). The topical concepts shown by the blue cluster were “unmanned aerial vehicles (UAV)”, “precision agriculture”, “support vector machine”, “regression analysis”, “aircraft detection”, “decision trees” and “crop height” (Figure 2.3). This cluster directly implies the extensive utility of UAVs cutting-edge technology, combined with plant height data and machine learning techniques to precisely predict maize yield. The red cluster shows the following keywords: “maize”, “above ground biomass”, “leaf area index”, “NDVI”, “*Zea mays*” “crop yield”, “multispectral image”, “agricultural robots”, and “algorithm” (Figure 2.3). This cluster articulates incorporation of advances in agricultural robots and maize yield estimation parameters such as the multispectral dataset, NDVI, AGB, and LAI. The green cluster shows the following keywords: “machine learning”, “forecasting”, “grain (agricultural product)”, “vegetation indices”, “deep learning”, “infrared devices”, and “yield prediction” (Figure 2.3). This cluster articulates adoption of infrared device-derived datasets and deep learning computer advances in the context of maize yield prediction.

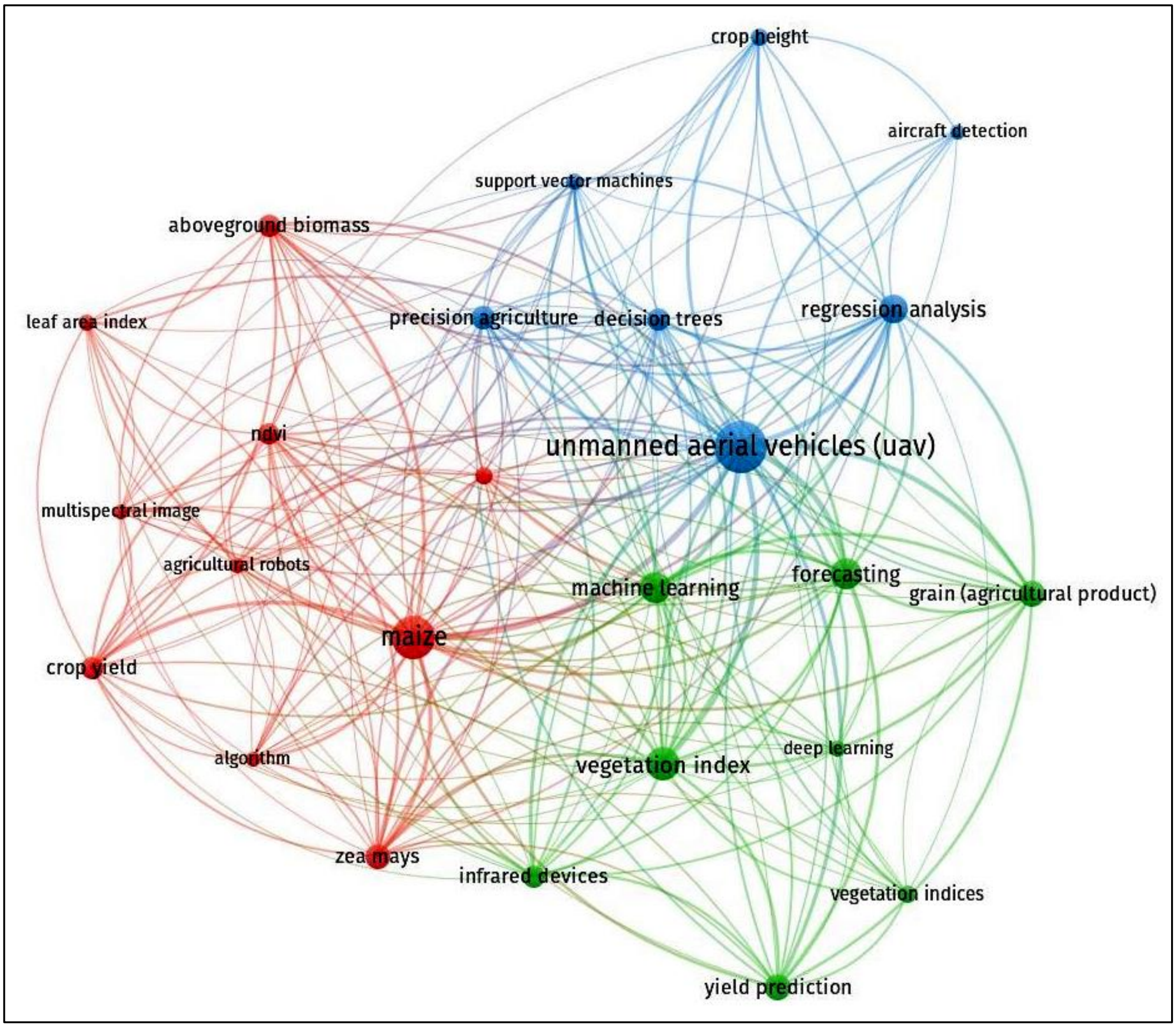

Figure 2.3: Cloud tag indicating topical concepts in predicting maize yield derived from abstracts and titles.

2.3.2 Progress in publications focusing on maize yield prediction

The study identified 35% and 65% of studies characterising maize AGB and grains as yield, respectively. Maize grains are predominantly used for cereal and milled flour production for the majority of Africa, USA, and China (Erenstein et al., 2022). However, some regions including Brazil, Spain, Canada, and Iran crush the entire maize foliar for livestock fodder (Ramzan et al.). In addition, literature has shown that characterising the entire maize above-ground biomass is a robust approach for estimating grain yield, due to the strong correlation observed between maize AGB and yield (Cheng et al., 2020, Yang et al., 2021, Yue et al., 2023a). Therefore, the entire AGB, including both the maize cob and stalk is considered productivity in determining maize yield (Verbytskyi, 2023). Figure 2.4 shows publication and trends of studies that used UAV-remote sensing and machine learning to estimate maize yield, with the year 2014 recording the first publication. The year 2023 (31%) and 2021 (22%) recorded the highest number of publications, and no articles were published during the year 2015 and 2017 (Figure 2.4). A gradual increase in the number of publications from year 2014 to 2021, with a slight decline in 2022, and significant increase in 2023 is noted in Figure 2.4. Nevertheless, the significant increase in publications shows the popularity of cutting-edge UAV-technology and machine learning for predicting maize yield.

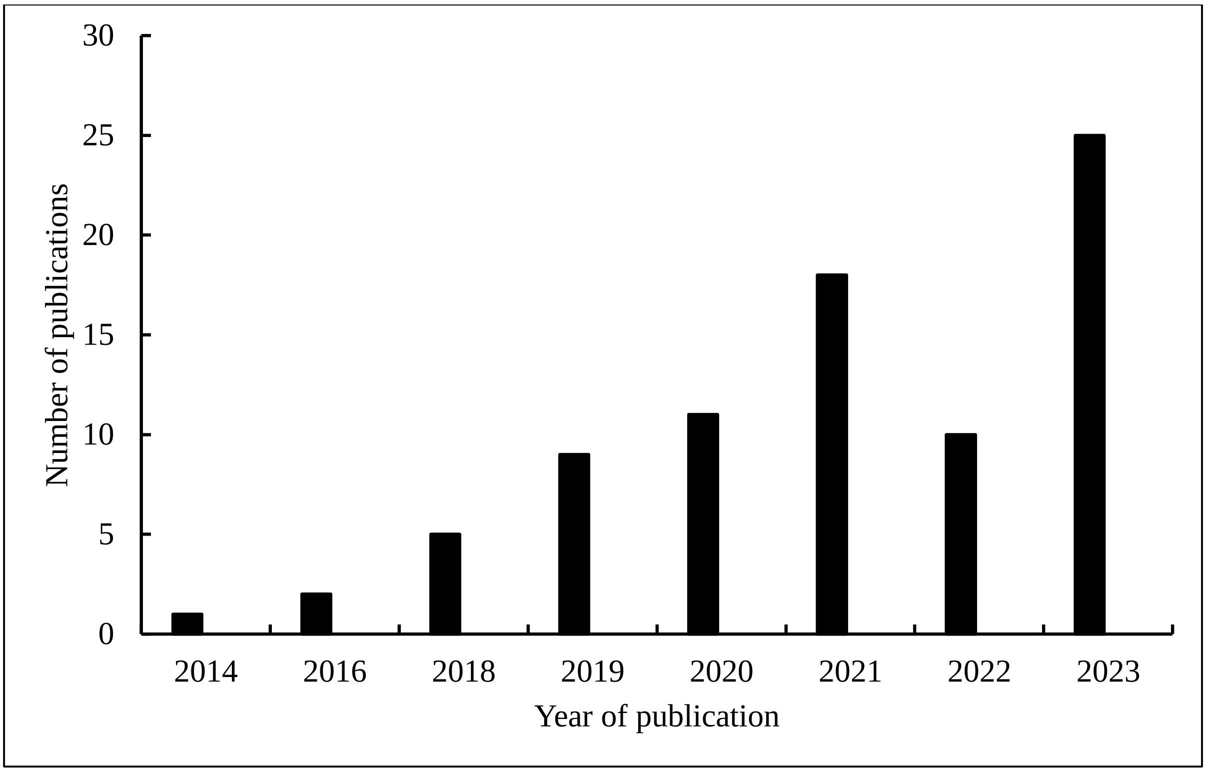

Figure 2.4: The temporal distribution of publications using UAV remote sensing and machine learning for maize yield estimation.

2.3.3 Geographic distribution of publications

Figure 2.5 illustrates the spatial distribution of publications at a global scale. A concentration of publications in the global north, in contrast to the global south, is distinguishable. Notably, the Asian region (38%) and North American region (33%) exhibit a substantial prevalence of publications compared to other continents, including Africa (7%), Europe (12%), and South America (9%). Examining individual countries reveals that most publications originate from China (30%), followed by the United States of America (27%). Within the South and North American region after the United States of America, Brazil (7%) and Canada (5%) have the highest publication frequencies. In other regions, Zimbabwe (4%) and Portugal (4%) had the highest publication rates. Iran and Germany had relatively higher publication frequencies (3%). Remarkably, the remaining countries (see Figure 2.5) exhibit a consistent distribution of 1% publications over the 11-year timeframe, portraying a global spread of publications addressing the application of UAV-remote sensing and machine learning intelligence in predicting maize yield worldwide. In addition, most publications (78%) were carried out in experimental plots, 19% on commercial farms, and only 4% on small-scale farming systems. This implies that most studies were experimental, rather than applications to small-scale and commercial farming systems.

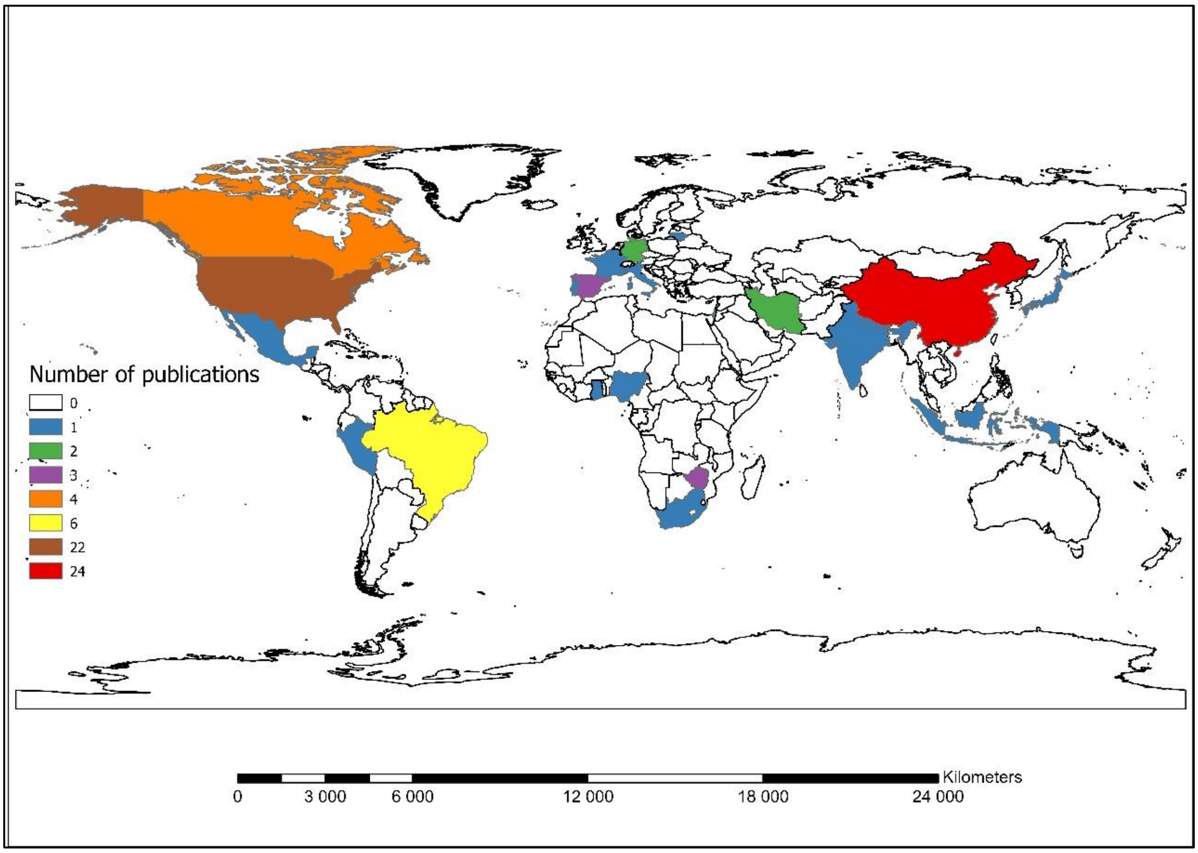

Figure 2.5: The global distribution of publications using UAV systems and machine learning to predict maize yield.

2.3.4 Unmanned Aerial Vehicles platforms

The development of UAV-platforms has facilitated efficient and timely crop monitoring in predicting maize yield (Fan et al., 2022). Unmanned Aerial Vehicles are typically operated autonomous from the ground using a controller (Zuo et al., 2022). Unmanned Aerial Vehicles incorporate a Global Navigation Satellite System (GNSS), a gimbal connector, and a controller (Okulski and Ławryńczuk, 2022). Three types of UAV platforms are commonly used; the rotary-wing, unmanned gas helicopter, and fixed wing UAV. The rotary and fixed wing UAVs are commonly embedded with sensors, allowing for data collection in agricultural crops (Xie and Yang, 2020). The rotary-wing UAV offer several advantages such as Vertical Take-off and Landing (VTOL) and hovering and manoeuvring in tight spaces, subsequently facilitating efficient data collection at a farm scale (Hashim et al., 2023). A selection of UAV models employed in more than one publication has been illustrated is Figure 2.6 to depict preferred drone systems. The DJI series is fully rotary wing, and has experienced a substantial increase in market presence, featuring multiple UAV platforms (Figure 2.6). For instance, the DJI

Phantom 4/pro/pro v2.0 has been used in 24% of the studies followed by the DJI Matrice series (12%).

The development and frequent use of fixed wing UAV models such as Tufwing UAS, Sensefly eBee, and eBee fixed wing, and eQuantix mapper has been noted in this study. However, only 19% of the frequently used fixed wing UAV systems have been used for maize yield prediction. This is because fixed wing UAV excel in endurance and long-range tasks, such as commercial farming and forest monitoring (Misra et al., 2022). Nevertheless, UAV market has drastically increased, allowing for reduced pricing, and purchase of cost-effective drone models that can facilitate maize yield predictions. The substantial increase in the UAV platform market has allowed researchers a wide range of choice, enabling low-income regions to option for cost-effective drones. Moreover, the substantial increase of UAV market allows researchers to evaluate different UAV models for informed drone model selection in future research (Zhu et al., 2019b, Guo et al., 2022, Adak et al., 2023).

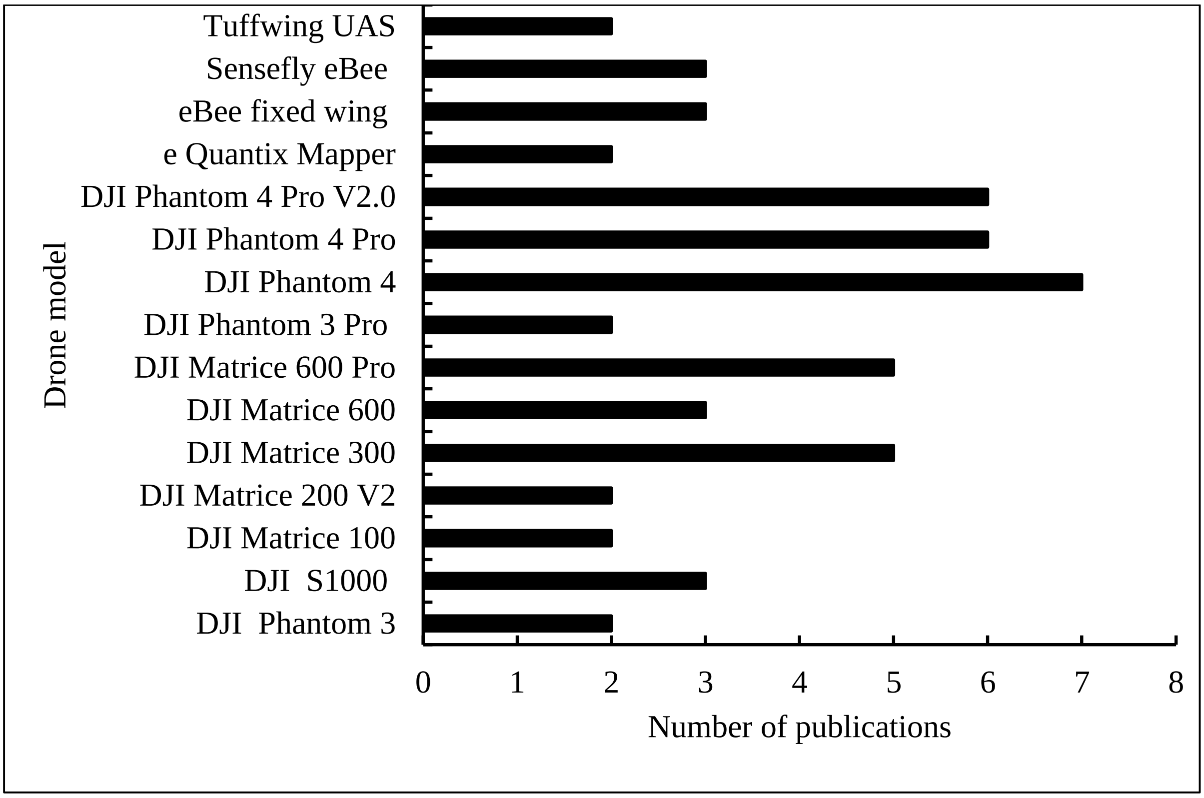

Figure 2.6: The distribution of publications based on the most popular UAV platform models.

2.3.5 Unmanned Aerial Vehicles mounted sensors

In remote sensing, UAVs serve as aerial platforms for image sensors (FEI, 2014). A gimbal connector combines the camera and the drone through the Inertial Measurement Unit (IMU), facilitating orientation and ensuring steady motion for precise image capture (Nex et al., 2022).

Figure 2.7 illustrates the frequency of UAV-mounted sensors used in the prediction of maize yield. Specifically, the multispectral and Red-Blue-Green (RGB) derived datasets have been extensively used in 44% and 27% of the reviewed publications (Figure 2.7). Typically, RGB sensors only capture data within the visible portion of the electromagnetic spectrum, ranging from 400 to 700 nm wavelength (Wang et al., 2021). In contrast, the multispectral remote sensing involves the acquisition of visible, Near-infrared (NIR), and Short-Wave Infrared (SWI) images in several broad wavelength bands (Olson and Anderson, 2021). Multispectral sensors provide additional spectral information, facilitating enhanced analysis and precise maize yield predictions compared to RGB.

Figure 2.7 illustrates that only 6% of the publications have used hyperspectral derived datasets to predict maize yield. Hyperspectral remote sensing has many narrow bands compared to multispectral sensors (Sibanda et al., 2021). Hyperspectral remote sensing offers high spectral resolution bands, making them more sensitive to small changes in maize canopy, facilitating finer pixels and precise yield predictions (Udelhoven et al., 2013, Elsayed and Darwish, 2017). Despite the robustness of this approach, its use remains limited due to high cost and computational power demand during pre-processing (Wang et al., 2016, Khanal et al., 2020). In addition, 21% of the studies integrated multiple sensors as shown in Figure 2.7 for image fusion and comparisons, allowing for efficient maize yield predictions (Nguyen et al., 2023, Guo et al., 2023, Dilmurat et al., 2022a).

Figure 2.7 further illustrates the prediction accuracies of various UAV-coupled image sensors, with hyperspectral, multispectral, RGB, and LIDAR achieving average accuracies of $R^2 = 0.84$, $R^2 = 0.78$, $R^2 = 0.89$, and $R^2 = 0.98$, respectively. Additionally, some studies have incorporated a combination of sensors, such as RGB + multispectral, attaining a highest prediction accuracy of $R^2 = 0.9$ (Figure 2.7). Other combinations demonstrate reasonable accuracy while the RGB + NIR combination shows the lowest ($R^2 = 0.57$) prediction accuracy (Figure 2.7). Notably, literature reveals a trend where multispectral sensors are often preferred due to their intermediate position between the less effective RGB and the superior hyperspectral and LIDAR systems, providing a balanced and reasonably accurate maize yield prediction (Peng et al., 2021, Preethi et al., 2021, Quan and Doluschitz, 2021).

Debates persist on the choice between RGB and multispectral sensors for maize yield prediction. Some researchers advocate for RGB due to its cost-effectiveness, while others emphasize the limitations of RGB that provide data restricted to visible sections of the electromagnetic spectrum, missing on the value of crucial bands like the Red-edge, NIR, and thermal sections (Danilevicz et al., 2021, Herzig et al., 2021). However, the choice depends on the specific application, as use of the visible bands with advanced machine learning techniques may be sufficient for accurate maize yield prediction (Aslahishahri et al., 2021). Considering the goal of precision agriculture to cost-effectively maximise outputs, it may be necessary to option for low-cost sensors, provided it yields satisfactory results.

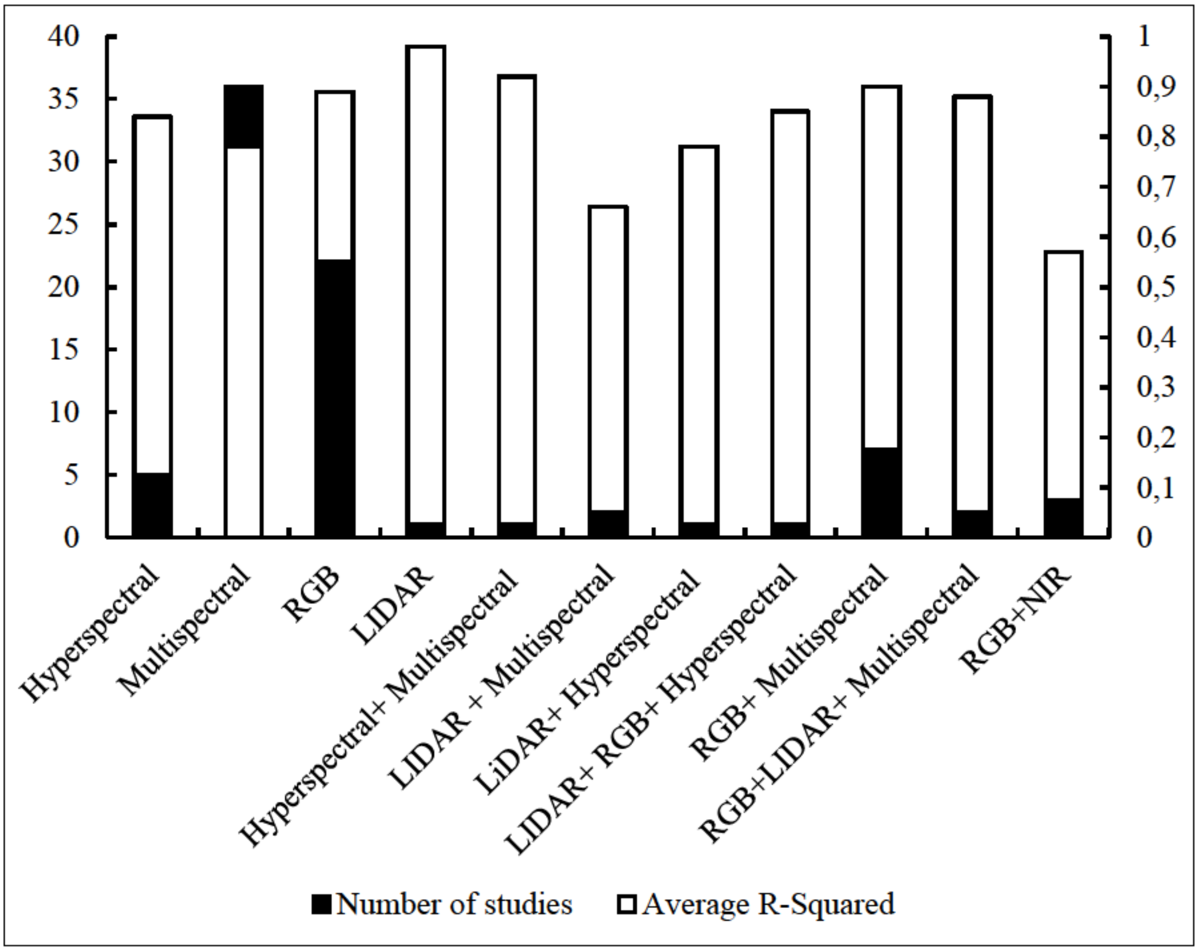

Figure 2.7: The distribution of image sensors used to derive data for estimating maize yield and obtained prediction accuracy.

A selection of image sensor models that were in most publications for maize yield prediction is displayed in Figure 2.8. The MicaSense RedEdgeM sensor, Parrot Sequoia, and Red edge MX MicaSense derived datasets were extensively used to predict maize yield. According to Sibanda et al. (2021), the aforementioned sensors incorporate a wide range of the electromagnetic bands, i.e., the visible, Red-edge, and NIR portions. The findings further illustrate the adoption of low-cost digital cameras such as the Sony A74 II RGB, Canon Ixus 110 IS RGB consumer, and 1-inch 20MP CMOS for cost effective yield prediction. However, despite their cost effectiveness, the sensors only provide data in the visible section of the electromagnetic bands, thereby hindering extensive use in maize yield prediction. Moreover, there is a noticeable emergence of hyperspectral sensors such as the Resonon MT 59715, UHD 185 sensor, and MiniMCA12 in the application of maize yield prediction (Herrmann et al., 2020, Yang et al., 2021, Zhang et al., 2021d).

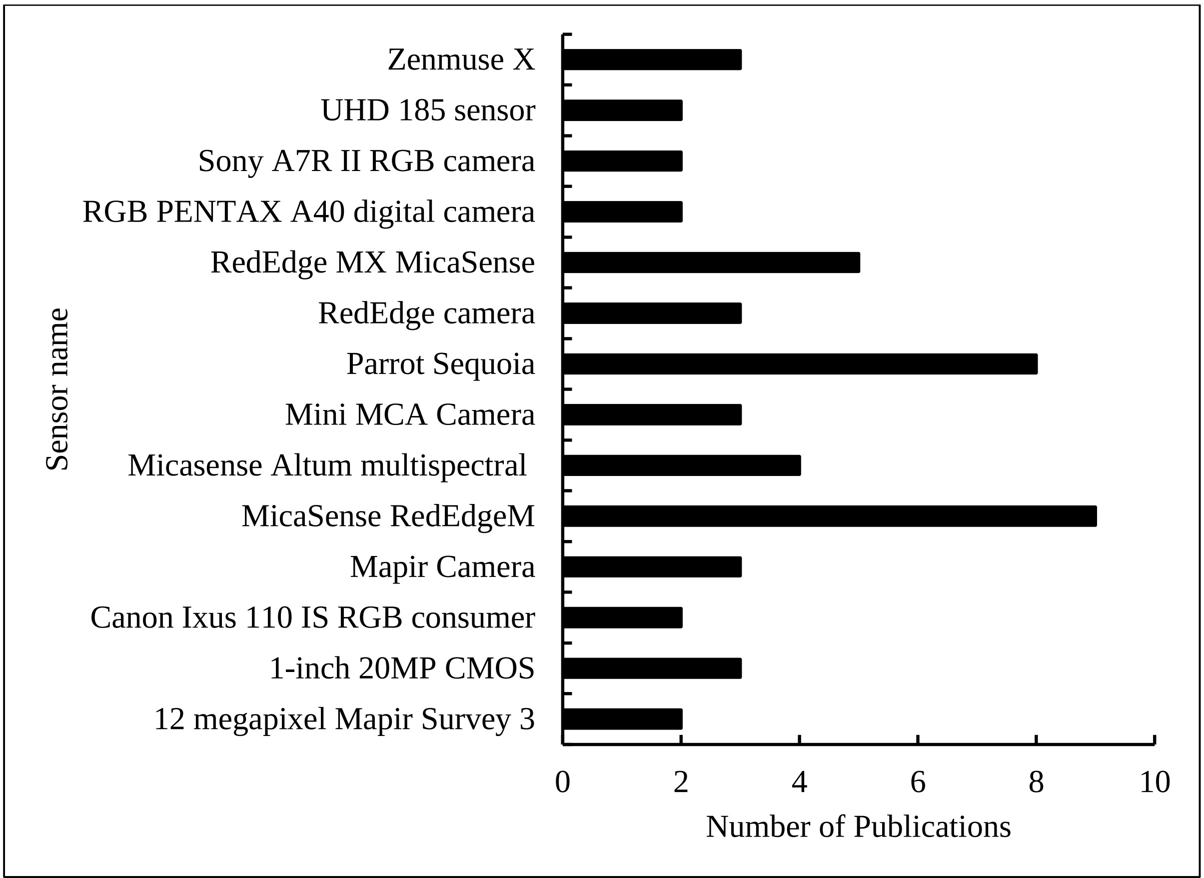

Figure 2.8: The most popular image sensor models for predicting maize yield in the reviewed publications.

2.3.6 Predictor variables incorporated with UAV derived datasets to predict maize yield

Maize crop at a farm scale exhibit comparable vegetation canopy index, yet variations exist in stalk density, height and key biophysical variables such as chlorophyll content and leaf area index (LAI). Whereas UAVs have proven valuable in providing near-real-time and site-specific data on maize crop attributes, enhancing their utility through integration with additional datasets such as biophysical and landscape variables can enhance prediction accuracy. The results indicate that 60% of the publications utilised UAV-derived dataset with other predictor variables (see Figure 2.9) to forecast maize yield, attaining an average prediction accuracy of 80%. Conversely, 40% of the publications estimated maize yield using solely UAV-derived vegetation indices with an average of 79% prediction accuracy (Argolo dos Santos et al., 2020, Baio et al., 2023, Ballesteros et al., 2021).

Figure 2.9 shows that plant biophysical variables including plant height, leaf chlorophyll content, and LAI have been significantly incorporated with UAV-derived dataset to predict maize yield. These variables subdue challenges associated with predictions solely based on UAV remote sensing by increasing variability within the maize population, facilitating more precise estimations. Maresma et al. (2016) improved maize yield prediction accuracy from 24% to 62% by incorporating plant biophysical variables with UAV-derived vegetation indices, while García-Martínez et al. (2020) predicted maize yield using UAV-derived vegetation indices with plant canopy and density with a 95% prediction accuracy. Despite the potential proficiency provided by incorporating multi-source data in maize yield prediction, 40% of the studies utilised only UAV-remotely sensed data to estimate yield, necessitating an increased adoption of this approach to optimise predictions.

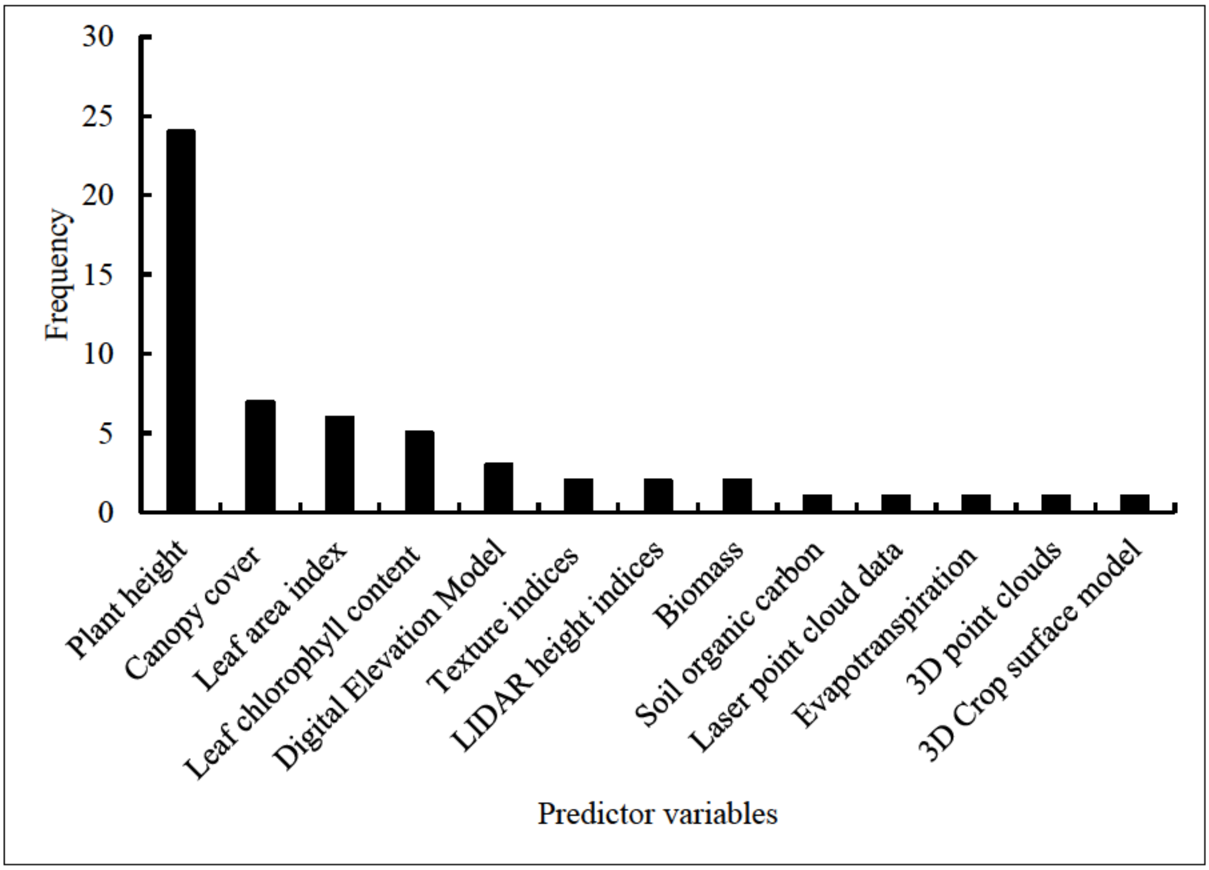

Figure 2.9: The frequency of maize yield predictor variables used in publications.

2.3.7 Machine learning algorithms for predicting of maize yield

Machine learning techniques have demonstrated a remarkable capability to accurately predict yield over other traditional statistical approaches (Adak et al., 2021, Guo et al., 2023, Zhai et al., 2023b, Panda et al., 2010, Bao et al., 2023). According to Sibanda et al. (2021), accurate models are achievable using robust machine learning algorithms and sensitive spectral data. Random forest and linear regression models have been extensively used in 36% and 35% of the reviewed publications, respectively, to predict maize yield (Figure 2.10). Linear regression is a parametric machine learning technique that relies on linear and simple datasets to make accurate predictions (Aslahishahri et al., 2021). Adewopo et al. (2020b) noted that this approach is user-friendly due to among others; ease of implementation, quick training time, and transparency, making it a popular choice in modelling scenarios using remotely sensed data. However, parametric machine learning techniques are often constrained by complex and non-linear datasets, limiting their ability to effectively capture and model intricate relationships within the data (Nyéki et al., 2021). The combination of multi-source datasets often results into non-linear and complex datasets, thereby restricting the adoption of parametric machine learning techniques such as linear regression (Wang et al., 2020).

Conversely, non-parametric machine learning algorithms such as Random Forest and deep learning, including CNN, DNN, and RNN are known for their versatility and effectiveness in remotely sensed data processing (Duarte et al., 2022). Random forest (used in 36% of the publications) is particularly capable of handling non-linear and complex datasets and can mitigate overfitting through the combination of multiple decision trees (Marques Ramos et al., 2020). This approach is considered user friendly due to minimum hyperparameters tuning requirements, making it useful for a wide range of applications (Shahhosseini et al., 2020). Whereas recent novel machine learning techniques such as deep learning algorithms have become popular. Figure 2.10 shows that only 28% of the reviewed publications have used this approach for maize yield prediction.

As aforementioned, deep learning algorithms are potent non-parametric machine learning models utilising neural networks inspired by the architecture of the human brain (Jimenez-Mesa et al., 2023). Deep learning exhibit extraordinary capabilities, often surpassing the predictive prowess of human experts (Fitz and Romero, 2021). In maize yield prediction, this approach holds significant promise due to its ability to apprehend complex patterns and navigate non-linear relationships within the maize data, potentially improving prediction accuracy (Kumar et al., 2023). Despite the robustness demonstrated by deep learning methodologies, their adoption in maize yield prediction and crop modelling in general has been limited (Figure 2.10). Hence, further research is imperative to unlock the full potential of deep learning algorithms in predicting maize yield and other crop modelling applications. In addition, other non-parametric machine learning techniques illustrated in Figure 2.10, such as support vector machine and Extreme Gradient Boost (XGBoost) amongst, have shown potential for accurate yield estimation.

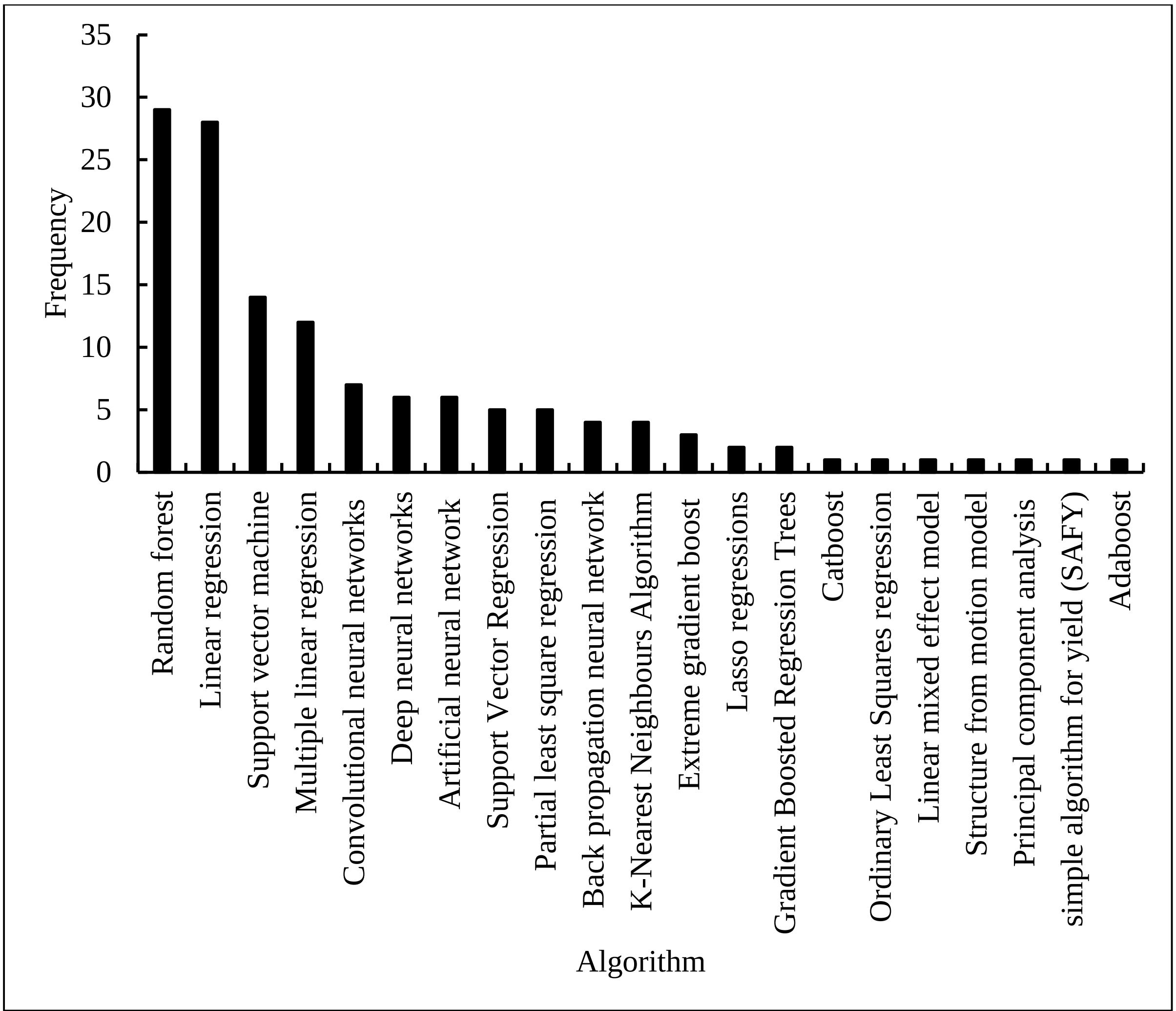

Figure 2.10: The frequency of machine and deep learning algorithms used in predicting maize yield.

2.3.8 Maize phenological stages used to predict maize yield

Maize phenological stages represent unique developmental phases in the crop's life cycle (Yang et al., 2022a). These stages are characterised by unique phenological features such as emergence, silking, grain filling, and maturity (Liu et al., 2021). Maize canopy undergoes significant changes as the phenological stages progress, with early phases characterised by limited canopy cover, as the crop establishes a basic foliar structure during this stage (Kumar et al., 2019). During the mid-vegetative stages, the maize crop canopy cover grows rapidly, thereby increasing leaf area and establishing a dense foliage (Song et al., 2023). A fully developed maize canopy surface area is essential for maximum sunlight capturing, there by facilitating the process of photosynthesis (Han et al., 2018). In remote sensing, full canopy in maize crops facilitate adequate light reflectance, and minimise the influence of soil background (Oehme et al., 2022). Hence, selecting the optimal maize phenological stage for UAV remote sensing is imperative, as it influences the precision and efficiency of data acquisition, thereby facilitating a more precise yield estimation (Yang et al., 2022a). In addition, identifying the optimal maize phenological stage for UAV-remote sensing is imperative as it significantly contributes to cost savings in subsequent seasons of repeated crop monitoring.

Various studies in this review estimated maize yield at various phenological stages, ranging from Vegetative (V) to Reproductive (R) phases (Figure 2.11). Figure 2.11 illustrates the relationship between maize phenological stages and the achieved prediction accuracy for the reviewed publications. The phenological stages range from Emergence (VE) to End of mass gain (R6). The highest prediction accuracy recorded is $R^2 = 0.98$, indicating a strong predictive performance in these publications. Most publications (96%) achieved a prediction accuracy greater than $R^2 = 0.5$, suggesting a general competence in predicting maize yield at these phenological stages. Furthermore, a substantial portion of the publications (85%) attained a prediction accuracy surpassing $R^2 = 0.7$, indicating a higher level of accuracy.

However, these results reveal variability in prediction accuracy among publications that utilised the same range of phenological stages. This suggests an unclearly defined optimal phenological stage for accurate maize yield prediction. Therefore, while a general trend of high prediction accuracy is observed across phenological stages, the specific stage that yields optimal accuracy remains ambiguous and may vary based on the approach or methodology employed. Hence, further research is recommended to comprehensively determine the optimal phenological stage where maize can be accurately estimated. Future research should extend beyond identifying the optimal stage, and further explore and analyse various factors that might influence the predictive performance at that stage. In identifying the optimal maize phenological stage and understanding the associated factors, researchers can streamline data collection efforts, avoiding repetitive and unnecessary data gathering across various stages.

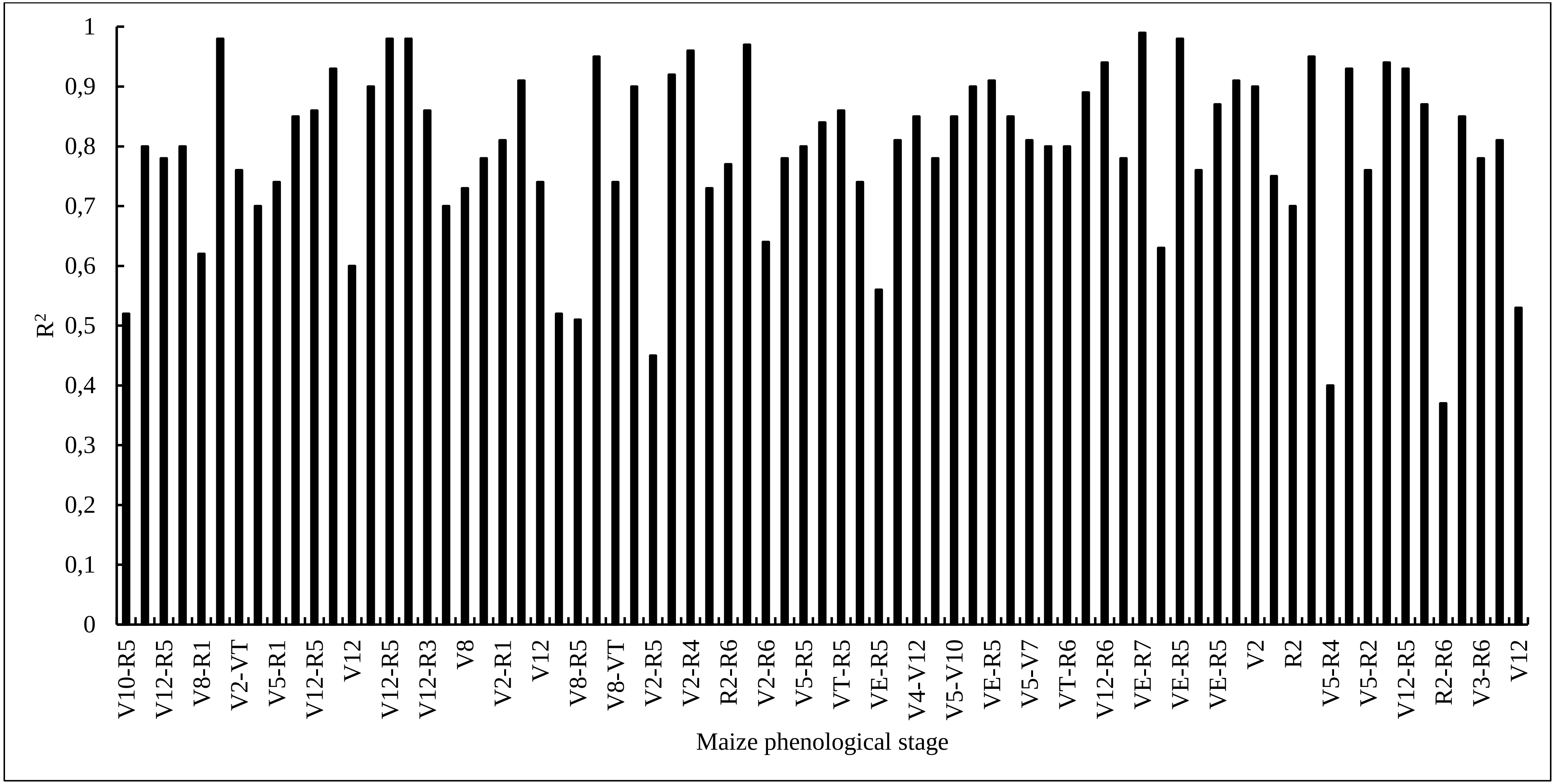

Figure 2.11: The prediction accuracy as influenced by the maize phenological stage employed in the study.

2.4 Discussion

2.4.1 Progress in the application of UAV datasets and machine learning in predicting maize yield

2.4.1.1 Publication trends and their geographic distribution

The recent developments in UAV platforms and smart sensors have allowed for timely and accurate estimations of plant agronomic traits such as maize yield (Danilevicz et al., 2021). A significant increase in the publications from the year 2014 to 2023 has leveraged the value of these platforms and sensors in maize yield prediction. Whereas this review indicates a 44% decrease of publications from the year 2021 to 2022, there was a significant increase in publications after the year 2022 by 150%. Generally, the adoption of UAV technology in various fields of precision agriculture experienced a significant drop during the year 2021 (Gokool et al., 2023, Sibanda et al., 2021, Muruganantham et al., 2022), attributed to the widespread impact of the COVID-19 pandemic. Paraschivu and Cotuna (2021) reported that lockdown measures during the COVID-19 pandemic significantly constrained travel, trade, and research within the agricultural sector. Despite a decrease in publications on maize yield prediction in 2021, a noteworthy recovery has been observed subsequently after 2022, indicating a widespread dominance of UAV systems and smart sensors in precision agriculture.

The findings of this review show that most studies were conducted in China and the United States of America. These countries are regarded as among the most technologically advanced nations, making substantial contribution in artificial intelligence research. Sibanda et al. (2021) reported that initial UAV technologies emerged from China and the United States of America, including Europe, between 1849 and 1916. For instance, in 2006, China, has developed Da-Jiang Innovations (DJI) Science and Technology Co., Ltd that specializes in assembling cost-effective UAV platforms (Xu and Muneyoshi, 2017). This is supported by the findings of this review, indicating that DJI models are the most popular, with China having the highest publications. The United States of America is ranked as one of the top high-income countries with a diverse economy (Freeman and Freeland, 2015). This enables flexible adoption of new artificial intelligence driven technology such as UAV-remotely sensed data for precision agriculture to improve food production. Moreover, the rapid and wide adoption of these technological abilities in precision agriculture has enabled a reduction of purchase costs of UAV systems. Hence, various nations globally have swiftly embraced this cutting-edge technology, as evidenced in this study

Despite the African continent having 60% of global arable land (Jayne et al., 2014), only 7% of the studies were carried out in this region. The Sub-Saharan region is generally characterised by limited economic development, which restrict adoption of artificial intelligence driven technology in agricultural applications (Abrahams et al., 2023). Moreover, effective use of UAV systems in agriculture requires piloting and data processing expertise (Tsouros et al., 2019). The cost of attaining these skills is often prohibitive in the region due to budget constraints. Hence, adopting this UAV cutting-edge technology to effectively predict maize yield has become a challenge in Africa. Furthermore, whereas maize is considered a commercial crop in various regions such as China and United States of America, in Africa its production is mainly in rural small-scale holdings situated in rural areas with limited resources (Grote et al., 2021). Hence, a swift embracement of modern technology is often regarded as not of significance in this region. Considering that Africa (18%) holds second position after Asia (59%) for the largest world human population size, it is imperative to improve maize yield prediction studies to sustain food security in the region (Soko et al., 2023).

This review shows that most studies have been conducted on experimental plots (78%) and commercial farming systems (19%), highlighting a significant gap in the existing literature for studies conducted in small-scale holdings (4%). Maize is a commercial crop and associated with commercial capitalisation, hence more research is based on commercial farming (Kusi et al., 2015, Sitko et al., 2020). On the other hand, more than 80% of maize is produced by small-scale farming systems, with 65%-80% consumed by producers and 20-35% for sale, globally (Malhotra, 2017). This underscores the significant economic value played by small-scale farming systems, while simultaneously sustaining local food security in marginalised communities (Wahab et al., 2018). Hence, there is a pressing need to integrate cutting-edge UAV technology and research on small-scale farming systems to optimise maize production and achieve global sustenance (Adewopo et al., 2020b).

2.4.1.2 Unmanned Aerial Vehicles systems and spectral sensor technologies

The development of various drone models and sophisticated high-resolution sensors has allowed for better articulation of maize yield information (Fathipoor et al., 2019). This study has demonstrated numerous publications (36%) employing the DJI series UAV platform, with a particular emphasis on its utilisation in China and the United States of America. Given China's robust technological capabilities, coupled with DJI being their domestic product, this series has been widely adopted in this region, and its value has been actively promoted globally. Additionally, the United States of America and other middle-income regions, has seamlessly embraced this technological innovation due to its cost-effectiveness. The popularity of the DJI series UAV is attributed to its cutting-edge technology such as VTOL, cost-effectiveness, and the wide variety of models (Misra et al., 2022). Vertical Take-off and Landing allows the UAV to take-off and land vertically, facilitating operation in confined spaces (Okulski and Ławryńczuk, 2022). Furthermore, Vertical Take-off and Landing allows horizontal flight mission after taking off, facilitating broader coverage of the maize field in a single mission (Hashim et al., 2023). Also, various DJI series UAVs allow for GPS payload mounting, which facilitates precise georeferencing of the captured images and subsequently precise maize yield monitoring (Czyża et al., 2023). Georeferenced images allow better integration with other data types such as ground based biophysical measurements for validation purposes (Alexopoulos et al., 2023). Hence, the DJI series with its versatile characteristics for maize crop monitoring offer a promising tool for precise yield estimates.

Advancements in data pre-processing methodologies has facilitated the integration of diverse sensor types, enabling the combination of spectral, spatial, and temporal information from multiple images into unified representation for a specific application (Pandit and Bhiwani, 2015). For instance, Nguyen et al. (2023) achieved satisfactory results (R^2 = 0.34-0.85) by combining LIDAR, RGB, and multispectral images to form one hybrid and superior image for precise estimation of maize grain yield. Certain studies employ varied sensors, utilising them exclusively for specific applications, such as Adak et al. (2023) for instance who used the RGB and multispectral datasets independently to predict maize grain yield with satisfactory results (R^2 = 0.8). This review indicates various studies such as Guo et al. (2023), Guo et al. (2022), She et al. (2020) that combined different datasets from various sensors to enhance the precision of maize yield prediction. Generally, the combination of multi-sensor derived data offer a more comprehensive insight into maize crop growth information and enhanced yield estimations.

Due to cost-effectiveness and easy processing, multispectral and RGB sensors have been widely used to predict maize yield as evidenced in this review (Argolo dos Santos et al., 2020, Baio et al., 2023, Ballesteros et al., 2021, Ballesteros et al., 2018). The MicaSense series is particularly popular due to its extended electromagnetic region that incorporate the Red-edge, NIR, and thermal section, allowing for cost effective assessment of intricate maize crop physiological parameters with high accuracy (Sunoj et al., 2023, Shao et al., 2022). On the other hand, hyperspectral remote sensing provides a significant wide range of the electromagnetic spectrum (100 to 200 spectral bands) with many narrow band widths, providing high spectral resolution images (Herrmann et al., 2020). Despite its remarkable accuracy observed in this study ($R^2 = 0.84$ on average), this dataset is associated with high costs and limited by data complexity and high computational power demand (Zhang et al., 2021c, Shukla and Kot, 2016, Zandler et al., 2015). Hence, few studies swiftly embracing hyperspectral remote sensing in the predicting maize yield are limited. While not reaching the same level of detail as hyperspectral remote sensing, multispectral sensors are preferred because they provide adequate crop information, enabling accurate crop yield predictions (Ali et al., 2022). Furthermore, whereas RGB sensors offer a reasonable maize crop discrimination and sensing at low costs, the dataset may restrict the detection of critical physiological parameters and considerably reducing the reliability of maize yield prediction (Shu et al., 2023). Considering the aim of precision agriculture of maximising outputs at low inputs, it is imperative to adopt low-cost sensors with efficient attributes such as multispectral remote sensing for precise yield estimates.

2.4.1.3 The role of machine learning algorithms in predicting maize yield

Machine learning algorithms have become popular for accurate maize yield prediction, surpassing the existing traditional statistical approaches (Matiza et al., 2023). This review highlights the predominance of parametric and non-parametric machine learning techniques in maize yield prediction using UAV-remote sensing datasets. These machine learning approaches have shown value in various aspects of remotely sensed data processing, including multi-source and non-linear datasets (Nguyen et al., 2023). Parametric approaches such as linear and multi-linear regression approaches for instance, have shown popularity in UAV-remote sensing-based yield prediction (Sapkota and Paudyal, 2023). This approach is preferred because of its simplicity, and predefined parameters, making it suitable for handling small datasets and linear relationships (Saravia et al., 2022). Despite these advantages, parametric approaches cannot adequately handle non-linear and complex relationships in datasets for accurate maize yield prediction.

Non-parametric approaches such as Random Forest, amongst other extensively used algorithms, has demonstrated an ability to surpass parametric machine learning and enhance the accuracy, visualisation, and estimation of maize yield in various studies (Killeen et al., 2022, Adak et al., 2023, Baio et al., 2023). Specifically, Random Forest is preferred because it uses bagging concept and independent trees, facilitating low model bias and quick training (Liu et al., 2023b). In addition, advanced computer techniques such as deep learning algorithms, including Deep Neural Networks (DNN), Convolutional Neural Networks (CNN), and Recurrent Neural Networks (RNN) have shown a remarkable ability to handle large, non-linear, and complex datasets surpassing many algorithms (Khan et al., 2023, Kumar et al., 2023). Deep learning is a branch of non-parametric machine learning that simulates human brain neurons in computer systems and is capable of making accurate predictions (Guo et al., 2023). Despite its robustness, this study indicates that it is still underutilised in maize yield prediction studies. Deep learning is a challenging model that requires large datasets to learn from, which is often difficult to obtain especially in small-scale farming systems (Shaikh et al., 2022). Additionally, this machine learning technique is significantly prone to overfitting (García-Martínez et al., 2020). Hence, few studies have embraced this advanced machine learning technique in maize yield prediction. However, there are regularisation and dropout neural network packages designed to mitigate overfitting, and fine-tuning optimal hyperparameters can lead to an accurate model for predicting maize yield (Nguyen et al., 2023). Due to its potential, there is need for an exhaustive investigation into the full potential and capability of deep learning algorithms for maize yield prediction to optimise production.

2.4.2 Challenges and future directions in maize yield prediction

Unmanned Aerial Vehicles mounted with smart-high-resolution sensors in concert with machine learning algorithms hold great promise for the precise prediction of maize yield (Teshome et al., 2023). Nevertheless, challenges associated with 2-dimensional remote sensing, such as instances where maize crops exhibit identical canopy vegetation indices despite variations in biophysical and landscape variables, contribute to yield prediction errors (Adewopo et al., 2020b). This presents a pressing need to use 3-Dimensional remote sensing such as LIDAR datasets, and field in-situ measurements for accurate crops visualisation and improved prediction accuracy. However, LIDAR datasets and in-situ measurements can be expensive, and labour intensive particularly for large spatial extents, respectively (Jin et al., 2020, Khun et al., 2021). In addition, restricted access to sophisticated sensors like hyperspectral cameras and limited computational power for pre-processing has significantly hindered effective maize yield prediction, despite their recognised potential outlined in this review. Moreover, deep learning capabilities hold promise for precise yield predictions, however, the model necessitates extensive datasets for effective learning (Nyéki et al., 2021). Acquiring such large datasets, especially in confined spatial extents, poses a challenge, consequently restricting their utility (Yu et al., 2023). In addition, deep learning computer techniques are sophisticated and complex models, requiring adequate training for users, thus limiting its widespread adoption (Fitz and Romero, 2021). Despite the successes of machine learning and UAV-based observations, the adoption of this approach in marginalised and high potential agricultural regions such as Africa remains limited.

Africa holds more than 60% of global arable land, however the region lacks funding to invest in cutting-edge technology to optimise maize production (Langyintuo, 2020). Unmanned Aerial Vehicles systems tend to be affordable in countries with high and mid-range incomes, however, their accessibility remains limited in many parts of Africa due to economic constraints (Haula and Agbozo, 2020). In addition, the insufficient availability of funding further restricts the provision of adequate training for operating UAV systems in Africa, thereby slowing the adoption of the technology (Mugala et al., 2020). Given the significant intrinsic value of African land for agricultural production, along with the pivotal role played by small-scale farming systems in maize cultivation, it is imperative to prioritize funding allocations in this region. Therefore, it is essential to foster increased collaboration between public and private organisations in the investment of cutting-edge technologies in this region, aimed at optimising maize production and sustenance.

In this regard, this study recommends future research to embrace the utility of UAV systems and machine learning approaches in the global south to address the evident research gap. Prioritising studies that focus on optimising agricultural production in small-scale farming systems is essential for achieving local and global food security. In addition, future research should also explore the full potential of deep learning computer advances, especially for yield prediction, considering their promising ability for accurate predictions. Furthermore, there is need for studies that investigate the optimal phenological stages for data collection, aiming to streamline processes and reduce costs associated with repeated observations. Identifying optimal phenological stages for accurate yield estimation can significantly improve precision of data collection efforts. Moreover, researchers should embrace a holistic approach by incorporating various predictor variables to address the limitations associated with relying solely on UAV remote sensing. Integrating diverse data sets can enhance the robustness of analyses, providing a more comprehensive understanding of agricultural landscapes and maize crops biophysical variables, contributing to informed decision-making for sustainable farming practices.

2.5 Conclusion

This study has provided a comprehensive systematic review on the adoption of UAV-remotely sensed data and machine learning techniques for predicting maize yield. The literature review underscores that UAV-remotely sensed data is capable of providing high resolution near-real time data, and machine learning allows for drawing meaningful findings from the dataset, facilitating accurate maize yield prediction. Despite the significant contribution of small-scale farming systems towards maize production, and the majority of arable land being located in the global south, a noticeable lack of research in these settings has been established. This is mainly due to lack of funding opportunities and skilled personnel for purchasing and operating drones in this region. This review identified a substantial integration of plant biophysical variables, including plant height, with UAV-remotely sensed data, aiming to enhance the accuracy of yield estimation and address limitations inherent in predictions solely based on UAV-remote sensing. Unmanned Aerial Vehicle systems and machine learning computer advances offer promising solutions to optimising maize production and sustaining food insecurity. Hence, this study recommends a wide adoption of artificial intelligence driven approaches such as UAV-remotely sensed data and deep learning approaches in small-scale faring systems, particularly in the global south to enhance production and sustain food security.

Chapter Three

The use of Unmanned Aerial Vehicle (UAV) remotely sensed data and biophysical variables to predict maize Above-Ground Biomass (AGB) in small-holder farming systems

This chapter is based on:

Dlamini, C., Odindi, J., Mutanga, O., and Matongera, T. (Under review). The use of Unmanned Aerial Vehicle (UAV) remotely sensed data and biophysical variables to predict maize above-ground biomass in small-scale farming systems. *Precision Agriculture*, Manuscript ID: PRAG-D-24-00127.

Abstract

Considering the current and projected increase in human population, approaches to optimise crop productivity to meet the rising demand are paramount. Hence, timely and accurate maize above-ground biomass (AGB) measurements allow for development of models that can precisely predict yield prior to harvesting, useful for food production management and sustenance. The development of Unmanned Aerial Vehicles (UAVs) as a new generation of robust remote sensing platforms, mounted with high-resolution sensors allow for timely and accurate prediction of maize AGB in pursuit of sustaining food security. Given that the majority of maize is produced in small-scale farming systems characterised by technical inadequacy of existing satellite data, employing high spatial and temporal resolution datasets, such as UAV-remotely sensed data offer a unique opportunity for efficient AGB monitoring in small holdings. Therefore, this study aimed to predict maize crop AGB in small-scale farming systems using UAV-remotely sensed data and landscape biophysical variables. The DJI Matrice 300 UAV platform mounted with a MicaSense multispectral sensors were used to acquire high-resolution images at four phenological stages that covered the vegetative (V8 &V12) and reproductive stages (R2 & R5). Furthermore, in-situ leaf area index, leaf chlorophyll content, and soil moisture measurements were acquired and combined with aspect, slope, elevation and vegetation indices to model maize AGB using deep neural network (DNN) model. Results showed that the V12 phenological stage yielded a better overall prediction accuracy (R^2 = 0.74) than the V8 (R^2 = 0.65), R2 (R^2=0.71), and R5 (R^2=0.67) phenological stages. The DNN model prediction error was less than 10% across all four phenological stages, which was considered satisfactory. All the landscape biophysical variables and the derived vegetation indices were influential in predicting the maize AGB and enhanced the DNN model performance. The study concludes that the V12 and R2 phenological stages are optimum for estimating maize AGB. This study contributes to more comprehensive understanding of leveraging cutting-edge technology in precision agriculture to enhance maize production and achieve sustenance.

Keywords: Unmanned Aerial Vehicles; Deep Learning; Maize; Above-Ground Biomass; Landscape Variables; Biophysical Variables; Smallholder Farming

3.1 Introduction

Small-holder crop farming plays a critical role in the economies of developing countries and is crucial for sustaining food security (Fan and Rue, 2020). However, productivity in smallholdings is often adversely affected by unfavourable bio-climatic conditions, climate change, and lack of farming resources (Mgbenka et al., 2016). Maize (*Zea mays*) is ranked as one of the most extensively cultivated crops worldwide (Squires et al., 2020). In South Africa, maize is widely produced and consumed as a staple food by the majority population and also used for livestock fodder (Luo et al., 2019, Ngoune Tandzi and Mutengwa, 2019). Other uses of maize include the production of starch, ethanol, and fuels (Mgbenka et al., 2016). Although the demand for maize has significantly increased in South Africa, challenges related to production and yield remain prevalent (Verschuur et al., 2021, Haarhoff et al., 2020). Hence, it is imperative to adopt prompt and robust techniques such as crop yield prediction to accurately counteract these challenges.

Maize above ground biomass (AGB) is an essential basis for crop yield formation as it indicates plant growth and productivity (Tang et al., 2023, Meiyan et al., 2022). A higher maize AGB signifies a superior crop performance in capturing and converting sunlight, nutrients, and water into energy for grain development and increased yield (Luo et al., 2019). A direct positive correlation between maize AGB and yield is well established in literature (Tollenaar and Lee, 2002, Leroux et al., 2019, Zhang et al., 2021c). Hence, timely and accurate maize AGB measurements allows development of models that can precisely predict yield prior to harvesting, useful for strategic evaluations, financial planning, efficient irrigation, and food production management (Guo et al., 2020b). Furthermore, maize AGB serves as a crucial source of nutrition for livestock during periods of limited forage availability, such as the dry season (Venkatesh et al., 2024). Therefore, the assessment of maize AGB to optimise yield, particularly in small-scale farming systems, is essential to optimising productivity and mitigating potential losses.

Traditionally, quantifying maize AGB involves in-situ measurements of foliar weight, which is destructive and laborious, hence unsuitable for large spatial extents and repeated observations (Han et al., 2019b, Gerke, 2019). Recently, satellite-based remote sensing has found widespread application in precisely monitoring agricultural crops, with numerous studies demonstrating a favourable correlation between variables captured through remote sensing and AGB (Leroux et al., 2019, Battude et al., 2016, Kayad et al., 2019). For instance, Geng et al. (2021) estimated maize AGB using Moderate Resolution Imaging Spectroradiometer

(MODIS) reflectance data and machine learning, achieving a coefficient of determination of 0.77 (R^2 = 0.77). However, despite these achievements, the utilisation of satellite remote sensing is limited by among others cloud cover, which significantly restricts maize crop monitoring requirements for small-scale farming systems (Zhang et al., 2021c). Furthermore, small-scale farming systems are characterised by small spatial extents of less than two hectares, necessitating higher spatial resolution sensors for effective capture of crops spectral information (Xie et al., 2021). In addition, the transition between phenological stages in maize crops occurs rapidly, hence the need for high-temporal-resolution sensors and on-demand dataset to accurately monitor and capture the changes in AGB at each growth stage (Yang et al., 2022a).

Recently, Unmanned Aerial Vehicles (UAVs), also known as drones, have demonstrated a remarkable capability to bridge the gap between satellite remote sensing and ground-based observations (Gargiulo et al., 2023). This is attributed to their ability to provide cloud-free, near-real-time data at ultra-high spatial resolution (Li et al., 2022c, Sharma et al., 2022). UAVs offer several benefits for agricultural crop monitoring that include the ability to hover over areas of interest and fly beneath cloud cover at flexible altitudes, allowing for high resolution imagery and precise monitoring of individual crops (Aasen et al., 2018). Additionally, their flexible flight mission make them ideal for capturing data during optimal periods, such as the short-window peak photosynthetic phase in maize crops (Yang et al., 2022a). However, despite these advancements and capabilities, studies on the use of UAV technology on small holder farms, particularly in the global south, remain scarce (Dhillon and Moncur, 2023). This underscores the need for studies that investigate the potential of UAV systems, equipped with smart and high resolution sensors, in predicting maize AGB in small-scale farming systems.

High resolution sensors mounted onto UAV platforms cover a wide range of the electromagnetic bands including the visible, near-infrared, and red-edge sections that are useful in predicting maize AGB and deriving vegetation indices to support yield estimations (Li et al., 2016). For instance, vegetation indices derived from the near-infrared and red-edge wavelengths such as the Normalised Difference Vegetation Index (NDVI), have demonstrated the ability to detect subtle changes in crops properties such as canopy structure, photosynthetic activity, and crop health (Che et al., 2022, Vélez et al., 2023). For example, Brewer et al. (2022) obtained satisfactory results by using various multispectral derived vegetation indices such as NDVI and Soil Adjusted Vegetation Index (SAVI) for estimating leaf chlorophyll content to determine crop health and vigour.

Typically, maize crops are characterised by variable stock height, density, and greenness, while canopy vegetation index remains unchanged (Adewopo et al., 2020b). Hence, vegetation index-based empirical approaches alone cannot accurately estimate maize AGB. Hence, to account for these variations, biophysical variables such as leaf chlorophyll content and leaf area index (LAI) can be combined with vegetation indices to accurately predict maize AGB (Meiyan et al., 2022). Leaf chlorophyll content and LAI have been identified as strong crop health indicators that positively correlate with maize AGB (Liu et al., 2019, Luo et al., 2019, Che et al., 2022). However, measuring the aforementioned biophysical variables is only ideal for small spatial extents (Liu et al., 2023a). In addition, considering that most small-scale farmlands are often characterised by challenging terrain featuring steep topography, it is essential to assess the influence of landscape variability on maize AGB (Polzin and Hughes, 2023). Therefore, landscape and landscape related variables that directly and indirectly influence crop growth such as soil moisture, slope, aspect, and elevation can provide a precise maize AGB estimation (Svedin et al., 2021, Fry and Guber, 2020, Goldenberg et al., 2022). In this regard, integrating drone-derived multispectral bands, with optimal vegetation indices, and biophysical landscape variables can provide better and precise estimates of maize AGB in small-scale farming systems.

Numerous regression techniques have been proposed in literature for the prediction of crop properties (Khan et al., 2022, Ali et al., 2022, Tripathi et al., 2022). Machine learning algorithms, combined with spectral variables from remote sensing datasets have proven superior for data analysis than other statistical approaches (Altaweel et al., 2022). Deep learning algorithms, such as Deep Neural Networks (DNN), have particularly gained popularity over the past decades for their ability to learn and discover patterns from large and complex datasets and generate accurate predictions (Li et al., 2022b, Muruganantham et al., 2022). DNN comprises a hierarchy of more than two hidden neural network layers and are subsequently called ‘deep learning’ (Odebiri et al., 2021). The primary limitation of this technique is its propensity to overfitting and requirement of large datasets for optimal performance (Odebiri et al., 2021, Cao et al., 2022). However, features such as regularisation and dropout in neural networks can counteract these effects (Vojnov et al., 2022). Numerous studies have successfully adopted DNN to predict maize agronomic variables and obtained results surpassing other machine learning algorithms (Khaki and Wang, 2019, Lischeid et al., 2022). Despite its potential, deep learning is the least used approach in agricultural monitoring applications, particularly at small-scale extents due to small acquirable datasets (Zhang et al., 2020). Therefore, there is need for further research on the potential of UAV-remotely sensed data combined with landscape and biophysical variables at estimating and mapping maize crop AGB using DNN machine learning techniques.

Studies have employed either plant biophysical, landscape variables or remotely sensed data to estimate maize AGB (Meiyan et al., 2022, Luo et al., 2019, Liu et al., 2019). Generally, studies have seldom integrated the three, with the landscape variables for precision agriculture. Therefore, this study sought to evaluate the utility of UAV-remotely sensed data combined with landscape and biophysical variables in estimating maize AGB in small-scale farming systems using DNN machine learning techniques. The main objective of this study was to predict maize AGB using a combination of UAV-remotely sensed data, landscape variables, and plant biophysical variables. Additionally, this study sought to determine the optimal phenological stage for timely and efficient maize AGB prediction in subsequent seasons. Finally, the study sought to assess the performance of DNN algorithm to identify an optimum model for predicting maize AGB using small spatial extent acquired dataset.

3.2 Materials and methods

3.2.1 Description of the study area

This study was conducted in Swayimane communal area (bounding coordinates: -29.525531°, 30.699976°: -29.523899°, 30.700111°) within the uMshwathi Municipality, in the KwaZulu-Natal Province, South Africa (Figure 3.1). The experimental field is approximately 1.4 hectares and exhibits distinct variations in slope, aspect, and elevation. Average air temperature is 17 ℃, while the minimum and maximum temperatures are 11.8 ℃ and 24 ℃, respectively (Ndlovu et al., 2021a). Annual rainfall ranges from 600 mm to 1100 mm, with most rainfall received in summer. Swayimane is characterised by wet-hot summers and dry-cold winters. Since cropping activities in the study area are rain fed, crops are grown during summer. The area has excellent bio-climatic and physical conditions, that include loam soils with efficient nutrient and water holding capacity as well as optimum terrain for efficient sunlight capture, making it suitable for crop farming. Farmers in the area mainly rely on traditional farming methods such as use of kraal manure as fertilizers and animal draft implements for ploughing and weeding. However, with recent socio-economic improvements in the area, some farmers are adopting artificial fertilizers and mechanised farming, particularly in larger fields. In addition to maize, legumes, sweet potatoes, taro and small holding sugarcane are grown in the study area.

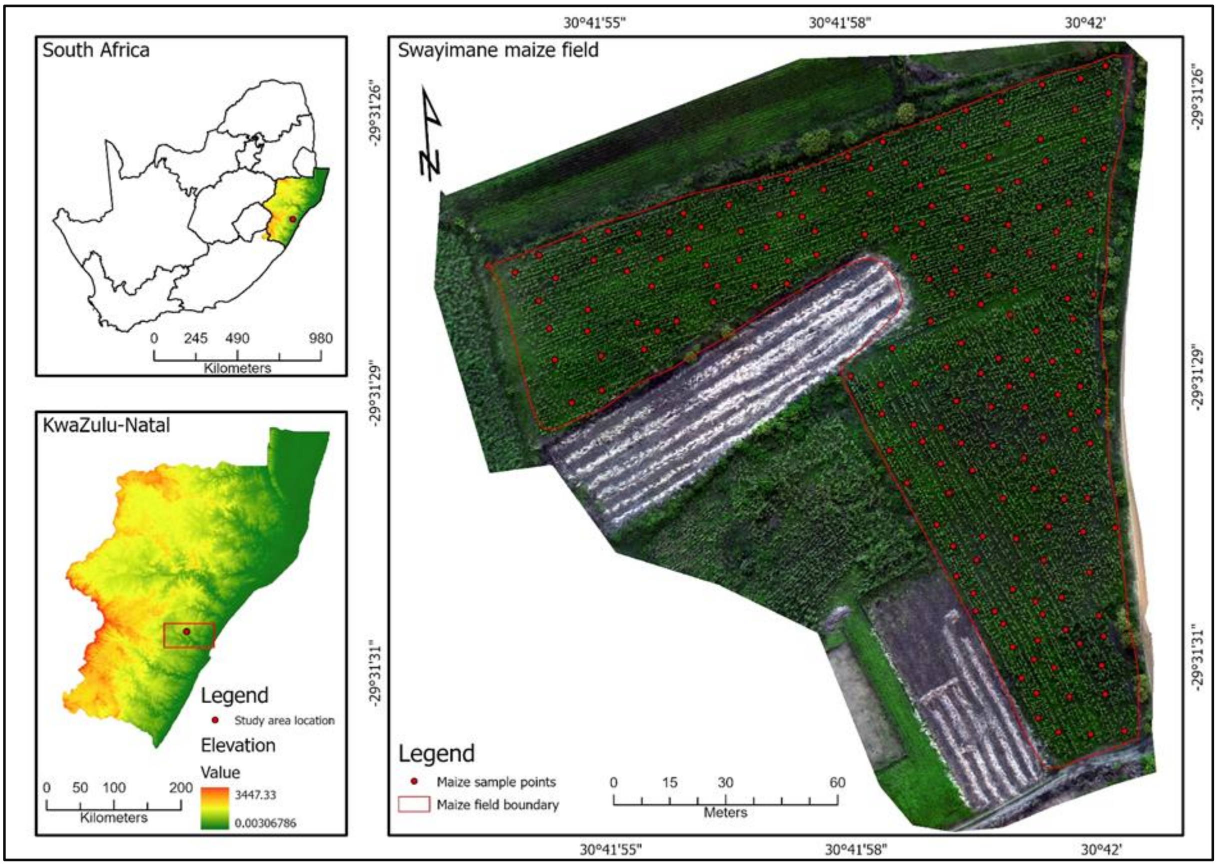

Figure 3.1: Location of the study site.

3.2.2 Maize phenotyping

The maize field was planted with the SC 701 hybrid (Pannar Seed Company, SA) on the 24th of February 2023, and harvested on the 7th of July 2023. The SC 701 seed type was chosen because of its high yield capacity estimated at more than 13 tons per hectare according to the seed producers. The SC 701 hybrid is late maturing (140-148 days) and known to be heat and drought tolerant (Zhang et al., 2021b, Asare et al., 2023). However, in such cases, irrigation is recommended for maximum yield. The maize was rain-fed throughout the growing season, and no drought and extreme temperatures were recorded. The maize was planted in rows perpendicular to the slope to minimize nutrient runoff and soil erosion during rainfall. The distance between the crops and rows was at least 20 cm and 70 cm, respectively, to avoid inter-competition within the crops and stunted growth. To eradicate weeds, an affordable water-soluble Basagran herbicide with a mixability of 480 g/l was applied when the maize was 30 days old, and a nitrogen-phosphorus-potassium [N: P: K (2:3:4=30)] fertilizers applied when the maize was 50 days old to enhance growth.

3.2.3 Data acquisition

3.2.3.1 Ground data collection

Data for the study was collected at four phenological stages ranging from the vegetative to reproductive growth phases i.e., V8 (32 days old), V12 (47 days old), R2 (96 days old) and R5 (123 days old) (Table 3.1). The vegetative stages were selected as they are characterised by fully developed leaves, which is essential for field measurements and light reflectance (Ning et al., 2020). The R2 is full canopy stage while R5 represents the end of mass gain in maize crop (Abreu Júnior et al., 2023). Field measurements were conducted at four-week intervals to capture the above-mentioned stages of the growth cycle. Using a handheld Trimble Global Navigation Satellite System (GNSS), 200 points were sampled using a stratified random approach within the experimental plot. The experimental plot was divided into sub strata based on slope, crop health, and crop size. Thereafter, random crops within the strata were sampled, ensuring variability capturing and a comprehensive and representative sample of the maize population. Each sample point was marked with red tape and labelled for consistent monthly measurements. Field measurements were conducted on clear sunny days between 10 a.m. and 14:00 p.m. to capture data at peak photosynthetic activity and maximum reflectance.

Table 3.1: Maize phenological stages used in the study.

Growth Stage	Vegetative Stages	
	V8	V12
Day after sowing	32	47
Maize Crop		
Growth Stage	**Reproductive stages**	
	R2	R5
Day after sowing	96	123
Maize Crop		

At each sampling point, LAI was obtained using a LiCOR 2200C plant canopy analyser (LI-COR GmbH, Germany). The analyser uses 7°, 22°, 38°, 52°, and 68° zenith angles to measure light interception and transmittance below and above the plant canopy and ultimately estimates the LAI (Buthelezi et al., 2023). Soil moisture content was measured using HH2 moisture probe (Delta-T soil moisture sensors, United states) at each sample point. The HH2 soil moisture probe is inserted in the soil close to the root systems of the crop and records soil moisture volume with a 5% accuracy based on standard calibration (Cheng et al., 2022). Leaf chlorophyll content was measured using a Konica Minolta Soil Plant Analysis Development (SPAD) 502 chlorophyll meter (Minolta corporation, Ltd., Osaka, Japan). The SPAD measures a unit-less chlorophyll reflectance in the leaf using the Red and Infrared sections of the electromagnetic spectrum (Brewer et al., 2022). Finally, at the R6 phenological stage, marking the end of the growing season, the designated maize crops were sampled by cutting the aboveground foliage and weighed to determine the fresh AGB values at each sampling point. No mass correction was performed on the maize crops, taking into account their crucial role in small-scale farming systems as a source of both livestock fodder and human consumption. The decision to retain moisture in the maize aligns with its practical use for easy swallowing, addressing the specific needs of both animals and humans during this stage of maturity.

3.2.3.2 Unmanned Aerial Vehicle platform and remotely sensed data acquisition

The multispectral image data were collected over four phenological stages using a DJI Matrice 300 series (M300) UAV platform (SZ DJI Technology Co., Ltd, China) mounted with a MicaSense Altum multispectral and thermal sensor (AgEagle Aerial Systems Inc, Kansas) (Figure 3.2a). The Altum sensor is equipped with six spectral bands [red (668 nm), green (560 nm), blue (475 nm), red edge (717 nm), near-infrared (840), and thermal band (8 to 14 nm)] (Figure 3.2c). The M300 is equipped with Internet of Things (IoT) technology, such as obstacle avoidance sensors and a locational GPS connected to the camera, making the drone safe to operate and capture automatically georeferenced images. The UAV flights were conducted simultaneously with field measurements. A flight path covering the experimental field was digitised from Google Earth Pro and imported into the drone controller (Figure 3.2b). Before and after each flight, a whiteboard calibration panel was used to calibrate the reflectance of the images (Figure 3.2d). The calibration panel was used to determine illumination and atmospheric conditions during the flight for accurate vegetation indices retrieval. The flights were conducted between 10:00 a.m. and 14:00 p.m. under open sky and suitable weather conditions for optimum sunlight reflectance. The drone was operated at 15 m/s speed and 100 m altitude with 80% forward and 70% side overlap. The images were collected at 6 cm per pixel spatial resolution, based on 8mm focal length and 48^{o} x36.8^{o} field of view (FOV) angle.

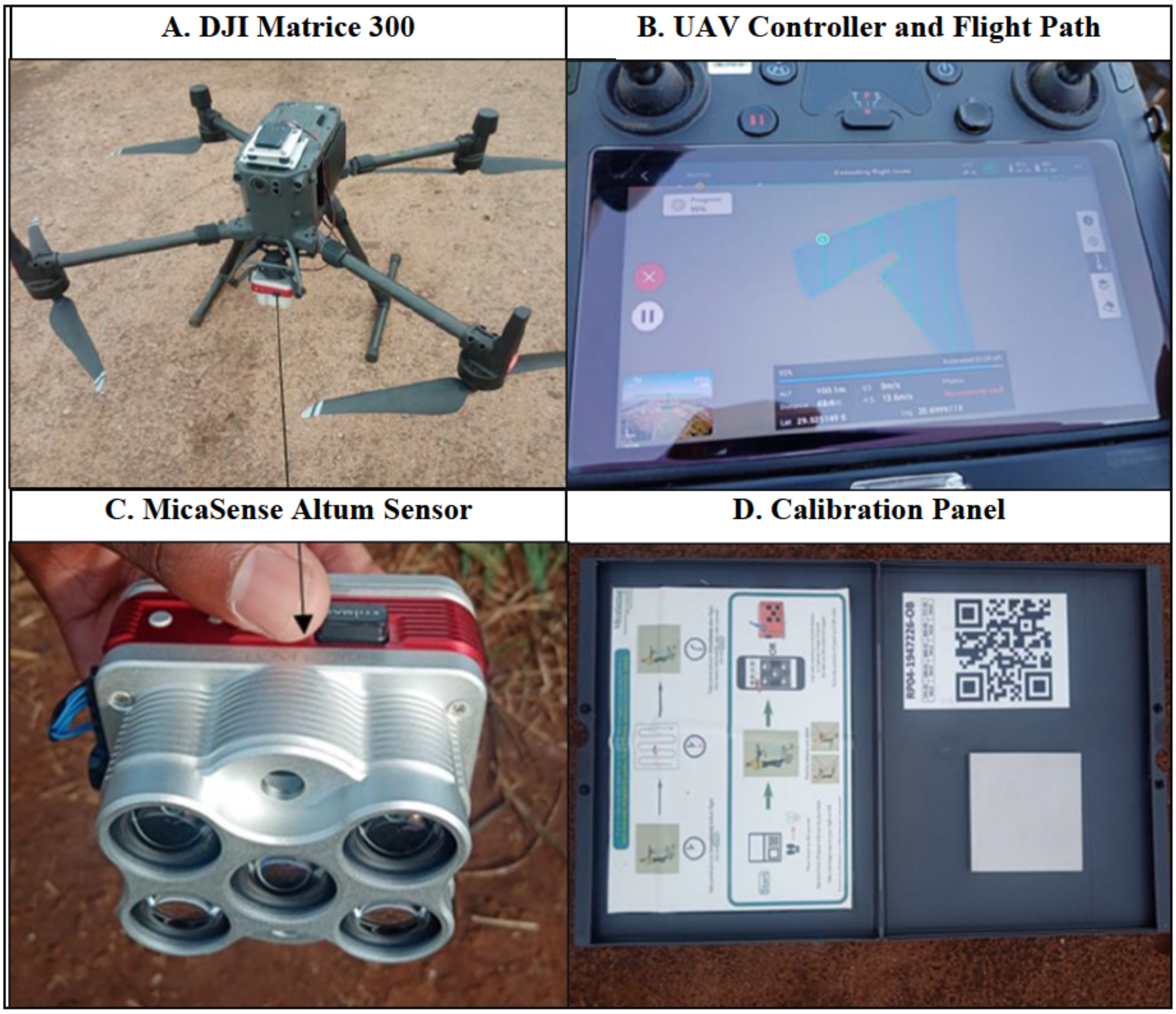

Figure 3.2: The UAV platform, controller with flight plan, image sensor, and calibration panel used for remotely sensed data acquisition in this study.

3.2.4 Image pre-processing and retrieval of vegetation indices

A total of 480 images were acquired during each flight at each sampled growth stage. During the flights, the digital images were automatically georectified by the GPS payload mounted on the M300 UAV platform. Subsequently, the Pix4D 4.6 Fields photogrammetry software (Pix4D Inc. Denver, USA) was used to pre-process the images and generate an orthomosaic image and a digital elevation model (DEM). In addition, the index calculator of the Pix4D photogrammetry software was used to calculate optimal vegetation indices for estimating maize AGB (Table 3.2). The Pix4D index calculator uses mathematical equations from the Index Data Base (IDB) (https://www.indexdatabase.de/) to compute vegetation indices and provide a raster data showing their spatial distribution (Veneros et al., 2023). The maize sample points, orthomosaic, and vegetation index raster images were imported into ArcGIS pro 10.7.1 software for data extraction using the 'extract multi-values to points' in the Arc Toolbox. The extracted bands and vegetation indices for each sample point were then exported into Microsoft Excel for statistical analysis. Evidence from literature has proven the efficiency of vegetation indices in predicting maize AGB (Han et al., 2019b, Yue et al., 2023b, Li et al., 2016, Li et al., 2020a).

Table 3.2: Optimal vegetation indices for maize AGB prediction.

Vegetation Index	Formula	Reference
NDVI	$\frac{NIR - RED}{NIR + RED}$	(Shi and Xingguo, 2011)
CVI	$NIR(\frac{RED}{(GREEN)(GREEN)})$	(Hunt Jr et al., 2011)
BNDVI	$\frac{NIR - BLUE}{NIR + BLUE}$	(Wang et al., 2007)
NDVI_Rededge	$\frac{Rededge - RED}{Rededge + RED}$	(Ehammer et al., 2010)
RBNDVI	$\frac{NIR - (RED + BLUE)}{NIR + (RED + BLUE)}$	(Wang et al., 2007)
ENDVI	$\frac{((NIR + GREEN) - (2 * BLUE))}{((NIR + GREEN) + (2 * BLUE))}$	(Ahamed et al., 2011)
CI_Rededge	$\frac{NIR}{Red - edge} - 1$	(Hunt Jr et al., 2011)
GLI	$\frac{2(GREEN - RED - BLUE)}{2(GREEN + RED + BLUE)}$	(Baroni et al., 2004)
EVI	$2.5 * \frac{(NIR - RED)}{(NIR + 6RED - 7.5BLUE) + 1}$	(Glenn et al., 2010)
EVI2	$2.4 * \frac{NIR - RED}{NIR + RED + 1}$	(Miura et al., 2008)
IPVI	$\frac{NIR}{\frac{NIR + RED}{2}}(NDVI + 1)$	(Kooistra et al., 2003)
SAVI	$\frac{NIR - RED}{NIR + RED + 0.5}(1 + 0.5$	(Heiskanen, 2006)
OSAVI	$(1 + 0.16)\frac{NIR - RED}{NIR + RED + 0.16}$	(Wu et al., 2008)
SR	$\frac{NIR}{RED}$	(Malthus et al., 1993)
CI_Green	$\frac{NIR}{GREEN} - 1$	(Ahamed et al., 2011)
GDVI	$NIR - GREEN$	(Tucker et al., 1979)

Where, NDVI= Normalised difference vegetation index, CVI= Chlorophyll Vegetation Index, BNDVI= Blue Normalised Difference Vegetation Index, NDVI_Rededge =Normalised difference vegetation index Red edge, RBNDVI= Red Blue Normalised difference vegetation index, ENDVI= Enhanced Normalised difference vegetation index, CI_Rededge= Chlorophyll Index Red edge, GLI= Green leaf index, EVI= Enhanced Vegetation Index, IPVI= Infrared Percentage Vegetation Index, SAVI= Soil Adjusted Vegetation Index, OSAVI= Optimised Soil Adjusted Vegetation Index, SR= Simple Ratio, CI_Green= Chlorophyll Index Green, GDVI= Generalised Difference Vegetation Index

3.2.5 Retrieval of landscape variables

To complete the objective of this study, landscape variables that significantly influence maize growth such as slope and aspect were acquired from the System for Automated Geoscientific Analyses (SAGA) Geographic Information Systems (GIS) 7.8.2 software (University of Hamburg, Germany). The digitised experimental field boundary and maize sample points were then used to clip and extract the landscape variables to the extent of the study area using ArcGIS Pro. Even though soil moisture was measured in-field together with biophysical variables, it was categorised under landscape variables because it quantifies the amount of water held by the soil. In addition, the DEM generated by Pix4D software was used to extract elevation data to the maize sample points as a landscape variable. The UAV-remotely sensed data was then combined with the extracted landscape variables and field-measured biophysical variables in an Excel file for statistical analysis (Table 3.3). The data was then split into training (70%), and testing (30%) datasets using randomisation, thereby ensuring non-bias splitting and ensuring representative subsets for model training and validation.

Table 3.3: Model input variables for maize AGB prediction.

Variable	**Data type**	**Number of variables**
Remotely sensed	Spectral bands Vegetation indices	21
Landscape variables	Aspect Elevation Slope Soil moisture	4
Biophysical variables	Leaf chlorophyll content LAI	2
Total	**8**	**27**

3.2.6 Maize Above-Ground Biomass prediction

3.2.6.1 Deep learning architecture

Jupyter notebook extended from Anaconda3 was used to build a fully connected DNN model featuring 17 inputs, three hidden, and one output layer using python programming environment for predicting maize AGB at four phenological stages (Figure 3.3). The combination of innovative computational tools and sophisticated DNN architecture facilitates precise AGB predictions, contributing to a deeper understanding of maize growth dynamics and potential applications in agriculture (Fuentes et al., 2017, Coulibaly et al., 2022). DNN models are powerful in capturing non-linear relationships by self-learning from large datasets and make precise predictions (Zhang et al., 2022). DNN models use multiple layers with fully connected neurons that are similar to human brain neurons and known to produce highly accurate results, surpassing human experts (Saranya et al., 2023, Zeng et al., 2022b). Therefore, DNN holds a great potential to enhance the prediction accuracy of maize AGB compared to other machine learning and traditional statistical approaches (Zhang et al., 2021c).

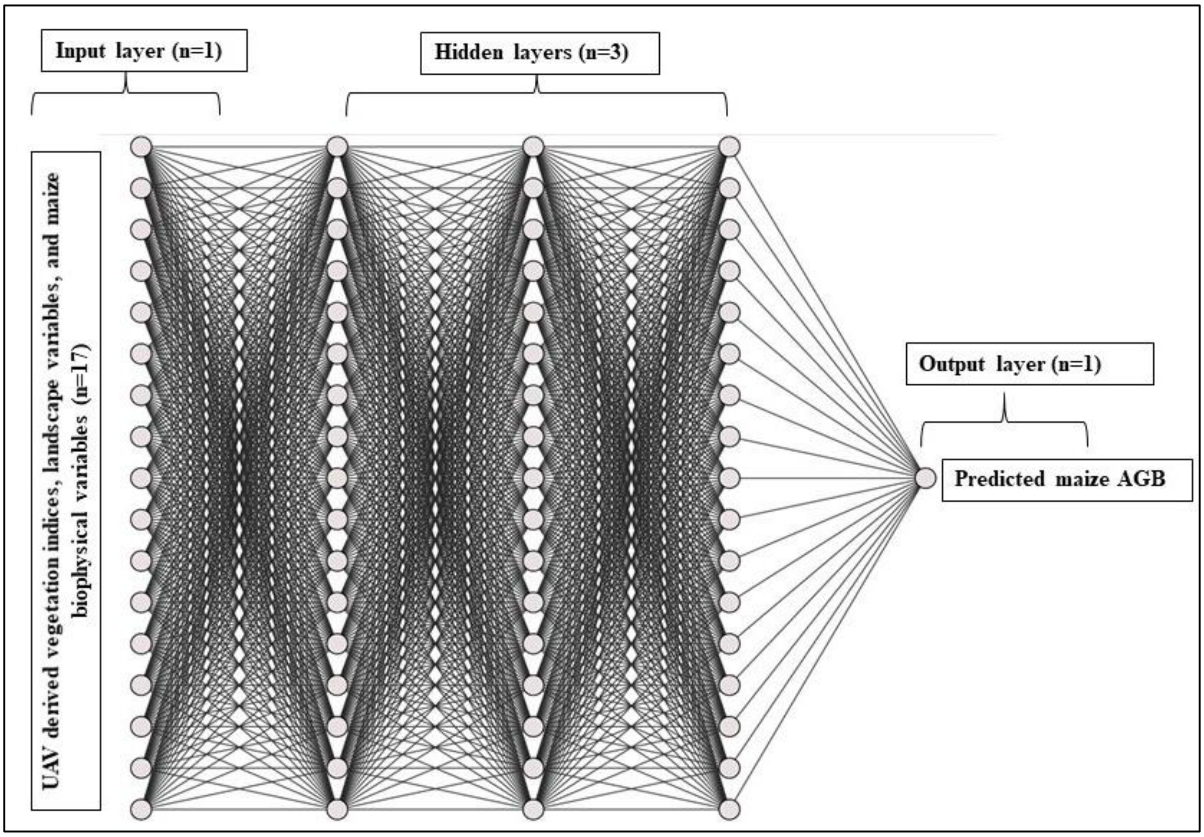

Figure 3.3: The diagrammatic illustration of the DNN model used to predict maize AGB.

A good selection of hyperparameters based on the dataset is essential for building an optimum model (Dominguez-Olmedo, 2019). Therefore, the rectified linear unit (ReLu) was used in the input and hidden layers, respectively, to introduce non-linearity in the model. Linearity in DNN imply that all hidden layers have the same power in predicting the output (Kapočiūtė-Dzikienė et al., 2020). Due to the complexity and non-linearity within datasets, the hidden layers must have different magnitude of power in predicting the output (Tsai and Fang, 2021). Therefore, it is essential to introduce activation functions in the neural network to distinguish the hidden layers from each other for better detection and learning of the non-liner relationship between the input and predictor variables (Dubey et al., 2022, Wang et al., 2022a, Jiang et al., 2022). The model was run over 500 epochs, implying that weights in the hidden layers were constantly adjusted five hundred times to minimise error and improve the maize AGB prediction accuracy. The input data is forwardly propagated to the hidden layers, where the weights and biases in the neurons predict the output by self-learning non-linear patterns from the input dataset. The loss functions quantify the deviation from the expected output and backwardly propagate the output to the hidden layers for adjustments in pursuit of minimising the prediction error (Dubey et al., 2022).

The output layer was fed with a SoftMax activation function and "Adam' optimiser for model optimisation and best results. Optimisers reduce the loss by selecting optimum weights in hidden layers to determine an optimum model for accurate prediction (Cho et al., 2020). Adam is known to surpass other optimisers such as stochastic gradient descent due to its ability of generalisation and convergence speed within new datasets (Wang et al., 2022b, Salem et al., 2022, Gaddam et al., 2022). A batch size of 32 and normal initialisation were also implemented in the model for best results. Neural network models are well known for overfitting, which is explained as when the training dataset yields significantly better results than the testing dataset (Frei et al., 2022). Such model cannot be generalised and cannot accurately predict from an unknown dataset. Therefore, the L2 regularisation (0.001) and a dropout of 0.4 were implemented in the layers of the model to minimise overfitting. The dropout and regularisation features in DNN minimise loss between the predicted output and observed input and nullify the contribution of "bad" neurons towards subsequent layers, hence a better prediction accuracy.

3.2.7 Accuracy assessment

The model was evaluated using the Root Mean Square Error (RMSE) and coefficient of determination (R^2) metrics. The RMSE is the difference between the predicted and the observed output, while the R^2 reflects the percentage of the AGB variance that is explained by the model. The best-performing model is represented by a higher R^2 value and a lower RMSE. The variable importance in predicting maize AGB was evaluated using the SHapley Additive exPlanations (SHAP) approach. The SHAP uses a theoretic approach that selects the top twenty variables of high magnitude impact in the performance of the model (Ekanayake et al., 2022).

3.2.8 Data preparation, variables selection, and model validation

3.2.8.1 Data preparation and variables selection

The correlation coefficient (R) was calculated between the predictor variables using correlation heat maps to choose significantly low correlated values for best results (Figure 3.4). Thereafter, highly correlated variables within the dataset were identified and removed to ensure maximum prediction accuracy as such variables have technically the same magnitude impact in the performance of the model.

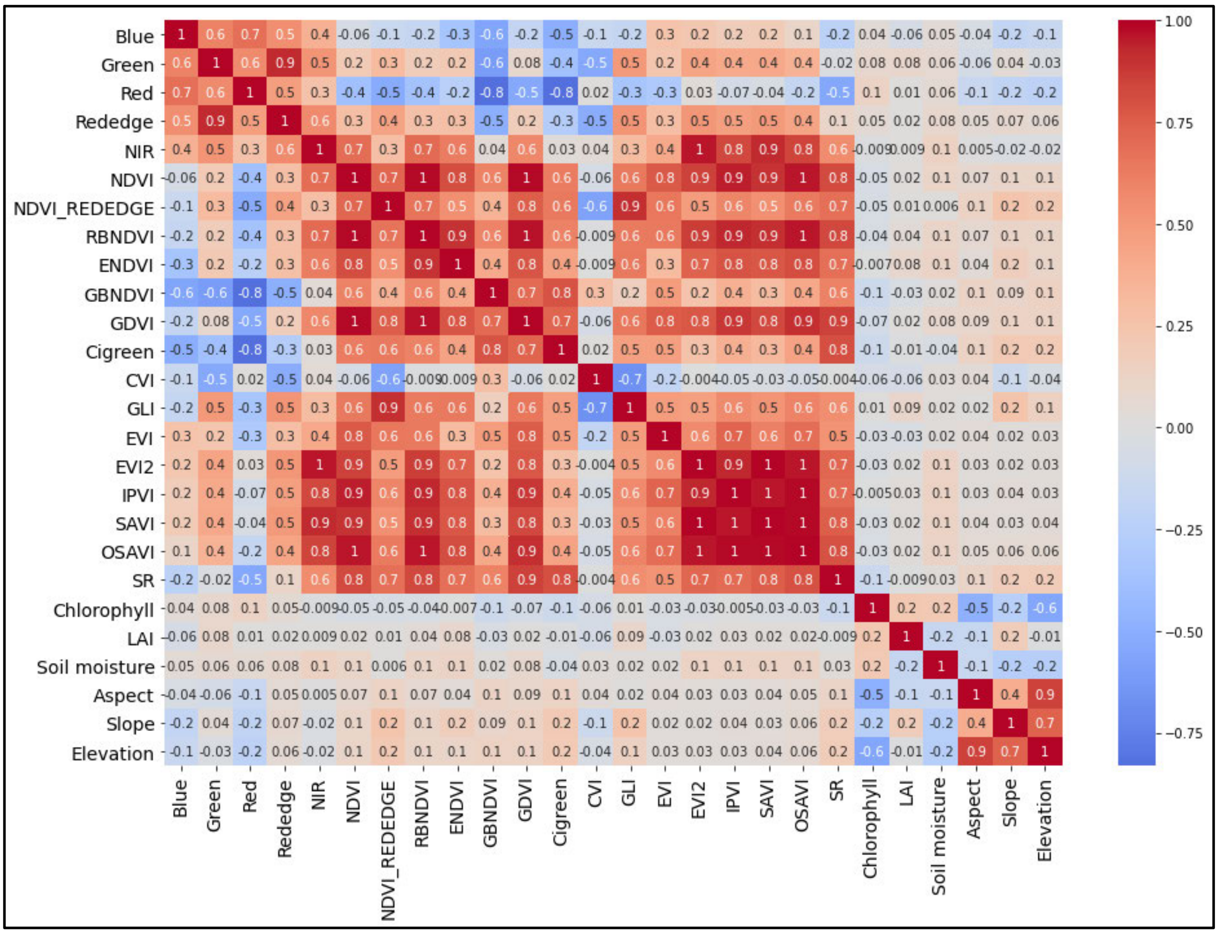

Figure 3.4: Pearson correlation (R) between the selected predictor variables for all the phenological stages.

3.2.8.2 Deep Neural Network model validation

Figure 3.5 shows loss curves during the validation of the DNN model using the training and test dataset over 500 epochs. Model validation is necessary for evaluating the performance of the DNN during self-learning from the dataset (Alzughaibi and El Khediri, 2023). The data was separated into 70% training and 30% testing dataset, and subsequently validated using the latter. The training and validation curves showed a uniform function, implying a gradual decrease in the maize AGB prediction error across all the phenological stages, hence the model was perfectly validated. An optimum model for predicting maize AGB was established and tested using the training dataset.

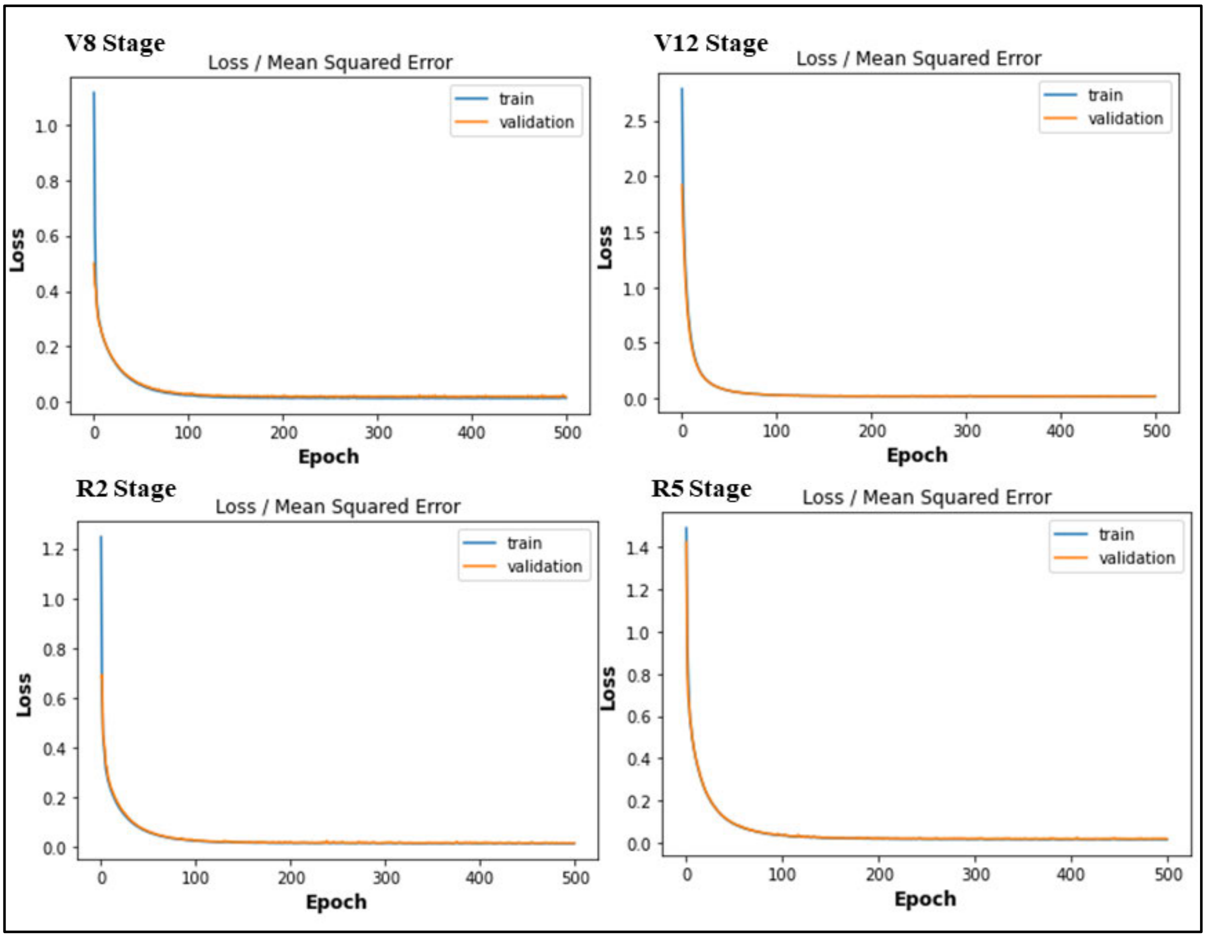

Figure 3.5: Loss graphs indicating DNN model validation during training for all maize phenological stages.

3.3 Results

3.3.1 Descriptive statistics

The variations in field-measured biophysical and landscape variables of maize crops are shown in Table 3.4. On average, the recorded SPAD unit-less leaf chlorophyll content was 39.26, 37.38, 31.22, and 41.36 during the V8, V12, R2, and R5 phenological stages, respectively. The R5 phenological stage recorded the highest average chlorophyll content of 41.36. Soil moisture averages were 21.87%, 21.41%, 16.97%, and 19.1% during the V8, V12, R2, and R5 phenological stages, respectively. It was observed that soil moisture content decreased with growth from the V8-R5 phenological stages. The averages for LAI were 3.64, 2.78, 3.25, and

3.16 during the V8, V12, R2, and R5 phenological stages, respectively, with V8 recording the highest average.

Landscape variables are not subjected to rapid changes over a short time and were therefore assumed to be the same throughout the duration of the study. The average slope, elevation, and aspect were 9%, 856 m, and 2.73 degrees, respectively. The slope, elevation, and aspect ranged from 2% to 14%, 847m to 862m, and 2.20 degrees to 3.42 degrees, respectively. The recorded maize AGB was 1.19 kg/m^2 on average and ranged from 0.4 kg/m^2 to 1.81 kg/m^2, with 2.03 kg/m^2 and 2.11 kg/m^2 recorded as outliers. The outliers were due to measurement errors in the field and were therefore removed from the analysis for best results.

Table 3.4: Descriptive statistics of field measured biophysical and landscape variables across all phenological stages.

Field measured variables		**V8 Stage**			
		Range (Min-Max)	**Mean**	**Median**	**Std.**
	Chlorophyll	31.36-49.61	39.26	38.99	2.59
	LAI	13.99-27.01	21.87	22.16	2.21
	Soil Moisture (%)	2.48-4.64	3.64	3.64	0.25
				V12 Stage	
		Range (Min-Max)	**Mean**	**Median**	**Std.**
	Chlorophyll	29.70- 44.76	37.38	37.60	2.62
	LAI	15.67- 30.41	21.41	21.06	1.57
	Soil Moisture (%)	1.62- 4.58	2.78	2.74	0.23
				R2 Stage	
		Range (Min-Max)	**Mean**	**Median**	**Std.**
	Chlorophyll	21.36- 47.49	31.22	31.55	4.17
	LAI	13.52- 23.67	16.97	16.64	1.36
	Soil Moisture (%)	1.92- 7.75	3.25	3.38	0.49
				R5 Stage	
		Range (Min-Max)	**Mean**	**Median**	**Std.**
	Chlorophyll	21.6-59.4	41.36	41.7	6.27
	LAI	10.6-31.3	19.68	19.4	4.13
	Soil Moisture (%)	1.41-6.8	3.16	3.03	4.85
Landscape variables		**Across all stages**			
		Range (Min-Max)	**Mean**	**Median**	**Std.**
	Slope (%)	2-14	9	10	4
	Elevation (m)	847-862	856	857.6	4.02
	Aspect (degrees)	2.20-3.42	2.73	2.68	0.30

3.3.2 Deep Neural Network model evaluation in maize above-ground biomass prediction

Figure 3.6 illustrates the maize AGB prediction results obtained when the most important and best performing variables were combined for all phenological stages. The V8 (R^2=0.65, RMSE= 0.1 kg/m^2, RMSE%=8.5%) and R5 (R^2=0.67, RMSE= 0.091 kg/m^2, RMSE%=7.6%) phenological stages had a relatively lower prediction accuracy. However, the prediction error was within the 10 % accepted range. The V12 (R^2=0.74, RMSE=0.07 kg/m^2, RMSE% =5.9%) and R2 (R^2=0.71, RMSE=0.086 kg/m^2, RMSE%=7.3%) phenological stages performed optimally, with relatively high prediction accuracy.

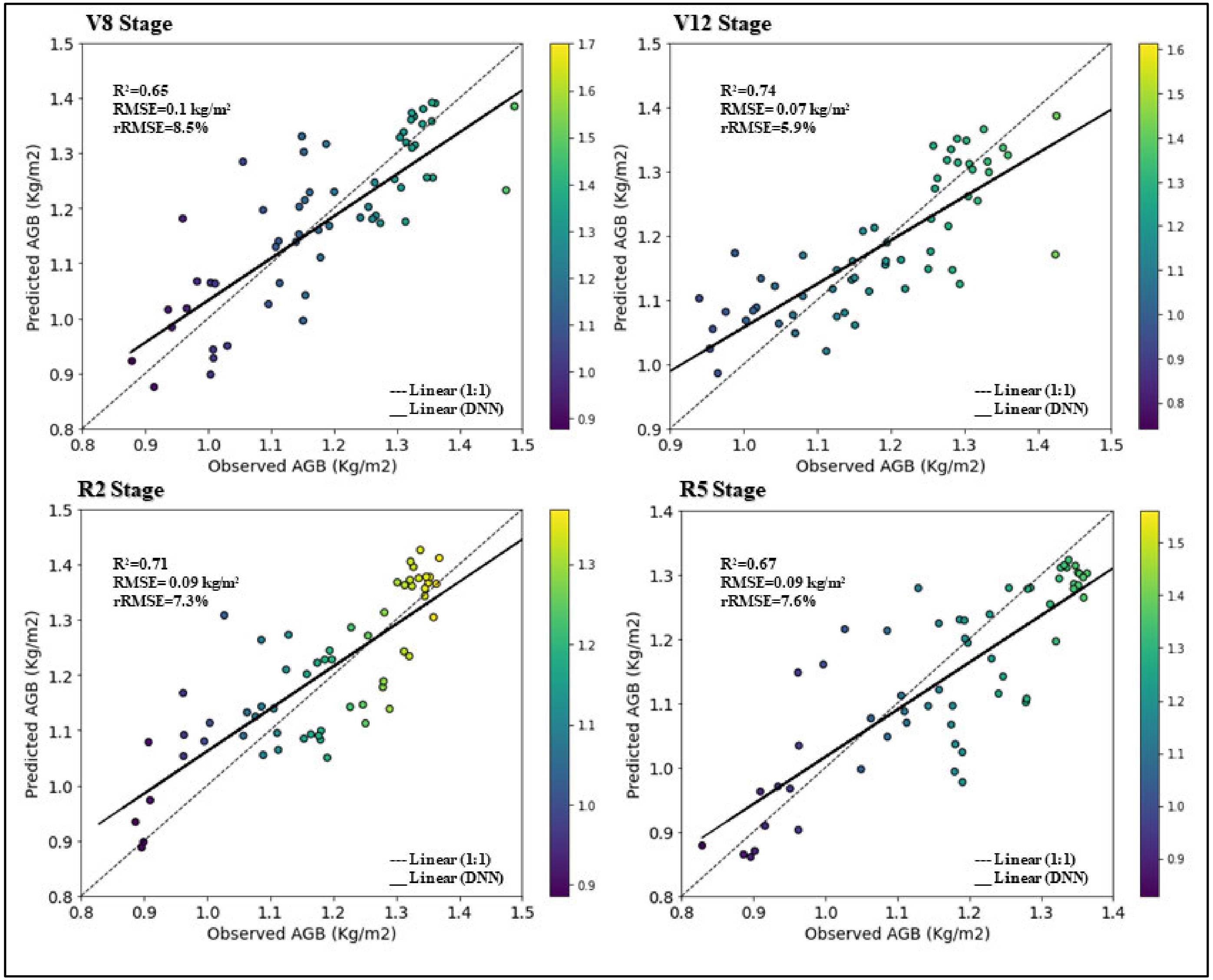

Figure 3.6: Predicted maize AGB using DNN model for the V8, V12, R2, and R5 phenological stage.

3.3.3 Variable importance assessment

Figure 3.7 shows the most important variables in the prediction of maize AGB by the DNN model using the SHAP approach. SR was most important during the V8 and R2, while leaf chlorophyll content and elevation were most influential during the V12 and R5 phenological stages. The figure shows that all landscape variables were important in the prediction of maize AGB across all phenological stages. The biophysical variables (LAI and leaf chlorophyll content) were among the top six important variables during the V8, V12, and R5 phenological stages, while the Red spectral band was the least important variable in maize AGB prediction across all phenological stages. EVI had an extremely low importance in predicting maize AGB during the V12 and R5 phenological stages.

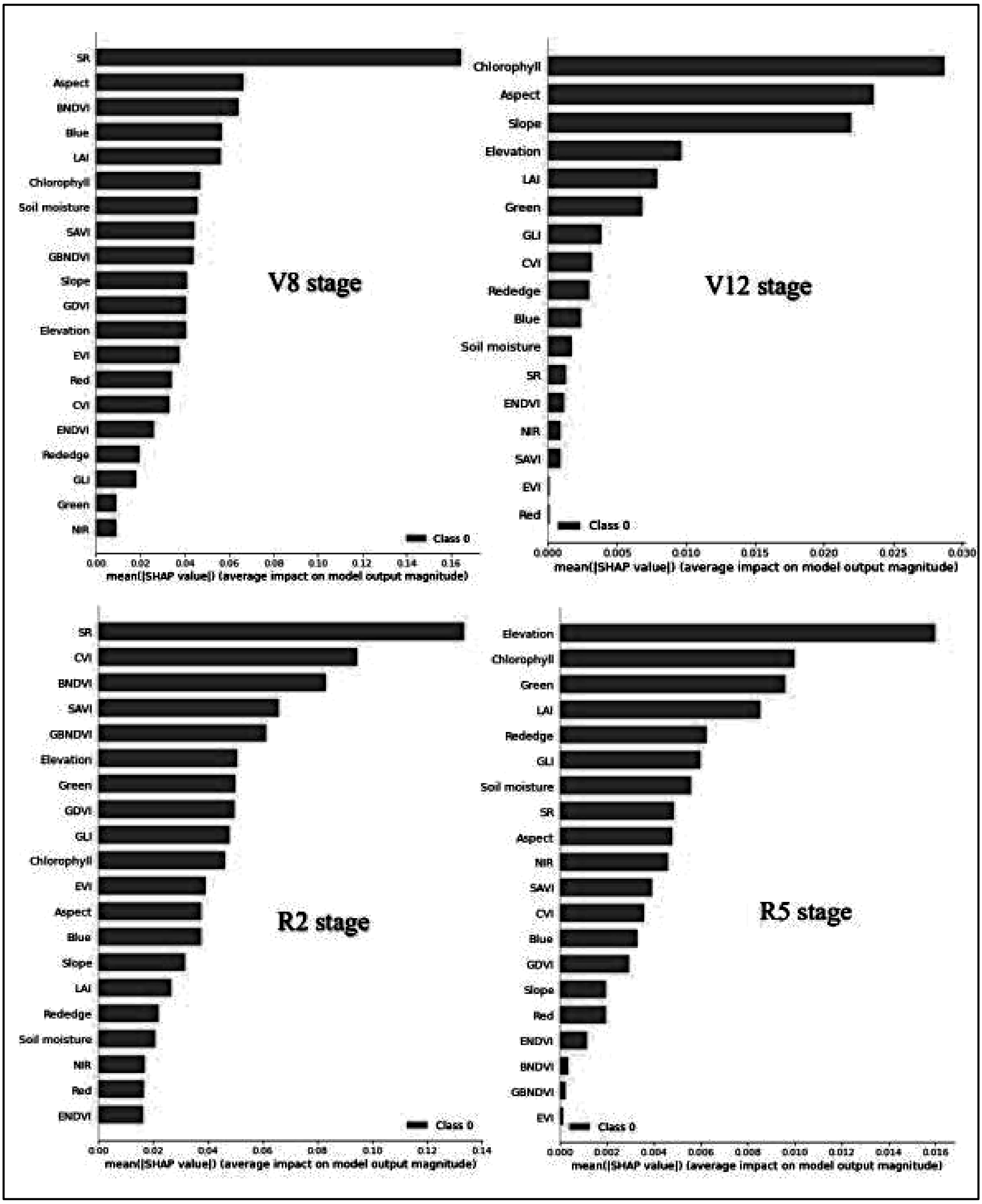

Figure 3.7: SHAP generated variable importance ranking of the model's input variables for all the phenological stages.

3.3.4 Mapping the spatial distribution of predicted above-ground biomass across the phenological stages

Figure 3.8 shows the spatial distribution of predicted maize AGB during all the phenological stages. The spatial distribution map was generated utilising the important predictor variables

(Figure 3.7) for maize AGB prediction and the equation of the line of best fit derived from scatter plots comparing predicted and observed AGB at each phenological stage. Typically, a raster file of the most important maize AGB predictor variable is generated using ArcMap, and the equation y=mx+c is applied, substituting x with the raster file. The generated distribution maps show an increase in maize AGB from the V8 to the R2 phenological stage. There was a slight decrease in the concentration of AGB during the R5 stage. This distribution is also shown by the prediction accuracy previously presented in Figure 3.6, which shows relatively higher prediction accuracy during the V8 and the R1, and lower during the R5 and V8 phenological stages. Similarly, the distribution maps show the same relationship in maize AGB concentration. During all phenological stages, high AGB concentration was observed towards the edges and the field's downslope. In addition, during all the phenological stages, low AGB was observed in a middle of the experimental field.

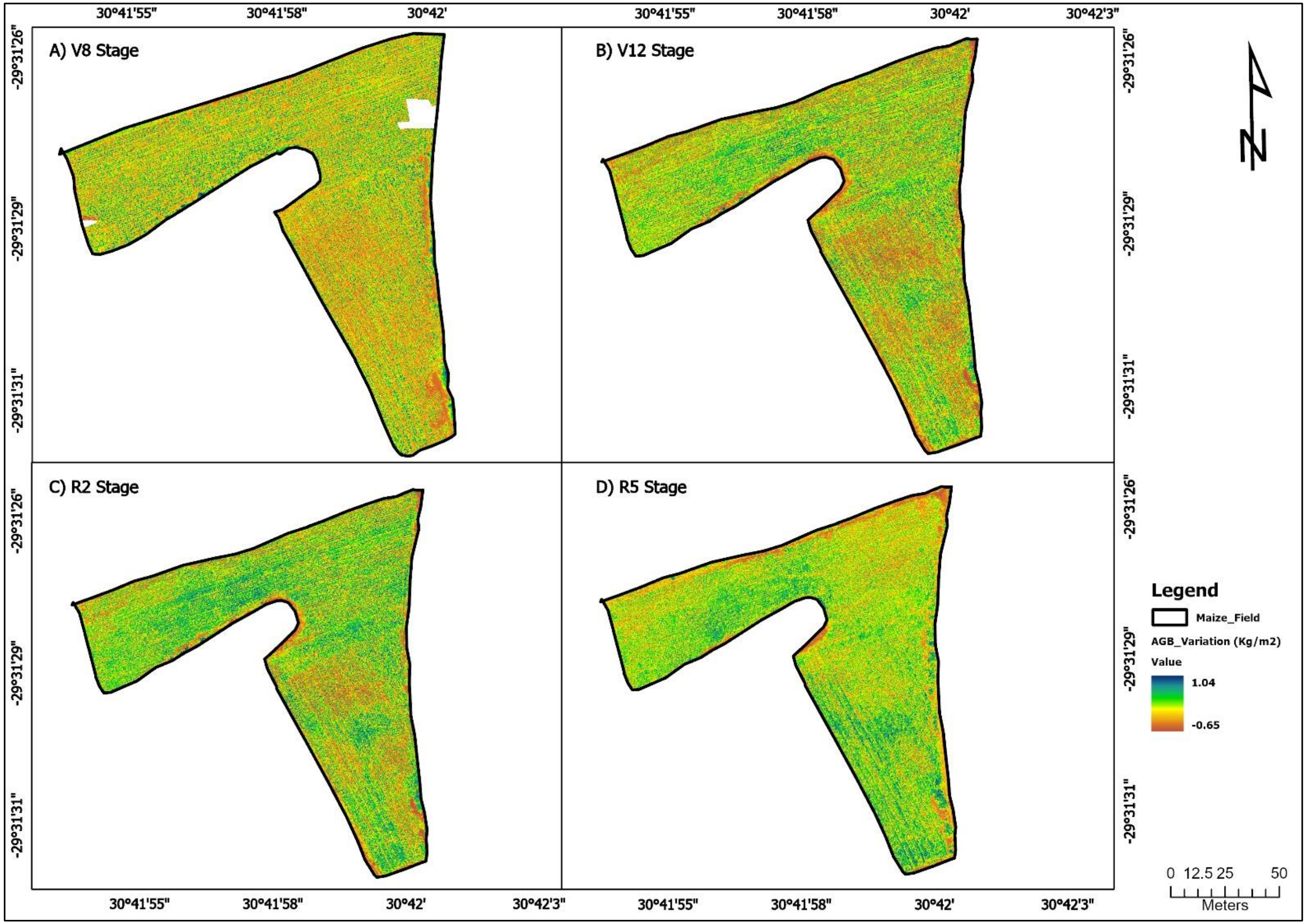

Figure 3.8: Spatial distribution of predicted maize AGB across all the phonological stage.

3.4 Discussion

In developing countries, small-scale farming systems typically lack crop monitoring resources and knowledge on techniques to optimise yield (Onyango et al., 2021). Hence, this study bridged the gap by implementing an affordable crop monitoring resources such as the in-situ instruments, the UAV platform and sensor to accurately estimate maize AGB, which can serve as a proxy to yield. Specifically, this study aimed to develop a model that can accurately predict maize AGB and determine the optimal phenological stage for maize AGB estimation.

3.4.1 The potential of UAV-remotely sensed data in predicting maize AGB

Unmanned Aerial Vehicle-remotely sensed data offer a promising capability to effectively estimate maize AGB in small spatial extents. This is attributed to the remarkable ability of the platform mounted with sophisticated sensors to provide high spatial resolution dataset, enabling individual sensing and assessment of maize crops for accurate AGB estimation (Niu et al., 2019, Khun et al., 2021). Unmanned Aerial Vehicle-mounted cameras such as multispectral sensors offer a broad range of the electromagnetic bands including the visible, NIR, Red-edge, and thermal sections, allowing for efficient retrieval of vegetation indices capable of estimating maize AGB (Olson and Anderson, 2021). This study successfully predicted AGB at various maize phenological stages using UAV-remotely sensed data and deep learning approach. The results indicated that the V12 and R2 phenological stage reported relatively high accuracy in AGB predictions (R^2=0.74 and RMSE=0.07 kg/m^2) and (R^2=0.71 and RMSE= 0.086 kg/m^2), respectively. The V12-R2 phenological stages are the mid-stages of maize growth cycle and portray dark green leaves, symbolising a high concentration of leaf chlorophyll content (Herrmann et al., 2010). Hence, the best results were obtained during the V12-R2 period due to optimum reflectance of maize leaves and minimal soil background noise. The findings of our study concur with Yang et al. (2022a) who used multi-temporal and mono-temporal UAV-remotely sensed data and noted that R3 was the most suitable phenological stage for maize AGB prediction. Similarly, Amanullah et al. (2009) investigated maize yield using traditional methods, and established that the V12-R1 phenological stages had relatively higher yield compared to other phenological stages. Therefore, based on our results, we can deduce that V12-R2 is the optimum phenological stage for maize AGB estimation.

The V8 phenological stage and R5 phenological stages had lower maize AGB prediction accuracies, i.e., R^2 = 0.65 and R^2 = 0.67, respectively. This was because the maize canopy was not fully developed and soil background was more pronounced at V8 stage, hence, interfering with maize reflectance signatures (Zeng et al., 2022a). The spatial distribution map shows a high maize AGB downslope and some parts of the field where soils were thick and appeared rich in nutrients (Figure 3.8). Thin soils were also observed upslope and in some parts of the field; low maize AGB was observed in those areas. Considering that the study area is small, there was a significant variation in soil thickness, which is why the predicted concentration of maize AGB is not uniform across the experimental field. Thick soils have a better water retention and nutrient holding capacity for crop's use, hence higher maize AGB (Mu et al., 2018).

Brewer et al. (2022) noted that NIR derived vegetation indices can surpass variable background effects compared to conventional bands. The soil-adjusted vegetation indices were selected to eliminate soil background and accurately predict maize AGB. As expected, SAVI was among the significantly influential variables in the estimation of maize AGB during all the phenological stages, including the V8 where vegetation cover was minimal. The R5 phenological stage was characterised by dry-denting leaves and marked the end of mass gain. We speculate that the dry leaves significantly reduced the reflectance; hence remotely sensed variables were less important and lower maize AGB prediction accuracy was observed during this stage. While Red-edge-based vegetation indices were influential, they did not have a significant contribution to AGB prediction as compared to NIR-derived indices. The findings of this study are supported by Gao et al. (2017) who confirmed the efficacy of vegetation index-based biomass estimation in maize crops.

3.4.2 Plant biophysical variables in maize AGB prediction

The relationship between LAI, leaf chlorophyll content, and AGB is crucial in understanding the physiological and agronomic aspects of maize growth and productivity (Ban et al., 2019). LAI represents the total leaf area per unit ground area and is often indicates the canopy structure and the light interception capacity of maize crop (Liu et al., 2022). It is positively correlated with photosynthetic activity, as a higher LAI generally implies a larger surface area for light absorption, hence high productivity (Li et al., 2023). Leaf chlorophyll content is a key factor influencing photosynthesis, as chlorophyll is responsible for capturing light energy and transform it into chemical energy (Guo et al., 2020a). Higher chlorophyll content is generally associated with increased photosynthetic rates, contributing to greater biomass production (Meena et al., 2021). Hence, optimal LAI and chlorophyll content contribute to enhanced photosynthesis, leading to increased biomass accumulation in maize crops.

In this study, the recorded leaf chlorophyll content was higher in the early stage (V8) and the late reproductive stage (R5). This is supported by Brewer et al. (2022) who noted that high chlorophyll concentrations are associated with early vegetation and late reproduction stages when maize grows rapidly and kernelling, respectively. Similarly, leaf chlorophyll content in the early and late reproductive stages is associated with high LAI (Yang et al., 2022b). As shown by the SHAP variable importance approach, leaf chlorophyll content had a relatively high impact on maize AGB prediction across all the phenological stages. Our results concur with Liu et al. (2019) who established a positive co-relationship between maize AGB and leaf chlorophyll content. In addition, LAI also had a relatively high impact on maize AGB prediction during the V8, V12, and R5 phenological stages. Contrary to our results, Tang et al. (2023) also established a strong relationship between LAI and maize yield after the R1 phenological stage in maize crops.

3.4.3 The potential of landscape variables on improving maize AGB prediction

Landscape variables significantly increased the maize AGB prediction accuracy and were all important during all the phenological stages (Figure 3.7). In addition, the landscape variables were less correlated to each other, hence the DNN model performed well with their inclusion. A study by Sun et al. (2023) successfully combined topographic variables and vegetation and texture indices to predict maize yield and obtained satisfactory results (R^2 = 0.81, RMSE = 0.297t/ha), which confirms the value of landscape variables in maize AGB prediction. Similarly, Behera et al. (2023) used elevation, slope, and aspect to model maize AGB, and obtained satisfactory results (R^2 = 0.72 and RMSE= 69.18 mg/ha). Salinas-Melgoza et al. (2018) modelled a relationship between landscape variables and noted that landscape variables explained 21% of AGB in reforested areas. Salinas-Melgoza et al. (2018) argued that human activities such as deforestation, land degradation, improper irrigation methods, changing land uses, and pollution have a significant impact on landscape alteration, while crops productivity heavily depend on landscape variables. These human activities facilitate soil erosion, urban expansion, and alterations of soil productivity which significantly affect the slope, aspect, elevation and soil water holding capacity (Mariye et al., 2022). Considering the ever-altering landscape influenced by human activities, including soil erosion, urban expansion, and changes in soil productivity, it is imperative to incorporate landscape variables when predicting maize AGB (Li et al., 2016). Incorporating these landscape variables not only enhances the accuracy of maize AGB estimation but also adds dynamism to the datasets, thereby enabling the prediction model to capture the detailed interactions between landscape and maize growth (Han et al., 2019a).

3.4.4 The performance of deep neural network model in maize AGB prediction

The deep learning approach in maize yield prediction was evaluated using UAV-remotely sensed data combined with biophysical and landscape variables. Furthermore, with DNN requirements for large datasets, the three variables used in this model were adequate to feed enough information to the model for accurate maize AGB prediction. The main objective of this study was to evaluate deep learning approach in maize AGB prediction, particularly with minimal dataset obtained from small spatial extent. To obtain a reliable statistical relationship, DNN require large sample size to effectively learn and discover patterns between the predictor and test variables (Zhang et al., 2021c). Therefore, we sampled 200 points to generate an effective model. Based on the overall RMSE and RMSE% achieved in this study, our model had minimal prediction errors (< 10%) across all the phenological stages. In addition, combining three different sources of datasets improved the prediction accuracy of maize AGB. This was because DNN require a lot of complex and nonlinear datasets to perform effectively. Han et al. (2019c) successfully modeled maize AGB in commercial farming systems using DNN and other machine learning algorithms and achieved satisfactory results. However, this study argues that DNNs require significant repeat training, necessitating a lot of computational power to obtain an optimal model in minimal time.

Despite the high computational power requirement of the DNN model, and the need for repeated training, this model has demonstrated remarkable robustness in this study. Literature emphasises its effectiveness in remotely sensed data analysis, such as predicting maize AGB (Killeen et al., 2024, Du et al., 2022, Feng et al., 2020). However, despite the robustness of the model, its utilisation in studies remains limited (Han et al., 2019a). Considering the urgent necessity to provide actionable insights to farmers for optimised production, exploring the full potential of this model can provide valuable statistical insights (Yu et al., 2023). Therefore, further exploration of its capabilities is warranted, as it can assist in the creation of robust models for modelling future yields, thereby enhancing agricultural productivity and sustainability (Varela et al., 2021).

3.4.5 Implications and recommendations

Unmanned Aerial Vehicle-mounted multispectral sensors provide high resolution dataset, allowing for detection of crop agronomical characteristics facilitating maize AGB estimation

(Zhai et al., 2023a). However, the spectral information of crops remains coarse due to multispectral wide bands portraying lower spectral resolution. Therefore, hyperspectral remote sensing for precise spectral information retrieval and effective maize AGB prediction is highly recommended. Additionally, the study concluded that landscape variables have a significant impact on maize AGB prediction. However, the analysis did not include an assessment of the magnitude of each landscape variable's influence on maize AGB prediction. Hence, it is recommended that forthcoming research endeavours explore the specific impact of individual landscape variables in the prediction of maize AGB. This will contribute to the improvement of validated data availability for further yield predictions. The DNN model requires extensive hyperparameter adjustments to obtain an optimal model. Consequently, its suitability for tasks demanding rapid turnaround times is not recommended. The acquired DNN model was trained using maize derived datasets, and validated using unknown maize dataset, thereby enhancing its applicability in other locations with variability in landscape variables. However, the performance of the acquired model remains limited to adequate dataset and applicable to maize AGB prediction only. Despite the success of the DNN model in adequately predicting maize AGB, more studies need to extensively explore the full potential of this approach, considering its promising potential to make accurate predictions. Despite the success of the DNN model in adequately predicting maize AGB, more studies need to extensively explore the full potential of this approach, considering its promising potential to make accurate predictions.

3.5 Conclusion

The study sought to assess the utility of landscape and biophysical variables combined with UAV-remotely sensed data in predicting maize AGB using the DNN algorithm at four phenological stages (V8, V12, R2, and R5). Based on the attained results, it can be concluded that:

- The V12-R1 phenological stages are optimal for maize AGB prediction when vegetation reflectance is at peak.
- Landscape variables improve the prediction accuracy of maize AGB and can therefore be used in maize AGB estimation.
- The Near infrared spectral bands were the most influential variables in predicting maize AGB prediction.
- Landscape variables, biophysical variables, and UAV-remotely sensed vegetation indices demonstrated significant importance in predicting maize AGB. Hence, the

combination of these variables has demonstrated the ability to improve maize AGB prediction, underscoring the effectiveness achieved through their collaborative utilisation in this study.

- Finally, the DNN algorithm yielded satisfactory results, attributable to the combined dynamic and non-linear datasets in pursuit of a good model.

The results of this study have a significant contribution to precision agriculture particularly in underprivileged small-scale farming systems. Furthermore, the findings of this study address gaps in the current literature, notably by introducing smart agriculture concepts to the global south for improved maize production and sustenance.

Chapter Four

The Synthesis

4.1 Introduction

Approximately 820 million people around the world are food insecure, and considering the proliferating global human population, food production needs to be maximised to sustain food security both locally and globally (Berry, 2020). Considering the significant contribution of maize towards food security, enhancing its production is paramount (Gebre et al., 2021). In this regard, early maize yield prediction has become important to quantify food availability for the proliferating human population, thereby facilitating informed decision making and improving farming practices for food sustenance (Schumacher et al., 2023). The development of artificial intelligence facilitated technologies such as high spatial and temporal UAV-remotely sensed data, and machine learning techniques has proven proficiency in providing precise maize yield estimates over conventional approaches (Yang et al., 2021). In this regard, this study sought to assess the utility of UAV-remotely sensed datasets and machine learning to predict maize yield. The specific objectives were:

- To review the progress and challenges in the application of UAV systems and machine learning approaches in estimating maize yield.
- To combine UAV-remotely sensed data with landscape and plant biophysical variables to predict maize AGB using deep learning approach.

4.2 The Integration of Unmanned Aerial Vehicles (UAVs) and Machine Learning Techniques for Predicting Maize Yields for Enhanced Food Security: A Systematic Review

Previous studies on assessing the progress and challenges of remote sensing application in crop monitoring have noticeable gaps. This includes studies reviewing the potential of the new cutting-edge UAV technology and potent machine learning techniques on staple crops like maize, aiming to achieve food security. In this regard, the first objective of this study sought to systematically provide comprehensive review of the temporal and spatial distribution of studies and seeking to assess the progress and challenges associated with the application of UAV systems and machine learning approaches in estimating maize yield. Significant progress of studies in this context was observed, however, few studies have been conducted in the global south, particularly in small-scale farming systems. The application of the potent machine learning techniques such as deep learning is still limited in maize yield prediction using UAV-remote sensing. Moreover, there is no clear benchmark established in literature for an optimal maize phenological stage for accurate yield estimation, necessitating exhaustive research. Estimating maize AGB through UAV-remote sensing not only directly informs livestock fodder productivity, but also facilitates a more efficient and rapid indirect estimation of grain yield, underscoring the scientific significance of employing this approach for yield prediction. Hence, future studies should delve into and validate the potential of utilising UAV remote sensing for estimating maize AGB, emphasising its ability to optimise precision agriculture in yield prediction. Finally, an explicit incorporation of other datasets such as landscape and plant biophysical variables with UAV-remotely sensed data to account for limitations associated with estimations based on drone-derived datasets alone, has proven proficient in accurate yield estimation. This study advocates for more studies to explore the potential of UAV-remote sensing alongside with multi-source datasets and deep learning computer advances, in the global south, particularly in small-scale farming systems to optimise maize yield prediction.

4.3 The use of Unmanned Aerial Vehicle (UAV) remotely sensed data and biophysical variables to predict maize Above-Ground Biomass (AGB) in small-scale farming systems

Unmanned Aerial Vehicle remotely sensed data was combined with landscape and plant biophysical variables to predict maize AGB using a DNN model in small-scale farming systems in KwaZulu-Natal, South Africa. The V12 phenological stage yielded a better overall prediction accuracy (R^2 = 0.74) than the V8 (R^2 = 0.65), R2 (R^2 = 0.71), and R5 (R^2=0.67) phenological stages. The DNN model prediction error was less than 10% across all four phenological stages, which was considered satisfactory. All the landscape biophysical variables and the derived vegetation indices were influential in predicting the maize AGB and enhanced the DNN model performance. The study concluded that the V12 and R2 phenological stages are optimum for estimating maize AGB. This study makes a substantial contribution in addressing significant gaps in literature, particularly in absence of innovative techniques such as deep learning and UAV remote sensing on marginalised small-scale farming systems in the global south, thereby enriching a deep understanding of precision agriculture and advanced machine learning applications in crucial agricultural settings.

4.4 Conclusion

The overall study sought to assess the utility of UAV-remote sensing datasets and machine learning to predict maize yield. The first objective systematically reviewed literature pertaining to the application of machine learning algorithms for maize yield predictions, specifically utilising UAV-derived datasets. The systematic review established that few studies have been conducted in the global south, particularly in small-scale farming systems, and the potent utility of deep learning computer advances in predicting maize yield is still limited. In addition, the first objective established the value of incorporating other data types such as landscape and biophysical variables in predicting maize yield. Finally, this study established valuable opportunities for diverse and innovative approaches for estimating yield, such as the direct use of maize agronomic traits including AGB as yield indicators for human consumption and livestock feed.

The second objective sought to bridge the aforementioned gaps and explore opportunities by combining UAV-remotely sensed data with biophysical and landscape variables to predict maize AGB using deep learning approach, in a small-scale farming system of South Africa. The study established that maize AGB can be optimally estimated at V8-V12 phenological stage using a combination of UAV-remotely sensed data with plant biophysical and landscape variables. The study established a significant contribution of biophysical and landscape variables in modelling maize AGB. The results of this research enhance our comprehension of the health of maize crops and improve initiatives for monitoring crops, ultimately contributing to enhanced food security. Finally, this study contributes to better understanding of precision agriculture facilitated by artificial intelligence and serve as a stepping stone towards maximising maize yield prediction and ensuring food security, particularly in marginalised global south small-scale farming systems.

4.5 Recommendations and directions for future research

Despite the success achieved by this study in pursuit of extensively bridging existing gaps on literature, more work is still required to explore the full potential of these cutting-edge approaches in precision agriculture. Future studies can:

- Extensively evaluate the full potential of UAV-remote sensing alongside with landscape and plant biophysical variables to predict maize yield in the context of global south small-scale farming systems.
- Evaluate the utility and full potential of deep learning computer advances approach in maize yield prediction.
- Evaluate and invest on high spectral resolution datasets such as hyperspectral remote sensing for more accurate yield predictions.

- Further explore the phenological stages where maize yield can be optimally predicted, aiming to mitigate costs linked to repetitive data collections. This approach will contribute to optimising sustainable farming practices

There is a compelling need for future studies to broaden their focus beyond grain yield and instead adopt a holistic approach in assessing maize crop productivity such as AGB, considering the explicit value derived from fodder for livestock and other economic uses of maize. The integration of UAV systems technology and machine learning computer advances in yield estimation offer a promising avenue to more effectively address food insecurity challenges.

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