The utility of very-high resolution unmanned aerial vehicles (UAV) imagery in monitoring the spatial and temporal variations in leaf moisture content of smallholder maize farming systems

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A thesis submitted in the fulfilment for the degree of Master of Science in Environmental Sciences, in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal.

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Pietermaritzburg, South Africa

December 2021

ABSTRACT

Maize moisture stress, resulting from rainfall variability, is a primary challenge in the production of rain-fed maize farming, especially in water-scarce regions such as southern Africa. Quantifying maize moisture variations throughout the growing season can support agricultural decision-making and prompt the rapid and robust detection of smallholder maize moisture stress. Unmanned Aerial Vehicles (UAVs), equipped with light-weight multispectral sensors, provide spatially explicit near real-time information for determining maize moisture content at farm scale. Therefore, this study evaluated the utility of UAV derived multispectral imagery in estimating maize leaf moisture content indicators on smallholder farming systems throughout the maize growing season. The first objective of the study was to conduct a comparative analysis in order to evaluate the performance of five regression techniques (support vector regression, random forest regression, decision trees regression, artificial neural network regression and the partial least squares regression) in predicting maize water content indicators (i.e. equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA)), and determine the most suitable indicator of smallholder maize water content variability based on multispectral UAV data. The results illustrated that both NIR and red-edge derived spectral variables were critical in characterising maize moisture indicators on smallholder farms. Furthermore, the best models for estimating EWT, FMC and SLA were derived from the random forest regression algorithm with a relative root mean square error (rRMSE) of 3.13%, 1% and 3.48 %, respectively. Additionally, EWT and FMC yielded the highest predictive performance of maize leaf moisture and demonstrated the best correlation with remotely sensed data. The study's second objective was to evaluate the utility of UAV-derived multispectral imagery in estimating the temporal variability of smallholder maize moisture content across the maize growing season using the optimal maize moisture indicators. The findings illustrated that the NIR and red-edge wavelengths were influential in characterising maize moisture variability with the best models for estimating maize EWT and FMC resulting in a rRMSE of 2.27 % and 1%, respectively. Furthermore, the early reproductive stage was the most optimal for accurately estimating maize EWT and FMC using UAV-proximal remote sensing. The findings of this study demonstrate the prospects of UAV- derived multispectral data for deriving insightful information on maize moisture availability and overall health conditions. This study serves as fundamental step towards the creation of an early maize

moisture stress detection and warning systems, and contributes towards climate change adaptation and resilience of smallholder maize farming.

PREFACE

This study was conducted in the School of Agricultural, Earth and Environmental Sciences, University of KwaZulu-Natal, Pietermaritzburg, South Africa, from February 2020 to December 2021, under the supervision of Professor John Odindi, Dr Mbulisi Sibanda and Professor Onisimo Mutanga.

I declare that the work presented in this thesis has never been submitted in any form to any other institution. This work represents my original work except where due acknowledgements are made.

Helen Snethemba Ndlovu Signe[redacted] Date: 1 December 2021

As the candidate's supervisor, I certify the aforementioned statement and have approved this thesis for submission.

Professor John Odindi Signed………………... Date: 1 December 2021

Dr Mbulisi Sibanda Signed… ……………... Date: 1 December 2021

Professor Onisimo Mutanga Signed… ……………... Date: 1 December 2021

DECLARATION

I Helen Snethemba Ndlovu, declare that:

1. The research reported in this thesis, except where otherwise indicated is my original research.

2. This thesis has not been submitted for any degree or examination at any other institution.

3. This thesis does not contain other person's data, text, graphics, tables, graphs or other information, unless specifically acknowledged, and the source being detailed in the thesis and in the references section.

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Signed: [redacted].. Date: 1 December 2021

ACKNOWLEDGEMENTS

I would like to thank the School of Agricultural, Earth and Environmental Science for granting me an opportunity to pursue my studies. My sincere appreciation to my thesis supervisor, Professor John Odindi for his unreserved constructive criticisms, comments and guidance that he provided to me throughout the course of this research. Your professional expertise and mentorship is greatly appreciated. To my co-supervisor, Dr Mbulisi Sibanda, I extend my heart-felt gratitude to you for your inestimable technical and narrative guidance throughout the years. Your excellence, enthusiasm and commitment towards my professional development is truly cherished. Thank you to Professor Onisimo Mutanga for his continuous academic and financial support and resource provision throughout the research. Other than my advisory committee, I am thankful to all my colleagues in the Department of Geography; Siphiwokuhle Buthelezi, Duduzile Diza, Trylee Nyasha and Israel Odebiri for the endless support and assistance with fieldwork and laboratory logistics.

A special gratitude to my loving parents, who have always loved me unconditionally and whose good examples have taught me to work hard for the things that I aspire to achieve. To Lindokuhle Luthuli, thank you for your constant support and encouragement to pursue my dreams and finish my thesis. You are my pillar of strength! I thank my little sister for her endless love, support and reassurance.

Finally, this work was funded by the Water Research Commission of South Africa (WRC) through the Project WRC K5/2971//4 titled the “Use of drones in monitoring crop health, water stress, crop water requirements and improve on crop water productivity to enhance precision agriculture and irrigation scheduling” and in part by the National Research Foundation of South Africa (NRF) Research Chair in Land Use Planning and Management (Grant Number: 84157) as well as NRF grant number 119409.

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A	Leaf Area
ANNR	Artificial Neural Network Regression
AWS	Automatic Weather Station
CI_{green}	Green Chlorophyll Index
$CI_{rededge}$	Red Edge Chlorophyll Index
CV	Coefficient Of Variation
DOY	Day Of Year
DTR	Decision Tree Regression
DW	Dry Weight
EWT	Equivalent Water Thickness
FMC	Fuel Moisture Content
FW	Fresh Weight
GPS	Global Positioning System
IPCC	Intergovernmental Panel On Climate Change
Landsat	Land Remote Sensing Satellite
M300	Matrice 300 Series
MLR	Multiple Linear Regression
MODIS	Moderate Resolution Imaging Spectroradiometer
MSI	Moisture Stress Index
NDII	Normalized Difference Infrared Index
NDRE	Normalized Difference Red-edge Index
NDVI	Normalised Difference Vegetation Index
$NDVI_{rededge}$	Red-edge Normalised Difference Vegetation Index
NDWI	Normalized Difference Water Index
NGRDI	Normalized Difference Green/Red Index
NIR	Near-Infrared
OLI	Operational Land Imager
OSAVI	Optimised Soil Adjusted Vegetation Index
PLSR	Partial Least Squares Regression
R^2	Coefficient Of Determination
RFR	Random Forest Regression

RMSE	Root Mean Square Error
rRMSE	Relative Root Mean Square Error
SEM	Standard Error Of The Mean
SLA	Specific Leaf Area
SR	Simple Ratio
Std.	Standard Deviation
SVR	Support Vector Regression
SWIR	Shortwave Infrared
UAV	Unmanned Aerial Vehicle
VIs	Vegetation Indices

CHAPTER ONE: GENERAL INTRODUCTION

1.1 Introduction

Maize (*Zea mays L*) is an essential rain-fed grain crop grown throughout Southern Africa (Adisa *et al.*, 2018; Ndlovu *et al.*, 2021a). It is the most widely produced food crop and serves as a primary staple food and source of carbohydrates for the majority of the region's population (Adisa *et al.*, 2019; Haarhoff *et al.*, 2020). Furthermore, the maize industry contributes over R9 billion per annum to South Africa's economy and accounts for approximately 45% of the agricultural sector's gross domestic product (Adisa *et al.*, 2019). However, in the face of climate variability, maize production is highly threatened by crop moisture availability (Sah *et al.*, 2020). According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC), unprecedented changes in global climate are inevitable as current climate projections indicate a warmer future with an increase in drought events (Rosenstock *et al.*, 2019; IPCC, 2021). Literature has confirmed that the impacts of climate change will be detrimental to crop production, especially in Southern Africa, where the majority of the region is expected to become drier, particularly under low climate change mitigation measures (Sah *et al.*, 2020; Nembilwi *et al.*, 2021). This is a serious concern as maize farming in the region predominantly occurs at smallholder scales that predominately depend on precipitation and rudimentary technological inputs (Ngoune Tandzi and Mutengwa, 2020; Rosenstock *et al.*, 2019). Whereas such scale of production plays an essential role in ensuring food security and sustaining local livelihoods, they are seriously impacted by the lack of water due to rainfall variability (Sah *et al.*, 2020; Nembilwi *et al.*, 2021). Therefore, there is need for mechanisms to monitor maize moisture stress through development of climate-smart agricultural practices.

When maize crops are in water deficit, leaf photosynthetic activity and metabolism decrease, resulting in stunted growth and possible plant mortality or premature leaf senescence (Zhang *et al.*, 2019a; Ndlovu *et al.*, 2021a). Furthermore, water stress limits the ability of maize to photosynthesise and produce new dry matter leading to significant reduction in maize harvest (Earl and Davis, 2003). Literature has confirmed that maize crop experiences apparent variations in moisture content as a result of numerous factors that include soil properties, topographic influence, and climatic conditions such as extreme temperatures and in-season drought (Wang and Singh, 2017; Chivasa *et al.*, 2020). A study by Ghooshchi *et al.* (2008) reported that the reproductive growth stages of maize are the most sensitive to moisture stress, with the possibility of reducing yield by up to 42%. Therefore, it is imperative to quantify the spatial distribution of maize moisture content and its temporal variation during the growing season as it can provide essential information on crop water availability and can be used to identify maize moisture-sensitive growth stages for optimising maize productivity.

Conventionally, maize leaf moisture content is estimated directly through in-situ measurements of crop conditions (Avetisyan and Cvetanova, 2019; Ustin *et al.*, 2012; Zhang and Zhou, 2019). However, these methods are time-consuming, labour intensive, and less feasible for continuous monitoring of maize fields through the growing season (Yue *et al.*, 2018a; Kalisperakis *et al.*, 2015). Over the past few decades, the use of remote sensing has provided a valuable alternative to quantifying vegetation properties (Pasqualotto *et al.*, 2018). Remote sensing can capture canopy spectra, which provide information on crop biochemical and biophysical composition (Sibanda *et al.*, 2021b). The rationale of estimating leaf moisture content using remotely sensed data stems from the fact that reflectance in the near-infrared (750-1300 nm) and shortwave infrared (1300-2500 nm) regions of the electromagnetic spectrum is largely influenced by water and dry matter in vegetation (Colombo *et al.*, 2008). Water produces maximum absorption features in the shortwave infrared (SWIR) region, centered at 1450nm, 1940nm, and 2500 nm, while weak water bands can be found in the near-infrared (NIR) region at 970nm and 1200nm (Pasqualotto *et al.*, 2018; Zhang *et al.*, 2017; Chemura *et al.*, 2017). Therefore, with the understanding of water absorption spectra, spatial and temporal variations in maize leaf moisture content based on changes in reflectance can be identified and quantified (Zhang *et al.*, 2017).

Several satellite imageries have been useful in monitoring biophysical characteristics (Ambrosone *et al.*, 2020; Ali *et al.*, 2017a; Avetisyan and Cvetanova, 2019; Xu *et al.*, 2020). For example, Han *et al.* (2019a) utilized a combination of Sentinel-2 multispectral imager (10m spatial resolution) and linear regression model to predict maize-above ground biomass to an optimal of $R^2 = 0.72$ and RMSE of 1.06 kgm^{-2}. Additionally, a study by Xu *et al.* (2020) estimated daily maize water levels using a fusion of optical measurements derived from the SWIR and NIR bands of Land Remote Sensing Satellite (Landsat) Operational Land Imager (OLI) and the Moderate Resolution Imaging Spectroradiometer (MODIS) to an $R^2 = 0.66$. Despite such opportunities, satellite data does not fulfil the increasing need for high spatial and temporal resolution data which is important for estimating maize parameters, especially at a plot level (Psirofonia *et al.*, 2017). Additionally, weather conditions remain a challenge for satellite imagery, thus limiting its applicability for the continuous monitoring of maize leaf moisture content (Myers *et al.*, 2015). Given these limitations, innovative technologies are necessary for the routine monitoring of crop moisture content at a field scale.

The advent of Unmanned Aerial Vehicles (UAVs), also known as drones, has pioneered an era of sensing, mapping, and data analysis technologies within precision agriculture (Maes and Steppe, 2019; Tang *et al.*, 2019; Sibanda *et al.*, 2021a). Initially developed for military purposes, drone technology has recently gained widespread popularity in agricultural research (Gago *et al.*, 2015). Unlike satellite data, UAV-derived multispectral imagery can provide data of exceptional spatial and temporal resolutions (Hoffmann *et al.*, 2016). Tsouros *et al.* (2019) note that the ability of UAVs to fly at lower altitudes allows for imagery to be acquired at ultra-high spatial resolutions with the capacity of providing spatially explicit datasets for characterising in-field maize moisture variation. Furthermore, aerial imagery acquired using drones have a relatively low acquisition cost and can provide near-real-time information on maize water content (Chivasa *et al.*, 2020; Gago *et al.*, 2015). Additionally, UAV platforms allow for frequent image acquisition useful for quantifying maize leaf moisture over a multi-temporal scale (Chivasa *et al.*, 2020). Also, UAV imagery is less susceptible to the effects of cloud cover and other atmospheric impurities since the flight height is below the clouds, hence the built-in calibration of the UAV platform allow for more viable and high resolution images (Myers *et al.*, 2015). Hence, UAVs equipped with multispectral sensors could provide a viable option for monitoring maize moisture-related properties for the rapid analysis and early detection of maize moisture stress.

Numerous biophysical indicators have been developed for characterising crop moisture content at a leaf level. Literature has confirmed that indicators such as equivalent water thickness (EWT) and fuel moisture content (FMC) are valuable indicators of crop moisture status as they are closely related to crop water and leaf biochemical processes such as plant metabolism, photosynthesis and evapotranspiration (Zhang and Zhou, 2015; Ustin *et al.*, 2012; Pasqualotto *et al.*, 2018; Ndlovu *et al.*, 2021a). EWT is a vegetation water status metric that represents the total volume of water per unit leaf area (Elsherif *et al.*, 2019; Zhang *et al.*, 2019b; Niinemets, 2001), while FMC is the proportion of water in dry matter per unit leaf area (Matthews, 2013; Qi *et al.*, 2012; Oddi *et al.*, 2019). In addition to being an indicator of fire susceptibility, FMC is widely used in drought assessment and is an essential input for modelling vegetation productivity (Sibanda *et al.*, 2021b). Furthermore, studies have demonstrated the potential of the specific leaf area (SLA), defined as the ratio of leaf area to leaf dry mass, as an indicator of crop moisture content (Ali *et al.*, 2017a; Gonzalez *et al.*, 2009; Garnier *et al.*, 2001). Hussain *et al.* (2020) note that the significant relationship between SLA and water use efficiency permits its applicability in assessing crop water status. Although various studies have evaluated the utility of biophysical indicators in characterising vegetation water status (Zhang and Zhou, 2015; Zhang and Zhou, 2019; Liu *et al.*, 2015), there is still disagreement on which is the most suitable indicator of maize leaf moisture content.

A large and growing body of literature has demonstrated the optimal performance of vegetation indices (VIs) in retrieving information on maize leaf moisture content (Zhang *et al.*, 2019b; Pasqualotto *et al.*, 2018; Colombo *et al.*, 2008; QiuXiang *et al.*, 2012). A frequently used index to monitor vegetation parameter is the Normalised difference Vegetation Index (NDVI) (Xue and Su, 2017). Even though NDVI is criticised for its high susceptibility to noise and saturation, it is significantly interrelated to plant water status, hence has excellent potential of characterising maize moisture content (Krishna *et al.*, 2019a; Jackson *et al.*, 2004). Furthermore, studies by Zhang and Zhou (2019) and Zhang and Zhou (2015) confirmed that maize moisture availability is associated with crop greenness and chlorophyll, therefore, chlorophyll indices such as the Green Chlorophyll Index (CI_{green}) and the Red Edge Chlorophyll Index ($CI_{red\ edge}$) could be valuable in estimating crop moisture-related elements (Easterday *et al.*, 2019; Zhang and Zhou, 2015). Considering that the SWIR channel is sensitive to variations in vegetation water status, various moisture indices, including the Normalized Difference Water Index (NDWI), Moisture Stress Index (MSI) and Normalized Difference Infrared Index (NDII), have been developed from the SWIR region to assess crop moisture content (Zhang *et al.*, 2017; Feng *et al.*, 2013). However, the majority of UAV sensors are not equipped with the SWIR channel, therefore, there are prospects of evaluating other sections of the electromagnetic spectrum in estimating maize leaf moisture content (Sibanda *et al.*, 2021a). Hence, there is a need to evaluate the performance of various VIs that are derived from UAV spectral channels in estimating maize leaf moisture indicators.

Literature confirms that the integration of UAV proximal sensors, VIs and regression techniques allow for the estimation of vegetation functional traits at different spatiotemporal scales (Ali *et al.*, 2019). In this regard, various regression algorithms have been developed to predict plant physiological parameters from remotely sensed data (Yue *et al.*, 2018b; Ali *et al.*, 2019). For example, the partial least squares regression (PLSR) is a well-known conventional technique used to establish meaningful relationships between environmental parameters and vegetation attributes, for instance EWT, FMC and SLA (Li *et al.*, 2014a; Zheng *et al.*, 2018). In comparison, machine learning ensembles such as random forest regression (RFR), support vector regression (SVR), and artificial neural networks regression (ANNR) have the potential to outperform conventional regression methods due to their ability to capture subtle variations and handle nonlinearities and complexities among environmental variables (Yue *et al.*, 2018b; Wang *et al.*, 2016a). In addition, machine learning ensembles can efficiently manage large datasets, handle multicollinearity, and effectively deal with over-fitting and noise (Lu and He, 2019). However, literature indicates that regression techniques are often site-specific and rarely transferable to other vegetation types or data acquired from different sensors (Yue *et al.*, 2018b; Ali *et al.*, 2019). In this regard, it is necessary to validate the performance of various regression techniques and identify a suitable algorithm for estimating maize leaf moisture content using UAV-based multispectral data.

1.2 Research aims and objectives

This study aimed to evaluate the utility of UAV-derived multispectral data in estimating maize leaf moisture content on smallholder farming systems throughout the maize growing season. The following objectives were set:

- To conduct a comparative analysis in order to evaluate the performance of five regression techniques in predicting maize water content, and determine the most suitable indicator of smallholder maize water content variability based on multispectral UAV data.
- To evaluate the utility of UAV-derived multispectral imagery in estimating the spatio-temporal variability of smallholder maize leaf EWT and FMC across the maize growing season.

1.3 Key research hypothesis

- UAV-derived multispectral data will successfully determine the most suitable leaf moisture indicator to estimate maize leaf moisture content using an optimal regression algorithm.
- UAV-derived multispectral data will successfully detect the temporal variations in maize leaf moisture content across the phenological cycle of the growing season.

1.4 Significance of the study

Maize moisture stress is the most significant environmental stressor negatively affecting maize growth and development in smallholder farming systems. Therefore, it is critical to characterise the spatial and temporal variation of maize moisture content to implement scientifically proven measures of reducing the adverse impacts of moisture deficiency on maize yield. Such investigations will provide valuable information that will allow for the decreased vulnerability and increased resistance of these agronomic systems to rainfall variability. Furthermore, estimating maize moisture variations throughout the growing season will support in-field agricultural decision-making and prompt rapid and robust detection of smallholder maize moisture stress. The findings of this study will demonstrate the capacity of UAV-derived multispectral data for deriving insightful information on maize water availability and overall health conditions. Therefore, this study is beneficial to the agricultural sector as it provides baseline information required for developing policies and frameworks for maximising maize production of smallholder farming systems. Furthermore, this research will serve as a footstool for future studies that wish to understand the impacts of climate change on agricultural production in water-scarce regions such as Southern Africa, where small-scale agronomy plays a vital role in rural livelihoods and local food security.

1.5 The general structure of the thesis

The thesis comprises four chapters, including two research papers that address the objectives mentioned in section 1.2 and the research questions discussed in section 1.3. The presented research papers could be read independently, however, the methodology used in paper two is influenced by the results of the first paper. Both papers contribute to the general introduction and overarching research questions, hence, duplication and overlap could be present within the dissertation. The outline of each chapter is as follows:

1.5.1 Chapter One: *General Introduction*

This chapter provides a conceptualization and overview of the thesis by highlighting the importance of the research in precision agriculture. Furthermore, the chapter presents the trends, techniques and technologies for assessing crop functional traits. Finally, the research aim and objectives as well as the significance of the study are provided in this chapter.

1.5.2 Chapter Two: *A comparative estimation of maize leaf moisture content on smallholder farming systems using Unmanned Aerial Vehicle (UAV) based proximal remote sensing*

This chapter investigates the utility of UAV-derived multispectral imagery and regression techniques in estimating maize moisture content on smallholder farms. Specifically, a comparative assessment is conducted between maize leaf EWT, FMC and SLA to determine the most suitable indicator of maize moisture status. Furthermore, this chapter evaluates the performance of multiple regression techniques to identify a robust and accurate algorithm for estimating maize leaf moisture content at a field scale.

1.5.3 Chapter Three: *A multi-temporal remote sensing of smallholder maize leaf equivalent water thickness and fuel moisture content variability using an unmanned aerial vehicle (UAV) derived multispectral data*

This chapter assesses the utility of the optimal leaf moisture indicator and regression technique in characterising the spatial and temporal variation in maize leaf moisture content throughout the growing season. This chapter further investigates the influence of rainfall variability on leaf moisture content at different maize growth stages.

1.5.4 Chapter Four: *Synthesis*

This is the final chapter of the dissertation and provides a summary of the significant finding. This chapter also highlights the critical conclusion of the study. Furthermore, this chapter highlights the implication of the research and provides recommendations for similar studies in future.

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CHAPTER TWO

A comparative estimation of maize leaf moisture content on smallholder farming systems using Unmanned Aerial Vehicle (UAV) based proximal remote sensing

This chapter is based on a published paper:

Ndlovu, H. S., Odindi, J., Sibanda, M., & Mutanga, O. 2021. A Comparative Estimation of Maize Leaf Water Content Using Machine Learning Techniques and Unmanned Aerial Vehicle (UAV)-Based Proximal and Remotely Sensed Data. *Remote Sensing,* 13(20), 4091.

Abstract

Determining maize moisture conditions are necessary for crop monitoring and developing early warning systems to optimise agricultural production in smallholder farms. However, spatially explicit information on maize moisture content, particularly in Southern Africa, remains elementary due to the shortage of efficient and affordable primary sources of suitable spatial data at a local scale. Unmanned Aerial Vehicles (UAVs), equipped with light-weight multispectral sensors, provide spatially explicit near real-time information for determining maize moisture content at farm scale. Therefore, this study evaluated the utility of UAV derived multispectral imagery and machine learning techniques in estimating maize leaf moisture indicators; equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA). The results illustrated that both NIR and red-edge derived spectral variables were critical in characterising maize moisture indicators on smallholder farms. Furthermore, the best models for estimating EWT, FMC and SLA were derived from the random forest regression (RFR) algorithm with rRMSE of 3.13%, 1% and 3.48 %, respectively. Additionally, EWT and FMC yielded the highest predictive performance and were the most optimal indicators of maize leaf moisture. The findings are critical towards developing a robust and spatially explicit monitoring framework of maize water status and serve as a proxy of crop health and overall productivity of smallholder maize farms.

Keywords: maize moisture stress, smallholder farms, unmanned aerial vehicle, machine learning, precision agriculture.

2.1 Introduction

Crop moisture stress is one of the most drastic limiting factors of maize crop production (Avetisyan and Cvetanova, 2019). Maize (*Zea mays L.*) is an important grain crop that is mostly grown under rain-fed conditions and consumed by the majority of Southern Africa's population as a staple food (Ngoune Tandzi and Mutengwa, 2020). Due to high population growth and the increase in food and nutrition insecurities, smallholder farmers now play a critical role in maize production and foster food security, particularly in developing nations such as those in South Africa (Agbugba *et al.*, 2020; Sibanda *et al.*, 2019). Despite their key role, smallholder farms are constantly facing a challenge of intermittent water stress and drought, resulting in significant yield losses (Gomez y Paloma *et al.*, 2020). More so, when stress occurs from the pre-flowering to late grain-filling stages, it is often difficult to detect the onset and magnitude of intermittent water stress (Daryanto *et al.*, 2016). In addition, spatial and temporal crop management, cultivar selection, soil and topography affect its extent and impacts on maize yield (Daryanto *et al.*, 2016). As such, there are no clear cut spatially explicit methods of quantifying its water stress near-real-time in smallholder farms of the global south with limited resources. It is therefore imperative to develop optimal methods for quantifying maize water stress in a spatially explicit manner. This provides a key pathway towards effectively monitoring drought impacts and deriving useful information that can be used to inform irrigation decisions.

When maize crops are in a state of moisture deficit, there is a decrease in leaf photosynthesis, stomatal conductance, leaf expansion and transpiration, subsequently resulting in impaired growth (Zhang *et al.*, 2019b). Lack of water molecules results in the loss of turgor driven cell expansion and primary productivity of maize crops as this has detrimental impacts on its growth (Pasqualotto *et al.*, 2018; Chivasa *et al.*, 2020). Crop water deficits result in a decline in the quantity and quality of maize produce (Afzal and Mousavi, 2008) and considerably affects the phenotype, reproductive system and seed set (Afzal and Mousavi, 2008). Strong and positive correlations have been observed between grain yield and leaf water content (Zhang *et al.*, 2019b; Afzal and Mousavi, 2008). Therefore, knowledge on estimating maize leaf moisture conditions is necessary for crop monitoring and developing early warning systems to optimise agricultural production in exclusively rain-fed smallholder farms (Davidson *et al.*, 2006; Zhang and Zhou, 2015).

A variety of physiological indicators have been developed to quantify crop moisture stress. They include equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA) (Liu *et al.*, 2015; Zhang *et al.*, 2017; Zhou *et al.*, 2020). EWT is the ratio between a crops' leaf area and the quantity of water per unit area (Yi *et al.*, 2014). EWT is an improvement of dry matter content as it takes into account the thickness and area covered by the canopy. FMC represents the quantity of water per unit mass of leaf dry matter. It is an effective indicator of moisture stress or drought conditions and is commonly used in wildfire monitoring (Chivasa *et al.*, 2020). SLA is the ratio of leaf area per unit of dry mass (Gonzalez *et al.*, 2009). SLA is a fundamental indicator of crop physiology and the variability of crop's photosynthetic capacity and growth rate (Ali *et al.*, 2017b). Although there have been various studies conducted in monitoring crop water status (Zhang *et al.*, 2019b; Zhou *et al.*, 2020), there is still a disagreement on the best-suited indicator for maize moisture content prediction at a leaf level in small fields.

Several methods of quantifying maize moisture content indicators have been developed (Ustin *et al.*, 2012; Zhang *et al.*, 2018a; Xu *et al.*, 2020). Conventionally, variations in crop moisture status is measured through conventional methods such as the visual assessment or in-situ measurements conducted by trained experts (Chivasa *et al.*, 2020). However, such techniques are laborious, costly and comparatively time-consuming, hence not feasible for continuous and time-efficient crop monitoring (Yue *et al.*, 2018a). Over the decades, the use of satellite-borne earth observation technologies has proven to be effective in monitoring plant water status, variations in the physiology of water-stressed vegetation and indicating crop water requirements for improved irrigation efficiency (Sibanda *et al.*, 2021b). Xu *et al.* (2020) for instance, used multispectral data derived from Landsat-OLI and MODIS datasets to quantify crop moisture content with an optimal R^2 of 0.78. Additionally, Sibanda *et al.* (2021b) utilized Sentinel-2 MSI to estimate canopy water content and FMC to an rRMSE of 20.8 % and 18.45 % respectively while Krishna *et al.* (2019b) used the combination of hyperspectral sensors and partial least squares regression to estimate rice crop moisture stress with an R^2 of 0.94. However, despite these successes, the application of satellite data in characterising moisture indicators at a farm scale is restricted by their relatively coarser spatial and temporal resolutions (Hussain *et al.*, 2020). Although there are sensors that provide very-high-resolution (VHR) remotely sensed data, such as QuickBird and Worldview imagery, they are often costly and not ideal for monitoring maize moisture content on smallholder farms (Chivasa *et al.*, 2020).

In recent years, unmanned aerial vehicles (UAVs), commonly known as drones, have received widespread attention in precision agriculture (Maes *et al.*, 2018). UAVs, mounted with light-weight multispectral sensors with the capacity of providing spatially explicit near real-time information are valuable for crop physiology monitoring (Hussain *et al.*, 2020). Additionally, UAV proximal sensors with a sub-meter resolution deliver rapid, cost-effective and accurate measurements required for detecting maize water status at a plot level (Chivasa *et al.*, 2020). Compared with satellite imagery, UAV-based sensors can provide datasets of exceptional high spatial and temporal resolutions. In addition, UAV platforms can hover over a specific area of interest and can acquire imagery at lower altitudes, allowing for a finer ground sampling distance, hence suitable for better quantification of maize moisture content at a field scale (Chivasa *et al.*, 2020). Various studies have utilized UAV based proximal sensing in environmental applications (Castaldi *et al.*, 2017; Wijewardana *et al.*, 2019; Zhang *et al.*, 2018b). For example, Han *et al.* (2019b) used a DJI Spreading Wings UAV mounted with a RGB camera to estimate plant height of maize crops and attained a RMSE of 14.1 cm, while Zhang *et al.* (2018b) utilized a Phantom 3 UAV-based RGB image to investigate the optimal flight height for discriminating maize varieties. Additionally, studies have demonstrated the utility of UAV remote sensing approaches in maize yield prediction (Wahab *et al.*, 2018), maize pest and disease detection (Castaldi *et al.*, 2017) and crop physiology monitoring (Wijewardana *et al.*, 2019). However, these studies were conducted in controlled experimental plots in the global north. Very few studies have been conducted in the global south, particular in smallholder croplands with rain-fed maize and other crops. As a result, the potential application of UAVs equipped with high-resolution sensors for monitoring crop dynamics such as maize moisture content needs to be further investigated, especially in small, fragmented croplands of Southern Africa.

The prediction of maize moisture content using proximal remote sensing approaches is derived from the reflectance behaviour of water molecules and dry vegetation matter in the near-infrared (NIR) and the shortwave infrared (SWIR) sections of the electromagnetic spectrum (Wijewardana *et al.*, 2019). However, much of the available drone sensors that have been widely used in assessing crop moisture content and health have either covered the visible section of the electromagnetic spectrum or included the NIR. Very few of these studies have assessed the utility of drone sensors covering the red edge, NIR and the thermal sections of the electromagnetic spectrum in characterising crop moisture content. Furthermore, a large and growing body of literature has demonstrated the optimal performance of vegetation indices

(VIs) derived from water-sensitive sections of the electromagnetic spectrum as an instrument for the retrieval of crop water status (Zhang *et al.*, 2019b; Pasqualotto *et al.*, 2018; Colombo *et al.*, 2008). For example, the Normalized Difference Water Index (NDWI), Normalised difference Vegetation Index (NDVI), Green Chlorophyll Index (CI_{green}) and the Red Edge Chlorophyll Index ($CI_{rededge}$) have demonstrated significant correlations to crop moisture indicators (Zhang and Zhou, 2019; Zhang and Zhou, 2015). It is in this regard that the combination of the drone derived red-edge, NIR and thermal bands in conjunction with optimal vegetation indices were anticipated to yield accurate estimations of maize moisture content in smallholder farms.

A range of regression techniques have been proposed for the prediction of vegetation parameters using remotely sensed data. These may be broadly categorised into two: conventional regression methods and machine-learning techniques (Yue *et al.*, 2018b). However, a example of conventional regression technique is the multiple linear regression (MLR). A major limitation of conventional techniques, such as linear regression (MLR), is that they assume an explicit relationship between measured biophysical parameters and spectral observations, thus limiting their applicability to spatially complex datasets (Lu and He, 2019). Recently, machine learning regression techniques, such as support vector machines (SVM), random forest (RF), artificial neural network (ANN), partial least squares (PLS) and decision trees (DT), have gained popularity for their high performance in computing, quantifying and understanding complex processes in agricultural applications (Liakos *et al.*, 2018). Jin *et al.* (2017) for instance, applied the SVM model to estimate the leaf moisture content of maiden grass and achieved an exceptional model accuracy (R^2 = 0.98). Sibanda *et al.* (2021b) implemented the RF ensemble to predict the canopy moisture content of grasslands obtaining an R^2 of 0.98 and RMSE of 9.8 gm^{-2}, while, Yue *et al.* (2018a) applied machine learning techniques including DT, PLS and ANN in estimating the above ground biomass of winter wheat. The above studies illustrate the robustness and prediction capabilities associated with machine learning regression ensembles based on remotely sensed data. Although there are other algorithms that have been used in remote sensing applications, a large and growing body of literature shows that SVM, RF, ANN, PLS and DT are the most widely adopted. This is attributed to their ease of implementation, robustness especially in dealing with small sample sizes, optimal feature selection abilities as well as the high accuracies they yield. However, literature indicates that there is no specific algorithm that is suited for a specific context. There is, therefore, a need to assess and identify the most efficient algorithm that could accurately estimate maize foliar moisture content using UAV derived data in the context of smallholder croplands.

Although UAV based proximal sensing has become a powerful tool for estimating physiochemical variations in vegetation, only a few studies have been conducted on identifying the best method as well as the best moisture indicators to evaluate maize crop moisture stress at a farm scale. Therefore, operational and robust regression algorithms must be identified, tested and validated for their performance in predicting smallholder maize functional traits, such as moisture content. In this regard, this study sought to investigate the potential of UAV derived multispectral imagery and machine learning techniques in the remote estimation of smallholder maize moisture content. The objectives of this study were to conduct a comparative analysis to: (1) evaluate the performance of five regression techniques in predicting maize moisture content, and (2) determine the most suitable indicator of smallholder maize moisture content. The anticipated results will help provide a technical approach for the quick and accurate monitoring of changes in either EWT, FMC or SLA, as a result of moisture variability, to inform irrigation decisions and planning of smallholder maize crops.

2.2 Materials and Methods

2.2.1 *Description of the study area*

This study was conducted at Swayimane (29° 52’ S, 30° 69’ E), a communal area located within the uMshwathi Municipality, north-east of the city of Pietermaritzburg, South Africa (Figure 2.1). Swayimane is situated within the moist midlands mistbelt bioresource area, characterized by an average temperature ranging between 11.8 °C and 24 °C, and a mean annual temperature of 17 °C. The climate in the area is relatively hot with wet cool summers and dry winters. The area receives an annual rainfall that varies between 600-1100mm. Swayimane experienced an average air temperature of 23.94 °C and an average rainfall of 25 mm during the maize growing season 2020-2021 (Table 2.1). Swayimane is distinguished by arable clay loam soils and is ranked within the top 2% of the high-potential land in South Africa. Subsequently, such environmental conditions support the production of various grain and legume crops. Common crops produced within the study area are beans, sweet potato, sugarcane, spinach and maize. Swayimane is dominated by smallholder maize farms cultivated by the local community. Maize farmers in the area depend primarily on traditional methods of farming such as manual labour and livestock manure for fertilizer. Maize in Swayimane is cultivated both at a subsistence scale and for additional income generation. Moreover, Swayimane is a good example of a rural setup where organic farming is conducted on a semi-subsistence scale. This highlights the success of utilizing organic farming methods for optimizing maize yield at a minimal cost. Plot-level maize growth experiments were conducted in summer, which is the optimal maize growing season. The maize plot covered a spatial extent of 250 m^2 and was primarily rain-fed. The maize crop was sown in mid-November 2020. At the time the project commenced, the crop was 86 days' old, termed the reproductive phase of the growth cycle. Specifically, the maize seedlings were at an intermediate between the kernel blister stage (growth stage R2) and kernel milk stage (growth stage R3). This stage was selected because literature confirms that the early reproductive stages of maize are highly influenced by moisture and are most sensitive to water deficits (Ghooshchi *et al.*, 2008; Mi *et al.*, 2018).

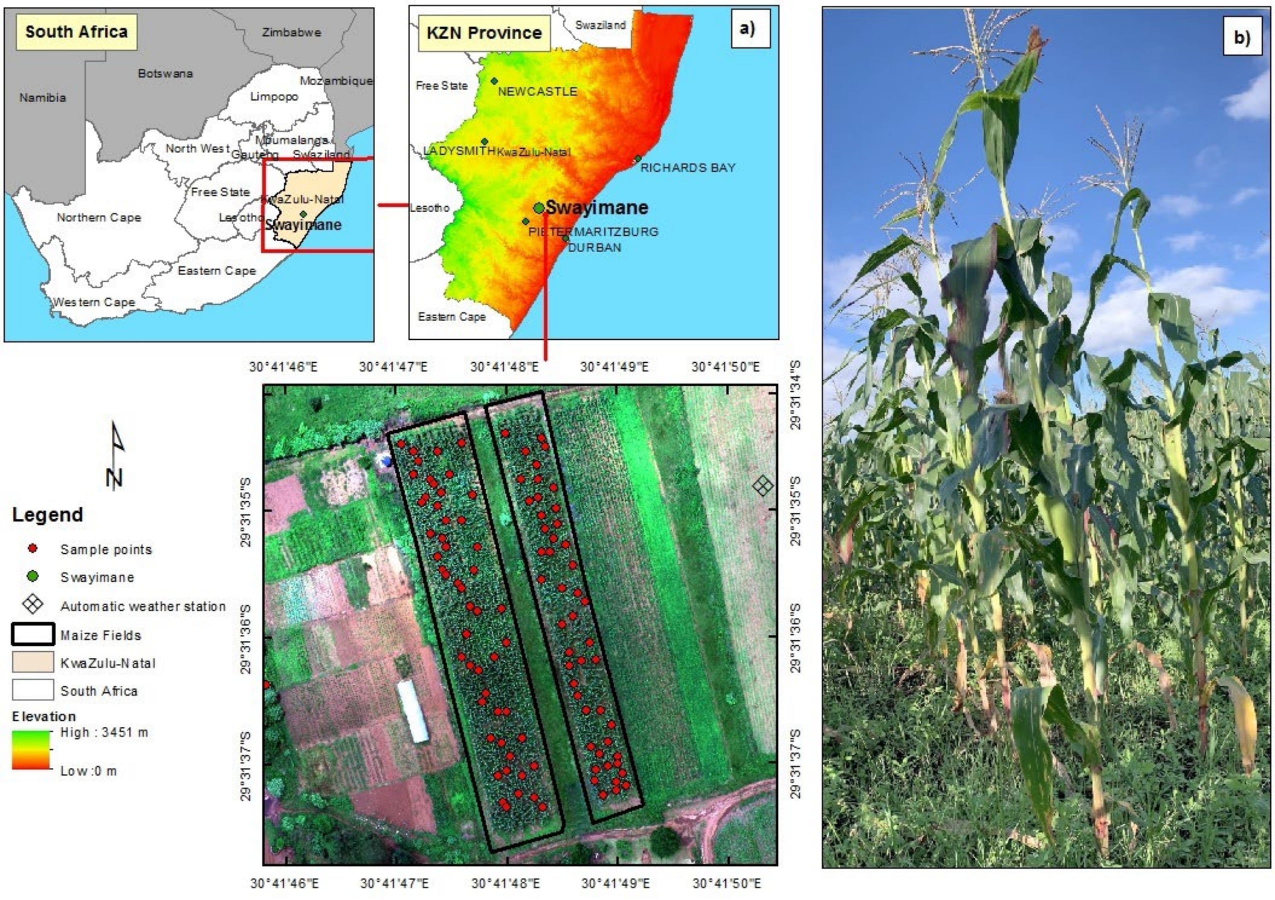

Figure 2. 1: (a) Location of the study area and (b) maize crop field in Swayimane, South Africa

Table 2. 1: Bioclimatic conditions of Swayimane during the maize growing season

Bioclimatic variable	**Data**
Total rainfall	25 mm
Average Air temperature	23.94 °C
Average wind speed	1.68 m/s
Average vapour pressure	2.55 kPa
Average atmospheric pressure	917.64 mbar

Source: On-site automatic weather station

2.2.2 Field Sampling and moisture content measurements

Field data collection was conducted on the 11th of February 2021 at the study site. An automatic weather station (AWS) was installed in proximity to the maize fields to acquire maize crop bioclimatic data. The AWS measured air temperature, relative humidity and wind speed. Wind direction sensors and a raingauge measured the daily wind direction and rainfall within the experimental plot. A stratified random sampling approach was used to generate a total 104 random sample points within the maize field. This technique was selected as it can provide a representative sample of the study area. A Trimble handheld Global Positioning System (GPS) with a sub-meter accuracy was used to navigate to the randomly generated sample points within the field. Sampling fully developed leaves from the top of the maize canopy ensures reliable measurements of plant physiological characteristics, especially since these leaves receive direct sunlight and have maximum spectral reflectance (Mulla, 2013). Sampling of young emerging leaves is not suitable for plant analysis as it can exacerbate plant stress leading to plant mortality (Zhang *et al.*, 2019a; Wahbi and Avery, 2018). In this regard, the first fully developed leaf (first leaf below whorl) was collected from the top of the maize canopy at each sample point to measure leaf moisture content indicators. A LI-3000C Portable Area Meter combined with a LI-3050C Transparent Belt Conveyer Accessory with one mm^2 resolution was used to measure the leaf area (A) of sampled maize leaves (Li-Cor, USA). The fresh weight (FW) of sampled maize leaves were obtained using a calibrated scale with a 0.5 g measurement error. Field measurements were conducted between 12:00 noon and 14:00 as this is the most optimal period of the day for crop photosynthetic activity (Sade *et al.*, 2015a). The sampled maize leaves were then dried in an oven at 70° C until a constant dry weight (DW) was reached (approximately 48 hours). The A, FW and DW were then used as input variables to compute maize leaf moisture indicators using the following equations:

$EWT_{leaf} = (FW – DW) / A$ units: gm^{-2}…………………..*eq.1*

$FMC_{leaf} = (FW – DW) / DW \times 100\ \%$ units: %...............................*eq.2*

$SLA_{leaf} = A/ DW$ units: $g^{-1}\ m^{2}$………………...*eq.3*

The computed data for each crop moisture indicator was integrated with the GPS location and converted into a point map that was overlaid with the UAV multispectral images of the study area.

2.2.3 The UAV platform, image acquisition and processing

The DJI Matrice 300 series (M300) and the MicaSense Altum imaging sensors were used to acquire images covering the maize field considered in this study (Figure 2.2 (a)). The M300 UAV specifications are further detailed in table 2.2. The Altum camera integrates a radiometrically calibrated thermal sensor with five spectral channels that measure reflectance in the visible to the non-visible light spectrum (i.e. blue (475 nm), green (560 nm), red (668 nm), red-edge (717 nm), NIR (840 nm) and thermal (8000-14000 nm)) at a ground sampling distance of 9.6 cm per pixel (Figure 2.2 (b)). The main advantage of this imaging platform is its ability to capture synchronised thermal and multispectral data simultaneously in an automated manner. A shapefile of the study area was created in Google Earth Pro and exported into the M300's handheld console to develop a UAV flight plan (Figure 2.2 (c)). Before and post-flight, an automatic calibrated reflectance panel was used to compensate for incident light conditions by using known reflectance values across the spectrum to radiometrically calibrate the Altum sensor (Figure 2.2 (d)). An automated flight mission was conducted at a flight height of 100m with an image overlap of 80%. The imagery derived from the imaging platform were orthomoisaced and pre-processed to enhance image features in Pix4D Fields photogrammetry software.

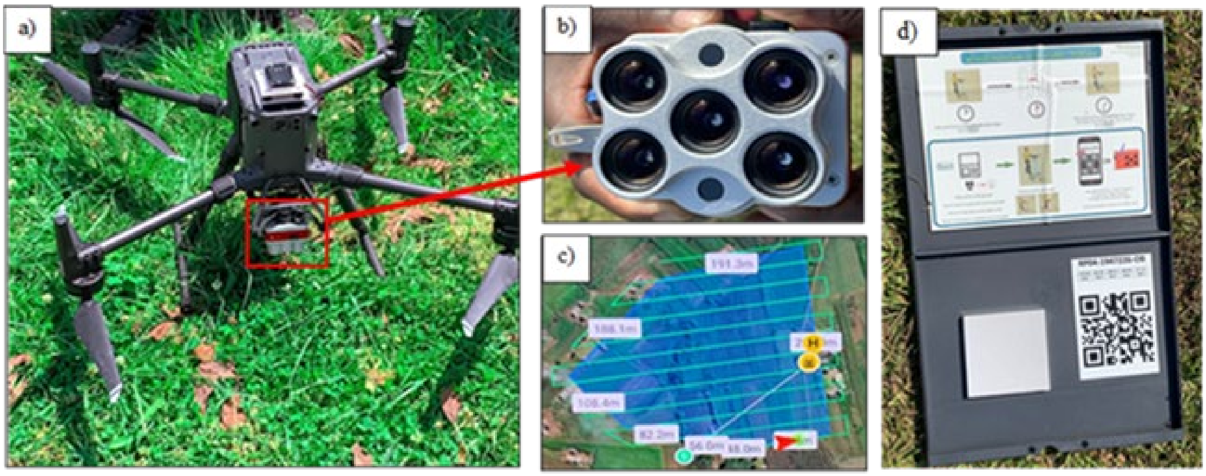

Figure 2. 2: a) Matrice 300 UAV integrated with the Altum sensor to form the imaging platform used in this study, b) Altum camera, c) flight plan of the study image and d) the calibrated reflectance panel

Table 2. 2: DJI M300 UAV specifications

Parameter	Specification
UAV type	Rotary wing
Weight	Approx. 4.53 kg
Size	887 (width)× 880 (length)× 378 (height) mm
Flight duration	55 min
Maximum speed	27 m/s
Maximum altitude	7000m
Maximum payload capacity	2.7 kg
Maximum take-off weight	6.14kg
Maximum flight range	7 km
Operating Temperature	-20° to 50° C

2.2.4 Model development and statistical analysis

The UAV imaging platform used in this study measures reflectance in the visible, red-edge and NIR regions of the spectrum, hence we sought to evaluate all possible combinations of UAV spectral bands to accurately predict crop leaf moisture indicators. In this study, the reflectance data obtained from the Altum multispectral and thermal bands were used to derive VIs. Table 2.3 shows a list of VIs that were selected for this study based on their direct and indirect correlation with plant water status indicators. As aforementioned, the prepared spectral data were then overlaid with the point data associated with measured maize moisture indicators to derive data that was used for the statistical prediction of maize moisture content.

Table 2. 3: List of vegetation indices (VIs) used in the modelling of crop moisture content and related source references

Index	Full Name	Formula	Reference
Direct water-sensitive spectral VI			
NDWI	Normalised Difference Water Index	Green - NIR / Green + NIR	(Ozelkan, 2020)
Indirect water-sensitive spectral VIs			
NDVI	Normalized Difference Vegetation Index	NIR - Red / NIR + Red	(Ali *et al.*, 2017b)
NGRDI	Normalized Difference Green/Red Index	Green - Red / Green + Red	(Hoffmann *et al.*, 2016)
NDRE	Normalized Difference Red-Edge Index	NIR - Rededge / NIR + Rededge	(Zhang and Zhou, 2019)
$NDVI_{rededge}$	Red-Edge Normalised Difference Vegetation Index	Rededge - Red / Rededge + red	(Zhang and Zhou, 2019)
CI_{green}	Green Chlorophyll Index	(NIR/Green) -1	(Zhang and Zhou, 2015)
$CI_{rededge}$	Red-edge chlorophyll index	(NIR/Rededge) -1	(Zhang and Zhou, 2019)

2.2.5 Spatial analysis

The sampled data were randomly split into training (70%) and validation data (30 %). The former was used to develop the model and the latter for assessing the accuracy of predictive models. A comparative analysis was conducted between the support vector regression, random forest regression, decision trees regression, artificial neural network regression and the partial least squares regression algorithms in predicting leaf moisture content indicators (i.e. EWT, FMC and SLA). According to Lary *et al.* (2016) RF SVM, DT, ANN, and PLS are the most widely used machine learning algorithms in geosciences. These non-parametric algorithms are robust, efficient and can be parameterised and implemented with ease (Yue *et al.*, 2018b; Liakos *et al.*, 2018). Above all, these algorithms have been used in literature and are renowned for their accuracy, which is facilitated by their ability to optimally select spectral features for accurate predictions (Lary *et al.*, 2016; Wang and Singh, 2017). It is in this regard that these algorithms were chosen for this study. Then, the variable selection was performed for each prediction model to identify variables that are most influential in the prediction of the named indicators. Variable selection reduces issues associated with variable redundancy and multicollinearity, which affect the performance of regression models (Chivasa *et al.*, 2021). Details on how each algorithm was used in this study are provided below.

Support vector regression (SVR): initially developed for classification problems, it has proven to be an effective tool in regression problems (Wang *et al.*, 2016b). As an intensive supervised learning technique, SVR is less sensitive to noisy inputs thus there are minimal estimation errors making the model more robust (Fan *et al.*, 2021). The greatest advantage of SVR is its robustness to outliers and its capacity to perform well in high dimensional datasets. Selecting the optimal hyperparameter settings of SVR is critical for optimising the model's predictive power (Bae *et al.*, 2019). Three parameters were tuned for the SVR model, specifically, penalty parameter (C), precision parameter (ε) and kernel parameter (γ). In this study, the grid search and 10-fold cross validation method, recommended by Shafiee *et al.* (2021), was performed on the training data and the SVR model was performed optimally at a C value of 8, ε equal to 0.5 and the γ kept at a default of 1.

Random forest regression (RFR): is a machine learning ensemble that uses bootstrap aggregation and binary recursive partitioning to grow a number of independent regression trees (Abdel-Rahman *et al.*, 2013). The strength of RFR lies in its ability to use bootstrap aggregation to build regression trees that are grown to their maximum sizes, with the results being combined by unweighted averaging to make predictions (Jeong *et al.*, 2016). The RFR algorithm is renowned for its ability to produce high prediction accuracies while it is easy and simple to implement (Sibanda *et al.*, 2021b). The quality of the RFR model depends on the proper setting of the RFR hyperparameters. The RFR model is generally optimized based on two parameters, namely *Ntree* which is the number of decision trees to be generated and *Mtry,* the number of predictor variables tested for the best split when growing the trees (Belgiu and Dragut, 2016). The *Ntree* and *Mtry* values were not set at the default, rather were derived after multiple iterations to determine the most optimal *Ntree* and *Mtry* parameters for the prediction of maize leaf moisture content (Mutanga *et al.*, 2012; Adam *et al.*, 2012). The optimal hyperparameter values for predicting maize moisture content in the study was determined to *Ntree* equal to 500 and a *Mtry* of 11.

Decision tree regression (DTR): uses tree structures to build a regression model based on the structural patterns of the input data (Liang *et al.*, 2018). The DTR formally creates decision rules that guide the prediction of the relationship between the objective variable and the predictor variables. The greatest advantage of the DTR model is its ability to avoid over-fitting, overcome missing data in explanatory and response variables and simplicity implementation (Pekel, 2020). In DTR, the hyperparameters were tuned using a pre-pruning technique, which stops the generation of a tree before it is fully constructed, to achieve optimal model performance (Bae *et al.*, 2019; Furuya *et al.*, 2020). In this study, the fine-tuning process of the DTR algorithm was performed until no improvements were observed and the model parameters were specified as follows; the minimum split, which is the minimum number of values that must exist at a node before the split is attempted (Furuya *et al.*, 2020), was fixed at 20 (Williams, 2011). The maximum depth of which the tree is allowed to grow was set to 30. Finally, the termination criteria for the regression tree was specified at 0.01 (Losing *et al.*, 2018). The hyperparameters of the DTR parameters are kept to their default values, except for the maximum depth which is a fixed parameter for all the models (Hu *et al.*, 2020; Williams, 2011).

Artificial neural network (ANNR): has been widely applied in the development of regression models. The quality of the ANNR model depends largely on the selection of the network structure, proper assignment of weights as well as the training dataset of the model (Wang *et al.*, 2016b). The robustness of the ANNR is derived from the algorithms ability to imitate the human neural system which allows it to detect complex trends and patterns often unnoticed by other regression models (Yuan *et al.,* 2017). Furthermore, the ANNR entails one or more hidden layers, in addition to the input and output layer, and discovers prominent features in the input data (Yeganefar *et al.*, 2019). As such, the hyperparameters of the optimal ANN model was determined to be 10 nodes and 2 hidden layers.

Partial least squares regression (PLSR): is a multivariate statistical technique that is characterised by its robust information recognition and modelling capabilities (Yue *et al.*, 2018b). The algorithm combines the theory of multiple linear regression with the theory of principal component analysis to effectively analyse the datasets with high dimensional and collinear predictors (Zhang *et al.*, 2018a). The PLSR is renowned as a powerful modelling technique, particularly in models with a large number of predictor variables and a high level of collinearity (Li *et al.*, 2014b).

To optimize the outputs of the above models, the variable importance scores were used to determine the most influential bands and indices for estimating leaf moisture content indicators (Ambrosone *et al.*, 2020). The least important predictor variables were progressively removed and the model re-developed (Bois *et al.*, 2020; Ambrosone *et al.*, 2020). The Caret Package was used to develop the regression models in RStudio software version 1.4.1564.

2.2.6 Accuracy assessment of derived maize moisture content models

An accuracy assessment was conducted to evaluate the performance of regression models in predicting leaf moisture content indicators. The coefficient of determination (R^2), the root mean square error (RMSE) and the relative root mean square error (rRMSE) were used to compare the accuracy of different models. Specifically, the R^2 was used to measure the variation between measured and predicted maize leaf moisture content and RMSE was used to assess the magnitude of error between the field measurements and the modelled moisture content. The rRMSE was used to compare the performance of regression models across different algorithms and maize moisture indicators. To compute rRMSE, the RMSEs from each model were normalised using the mean of each variable and then expressed as a percentage (Li *et al.*, 2021). The rRMSE has been widely used in literature to compare different variable predictions (Wocher *et al.*, 2018; Sibanda *et al.*, 2021b), hence it was adopted in this study. The optimal model for predicting leaf moisture content indicators was characterised by lower RMSE and RRMSE, and a high R^2 value. Additionally, the most suitable indicator of maize moisture content was estimated by comparing the R^2, RMSE and RRMSE. Similarly, the indicator that produces the highest R^2 and the lowest RMSE and RRMSE, will indicate a higher precision and accuracy in predicting maize moisture content.

2.3 Results

2.3.1 Descriptive analysis of maize crop moisture indicators and measured biophysical variables

A wide range of variations was recorded in both biophysical variables and crop moisture indicators of maize crops. Table 2.4 represents the descriptive statistics of leaf FW, DW, Leaf area, EWT, FMC, and SLA. Averages for FW, DW, and Leaf area were 37.06 g, 6.94 g and 0.09 m^2, correspondingly, while the averages for crop moisture indicators, particularly EWT_{leaf}, FMC_{leaf} and SLA_{leaf} were 356.52 gm^{-2}, 81.27 %, 29.86 gm^{-2} and 0.01 m^2g^{-1}, respectively. A Kolmogorov-Smirnov normality test revealed that all crop moisture indicators did not deviate significantly from the normal distribution curve.

Table 2. 4: Descriptive statistics of crop moisture indicators and biophysical variables

Parameter	Range (min-max)	Mean	Median	Std.	CV %	SEM
Biophysical variables						
FW (g)	31.02 - 45.52	37.06	36.73	3.82	10.31	0.53
DW (g)	3.22 - 8.76	6.94	6.95	1.02	14.69	0.14
Leaf area (m^2)	0.06 - 0.10	0.09	0.09	0.01	10.53	0.00
Crop water **indicators**						
EWT_{leaf} (gm^{-2})	290.91 – 473.18	356.52	344.14	42.42	11.90	5.88
FMC_{leaf} (%)	77.84 – 91.39	81.27	81.24	1.89	2.33	0.26
SLA_{leaf} (m^2g^{-1})	0.0009 – 0.025	0.01	0.01	0.00	18.16	0.00

SEM is the standard error of the mean, Std. is the standard deviation and CV is the coefficient of variation

2.3.2 Evaluation of maize moisture indicators and optimized regression models

Table 2.5 illustrates the model accuracies obtained in predicting leaf EWT, FMC and SLA based on the RFR, DTR, ANNR, PLSR and SVR regression techniques. The accuracies of the prediction models varied greatly for the crop moisture indicators.

For example, when estimating EWT_{leaf}, the DTR yielded the poorest model accuracy, with an RMSE of 25.16 gm^{-2} and R^2 of 0.73. The accuracy in predicting EWT_{leaf} improved slightly for the PLSR model (RMSE = 17.1 gm^{-2} and R^2 =0.74). Similarly, the SVR and the ANNR models predicted EWT_{leaf} at an improved accuracy of RMSE = 15.05 gm^{-2}, R = 0.76 and RMSE =14.29 gm^{-2}, R^2 = 0.84, respectively. The optimal algorithm in estimating EWT_{leaf} was derived from the RFR model with an RMSE of 10.28 gm^{-2} and R^2 of 0.89 (Table 2.5).

Similarly, the ANNR model exhibited the lowest prediction accuracy in estimating FMC_{leaf} (RMSE = 1.54 % and R^2 = 0.34). This was followed by the PLSR with a RMSE of 0.48 % and R^2 of 0.45. The prediction accuracy increased significantly with the DTR and the SVR models with a R^2 =0.65 and R^2 = 0.69, correspondingly. The RFR model optimally predicted FMC_{leaf} with the highest model accuracy of RMSE = 0.45 % and R^2 = 0.76 (Table 2.5).

When predicting SLA_{leaf}, the lowest RMSE of 0.0008 g^{-1} m^2 and R^2 of 0.6 was obtained using the PLSR model. The ANNR model improved the prediction by a magnitude of 8, i.e., R^2 = 0.68. The accuracy derived from the DTR and SVR in predicting SLA differed slightly with an RMSE = 0.0009 m^2 g^{-1} and R^2 = 0.7, and RMSE = 0.0005 g^{-1} m^2 and R^2 = 0.71. The optimal model for estimating SLA_{leaf} exhibited a RMSE of 0.0004 g^{-1} m^2 and R^2 of 0.73 (Table 2.5).

Table 2. 5: Prediction accuracies of EWT_{leaf}, FMC_{leaf} and SLA_{leaf} were derived using optimal models based on the RFR, DTR, ANNR, PLSR and SVR regression models

Model	**EWT_{leaf} (gm^{-2})**			**FMC_{leaf} (%)**			**SLA_{leaf} (m^2 g^{-1})**		
	R^2	**RMSE**	**RRMSE**	**R^2**	**RMSE**	**RRMSE**	**R^2**	**RMSE**	**RRMSE**
RFR	0.89	1028	3.13	0.76	0.45	1.00	0.73	0.0004	3.48
DTR	0.73	25.16	7.67	0.65	1.08	1.35	0.7	0.0009	8.16
ANNR	0.84	14.29	4.35	0,34	1.54	1.92	0.68	0.0007	6.60
PLSR	0.74	17.1	5.15	0.45	0.48	0.60	0.6	0.0008	19.33
SVR	0.78	15.05	4.76	0.69	0.70	0.89	0.71	0.0005	18.82

2.3.3 Optimal models for estimating maize moisture content indicators

Figure 2.3 illustrates the results obtained when all maize moisture content indicators were estimated based on the optimal regression models. The EWT_{leaf} performed optimally as an indicator of maize moisture content with an rRMSE of 3.13 % and an R^2 of 0.89. The most optimal variables that were selected in estimating EWT_{leaf} were NDVI, NIR, NDWI, CI_{green}, $NDVI_{rededge}$, Red, $CI_{rededge}$, NDRE and NGRDI, in order of importance (Figure 2.3 (a)).

Meanwhile, the FMC_{leaf} based on the PLSR model performed better than EWT_{leaf} by 2.53 % with an rRMSE of 0.6 %. The most suitable predictor variables included NDRE, NIR, NDWI, $CI_{rededge}$, $NDVI_{rededge}$, red-edge, CI_{green}, blue, thermal, NDVI, red and the green band (Figure 3 (b)). Additionally, the FMC_{leaf} SVR model produced a relatively high rRMSE of 0.89 %. However, although the rRMSE of these FMC_{leaf} models were high, there was a high variation between the measured and estimated FMC_{leaf} values with an R^2 of 0.45 and 0.69, respectively.

In comparison, the FMC_{leaf} based on the RFR model exhibited an optimally high R^2 of 0.76 and an acceptable rRMSE of 1%, making it the optimal FMC_{leaf} model.

The optimal model in predicting maize SLA_{leaf} exhibited an rRMSE of 3.48 % and $R^2 = 0.73$. The variables that had the highest influence in the SLA model were the NDVI, Thermal, NIR, NDRE, CI_{green}, red-edge, $NDVI_{rededge}$, $CI_{rededge}$, NGRDI and the NDWI, in order of descending importance (Figure 2.3 (c)).

The results revealed that the optimal indicators of maize moisture content based on the RFR models were FMC_{leaf} and EWT_{leaf}, followed by SLA_{leaf}. Additionally, the UAV multispectral bands and derived VIs were successful in predicting all maize moisture content indicators.

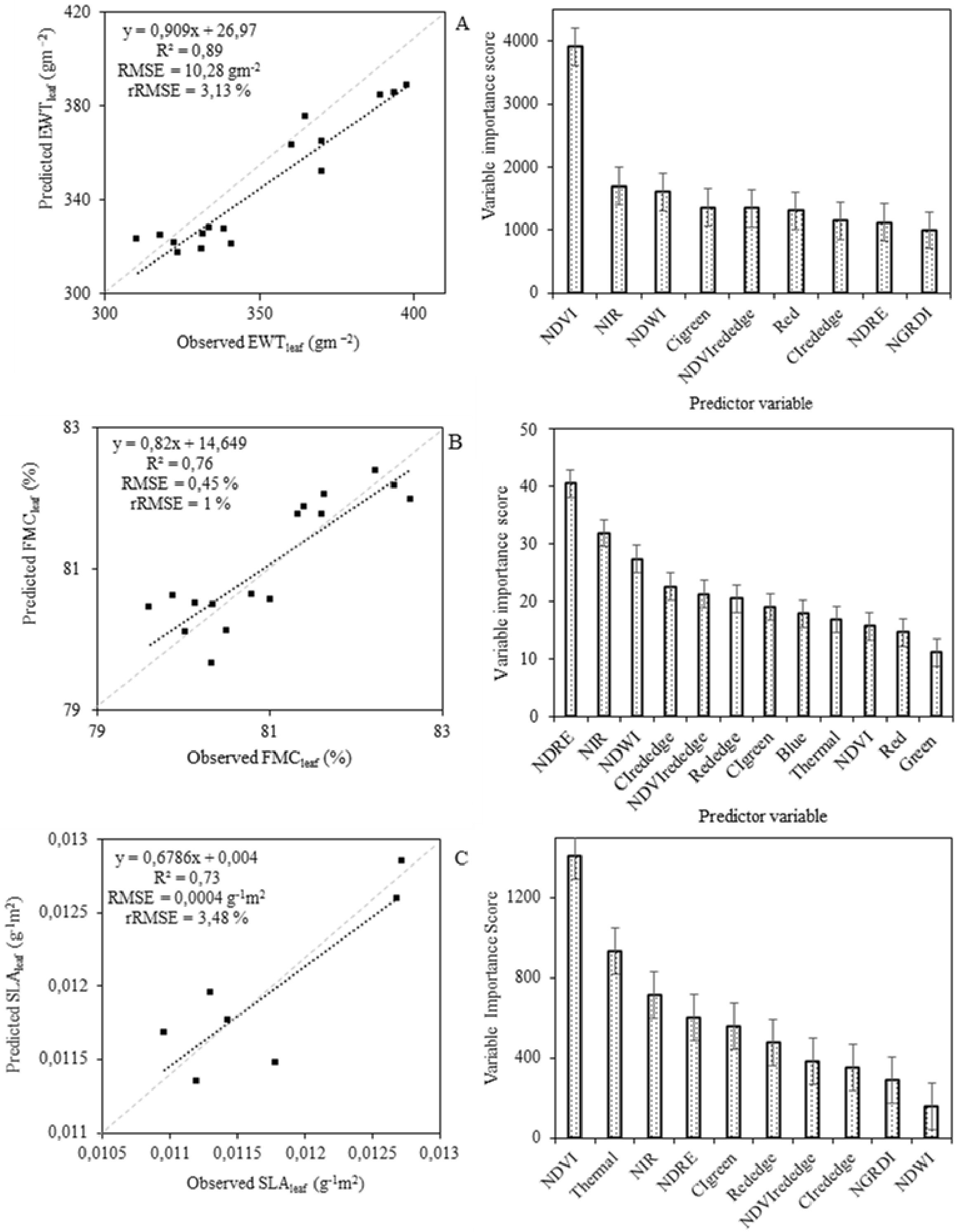

Figure 2. 3: Relationship between the predicted and observed (a) EWT_{leaf}, (b) FMC_{leaf} and (c) SLA_{leaf} of maize derived using optimal predictor variables and the model variable importance scores

2.3.4. Mapping the spatial distribution of maize leaf moisture content indicators

The spatial distribution of leaf EWT, FMC, and SLA was estimated based on the optimal models. Figure 2.4 illustrates the spatial distribution of maize moisture content indicators. It can be observed that the moisture content of maize is relatively high throughout maize fields and seem to decrease towards the edge of the maize plot, with exception of the FMC, which revealed small patches of lower maize moisture content within maize fields.

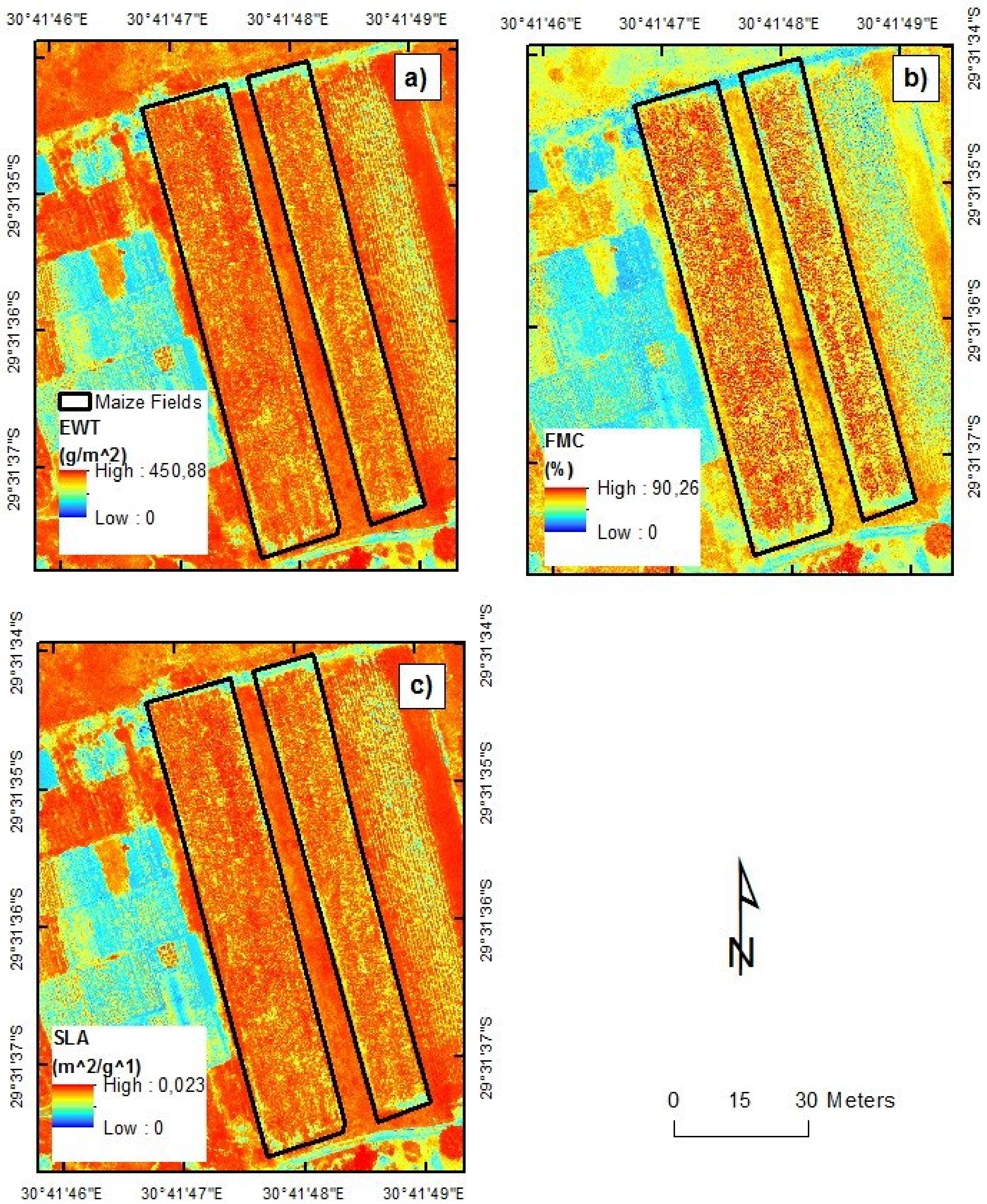

Figure 2. 4: Spatial distribution of (a) EWT_{leaf}, (b) FMC_{leaf}, and (c) SLA_{leaf} of smallholder maize crops

2.4 Discussion

Smallholder farmers are frequently faced with the need to optimize maize production, therefore, an assessment of maize water status through monitoring EWT, FMC and SLA could provide essential information for improving crop water use efficiency and enhancing maize productivity under water-limited conditions (El-Hendawy *et al.*, 2019). The essence of this study was to assess and identify a suitable indicator for maize moisture content and evaluate the predictive performance of robust algorithms in predicting maize moisture status. Thus, this study sought to investigate the use of UAV-derived remotely sensed data and machine learning techniques in estimating maize EWT, FMC and SLA.

2.4.1 Estimating maize moisture content indicators

Results in this study indicate that when estimating maize equivalent water thickness, an optimal estimation accuracy (rRMSE =3.13 % and R^2 =0.89) can be obtained based on spectral variables derived from the NIR section of the electromagnetic spectrum (NDVI, NIR, NDWI, and NDRE). Literature confirms that the quantity of water in crop leaves is statistically correlated with leaf reflectance across the spectrum (Mobasheri and Fatemi, 2013; Wijewardana *et al.*, 2019; El-Hendawy *et al.*, 2019). Specifically, the variation in water molecules present in the leaf cell strongly reflects solar radiation in the NIR region, hence, this section of the spectrum is commonly used to quantity leaf water status (Pasqualotto *et al.*, 2018; El-Hendawy *et al.*, 2019). Leaves which are characterised by high moisture status reflect highly in the NIR region due to multiple scattering within the leaf cell, which is primarily controlled by leaf cuticles, mesophyll thickness and intercellular air spaces and is directly linked to leaf moisture content (Sibanda *et al.*, 2021b; Romero-Trigueros *et al.*, 2017). Furthermore, the NIR section has widely proven to be related to the leaf water absorption zone, hence its optimal influence in estimating the leaf EWT of maize in smallholder farms. Correspondingly, studies by Mobasheri and Fatemi (2013) and Riaño *et al.* (2005) successfully illustrated the use of leaf optical reflectance in the NIR section of the electromagnetic spectrum in optimally predicting EWT with a R^2 of 0.95 and 0.75, respectively. EWT also displayed high sensitivity to chlorophyll-based indices, especially, CI_{green} and CIrededge. This could be explained by the fact that changes in the level of chlorophyll in leaves, which alters crop greenness and leaf pigmentation, is closely related to water status (Jurdao *et al.*, 2013; Zhang and Zhou, 2015) As in this study, Zhang and Zhou (2019) noted that these chlorophyll based indices presented a higher sensitivity to crop water indicators.

Fuel moisture content (FMC) was optimally predicted to a model accuracy of rRMSE of 1 % and $R^2 = 0.76$. The results of this study show that FMC is particularly sensitive to the red-edge waveband and associated derivatives of these spectral channels. For instance, there was a significant influence of the red-edge, NDRE, $NDVI_{rededge}$ and $CI_{rededge}$ in the prediction of maize FMC. Such sensitivity of the red-edge band in predicting FMC can be explained by its positive association with crop biomass as well as chlorophyll content, which is also positively correlated with FMC (Sibanda *et al.*, 2021b). Generally, the variations in crop moisture content are largely associated with chlorophyll activity and leaf area index, which influence the reflectance of leaf tissue in the red-edge section of the electromagnetic spectrum (García *et al.*, 2008). This was the case in studies by Bar-Massada and Sviri (2020) and Cao and Wang (2017) that confirmed a variation in the reflectance of green leaves under water-stressed conditions in the red-edge band, making this wavelength a significant predictor of FMC.

Furthermore, NDWI, which is primarily derived from the NIR band, has a significant influence in the prediction of FMC. This VI is particularly important in predicting moisture content as it is sensitive to the variations of leaf reflectance induced by water molecules and dry matter content, hence, strongly correlates to plant water stress (Zhang and Zhou, 2015). A study by Sow *et al.* (2013) demonstrated the importance of the NDWI in predicting FMC by achieving an R^2 of 0.85. In this regard, the literature supports the relationship between FMC and the red-edge as well as the NIR sections of the electromagnetic spectrum (García *et al.*, 2008; Sibanda *et al.*, 2021b).

Finally, the results in this study show that SLA could be estimated to an rRMSE of 3.48 %. R^2 of 0.73 and SLA was particularly sensitive to the UAV derived thermal, NIR and red-edge wavelengths. When crops are in a state of water deficit, there is an overall increase in crop surface temperature due to the closure of leaf stoma which decreases the evaporation cooling effect (Gerhards *et al.*, 2019). In this regard, the literature notes the fact that the thermal band has been well established as a key wavelength for early plant moisture stress detection (Gerhards *et al.*, 2019; Mangus *et al.*, 2016). Again, NDVI was the most influential predictor of maize SLA in this study. This could be explained by the fact that NDVI is proportional to chlorophyll content which is sensitive to the changes in crop moisture content (Wang *et al.*, 2016b). Furthermore, when crops are water-stressed, there is a decrease in absorption of chlorophyll at the red wavelength and a decrease in reflectance at the NIR region due to the shrinkage of leaf thickness during the wilting process (Lim *et al.*, 2020). In a similar study, Ali *et al.* (2017a) noted that NDVI was very effective in optimally estimating SLA (R^2 = 0.73 and RMSE = 4.68%). Wijewardana *et al.* (2019) confirmed that the combination of both the NIR and red wavelengths allows NDVI to be an invaluable predictor of photosynthetic activity and long-term water stress. Additionally, SLA was sensitive to the NDRE, NDVIredege as well as chlorophyll based VIs. The influence of these red-edge based VIs in predicting SLA stems from the fact that the variations in leaf thickness and area, as well as leaf pigmentation due to moisture stress, is promptly detected at the red-edge section (Easterday *et al.*, 2019). In this regard, the variations in leaf photosynthetic capacity provide essential information pertaining to maize leaf water vapour and moisture content (Ali *et al.*, 2017a).

Furthermore, results illustrate that all maize leaf moisture content indicators were optimally predicted using UAV-derived data. Accordingly, FMC and EWT yielded the highest predictive power of moisture content, while SLA was effectively estimated. In comparison, the FMC and EWT are the most ideal crop water indicators for monitoring moisture stress using field spectroscopy techniques (Liu *et al.*, 2015; Yi *et al.*, 2014).

2.4.2 The performance of machine learning algorithms in predicting maize moisture content indicators

Results in this study show that the RFR approach is the most suitable explorative tool to predict all maize moisture content indicators. For instance, RFR optimally predicted FMC, EWT and SLA, producing the highest prediction accuracy (rRMSE = 1%, 3.13 % and 3.48 %). The RFR algorithm can effectively establish the relationship between leaf reflectance and maize moisture at a farm scale. The strength of RFR could be explained by the fact that the algorithm is not highly affected by noise in the data, hence there is a reduced risk of producing overfitting models (Abdel-Rahman *et al.*, 2013; Zhu *et al.*, 2017). In a similar study, Sibanda *et al.* (2021b) confirmed the robustness of the RFR model in modelling moisture content elements, particularly FMC by achieving optimal R^2s as high as 1 and an RMSE of 16.4 %.

The SVR approach was also optimal in predicting maize leaf EWT, FMC and SLA. The strength of the SVR lies in its ability to circumvent outliers and exhibit a high generalization capacity to handle unseen patterns (Liang *et al.*, 2018). The results in this study reveal that the SVR is similar to the RFR in predictive power. This could be explained by the fact that the SVR and RFR ensembles optimally operate with a relatively small number of training samples, which is often the case for data acquired at a field scale after avoiding spatial autocorrelation (Zhu *et al.*, 2017; Wang *et al.*, 2016b). Research has indicated that the presence of spatial autocorrelation, defined as the systematic spatial variation of the mapped variable, could result in biased and statistically invalid results (Sinha *et al.*, 2019; Zhu *et al.*, 2017; Liang *et al.*, 2018). Therefore, the results of this study demonstrate that the model properties of RFR and SVR are well suited for the estimation of smallholder maize moisture content. Generally, DTR did not perform well in predicting maize moisture indicators. This could be explained by the fact that DTR does not have features such as the bootstrapping in RFR and hyperplanes in SVR for effectively encompassing all the samples during the prediction procedure (Liang *et al.*, 2018). This can result in the DTR algorithm being conservative in its prediction procedure, hence exhibiting lower prediction accuracies. In this regard, there are very few studies that have evaluated its predictive performance in the context of canopy and leaf moisture content. In comparison, the ANN and PLSR exhibited a poorer performance in predicting maize moisture content. This could be due to the fact that both the ANN and PLSR are best suited for a large training dataset to produce credible results (Wang *et al.*, 2016b; Yuan *et al.*, 2017). As such, this study prompts future studies to investigate the optimal sample size required to produce accurate predictions of smallholder maize moisture content when using a combination of UAV imagery and machine learning techniques. Additionally, there are prospects to evaluate the ability of other empirical models and deep learning methods in accurately modelling maize water variability.

2.5 Conclusion

The present study tested the utility of UAV-based multispectral data in a comparative approach of estimating moisture content using RFR, SVR, DTR, ANNR and PLSR machine learning techniques and EWT, FMC and SLA of maize crops in smallholder farms. Based on the findings of the study, it can be concluded that:

- EWT, FMC and SLA moisture content indicators of maize could be optimally predicted using NIR and red-edge derived spectral variables
- The RFR and SVR modelling techniques have a more robust capacity of predicting moisture content indicators of maize in comparison to the DTR, ANNR and PLSR
- FMC and EWT, in concert with the RFR approach, exhibited the highest predictive performance, therefore, are valid indicators of maize moisture content

This study demonstrates that UAV-derived multispectral data is capable of predicting maize moisture variations of smallholder farms with exceptional accuracy, hence can complement and inform farms drought-related water stress. However, there are research gaps that demand further inquiry, particularly on smallholder maize farms. Future studies should aim to evaluate the utility of UAV derived data and the optimal moisture indicators in characterising the variation of maize moisture content across different phenological stages. Furthermore, a key limitation of this study is the lack of the SWIR spectrum which would be valuable as it is an essential water absorption band. Therefore, additional studies are necessary to evaluate whether UAV sensors that measure spectral reflectance along the SWIR section of the electromagnetic spectrum improve the prediction of smallholder maize moisture content. Finally, this study was site and crop-specific, therefore, studies conducted across various climates, different smallholder crops and at a multi-temporal scale should be assessed to draw broad conclusions in characterising crop moisture stress.

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CHAPTER THREE

A multi-temporal remote sensing of smallholder maize leaf equivalent water thickness and fuel moisture content variability using an unmanned aerial vehicle (UAV) derived multispectral data

Abstract

Maize moisture stress, arising from rainfall variability, is a key challenge in the production of rain-fed maize farming, especially in water-scarce regions such as Southern Africa. Quantifying maize moisture variations throughout the growing season is valuable in supporting agricultural decision-making and rapid and robust detection of smallholder maize moisture stress. The emergence of unmanned aerial vehicles (UAV) equipped with multispectral sensors offer a unique opportunity for robust and rapid solution for continuously monitoring maize moisture content and stress. UAV proximal remote sensing offer near-real-time spatially explicit information on maize moisture variability at an exceptionally high temporal resolution. Furthermore, the use of physiological indicators such as equivalent water thickness (EWT) and fuel moisture content (FMC) provide a viable option for quantifying maize moisture content and detecting moisture stress in smallholder farming systems. Hence, this study evaluated the utility of UAV-based multispectral datasets for quantifying maize EWT and FMC throughout the phenological growth cycle of maize. Specifically, maize foliar moisture content indicators were measured at five different phenological periods from the early vegetative to the late reproductive growth stages. The random forest (RF) regression algorithm was used to predict maize leaf moisture content indicators at the different phenological growth stages of the growing season. The findings illustrated that the NIR and red-edge wavelengths were influential in characterising maize moisture variability with the best models for estimating maize EWT and FMC resulting in a rRMSE of 2.27 % and 1%, respectively. Furthermore, the early reproductive stage was the most optimal for accurately estimating maize EWT and FMC using UAV-proximal remote sensing. The findings in this study serve as a fundamental step towards the creation of an early maize moisture stress detection and warning system, and contribute towards climate change adaptation and resilience of smallholder maize farming.

Keywords: unmanned aerial vehicles, maize moisture, temporal variability, precision farming

3.1 Introduction

Maize (*Zea mays L.*) is an important and eminent food security crop that also serves as a valuable source of animal fodder, bio-energy and raw industrial material (Ge *et al.*, 2012; Sah *et al.*, 2020). However, maize moisture stress, arising from rainfall scarcity and variability, is a serious abiotic threat to maize production (Ge *et al.*, 2012; Ndlovu *et al.*, 2021a). Literature shows that maize is commonly grown in regions that receive annual average precipitation of 300-500mm, which is below the critical level of water supply for achieving a good maize yield (Sah *et al.*, 2020). This is a serious concern, particularly in Southern Africa, which is a water-scarce region that only receives an average and seasonal precipitation of 450 mm per annum (Nembilwi *et al.*, 2021; DAFF, 2017). Despite enduring a semi-arid climate, more than 85% of Southern Africa's smallholder maize farms are rain-fed (Ngoune Tandzi and Mutengwa, 2020). According to Sah *et al.* (2020), climatic conditions, specifically seasonal rainfall variability, is a significant limiting factor of maize moisture status, which ultimately regulates maize production. Therefore, there is a need for innovative and sustainable approaches of monitoring maize moisture status throughout the growing season for developing early detection and warning systems of moisture stress for the adoption of relevant mitigation measures.

Maize moisture stress results in numerous physiological and biochemical changes, including a reduction in crop metabolism, increase in stomatal closure and a decrease in dry matter production and leaf area (Song *et al.*, 2019; Zhang *et al.*, 2019b). Subsequently, water deficit negatively impacts maize productivity, impairs crop growth and development, which in turn significantly reduces yield (Ghooshchi *et al.*, 2008; Ge *et al.*, 2012). A study by Ge *et al.* (2012) and Avetisyan and Cvetanova (2019) noted that crop water status varies with crop development stages as well as response of environmental conditions, metabolic activity and hydraulic adaptations (Okunlola *et al.*, 2017). Ghooshchi *et al.* (2008) indicated that the maize tasselling and silking growth stages are most sensitive to impacts of moisture variability while Sah *et al.* (2020) noted that the earlier phenological stages of maize are less subjected to water stress due to favourable climatic conditions. Therefore, the quantitative assessment of maize moisture content throughout the growth cycle offer valuable knowledge of maize growth and development and is a key pathway towards developing adaptive strategies for increasing smallholder maize resilience to water stress.

The most widely used physiological indicators of maize moisture content are equivalent water thickness (EWT) and fuel moisture content (FMC) (Ndlovu *et al.*, 2021a; Mobasheri and

Fatemi, 2013; Yi *et al.*, 2014; Elsherif *et al.*, 2019). EWT is a leaf water status metric that is defined as the ratio between the quantity of water and leaf area (Elsherif *et al.*, 2019; Niinemets, 2001). Zhang and Zhou (2019) stated that EWT is closely associated with plant biochemical processes such as photosynthesis, plant metabolism and crop evapotranspiration, hence it is a suitable indicator of moisture stress. FMC is defined as the proportion of water to dry matter (Yi *et al.*, 2014; Matthews, 2013), and has been widely used for plant water stress, drought monitoring and as a measure of ignition and fire propagation potential (Sibanda *et al.*, 2021b; Yi *et al.*, 2014; Ndlovu *et al.*, 2021a). A study by Ndlovu *et al.* (2021a) confirm that EWT and FMC are valuable indicators of the maize water content of smallholder farming systems as these indicators demonstrated the highest correlation with spectral data. Therefore, quantifying maize leaf EWT and FMC can provide valuable information for the early detection of maize moisture stress and monitoring of maize physiology throughout the growth period to inform small-scale agricultural decision making.

Conventionally, variations in maize EWT and FMC relied on direct measurements and the visual assessment of maize physiology conducted by trained experts (Chivasa *et al.*, 2020). However, these methods are extremely time-consuming, tedious, subject to human error and cannot sufficiently reflect spatial and temporal variability in maize moisture status (Zhang *et al.*, 2012; Jin *et al.*, 2017; Mobasheri and Fatemi, 2013). Furthermore, field data collection requires continuous measurements throughout the maize growth cycle, hence, making implementation marginally feasible (Yue *et al.*, 2018a; Chivasa *et al.*, 2020). Meanwhile, a large body of literature has explored the potential of satellite remote sensing techniques in quantifying crop productivity, health and water status (Pasqualotto *et al.*, 2018; El-Hendawy *et al.*, 2019; Krishna *et al.*, 2019a). For example, a study by Kamali and Nazari (2018) estimated maize water requirement using Landsat-8 data to a rRMSE of 0.73 mm/day, while Ambrosone *et al.* (2020) quantified soil moisture content of rain-fed and irrigated fields using Sentinel-2 multispectral imagery and achieved an optimal R^2 of 0.80 and RMSE of 0.06 cm^3cm^{-3}. However, multispectral satellite sensors are restricted in their ability to accurately monitor variations in maize moisture content throughout the growing season as they are limited by coarse spatial resolution and a longer revisit time for plot-level maize observations (Chivasa *et al.*, 2020; Krishna *et al.*, 2019a). On the contrary, high-resolution multispectral sensors such as WorldView and new generation hyperspectral datasets such as QuickBird provide viable options for continuous water stress detection of maize crops at field scale (Chemura *et al.*, 2017; Easterday *et al.*, 2019). Nonetheless, these datasets are limited by the high image acquisition cost and operational complexity for application in smallholder maize crops (Chivasa *et al.*, 2020). Consequently, there is need for methods that can provide spatially explicit datasets with a high temporal resolution to monitor changes in smallholder maize leaf moisture content throughout the growth period.

Recent advances in technology, particularly the Unmanned Aerial Vehicle (UAV) has heralded a new era in remote sensing, mapping and data analytics within precision agriculture (Maes and Steppe, 2019; Hoffmann *et al.*, 2016; Tang *et al.*, 2019). The use of light weight multispectral sensors mounted on UAVs offer great possibilities for continuous near-real-time crop monitoring at a farm level (Chivasa *et al.*, 2020). UAVs are unique in that they can provide high-quality remote sensing data at unprecedented spatial, spectral and temporal resolutions (Maes and Steppe, 2019; Ndlovu *et al.*, 2021a). In addition, UAVs mounted sensors capture imagery at low altitudes and can hover over areas of interest, making them a desirable tool for monitoring changes in maize moisture content at different phenological stages (Tsouros *et al.*, 2019). Furthermore, UAVs provide a cost-effective option to obtain frequent imagery at an ultra-high spatial resolution, often in centimetres, which is necessary for the monitoring of crop physiology at a plot level (Maes and Steppe, 2019). For example, in a comparative study between UAV-based data and satellite imagery, Matese *et al.* (2015) confirmed that UAV-derived datasets are capable of detecting even the most subtle variations in crop physiological characteristics; a challenge even for high-resolution satellite imagery such as RapidEye. A study by Tang *et al.* (2019) demonstrated the value of UAV-derived multispectral data in predicting maize evapotranspiration with an R^2 of 0.81 and RMSE of 0.95 mm/day. Nonetheless, the ability of UAV imagery to adequately discriminate maize moisture content variability across the growing season remains untested. Therefore, the potential application of UAVs, equipped with multispectral sensors in characterising smallholder maize moisture status at different growth stages still requires investigation.

Considering that moisture content in leaf tissue is a critical influencer of crop survival, accurately monitoring crop water status using spectral reflectance measurements has been a key objective in environmental research (Pasqualotto *et al.*, 2018). The rationality of estimating maize moisture content stems from the fact that literature confirms the existence of a strong relationship between foliar water concentration and spectral absorption at specific near-infrared (NIR) and the shortwave infrared (SWIR) wavelengths of the electromagnetic spectrum (Chemura *et al.*, 2017). For instance, water molecules in leaf tissue produce maximum absorption features along the NIR (750-1300 nm) section of the spectrum as a result of a decrease in leaf reflectance (Pasqualotto *et al.*, 2018; Wijewardana *et al.*, 2019; Krishna *et al.*, 2019a). Furthermore, there are secondary effects of water absorption in the visible region of the electromagnetic spectrum (blue, green and red) which are influenced by leaf internal structure and water transmissivity (Chemura *et al.*, 2017; Mobasheri and Fatemi, 2013). This makes these sections of the spectrum sensitive to changes in water content and therefore a plausible proxy for crop water stress detection. To enhance the spectral characteristics of crop leaf reflectance, several studies have demonstrated the utilization of empirical models and vegetation indices (VIs) to predict crop moisture content (Pasqualotto *et al.*, 2018; Xue and Su, 2017). For example, studies have reported the Normalised Difference Water Index (NDWI) as a water content-sensitive index that can be used to predict crop moisture throughout the growing season (Xu *et al.*, 2020; Zhang and Zhou, 2015). Krishna *et al.* (2019a) noted that even though the Normalised Difference Vegetation Index (NDVI) is optimal for crop chlorophyll content estimations, the index is highly correlated to the plant water status, hence, is also a valuable predictor of maize moisture content. Therefore, with the understanding of crop leaf reflectance across the electromagnetic spectrum, UAV-derived spectral datasets provide a viable approach to quantifying intra-species moisture content variability of smallholder maize crops throughout the growth cycle.

Considering that limited studies have evaluated the feasibility of using UAV-based proximal remotely sensed data in accurately monitoring maize moisture content across all phenological stages (Zhang and Zhou, 2019), there is a need to assess the value of UAV-derived data in mapping crop moisture content variability. This study, therefore, sought to evaluate the utility of UAV-derived multispectral imagery in estimating the spatio-temporal variability of smallholder maize leaf EWT and FMC across the maize growing season.

3.2 Materials and Methods

3.2.1 Study site description

This study was conducted in Swayimane (29° 31’ S, 30° 41’ E), uMshwati Municipality, KwaZulu-Natal, South Africa (Figure 3.1). The study area experiences a sub-tropical climate, with a mean annual rainfall of 500-800 mm per annum and an average air temperature between 11.8 °C and 24 °C (Basdew *et al.*, 2017). Swayimane is located at an altitude of 886 m above sea level and is characterised by a relatively flat topography. The soil of the study area is classified as deep and dark clay loam soils, which indicate high organic matter and soil fertility (Ndlovu *et al.*, 2021b). The land in Swayimane is predominantly used for commercial and small-scale subsistence agriculture, with the cultivation of several crops including taro, sweet potatoes, spinach, beans, sugarcane and maize (Ndlovu *et al.*, 2021b). The study area is situated within the moist midlands mistbelt bioclimatic region prone to berg winds, extreme clouds, flash floods, seasonal hail and occasional periods of drought (Mahomed *et al.*, 2021). The area has been identified by the Umgeni Resillience Project as a climate change hot-spot region (Keen and Winkler, 2020). Climate projections of the area indicate an increase in temperature and unpredictable variations in annual precipitation resulting in an increased risk of climate-driven events, including an increase of drought (Mahomed *et al.*, 2021). As such, it is an area of interest to climatologists and agronomists studying means of combating the impacts of climate variability on smallholder agricultural systems.

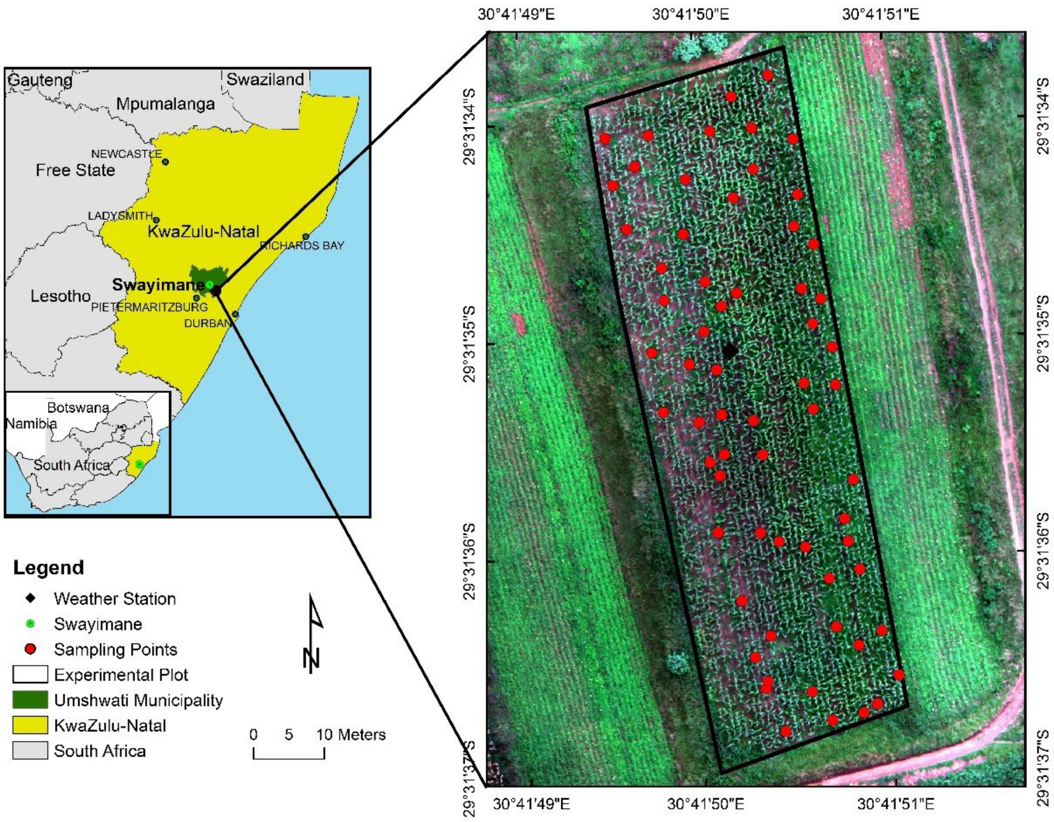

Figure 3. 1: Location of the study area in Swayimane, South Africa

3.2.2 Experimental design and crop management

The maize moisture content was continuously monitored through the maize phenological stages. Field measurements were conducted at two-week intervals for five growth stages: 8th leaf collar – 10th leaf collar (V8-V10), 14th leaf collar – tasselling (V14-Vt), silking – blister (R1-R2), blister – milk (R2-R3) and dough – dent (R3-R4). Figure 3.2 illustrates the biophysical condition of maize at the various phenological growth stages. The experimental plot was 50 m long and 30 m wide and occupied a gentle topography. Maize crops were sown on the 8th February 2021 and corn kernels harvested on the 17th May 2021. Cow urea and manure were applied as crop fertilizer before sowing and a combination of manual hand weeding and herbicide application conducted when the maize crops were 21 days old. The experimental plot relied primarily on precipitation for water supply. The study plots were not irrigated nor fertilizer applied during the entire growing season. Figure 3.3 presents the bioclimatic conditions of the study plot during the maize growing period; derived from an automatic weather station, located approximately 860 m from the experimental plot.

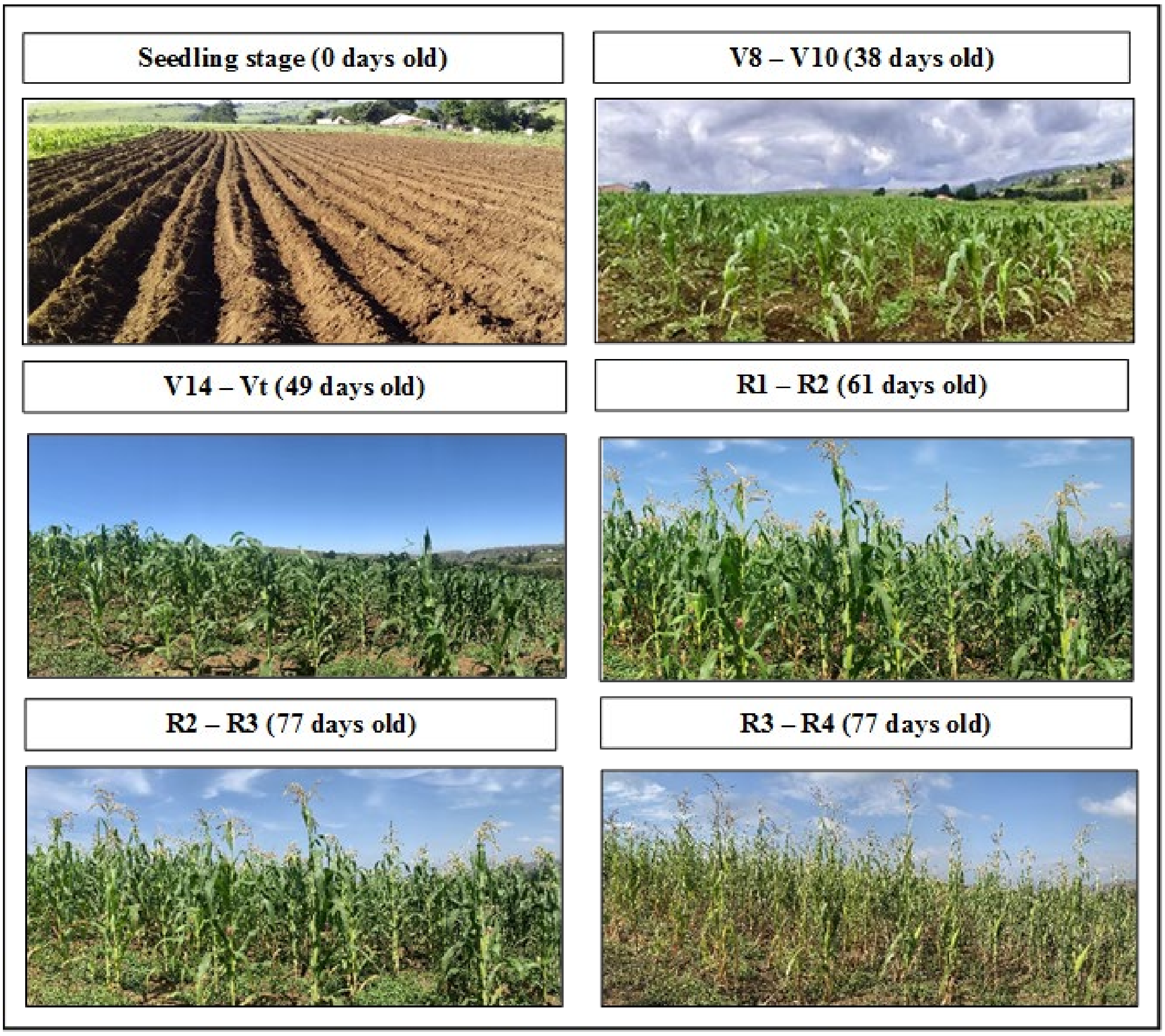

Figure 3. 2: Biophysical conditions of maize across the phenological growth period

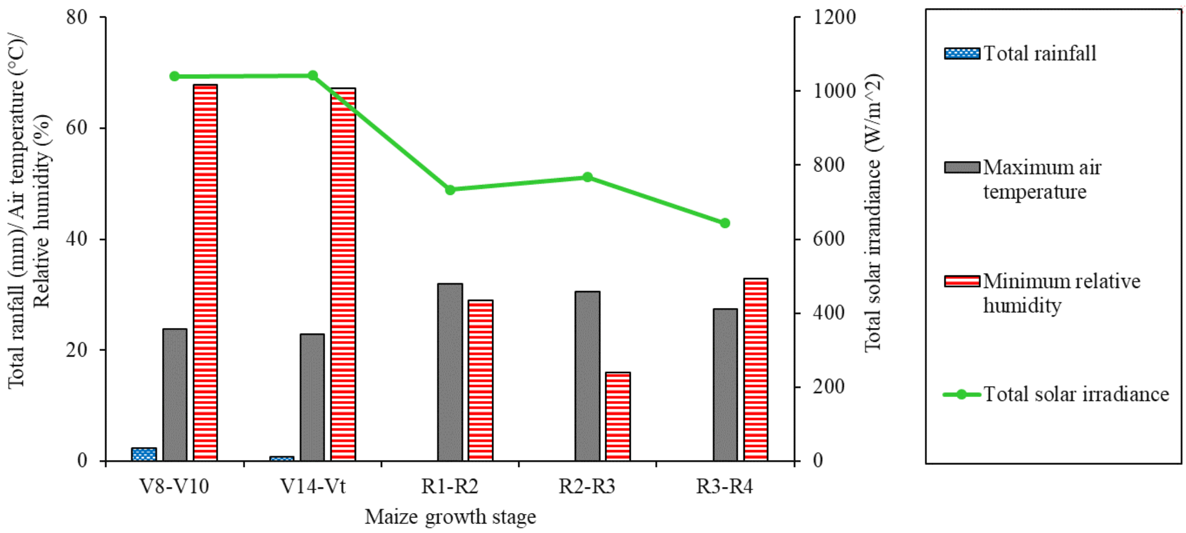

Figure 3. 3: Bioclimatic condition of maize across the phenological growth period

3.2.3 UAV platform, imagery acquisition and processing

The Altum MicaSense multispectral camera and a DJI Matrice 300 series UAV platform were used to acquire spectral images of maize at the five phenological growth stages of the season (Figure 3.4). The main advantage of this UAV platform is its ability to acquire imagery in a range of environmental conditions at a high speed (one capture per second) and to provide imagery with high geolocational accuracy. The UAV platform has a built-in Global Positioning System (GPS) unit which receives positional information for subsequent image georeferencing. The Micasense sensor consists of six spectral bands that capture spectral reflectance in the blue, green, red, rededge, NIR and thermal regions of the electromagnetic spectrum (Figure 3.4 (b)). A flight plan was coordinated on Google Earth Pro using a shapefile of the study site and exported to the UAV handheld console for navigation. A calibrated reflectance panel was used to radiometrically calibrate the UAV sensor and improve image accuracy. The flight was then carried out autonomously at a flight height of 100 m, a ground sampling distance of 9.6 cm and an 80 % image overlap. The raw multispectral data, consisting of approximately 3400 images, were mosaicked to form a single image of the study area using Pix4D Fields photogrammetry software. The image was further georeferenced in QGIS 3.4.0 to optimise geolocation accuracy.

Figure 3. 4: a) UAV imaging platform and b) MicaSense multispectral camera used in this study

3.2.4 Field survey and measurements of maize moisture content

Field measurements were conducted on the 18th March (V8-V10), 31st March (V14-Vt), 12th April (R1-R2), 28th April (R2-R3) and 14th May (R3-R4) in 2021. A stratified random sampling procedure was used to generate a total of 65 random sampling points within the experimental plot. This method is optimal for acquiring an unbiased representative sample of the experimental maize plot. A Trimble handheld GPS with a sub-meter accuracy was used to navigate to these sampling points at each stage of the maize growth period. At each sample point, the third fully developed maize leaf from the top of the stalk was sampled. Literature states that to obtain reliable maize physiological measurements, fully developed leaf samples should be taken from the top of the canopy as there is maximum reflectance of light energy. Meanwhile, the sampling of young crops can lead to plant stress, which can ultimately cease crop growth (Mulla, 2013; Wahbi and Avery, 2018). In this regard, maize leaf sampling was not conducted during the emergence stages, specifically from germination to the 5th leaf collar growth stage. Crop moisture content measurements were conducted under near-cloud free conditions between 12:00 noon and 14:000 as this is the most optimal photosynthetic period of the day with radiation at maximum (Sade *et al.*, 2015b). A portable leaf area meter (LI-3000C) with one mm^2 resolution was used to measure the leaf area (A) of sampled leaves. A calibrated scale was used to obtain the fresh weight (FW) of maize leaf samples, which were then dried in an oven at 70° C until a constant dry weight (DW) was reached (± 48 hours). The leaf equivalent water thickness (EWT_{leaf} in gm^{-2}) and fuel moisture content (FMC_{leaf} in %) were then computed using the FW, DW and A of maize leaves based on the formula.

$EWTleaf = \frac{\mathrm{FW-DW}}{\mathrm{A}}$ Units: gm^{-2} ……………………………*eq.1*

$FMCleaf = \frac{\mathrm{FW-DW}}{\mathrm{DW}} x\ 100$ Units: %……………………………*eq.2*

Where FW is the fresh weight, DW is the dry weight and A is the leaf area. The computed EWT_{leaf} and FMC_{leaf} were recorded in an excel spreadsheet against the coordinate of each sampling point, which was later converted into a point map in ArcMap version 10.3.1.

3.2.5 Selection of vegetation indices

The six UAV-derived spectral bands were used to estimate maize EWT_{leaf} and $FMC_{leaf.}$ These bands were also used to compute vegetation indices (VIs) used to estimate maize moisture indicators. Studies have confirmed the ability of the visible and NIR channels of the electromagnetic spectrum to detect subtle variations in vegetation water characteristics (Chemura *et al.*, 2017; Pasqualotto *et al.*, 2018). Based on exisiting literature, a total of ten moisture content related VIs were computed based on their correlation with maize moisture content indicators. Table 3.1 includes further details on the VI used to estimate maize moisture content.

Table 3. 1: Selected vegetation indices (VIs) used for maize moisture content estimations

Vegetation Index	Equation	Reference
NDWI	(Green - NIR / Green + NIR)	(Miller *et al.*, 2020)
NDVI	(NIR - Red / NIR + Red)	(Krishna *et al.*, 2019a)
NGRDI	(Green - Red / Green + Red)	(Hoffmann *et al.*, 2016)
NDRE	(NIR - Rededge / NIR + Rededge)	(Zhang *et al.*, 2019b)
$NDVI_{rededge}$	(Rededge - Red / Rededge + Red)	(Zhang *et al.*, 2019b)
CI_{green}	((NIR/Green) -1)	(Zhang and Zhou, 2015)
$CI_{rededge}$	((NIR/Rededge) -1)	(Zhang and Zhou, 2015)
SR	(NIR/Red)	(Xue and Su, 2017)
OSAVI	((NIR - Red)/(NIR + Red + 0,16))	(Xue and Su, 2017)

3.2.6 Model development and statistical analysis

The random forest (RF) regression provides a reliable and efficient method for performing complex and multi-dimensional environmental data analysis that would naturally be time-consuming to observe (Lu and He, 2019). In this study, RF regression algorithm was used to predict maize leaf moisture content indicators (EWT_{leaf} and FMC_{leaf}) at different phenological growth stages of maize crops because of its simplicity and robustness (Sibanda *et al.*, 2021b).

The RF ensemble is a machine learning technique that uses bootstrap aggregation and binary recursive partitioning to construct several independent trees using a random subset derived from the training data (Lu and He, 2019). The robustness of RF originates from the capacity of the algorithm to use bootstrap aggregation to build regression trees that are grown to their maximum sizes, which are then used to allocate an input variable (spectral bands and VIs) to a response variable (EWT_{leaf} or FMC_{leaf}) using unweighted averaging (Jeong *et al.*, 2016). Additionally, the out-of-bag samples, which are samples that have been excluded from the bootstrap aggregation, are used by RF ensemble to evaluate the generated regression model (Abdel-Rahman *et al.*, 2013). However, a common challenge with regression models is multicollinearity which results from a high level of correlation between two or more predictor variables (Chivasa *et al.*, 2021). As such, it is advisable to use only the most suitable predictor variables in building regression models (Jeong *et al.*, 2016). Variable importance selection was adopted to resolve any potential collinearity and select the best and the fewest predictor variables for the RF model. RF can compute Gini impurity scores that are used to identify predictor variables that are most influential in prediction (Sibanda *et al.*, 2021b). Therefore, the most important predictor variable was identified by a higher Gini impurity score. The best predictor variables were then used to develop the final RF model of maize moisture content at each growth stage. Before the analysis, the dataset of randomly split into training data (70%:46 samples) and validation data (30 %:19 samples). The former was used to develop the regression model and the latter to evaluate the predictive performance of the model.

3.2.7 Accuracy assessment and model validation

The prediction accuracy of the derived RF models was assessed based on the coefficient of determination (R^2), the root mean square error (RMSE) and the relative root mean square error (rRMSE). The R^2 is a statistical measure of the variation between measured and predicted output. It also measures how well the response variable fits into the regression line. Additionally, the RMSE assesses the magnitude of error between field measurements and the modelled maize moisture content. Meanwhile, the rRMSE was used as a metric to compare the performance of EWT_{leaf} to FMC_{leaf} at the different maize growth stages. The optimal model for estimating maize moisture content indicators at different phenological stages was determined based on the highest R^2 and the lowest RMSE and rRMSE.

$$RMSE = \sqrt{\frac{\sum(predicted - actual)^2}{n}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots eq.1$$

$$rRMSE = \frac{RMSE}{Mean\ (actual)} \times 100 \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots eq.2$$

where *predicted* is the modelled variables and *actual* is the measured variables. Lastly, a map illustrating the spatial and temporal distribution of the predicted maize EWT_{leaf} or FMC_{leaf} at every growth stage was generated. The RMSE and the rRMSE were calculated based on the above formulas.

3.3 Results

3.3.1 Descriptive statistics and temporal variation in EWT_{leaf} and FMC_{leaf} during the maize phenological cycle

Figure 3.5 illustrates the temporal variation of measured EWT_{leaf} and FMC_{leaf} throughout the maize growing season. As expected, there was a variation in maize EWT_{leaf} and FMC_{leaf} measured across the maize phenological season. Both maize EWT_{leaf} and FMC_{leaf} displayed a decreasing trend in moisture content as the growing season progressed. The lowest mean EWT_{leaf} were observed at the late reproductive stages of maize development, particularly during the R2-R3 stage (96.45 ± 62.15 gm^{-2}) while, the highest EWT_{leaf} was at the V8-V10 growth stages (274.45 ± 43.25 gm^{-2}) (Table 3.2). The R2-R3 growth stage had the lowest mean FMC_{leaf} (48.59 ± 14.66 %) while the greatest mean FMC_{leaf} was observed at the R1-R2 maize growth stage (84.48±2.23 %) (Table 3.2). The results of a Kolmogorov-Smirnov normality test indicated that the distribution of the measured maize EWT_{leaf} and FMC_{leaf} were not significantly deviating from a normal distribution curve, hence a Pearson correlation was conducted to examine the relationship between maize EWT_{leaf} and FMC_{leaf}, and rainfall. Based on the Pearson correlation test, there was a statistically significant correlation between maize EWT_{leaf} and rainfall (R^2 = 0.97, r= 0.90, $p < 0.05$). Similarly, a correlation test between maize FMC_{leaf} and rainfall indicated a statistically significant (R^2 of 0.77, r= 0.81, $p < 0.05$).

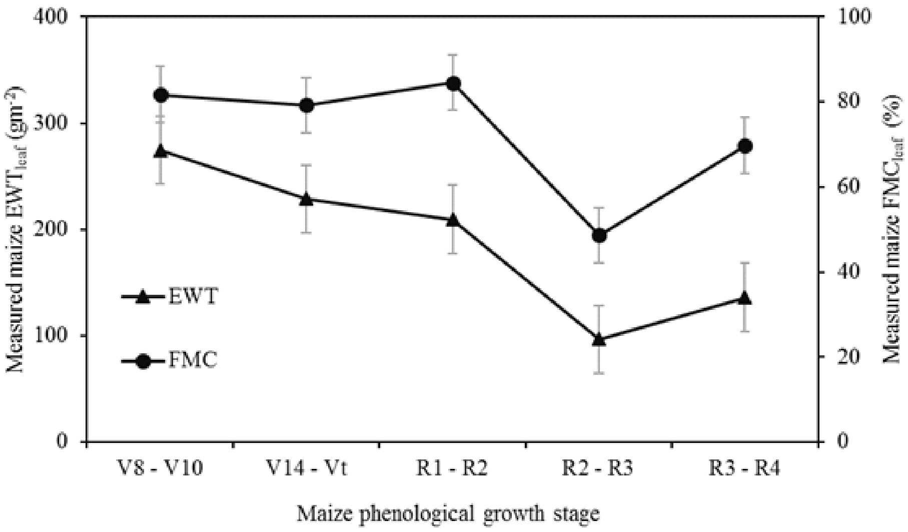

Figure 3. 5: Temporal variation of maize EWT_{leaf} and FMC_{leaf} during the maize growing season

Table 3. 2: Descriptive statistics of EWT_{leaf} and FMC_{leaf} at the different phenological stages

Maize growth stage	Variable	Range (min-max)	Mean	Median	Std.	CV %	SEM
V8 - V10	**EWT** (gm-2)	169.35 - 462.73	274.45	270.47	43.25	15.76	5.45
	FMC (%)	73.72 - 90.91	81.72	81.63	2.32	2.84	0.29
V14 - Vt	**EWT** (gm-2)	154.76 - 329.33	228.57	229.13	49.67	21.73	6.26
	FMC (%)	69.93 - 86.05	79.17	79.01	2.89	3.65	0.36
R1 - R2	**EWT** (gm-2)	159.86 - 249.66	209.38	211.34	17	8.12	2.14
	FMC (%)	77.78 - 91.59	84.48	84.23	2.73	3.24	0.34
R2 - R3	**EWT** (gm-2)	11.66 - 448.71	96.48	91.9	62.15	64.41	7.83
	FMC (%)	8.11 - 85.98	48.59	50	14.66	30.18	1.85
R3 - R4	**EWT** (gm-2)	25.33 - 360.21	135.7	121.01	62.66	46.17	7.89
	FMC (%)	59.52 - 82.14	69.72	69.77	4.04	5.79	0.51

3.3.2 Estimating maize EWT_{leaf} and FMC_{leaf} throughout the maize growing season

Table 3.3 illustrates the accuracies obtained in estimating maize EWT_{leaf} *and* FMC_{leaf} throughout the growing season based on UAV bands only, vegetation indices (VIs) as well as the combination of UAV bands and VIs. Generally, UAV bands resulted in relatively lower model accuracies at all maize growth stages. For example, when estimating EWT_{leaf}, UAV bands exhibited the lowest accuracy at the V14-Vt and R1-R2 growth stages yielding a RMSE of 47.58 gm^{-2} and R^2 of 0.53, and RMSE of 13.13 gm^{-2} and R^2 of 0.59, respectively. Similarly, in estimating maize FMC_{leaf}, the lowest RMSEs were obtained when using UAV bands at the R1-R2, R2-R3 and R3-R4 maize growth stage with RMSE of 1.13 gm^{-2} and R^2 of 0.59, RMSE of 11.05 gm^{-2} and R^2 of 0.53, and RMSE of 3.05 gm^{-2} and R^2 of 0.57, respectively.

The use of VIs improved model accuracies of maize EWT_{leaf} *and* FMC_{leaf}. For example, the EWT_{leaf} model slightly improved by a magnitude of 6.43 from a RMSE of 47.58 gm^{-2} to 41.15 gm^{-2} at the V14-Vt maize growth stage. Again, in estimating FMC_{leaf}, the use of VIs improved the model accuracy from 11.05 gm^{-2} to 7.94 gm^{-2} at the R2-R3 growth stage.

Table 3. 3: Estimation accuracies of EWT_{leaf} and FMC_{leaf} derived using UAV bands, vegetation indices and the combination of both

Maize growth stage	Predictor variables	*EWT_{leaf}*			*FMC_{leaf}*		
		R^2	**RMSE**	**rRMSE**	**R^2**	**RMSE**	**rRMSE**
V8-V10	UAV bands	0.52	14.38	4.89	0.42	2.22	2.69
	Vegetation indices	0.6	14.98	4.91	0.44	2.35	2.85
V14-Vt	UAV bands	0.53	47.58	23.01	0.52	1.93	1.98
	Vegetation indices	0.7	41.15	19.9	0.56	2.15	2.76
R1-R2	UAV bands	0.59	13.13	6.46	0.59	1.13	1.34
	Vegetation indices	0.78	11.17	5.5	0.76	0.9	1.09
R2-R3	UAV bands	0.63	16.71	17.73	0.53	11.05	26.72
	Vegetation indices	0.7	37.21	50.67	0.73	7.94	18.71
R3-R4	UAV bands	0.58	24.49	18.71	0.57	3.05	4.47
	Vegetation indices	0.66	40.39	32.95	0.67	2.68	3.94

The optimal models for predicting maize *EWT_{leaf} and FMC_{leaf}* at all growth stages were determined by combining UAV bands and VIs. For example, when estimating maize *EWT_{leaf}*, the combined datasets exhibited the highest model accuracies with a RMSE of 5.31 gm^{-2} and R^2 of 0.88 at the R1-R2 growth stage, and a RMSE of 10.28 gm^{-2} and R^2 of 0.89 at the R2-R3 growth stage. Similarly, when estimating *FMC_{leaf}*, the highest model accuracies were obtained when UAV bands and VIs were used (RMSE of 0.88 gm^{-2} and 0.45 gm^{-2} at the R1-R2 and R2-R3 stages, respectively).

Figure 3.6 illustrates the optimal models obtained for estimating maize EWT_{leaf} at each maize growth stage. During the early vegetation growth stages, maize EWT_{leaf} at the V8-V10 phenological stage was predicted to a RMSE of 13.03 gm^{-2} and R^2 of 0.69. The top-most suitable predictor variables in estimating EWT_{leaf} at this stage were $NDVI_{rededge}$, thermal, rededge, NGRDI, $CI_{rededge}$, NDVI, OSAVI, NDRE, NIR, red, NDWI, CI_{green} and SR, in order of importance (Figure 3.6 (a)). The V14-Vt exhibited the poorest prediction accuracy of maize EWT_{leaf} during the vegetative stages (RMSE = 23.99 gm^{-2} and R^2 of 0.76) using NDVI, $CI_{rededge}$, red-edge, NDRE, NDWI, CI_{green}, NIR, thermal, blue, $NDVI_{rededge}$, NGRDI, green and red, in descending order of importance (Figure 3.6 (b)).The most optimal maize growth stage for estimating EWT_{leaf} was observed in the early reproductive R1-R2 growth stage, which yielded the highest model accuracy across all phenological stages (RMSE of 5.31 gm^{-2} and R^2 of 0.88) based on $NDVI_{rededge}$, rededge, NIR, NDVI, NDRE, NGRDI, blue, $CI_{rededge}$, NDWI, and CIgreen, red, thermal and green, in order of importance (Figure 3.6 (c)). Hereafter, a decrease in EWT_{leaf} model accuracy was observed in all later stages of maize growth. For example, the estimation accuracy of EWT_{leaf} decreased by 4.97 gm^{-2} to an RMSE of 10.28 gm^{-2} in the R2-R3 maize growth stage, in comparison to 5.31 gm^{-2} from the R1-R2 stage. Nonetheless, an R^2 of 0.89 was attained from predicting maize EWT_{leaf} during the R2-R3 growth stage. The influential predictor variables on that model included NDVI, NIR, NDWI, CI_{green}, $NDVI_{rededge}$, red, $CI_{rededge}$, NDRE and NGRDI, accordingly (Figure 3.6 (d)). Furthermore, the maize EWT_{leaf} model accuracy depreciated at the R3-R4 growth stage yielding a RMSE of 12.66 gm^{-2} and R^2 of 0.77). The optimal from this model were NDVI, NIR, NDWI, CI_{green}, $NDVI_{rededge}$, and red, $CI_{rededge}$, NDRE and NGRDI, in order of descending importance (Figure 3.6 (e)).

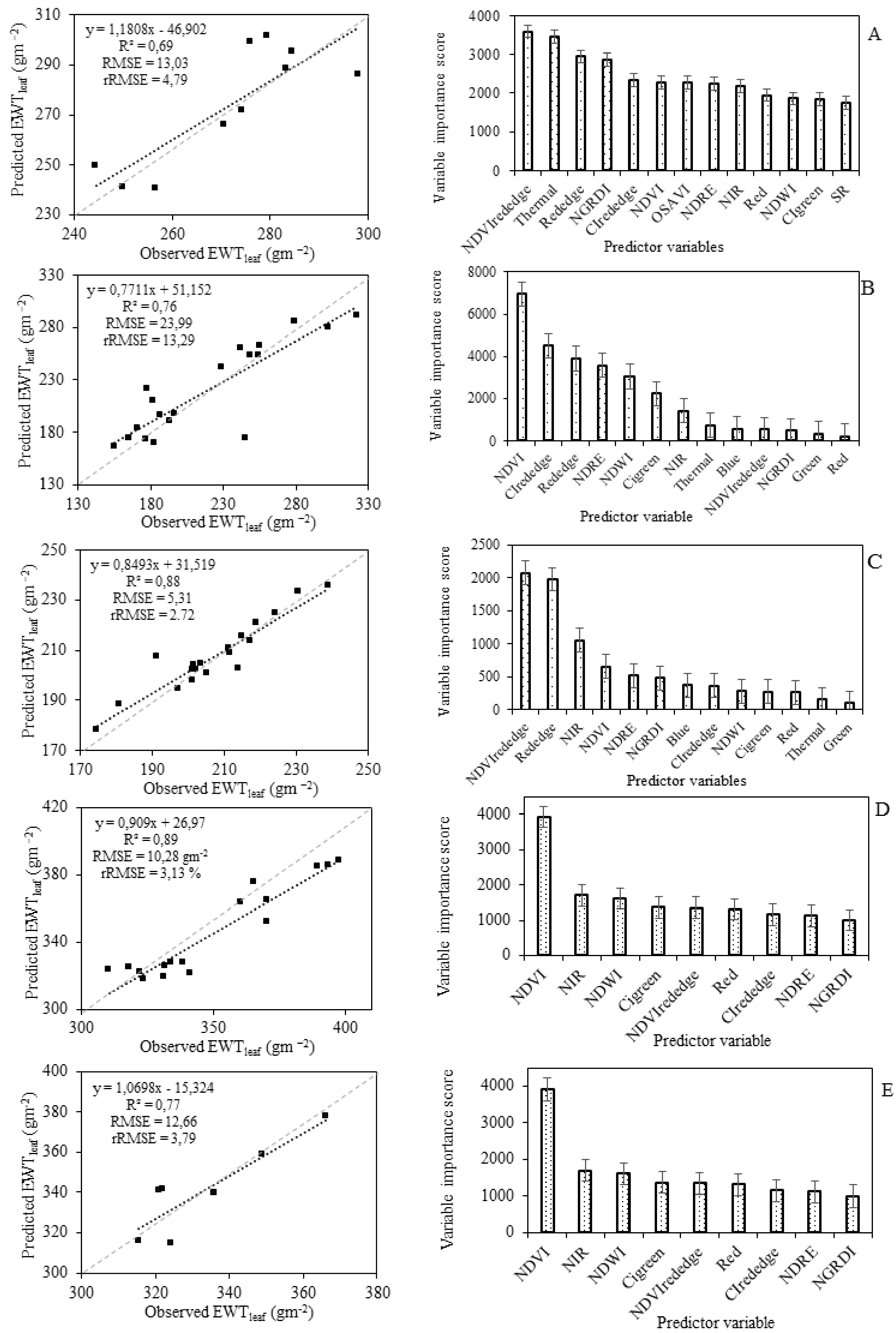

Figure 3. 6: Relationship between the predicted and observed maize EWT_{leaf} at (a), V8 - V10, (b) V14 – Vt, (c) R1-R2, (d) R2-R3 and (e) R3-R4 phenological growth stage and the optimal model variable importance scores

Figure 3.7 illustrates the optimal models attained in estimating maize FMC_{leaf} across all growth stages. The estimation of maize FMC_{leaf} at the V8-V10 growth stage yielded a moderate RMSE of 1.13 %, however, it exhibited a low R^2 of 0.66 based on NDVI, $NDVI_{rededge}$, thermal, red, SR, rededge, NGRDI, green, NDWI, NIR, NDRE, OSAVI, $CI_{rededge}$, CI_{green} and blue, in order of importance (Figure 3.7 (a)). Meanwhile, at the V14-Vt growth stage, the maize FMC_{leaf} 's yielded a RMSE = 1.44 % and an optimal R^2 = 0.73. The most suitable predictor variables included NDRE, rededge, CI_{green}, NIR, NDWI, $CI_{rededge}$, NDVI, $NDVI_{rededge}$, thermal, green, blue, NGRDI and red, in order of decreasing importance (Figure 3.7 (b)).

Meanwhile, the maize FMC_{leaf} prediction accuracy significantly increased in the early reproductive stages of the maize growing season. For example, the R1-R2 maize growth stage yielded a RMSE of 0.88 % and a R^2 of 0.87 using NDVI, rededge, $NDVI_{rededge}$, NIR, NDRE, $CI_{rededge}$, blue, NGRDI and red, in order of importance (Figure 3.7 (c)). The optimal phenological growth stage for optimally estimating maize FMC_{leaf} was the R2-R3 growth stage, which yielded the highest model accuracy with a RMSE = 0.45 % and R^2 of 0.76. This optimal maize FMC_{leaf} model was derived based on the NDRE, NIR, NDWI, $CI_{rededge}$, $NDVI_{rededge}$, rededge, CI_{green}, blue, thermal, NDVI, red and green predictor variables. (Figure 3.7 (d)).

Meanwhile, the later reproductive growth stages demonstrated the lowest FMC_{leaf} prediction accuracies. Maize FMC_{leaf} at the R3-R4 growth stage yielded the poorest prediction accuracy with a RMSE of 1.54 % and R^2 of 0.72. Finally, the most optimal variables that were selected in estimating maize FMC_{leaf} at this growth stage were $NDVI_{rededge}$, $CI_{rededge}$, NDRE, NDWI, CI_{green}, NDVI, red, green, NIR, NGRDI, red-edge, thermal and blue, in order of importance (Figure 3.7 (e)).

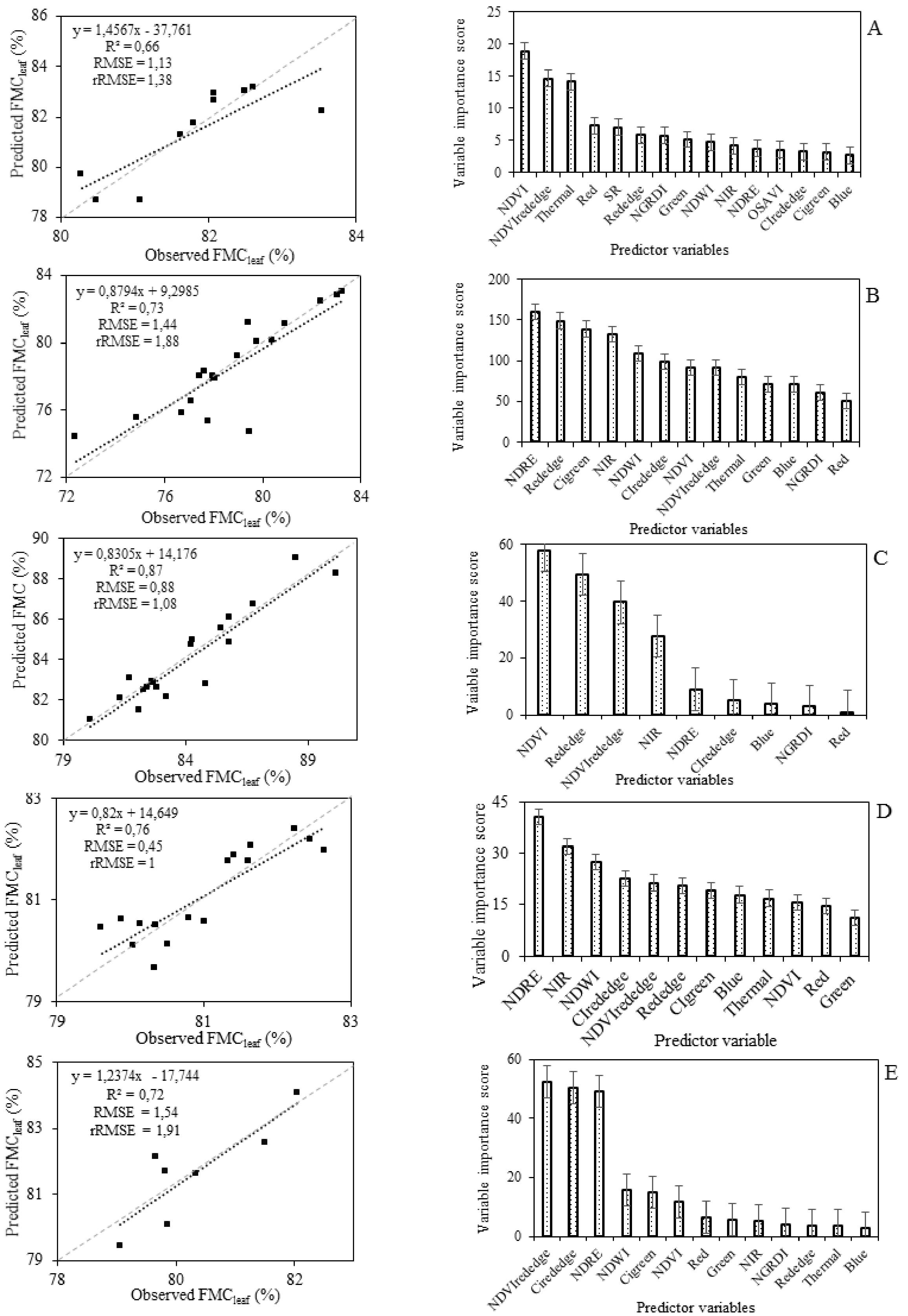

Figure 3. 7: Relationship between the predicted and observed maize FMCleaf at (a), V8 - V10, (b) V14 – Vt, (c) R1-R2, (d) R2-R3 and (e) R3-R4 phenological growth stage and the optimal model variable importance scores

In comparison, the results illustrate that the prediction accuracy of maize EWT_{leaf} and FMC_{leaf} vary for each phenological stage across the growing season. For example, the maize FMC_{leaf} outperformed EWT_{leaf} with an rRMSE of 1.38 % as opposed to rRMSE of 4.79% (Figure 3.6 and 3.7 (a)). Similarly, the prediction accuracy of maize FMC_{leaf} (rRMSE = 1.88%) was significantly higher than that of maize EWT_{leaf} (13.29 %) by a magnitude of 11.41 % (Figure 3.6 and 3.7 (b)). Again, at the R1-R2 maize growth stage, EWT_{leaf} exhibited an rRMSE of 2.72 % while FMC_{leaf} of maize had a higher prediction accuracy with rRMSE of 1.08 % (Figure 3.6 and 3.7 (c)). Similarly, model accuracies for predicting maize FMC_{leaf} were marginally higher than EWT_{leaf} at the R2-R3 growth stage, with an rRMSE = 1% and 3.13 % respectively. Nonetheless, EWT_{leaf} at this stage produced the highest R^2 of 0.89 in comparison to FMC_{leaf} which yielded a R^2 of 0.76 (Figure 3.6 and 3.7 (d)). Finally, FMC_{leaf} produced an rRMSE of 1.91 % at the R3-R4 maize growth stage, as compared to the rRMSE of 3.79 % which was exhibited by the maize EWT_{leaf} model (Figure 3.6 and 3.7 (e)).

Figure 3.8 and Figure 3.9 illustrate the spatial distribution of maize EWT_{leaf} and FMC_{leaf} across the five maize phenological growth stages. It can be observed that maize EWT_{leaf} and FMC_{leaf} was higher in the eastern region and decreases towards the western section of the experimental maize plot.

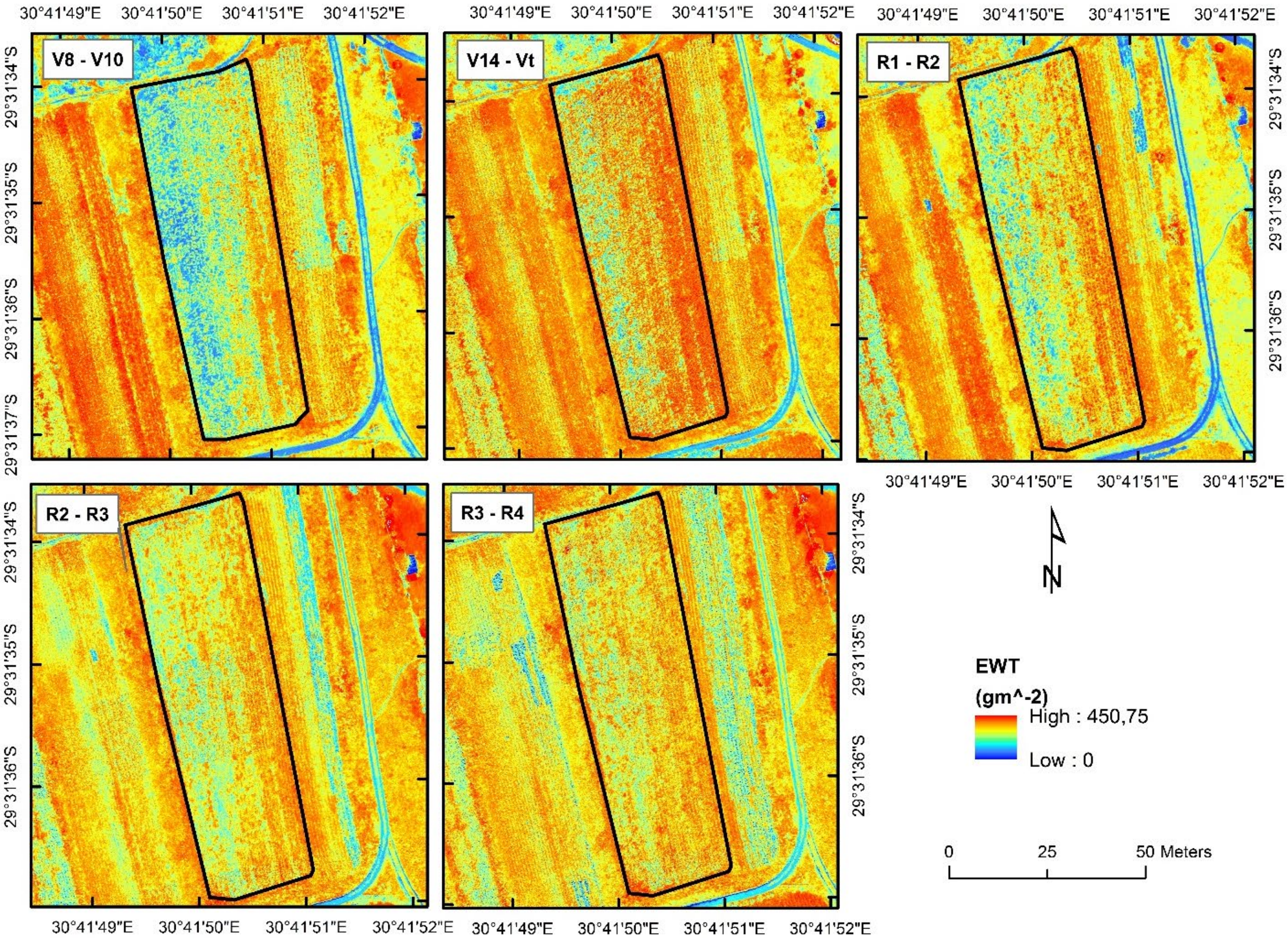

Figure 3. 8: Spatial distribution of modelled maize EWTleaf across the different stages of the growing season

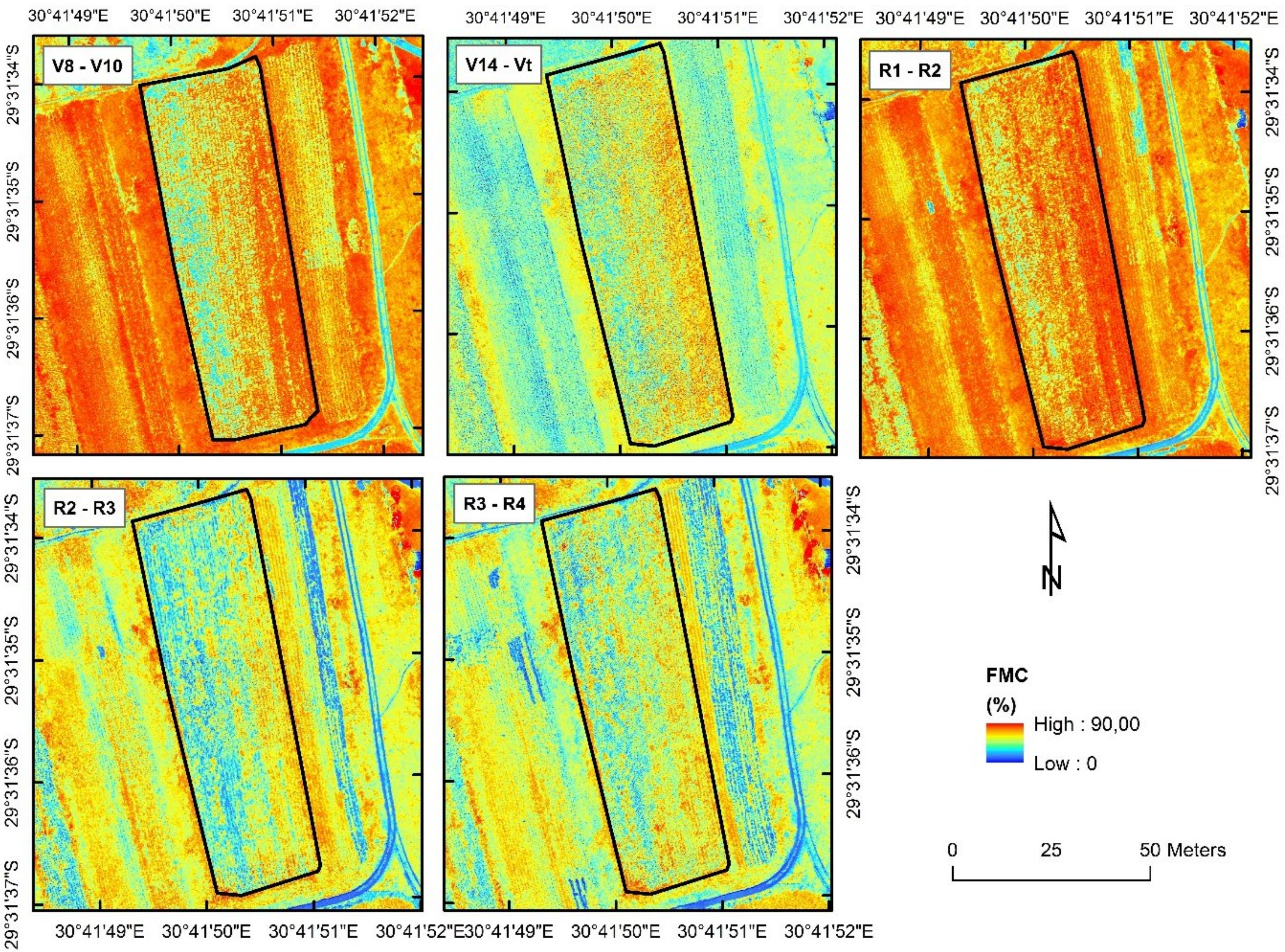

Figure 3. 9: Spatial distribution of modelled maize FMCleaf across the different stages of the growing season

3.4 Discussion

The emergence of UAV-derived data with high spatial and temporal resolution, presents a valuable tool for monitoring maize moisture content variability throughout the growing season (Chivasa *et al.*, 2020). Reliable determination of spatio-temporal variations in maize moisture is necessary for the early detection of moisture stress and identification of moisture-sensitive growth stages, necessary for the development of precision agricultural management practices (Zhang and Zhou, 2015; Wang *et al.*, 2016b; Ghooshchi *et al.*, 2008).

3.4.1 The influence of precipitation on maize moisture content variability

The findings of this study revealed a decreasing trend between precipitation and maize EWT_{leaf} and FMC_{leaf} across the growing season. The reduction of maize moisture content across the growing season along with the reduction in precipitation received in the study area implies that a decrease in precipitation results in a reduction in the amount of water available to maize crops (Zhang *et al.*, 2019b; Geneti, 2019). This finding is supported by a large and growing body of literature suggesting that climatic variables, such as rainfall, influence the amount of foliar moisture and ultimately crop growth and development (Zhang *et al.*, 2018a; Bois *et al.*, 2020; Geneti, 2019). Xu *et al.* (2012) argued that moisture availability is a serious challenge for rain-fed maize crops. The findings of this study are in agreement with those of Mumo *et al.* (2018) who confirmed that a substantial decrease in rainfall resulted in maize moisture deficiency which drastically reduced rain-fed maize yield by 67.53 %. Furthermore, the variation in maize moisture, specifically the decrease of maize EWT_{leaf} following the course of crop development, can be due to the reduction in leaf area as a result of moisture stress (Zhang *et al.*, 2018a). Literature has confirmed that when crops are in a state of water deficit, transpiration of the leaf surface is minimised by reducing leaf area expansion in order to maintain sufficient moisture levels (Song *et al.*, 2019; Gomez-del-Campo *et al.*, 2002). This finding supports the rationale of utilising EWT_{leaf} and FMC_{leaf} as a surrogate measure of crop water stress.

3.4.2 Estimation of maize moisture indicators from UAV-derived spectral reflectance

Results of this study showed that optimal estimation of EWT_{leaf} can be obtained at the silking – blister (R1-R2) growth stage of maize (R^2 = 0.88, RMSE = 5.31 gm^{-2} and rRMSE = 2.72 %) while for FMC_{leaf} was the blister to milk (R2-R3) stage with a R^2 = 0.76 and RMSE = 0.45 % (rRMSE = 1 %). Literature confirms that the early reproductive growth stages are best suited for the detection of physiological characteristics, such as leaf moisture content using proximal remote sensing techniques (Prudnikova *et al.*, 2019; Daughtry *et al.*, 2000). This is because the transmittance spectra of the fully developed leaves and the canopy have minimal effects of soil background and maximum reflectance of leaf properties (Prudnikova *et al.*, 2019; Daughtry *et al.*, 2000). Furthermore, Prudnikova *et al.* (2019) argued that estimating crop physiology at the early seedling and emergence vegetative growth stages is not optimum because sparse vegetation cover increases the interference of open soil surface reflectance, hence reducing prediction accuracy.

The findings of this study illustrate that vegetation indices (VIs) were the most optimal predictor variables of maize moisture content indicators, in comparison to raw UAV-multispectral bands. This is not surprising since a large and growing body of literature has proven that the use of VIs derived from water-sensitive sections of the electromagnetic spectrum improves prediction accuracies and outperforms conventional bands in estimating crop moisture content indicators (Pasqualotto *et al.*, 2018; Zhang *et al.*, 2019b; Zhang and Zhou, 2015). This is explained by the fact that VIs are derived from a combination of spectral channels which measure reflectance at different wavelengths of the spectrum with different strengths, hence their optimal performance in comparison to bands-only model (Sibanda *et al.*, 2021b). Furthermore, VIs tend to enhance leaf reflectance while minimising the influence of solar irradiance, atmospheric noise, topology and soil background effects (Prudnikova *et al.*, 2019; Sibanda *et al.*, 2021b; Xue and Su, 2017). This makes them more robust and sensitive to moisture and other plant foliar physiochemical elements.

The results in this study demonstrated that maize moisture indicators were sensitive to VIs derived from the NIR and red-edge wavebands of the electromagnetic spectrum. For example, the estimation of maize EWT_{leaf} was greatly influenced by $NDVI_{rededge}$, rededge, NIR, NDVI, while, NDRE, NIR and NDWI had the highest predictive power in optimally estimating FMC_{leaf} of smallholder maize crop. The influence of NIR based indices stems from the fact that this section of the electromagnetic spectrum is highly correlated to the quantity of water in leaf cells (Pasqualotto *et al.*, 2018). Literature confirms that the variation in leaf reflectance of turgid vegetation along the NIR wavelength, as a result of the changes in water transmissivity, and leaf internal structure, can be used to quantify crop moisture content and detect plants that are in a state of water deficit (Chemura *et al.*, 2017; Mobasheri and Fatemi, 2013). Additionally, the sensitivity of the red-edge band in maize moisture prediction can be explained by the fact that the red-edge is closely related to leaf chlorophyll composition and when crops are experiencing moisture stress, there are declines in crop physiochemical characteristics such as foliar pigmentation and leaf area, which are directly linked to leaf water status (Sibanda *et al.*, 2021b; Easterday *et al.*, 2019). A reduction in moisture content results in the deceleration of the photosynthetic activity, which in turn reduces the chlorophyll concentrations as the leaf halts its stomatal activities while losing turgidity and pigment (Liu *et al.*, 2015; Zhang and Zhou, 2015). These transitions are then detected from the rededge spectrum which tends to shift towards the long-wavelength section (Sibanda *et al.*, 2021b; Ndlovu *et al.*, 2021a). The results of this study are in agreement with Liu *et al.* (2016) who found that the changes in the vegetation moisture content were spectrally discernible in the NIR spectral reflectance section. In a similar study, Zhang and Zhou (2015) combined the NIR and rededge bands to form the NDRE, which became the most sensitive index to variations in maize moisture content (R^2 = 0.75). Furthermore, the results of this study concur with Sow *et al.* (2013) who used NDWI to predict vegetation FMC to an optimal accuracy of $R^2 = 0.85$.

Finally, the results of this study also revealed that chlorophyll-based indices such as CI_{green} and $CI_{rededge}$ were important predictors of maize moisture content as they were also among the most influential spectral variables on V14 - Vt and R3 – R4 stages when estimating maize EWT_{leaf} and FMC_{leaf}. Again, this can be explained by the positive correlation between leaf chlorophyll content and water status, as prolonged moisture stress ultimately reduces chlorophyll pigmentation of maize leaves, thus changing leaf absorbance and reflectance characteristics (Zhang *et al.*, 2019b; Liu *et al.*, 2015; Ndlovu *et al.*, 2021a). In a similar study, Zhang *et al.* (2019b) concluded CI_{green} and $CI_{rededge}$ to be among the most influential predictors of maize EWT and FMC as they are highly sensitive to crop water variation. Despite the apparent limitations of NDVI as stated in literature (Jackson *et al.*, 2004; Xue and Su, 2017), this index was an important predictor of maize moisture indicators in this study. This is explained by the fact that the NDVI is an effective indicator of leaf photosynthetic capacity which is correlated to leaf greenness and water status (Wijewardana *et al.*, 2019; Ndlovu *et al.*, 2021a). The results in this study concur with those of Wang *et al.* (2016b) who successfully used NDVI to monitor maze water variability using a seasonal NDVI time series analysis, while, Easterday *et al.* (2019) noted that the NDVI could discriminate variations in vegetation moisture stress and accurately predict leaf water content to an R^2 of 0.89.

3.5 Implications of the findings

UAVs are fast becoming a key component of precision agriculture as they provide opportunities for mainstreaming climate-smart agricultural practices into smallholder farming systems for improved crop health monitoring and water resource management. Understanding the spatio-temporal variation in maize moisture can support smallholder agricultural decision-making to facilitate the development of crop-specific management plans to increase maize resilience and reduce the susceptibility of smallholder maize farming systems to the future impacts of climate change. Furthermore, the methods used in this study could be adapted for monitoring the moisture content of other crops within smallholder farming systems. Future studies should assess maize moisture variability across various climates and evaluate the influence of other agronomical factors such as soil structure and topographic effects on leaf moisture status.

3.6 Conclusion

This study sought to test the utility of UAV-based multispectral data in estimating leaf EWT and FMC of smallholder maize crops across the growing season. The results showed that the UAV-derived multispectral data can be useful in quantifying maize moisture variability at a high spatial and temporal resolution. Therefore, it can be concluded that:

- UAV-derived multispectral data can optimally characterise maize EWT and FMC, foliar moisture, variations using the NIR and red-edge wavelengths of the electromagnetic spectrum which demonstrated great sensitivity to the variation in maize moisture content
- The phases between silking and milk reproductive growth stage are the most optimal growth stages for predicting maize moisture content using UAV-derived data

This study demonstrates the potential of UAV-based proximal remote sensing techniques in providing near-real time and spatially explicit information on maize moisture variability across the growing season. Finally, this study will serve as a proxy towards accomplishing sustainable development goal 15, life on land, that seeks to ensure sustainable food security, thus enhancing livelihoods and wellbeing.

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CHAPTER FOUR: SYNTHESIS AND CONCLUSIONS

4.1 Introduction

Smallholder farmers are frequently faced with the need to optimize maize production. With the rapid increase in climate change related-stress, population growth as well as the increasing demand for food, sufficient production of maize is essential for food and nutrition security. However, water stress often challenges maize productivity due to prolonged drought conditions resulting from climate variability (Ndlovu *et al.*, 2021a; Sibanda *et al.*, 2021b). Therefore, assessing maize water status through monitoring equivalent water thickness (EWT), fuel moisture content (FMC) and specific leaf area (SLA) can provide essential information for enhancing maize productivity under water-limited conditions (El-Hendawy *et al.*, 2019). The advent of remote sensing technologies, including unmanned aerial vehicle (UAV)-derived data, characterised by a rich spatial and temporal resolution, presents a stepping stone towards achieving spatially explicit and multi-temporal information on maize moisture conditions (Chivasa *et al.*, 2021; Zhang *et al.*, 2019b; Sibanda *et al.*, 2021a). In this regard, this study sought to evaluate the utility of UAV-based proximal remote sensing in estimating maize leaf moisture content on smallholder farming systems throughout the growing season. The key objectives of this study were, (1) to conduct a comparative analysis to evaluate the performance of five regression techniques in predicting four maize moisture content elements, and determine the most suitable moisture content indicator of smallholder maize water content variability based on multispectral UAV data and, (2) to evaluate the utility of UAV-derived multispectral imagery in estimating the spatio-temporal variability of smallholder maize leaf EWT and FMC across the maize growing season. This chapter provides a reflection of the research aims and objectives established in the introduction (chapter one) and highlights the main conclusions and recommendations for future studies.

4.2 Objectives review

4.2.1 A comparative estimation of maize leaf moisture content on smallholder farming systems using Unmanned Aerial Vehicle (UAV) based proximal remote sensing

The essence of this component of the study was to assess and identify a suitable indicator of maize moisture content and evaluate the predictive performance of robust algorithms in predicting maize moisture status. Based on the findings of the component of the study, it was concluded that EWT and FMC are valid indicators of maize moisture content and can be optimally estimated using the near-infrared and red-edge derived spectral variables. This can be associated with the close correlation between crop water transmissivity, leaf chlorophyll composition and leaf reflectance along the near-infrared and red-edge sections of the electromagnetic spectrum (Sibanda *et al.*, 2021b). Furthermore, the results from this study demonstrated the robust capabilities of the random forest regression algorithm in predicting all maize moisture content indicators in comparison to other regression techniques. The performance of the random forest regression can be attributed to the fact that the algorithm is not subjected to over-fitting and can optimally operate with a relatively small number of training samples, which is often the case for data acquired at a field scale after avoiding spatial autocorrelation (Zhu *et al.*, 2017). Based on these research findings, it can be concluded UAV-based multispectral data can be optimally used to estimate maize leaf EWT and FMC using the random forest regression algorithm. Subsequently, the random forest algorithm along with the EWT and FMC were then selected based on their optimal accuracies to conduct the second component of the study.

4.2.2 A multi-temporal remote sensing of smallholder maize leaf equivalent water thickness and fuel moisture content variability using an unmanned aerial vehicle (UAV)-derived multispectral data

This section of the study focused on the utility of UAV-derived imagery in estimating the spatio-temporal variation in maize leaf EWT and FMC across the maize growing season. Specifically, the accuracies of EWT and FMC random forest models derived using spectral data from different maize phenological stages were compared. The findings from this component of the study demonstrated a positive relationship between precipitation and maize leaf moisture content throughout the phenological cycle, which can be attributed to biomass accumulation and productivity across the growing season (Zhang *et al.*, 2018a). The results of this study also highlight the prospects of using a combination of UAV-spectral bands and vegetation indices to estimate maize moisture content as this enhances leaf reflectance and minimises the influence of soil-background effects at different stages of the maize growth cycle (Xue and Su, 2017). Grounded on the findings of this study, it was concluded that the phases between silking and milk reproductive growth stage are the most optimal growth stages for predicting maize moisture content using UAV-derived data. The suitability of these stages can be attributed to the fact that the maize canopy has fully developed; hence there is maximum reflectance of leaf properties in comparison to the earlier maize growth stages, which are subject to the interference of open soil surface reflectance (Prudnikova *et al.*, 2019). The findings from this study provide evidence on the capability of UAV-derived multispectral data in quantifying maize moisture variability at a high spatial and temporal resolution across the growing season of maize smallholder farms.

4.3 General Conclusion

The overall aim of this research was to evaluate the utility of UAV-based multispectral imagery in estimating maize leaf moisture content on smallholder farming systems throughout the maize growing season as a proxy for crop water stress characterisation. Based on the findings of this study, it is concluded that: UAV-based data can accurately provide invaluable information on maize leaf moisture content across various stages of the growing season. UAV-derived multispectral data can successfully determine the most suitable leaf moisture indicator to estimate maize leaf moisture content using an optimal regression algorithm. Furthermore, the EWT and FMC, in concert with the random forest regression, provide a valuation option for accurately estimating maize moisture content of smallholder farming systems.

Based on these findings, UAV-derived multispectral data can optimally predict the maize moisture content of smallholder farms with exceptional accuracy, hence can complement and inform farms drought-related water stress. This illustrates the critical role of UAVs and drone technologies in monitoring maize moisture availability and its prospects for other precision agriculture applications. This research provides a pathway towards the rapid and robust detection of maize moisture stress and can proxy overall maize health. These findings confirm the need to adopt long-term maize moisture content monitoring systems that are crop-specific and site-specific, especially with the current climate change projections.

4.4 Recommendations for future research

The current study investigated the spectral capacity of UAV-derived imagery equipped with six multispectral channels covering the visible, near-infrared and thermal spectrums. Additional studies are necessary to assess the spectral ability of UAVs with different spectral characteristics. Valuable research would be to evaluate whether UAV sensors that measure spectral reflectance along the SWIR section of the electromagnetic spectrum improve the prediction of smallholder maize moisture content. Furthermore, future studies should assess the influence of variability of various factors such as climate and evaluate other agronomical factors such as soil moisture, temperature, soil structure and topographic effects on leaf moisture status**.** Finally, this study was site and crop-specific; therefore, there is a need for similar studies to be conducted across various climates, different smallholder crops and at a multi-temporal scale to draw broad conclusions about crop moisture availability.

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