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Spatial quantification of maize water stress using UAV-acquired data in smallholder farms of Swayimane in KwaZulu-Natal Province.

A thesis submitted in the fulfilment of the requirements for a master's degree in Geography and Environmental Studies in the Department of Geography, Environmental Studies and Tourism, University of the Western Cape.

by

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Kapari Mpho

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Abstract

The most important agricultural crop in southern Africa is maize, which grows on variety of environments and serves as an essential food source for the region. Most of the maize is grown in smallholder croplands both for subsistence and commercial purposes. It is one of the two main crops that are impacted by water stress globally. Therefore, determining maize water stress is essential for the development of timely response measures to boost farming production, especially on smallholder croplands. Unmanned Aerial Vehicles (UAVs) furnished by multispectral devices propose a technique aimed at spatially comprehensive data suitable to defining maize water stress at the farm scale. Therefore, this thesis intended toward assessing the use of UAVs-acquired information to quantitatively enumerate maize water stress. This overarching objective was addressed by two specific objectives which were to 1) conduct a systematic literature review of remote sensing data use in determining maize water stress at a farmstead level and 2) assess UAVs acquired data and machine learning (ML) techniques utility in estimating maize Crop Water Stress Index (CWSI) as an indicator for crop water stress and 3) estimate maize water stress across different phenological stages using UAVs acquired data in smallholder croplands. Particularly, the reviews assessed the distribution of publications, the types of methods used, and the types of results obtained, identifying gaps, challenges, and limitations associated with the remote sensing use for maize crop water use in smallholder farms. Thereafter, three machine learning algorithms, partial least squares (PLS) regression, support vector machines (SVM), and random forest (RF), were comparatively utilized for predicting maize CWSI based on UAV-derived remotely sensed data. The optimal model was thereafter adopted to predict CWSI for the maize vegetative and reproductive stages. The CWSI was computed using Tc-Ta and VPD. Review results showed that research efforts significantly increased from 2002 to the present, with most research articles (37%) being conducted in the United States and the least (12%) in the African continent. Specifically, 17 different Earth observation sensors were utilised to map maize water stress. Landsat is the most widely used sensor, particularly the Red and near-infrared electromagnetic spectrum sections, along with their derivatives. Providentially, UAV-based remote sensing technologies, which are relatively cheaper, have ultra-high spatial resolutions and user-defined acquisition times have emerged as suitable alternatives since 2015. Findings from machine learning algorithms' comparison revealed the best model in predicting CWSI was obtained from the RF algorithm (RMSE = 0.05, MAE = 0.04) when compared with PLS and SVM using the thermal infrared

NDRE, MTCI, CCCI, GNDVI, TIR Cl_RedEdge as optimal variables, in order of importance. When RF was applied to vegetation and reproductive stages (V5, V10, V14, and R1 stage), the optimal RF model was recorded for the V10 stage, with the red band as the optimal variable (RMSE = 0.03, MAE = 0.02). The Red, RedEdge, NIR and TIR UAV-bands and their associated indices (i.e., CCCI, MTCI, GNDVI, NDRE, Red, TIR) were significant in the prediction of CWSI. Overall, these findings suggest that data obtained from UAVs, coupled with RF, can effectively be employed for monitoring water stress in maize within small croplands.

Keywords: canopy temperature; crop water stress; machine learning algorithms; Maize; remote sensing; smallholder cropland; UAVs.

LIST OF PAPERS SUBMITTED AND UNDER CONSIDERATION

- **Remote Sensing maize water stress in smallholder farms: A systematic review of progress, challenges, and way forward in the utilisation of earth observation data. –** Accepted as a book chapter to be published by Springer as open access. The expected date of publication is 31 October 2024.
- **Comparing machine learning algorithms for estimating maize crop water stress index (CWSI) using UAV-acquired remotely sensed data in smallholder croplands. –** Published in *Drones* journal.
- **Assessment of Maize crop water stress index (CWSI) using unmanned Ariel vehicle (UAV) acquired data across different phenological stages. –** Submitted to the Journal of Applied Remote Sensing.

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1. Chapter 1: Introduction and Background

1.1.Introduction

One of the biggest reasons restricting crop productivity's rise is crop water stress (CWS) (Avetisyan et al. 2019). This concept is defined as a lack of water supply that can be detected by a reduction on the soil moisture otherwise as a result of plant physiological responses to the lack of water (Ihuoma and Madramootoo 2017). CWS is further exacerbated by recent lower seasonal rainfall combined with high temperatures which have generated severe constraints on crops cultivated in rain dependent agriculture (Cai et al. 2020), with no exception for maize crops (Adisa et al. 2018). Maize (*Zea mays L.*) which is mainly cultivated in rainfall dependent agriculture, is a staple food for the majority of Southern Africans (Ndlovu et al. 2021; Plessis 2003). Maize has become significant and dominant to rural smallholder farming systems of Southern Africa (Mathebula *et al.,* 2018). For instance, on roughly 3.1 million hectares of land, eight million tons of maize grain gets produced yearly in South Africa (SA) (Plessis, 2003). Furthermore, approximately 16.7 Tg of maize grain was produced during the production season 2016–2017 from 2.6 million ha of land (FAO 2018). Even though a high number of people practices smallholder farming systems (Thamaga-Chitja and Morojele 2014), they deal with issues related to crop production, such as water stress, which causes crop yields to generally fall short of the land's potential (Ndlovu et al. 2021). This is the case when CWS occurs from flowering stage to late grain-filling stages (Cai et al. 2020) since the onset and scale of intermittent water stress are often hard to detect. To remedy these negative impacts, it has become crucial to estimate the maize crop water stress in all its growing stages.

Numerous physical crop-based indicators have been introduced to determine crop water status, and these include stomatal conductance (Berni et al. 2009), stem water potential (Ahumada-Orellana et al. 2019), chlorophyll content, and vegetation water content (Mirzaie et al. 2014). However, the measurements on these indicators are time-consuming, leaf-destructive, and point-based despite their optimal accuracies (Yang, Gao, Zhou, et al. 2021). The development of portable infrared thermometers resulted in the utilization of canopy temperature for determining CWS (González-Dugo *et al.*, 2006; Testi *et al.*, 2008; Nanda, Giri and Bera, 2018). This method has been less destructive while producing explicit and quick measurements (Ballester et al. 2013). However, canopy temperature alone, without consideration of other atmospheric conditions, is insufficient in accurately determining crop water status (Yang, Gao, Zhou, et al. 2021). Therefore, the Idso's CWSI (Idso et al. 1981) for determining the lower as well as upper baseline canopy temperatures included the consideration of atmospheric circumstances including air temperature as well as relative humidity (Ru et al. 2020). Considering its simple and accessible input data variables, CWSI has been deemed dependable in optimally characterising canopy water stress and water demand of various crops like maize (Han et al. 2018) for decision-making processes (Costa-Filho, Chávez, and Comas 2020). However, CWSI is also point-based canopy temperature (Tc) readings; therefore, it is necessary to find spatially unambiguous strategies for accurately characterizing CWS in smallholder farms to optimize crop productivity. One of the major challenges of using on-ground indicators is that it requires many measurements that account for the entire field in order to accurately capture spatial variations of small croplands CWS (Ramírez-Cuesta et al., 2022). This limitation can, however, be overcome by adopting recent advanced remote sensing technologies that offer temperature readings in small croplands (Möller et al. 2007; Romero-Trigueros et al. 2019).

Earth observation technologies have emerged as the most optimal method of spatially characterizing crop attributes in a non-invasive explicit manner (Zhang *et al.,* 2019). Various studies revealed that remote sensing information for CWS is feasible, but they tend to rely primarily on satellite observation data (L. Zhang, Zhang, et al. 2019a). However, data acquisition by remote sensing sensors is dependent not only on clear skies but also the absence of wind conditions, unlike ground measured Tc that are obtained below the clouds (Agam et al. 2013). In addition, remote sensing satellite sensors have drawbacks of low spatial-temporal resolution and weather sensitivity (L. Zhang, Zhang, et al. 2019a), especially limiting to application in small-scale farms. For instance, Landsat remotely sensed data has spatial resolutions of 30m and revisit times of 16 day(s) (USGS, 2022). Consequently, the development of technology tools such as the utility of unmanned aerial vehicles (UAVs) became necessary to offer data captured in near real-time remotely sensed information obtained at high temporal and temporal resolution enabling application on small croplands aimed at agricultural observations (Ndlovu et al. 2021). Therefore, UAVs are adopted in CWS studies for potatoes (Duarte-Carvajalino et al. 2021), maize (Ndlovu et al. 2021; L. Zhang, Zhang, et al. 2019a), and olives (Berni et al. 2009) to improve production while practising sustainable agriculture. UAVs remote-sensing systems can capture data on crop parameters at user-defined spatial-temporal resolutions (L. Zhang, Zhang, et al. 2019a), it is used for identifying and mapping a variety of phenological changes including distinct canopy cover (Cucho-Padin et al. 2020). As a result, using such objective and time-efficient technologies has tremendous promise for providing near real-time crop data which provides information about crop water stress levels throughout all stages of the phenological process.

UAVs acquired data usage at field or farm scale has become increasingly important to access near real-time agro-meteorological information on crops in precision agriculture, as well as crop monitoring. Adopted UAVs for crop water requirements checks have variety of devices, comprising of multispectral, RGB, as well as thermal with varying degrees of sensitivity (Zhang *et al.*, 2019). The thermal sensor provides temperature readings that can be applied in the evaluation of CWS. For example, when Zhang *et al.* (2018) assessing cotton CWS using Tc readings from UAV thermal images, they found that crop water stress was sensitive to canopy temperature standard deviation (CTSD) with through a significant correlation between stomatal conductance and CTSD (coefficient of determination (R^2) = 0.88). Similarly, Martínez *et al.* (2017) evaluated thermal imaging potential captured from UAV to monitor plant water stress, they found that UAV Tc, as well as IRT and microcontroller board as data logger was reliable and robust. Despite the usefulness and potential to provide reliable crop monitoring data of UAVs, their application in agriculture in Southern Africa remains limited (Cucho-Padin et al. 2020). Aside from the technical competence required to collect, process and interpret UAV products, the cost and service of an agriculture drone could be prohibitively expensive, particularly for individual smallholder farmers in developing countries. Therefore, this technology requires low-cost implementation in Sub-Saharan African developing nations (Ramírez et al. 2021).

Literature states the UAVs utilization on smallholder croplands can potentially improve agricultural water management and ensure household food security in developing countries (Nhamo et al. 2020). Regardless, limited agricultural usage of UAVs obtained data in Southern Africa presents limited knowledge in literature. Moreover, multispectral UAV images provide an accurate description of crop variability at the local level through the canopy's response to absorbing and reflecting light. Vegetation index (VI) is derived from the vegetation and soil reflection at a respective electromagnetic region may be utilized to monitor surface vegetation' photosynthesis, canopy structure, and leaf moisture content, which shall correspond to the mathematical operation (L. Zhang, Zhang, et al. 2019a). The indices, which are responsive to visible (RGB), NIR and RedEdge parts of the electromagnetic spectrum, have been widely adopted. The popular indices used include normalised difference vegetation index (NDVI) (Caruso et al. 2017), renormalised difference vegetation index (RDVI) (Jiménez-Brenes *et al.*, 2019), optimization of soil-adjusted vegetation index (OSAVI) (Vanegas et al. 2018), soil-adjusted vegetation index (SAVI) (Jiménez-Brenes et al. 2019), and transformed chlorophyll absorption in reflectance index (TCARI) (Vanegas *et al*., 2018). In order to reduce TCARI's sensitivity to changes in the structure of the canopy, TCAR/OSAVI has been most commonly applied (Haboudane et al. 2002). Zhang *et al.* (2019) have also investigated the potential of these indices to explain the status of crop water and found that the ratio of TCARI/RDVI and TCARI/SAVI is best correlated with CWSI at R^2 0.81 and 0.80. Machine learning models have been used to detect important patterns in crop monitoring ground measurements and crop reflectance as opposed to past approaches based on only VIs (Behmann, Steinrücken, and Plümer 2014). For that reason, a number of ML and regression methods have been used to predict vegetation parameters in the prediction of CWS (Duarte-Carvajalino et al. 2021; Yue et al. 2018). Support vector machines (SVM) (Yue et al. 2018) , random forest (RF) (Yang, Gao, Zhou, et al. 2021), and partial least squares (PLS) (Mirzaie et al. 2014) have recently gained popularity for their high performance in computing, quantifying, and estimating crop attributes in agricultural applications. With regard to the other two algorithms described above, the RF ensemble has been widely proven to be optimal.(Jiang et al. 2022; Zhu et al. 2020).

However, these algorithms provide a robust and easily implemented solution to the challenges of small sample sizes (Krishna et al. 2019). In addition, they are able to select optimum features which lead to a higher degree of accuracy. However, it has been observed in literature that no special algorithm which is suitable for a particular context exists (Ndlovu et al. 2021). Therefore, the most efficient method of accurately estimating maize water stress in smaller crop areas must be evaluated and determined. However, the success of VIs, regression and ML techniques requires a high temporal frequency and a high spatial resolution of data acquisition (Matese et al. 2018). To meet these requirements, innovative and low-cost data collection tools are necessary to ensure the success of the accuracy of water stress estimation. Therefore, this study was designed to determine whether remotely sensed data from UAVs combined with machine learning algorithms might be used for the quantification of maize crop water stress in a typical Southern African smallholder farming area.

1.2.Research Aim

This study aimed to quantitively predict maize crop water stress at a field scale utilising UAV-acquired data.

1.3.Objectives

To address the overarching aim the following specific objectives were drawn:

- To systematically review the available literature on the use of remote sensing for determine maize water stress in smallholder croplands.
- To compare the performance of Random Forest, Partial Least Squares, and Support Vector Machines regressions in estimating maize crop water stress in smallholder croplands using remotely sensed data acquired by UAV.
- To predict crop water stress across different maize phenological stages using UAV-derived remotely sensed data in small croplands.

1.4.Thesis Structure

The thesis constitutes of five chapters which are three standalone manuscripts prepared for international peer review and the introduction and synthesis chapters. Specifically, chapters 2, 3, and 4 are standalone manuscripts. each chapter consists of both an introduction and a conclusion, creating a cohesive link to the subsequent chapter. Therefore, it is inevitable that in the scope of research there may be an overlap or a duplication of theory. This is due to a consistent circulation of principles underpinning the entire field of science at present. The following chapters of this thesis are set out:

> ***Chapter 1***: provides an introduction, background, study aims, and objectives. It outlines the background of applying UAV-obtained data for estimating crop water stress (CWS) and identifies its gap knowledge gap regarding the mapping of maize CWSI in smallholder croplands. The chapter articulates the study's contribution to addressing the outline gap through the stated aims and objectives.

Chapter 2: is a standalone systematic review of the literature utilised remotely sensed data in detecting and mapping maize stress. This chapter explores the progress, challenges, gaps and the way forward in the utilisation of remotely sensed data in detecting and mapping maize crop water stress. The review served as a roadmap, offering insights into the methodologies employed in this study.

Chapter 3: is also a standalone manuscript which sought to compare the prediction of Crop Water Stress Index (CWSI) as a proxy for maize water stress. CWSI is predicted using multispectral and thermal UAV remotely sensed data coupled with three different regression methods, i.e., Partial Least Squares, Support Vector Machine, and Random Forest in a smallholder cropland during the vegetative growth stage. The optimal model was determined using lowest RMSE.

Chapter 4: represents the third standalone manuscript, focusing on predicting maize Crop Water Stress Index (CWSI) using multispectral UAV-derived data coupled with a random forest regression. This analysis spans selected phenological stages of maize crops, with three images covering the vegetative growth stage and one covering the reproductive stage. The chapter compares the accuracies (RMSE and R^2) derived from random forest across all growth stages to assess the efficacy of UAV-acquired remotely sensed data in detecting and mapping maize crop water stress throughout various phenological stages.

Chapter 5: is a synthesis chapter, bringing together the findings from chapters 2, 3, and 4 of the thesis, along with their respective conclusions. This section not only provides an integrated overview of the thesis outcomes but also discusses the study's limitations and offers recommendations for future research endeavours.

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2. Chapter 2: Remote Sensing maize water stress in smallholder farms: A systematic review of progress, challenges, and way forward in the utilisation of earth observation data.

This chapter is based on a paper accepted for publication as a book chapter 4 titled "*Remote Sensing maize water stress in smallholder farms: A systematic review of progress, challenges, and way forward in the utilisation of earth observation data"* in the forthcoming Springer book titled *"Enhancing water and food security through improved agricultural water productivity: new knowledge, innovations and applications".*

2.1.Abstract

In Southern Africa maize is a basic food crop, grown mainly by small farmers in rain-fed conditions. Despite significant contributions to food production by smallholder farmers, they continue to face climate change-related challenges such as drought, resulting in crop water stress and significant yield losses. This is reinforced by the lack of funding, technical skills and adequate strategies for adaptation to climate change, which leads to higher yield gaps. Technological progress, such as precision farming systems, could address this issue. For complicated and technically based evaluations of crop production, e.g., a water stress on crops, remotely sensed systems are adequate and well designed for the job inexpensively. To this end, the literature on developments and new gaps as well as opportunities for use of remote sensing techniques to measure maize water stress has been thoroughly reviewed by this study. A total of 100 peer reviewed articles from the Web, Scopus, Google Scholar, and ScienceDirect have been examined in accordance with the PRISMA guidelines. Results significantly increasing research efforts have been exerted from 2002 to the present, with most research articles (37%) being conducted in the United States and the least (12%) in the African continent. In particular, the red and near infrared regions of the electromagnetic spectrum, together with their derivatives, were used in 17 different Earth observation sensors to map the maize water stress, and Landsat was the most widely used sensor. These Landsat spectral derivatives are used mostly in conjunction with the surface energy model in retrieved literature. However, there is a dearth of literature on remote sensing maize crop water stress in smallholder farming. Due to the extremely small size of these agricultural systems (<1ha) and heterogeneous to be detected by moderate spatial resolution sensors that are freely available. Furthermore, validation

mechanisms and data as well as fine spatial resolution suitable for these croplands are scanty if not expensive. Providentially, UAV-based remote sensing technologies, which are relatively cheaper, with ultra-high spatial resolutions, and user-defined acquisition times have emerged as suitable alternatives. To this end, there is a need for further research to assess the potential of such technologies and particularly smallholder farms across southern Africa that are adversely affected by scarce resources.

Keywords: remote sensing; precision agriculture; UAVs; food security; Maize.

2.2.Introduction

One of the world's largest cereals is maize (*Zea mays L.*) , providing a carbohydrate source for human health in developing countries as well as animal feeding in developed countries (Tandzi and Mutengwa 2020). In Southern Africa, maize is the primary cereal crop with increasing food needs as a result of population growth (Ndlovu et al. 2021). Therefore, to meet the growing demand for nutrition and food security, maize production needs to be increased (Ekpa et al. 2018). Maize is also the most dominant crop grown by smallholder farmers, especially in developing regions such as Southern Africa (Ndlovu et al. 2021). Unfortunately, smallholders are also susceptible to climate change shocks, such as reduction and high variability of precipitation and droughts, making it difficult to achieve the desired yields (Chitja et al. 2015). However, smallholders are the most affected by climate change shocks; they lack financial and mechanical skills, and are less equipped with infrastructure and agricultural equipment (Ruwanza *et al.*,2022) as well as sound adaptation strategies. Song, Jin and He (2019) stated that, growth of plants and leaf area is slowed down resulting in lower yields due to increasing water stress on maize vegetation. The moisture conditions are of major importance in the functioning of plants, water transfer to atmosphere and drought and fire risk (Mirzaie et al. 2014). To this end, it is important to consider water availability as a relevant factor for the assessment of climate change impacts on agricultural water management (Matese et al. 2018). Due to drought caused by climate change, agricultural water resources will be reduced in order to ensure a maximum yield per unit of water used for irrigation (Zhang *et al.*, 2019).

In addition, monitoring of maize water status is therefore essential for implementation of effective irrigation strategies and in order to avoid loss of crop yield while limiting water use and wastage (Ihuoma and Madramootoo, 2017; Zhang, Zhang, *et al.*, 2019a). In the meantime, to free up water resources for other sectors of society in view of growing demand, there is a need to reduce agricultural water use (Rossini *et al.*, 2015). Therefore, a number of studies examining the effects of water stress on maize in various stages of growth and development have been carried out (Dong et al. 2021; Sreelash et al. 2017). Maize CWS can be detected by assessing and monitoring crop physiological characteristics, soil moisture content, and remote sensing (RS) technology (Ihuoma and Madramootoo 2017). But traditional techniques for monitoring water stress in maize crop with soil moisture measurements and weather data depend on climate conditions to calculate the amount of water lost from a plant sowing scheme over an entire season (Elkatoury, Alazba, and Abdelbary 2020). Methods such as the lysimeter, eddy covariance, and atmometers, although accurate they are point-based (Padilla et al. 2011); hence they lack spatial representativeness. Furthermore, these methods involve time consumption, labour intensities, high cost and neglect spatial variability of soils and plants (Maes et al. 2018). With such a high volume of data available from various earth observation platforms, research in monitoring crop water stress using satellite and aerial RS techniques has emerged as the most spatially explicit method (Maes *et al*., 2018). This is because RS has been recognised as an extremely rapid, non-destructive method widely and is used to quantify biochemical parameters related to maize crop water stress at different scales (Mirzaie et al. 2014).

In the field of precision agriculture, RS provides an input for acquisition of very large spatial, spectral and temporal resolution data (Zhang et al. 2019). RS is one of the most important tools for monitoring crops (Ahmad, Alvino and Marino, 2021). Measurements of canopy reflectance by RS technology has the advantage to facilitate easy, non-destructive and of low labour-intensity means of data collection (Elmetwalli et al. 2021). Generally, crop physiology and structural conditions as well as environment influence the electromagnetic field reflected by plants (Wijesingha et al. 2021). In order to obtain accurate models for the estimation of crop parameters, the development of RS data acquisition and analysis techniques will be beneficial (Gerhards et al. 2019). Various earth observation sensor platforms (ground instruments, unmanned ariel vehicles (UAVs), airborne and satellite) for the estimation of plant growth and health parameters using a range of modelling approaches, have been deployed to collect data from remote sensing croplands (Rossini *et al.*, 2013; Zhang, Zhang, *et al.*, 2019). These include, multispectral (Mariapaola Ambrosone *et al.*, 2020), thermal infrared (Mangus, Sharda and Zhang, 2016), hyperspectral (Rossini *et al.*, 2013), red-edge (Shao *et al.*, 2021a), visible

(Genc *et al.*, 2013), and radar (van Emmerik *et al.*, 2015) sensors application on different platforms to detect these different reflected energies.

However, the temporal and spatial resolution requirements are very difficult to meet when it comes to applications for crop monitoring, including maize. The monitoring of plant water stress at local level has, therefore, often been difficult to do in the absence of further advances in technology. This is because the RS techniques shall have a minimum of 1-3 days' repeated data collection and spatial resolution below 10 m to meet the demand for farm scale monitoring (Zhang et al. 2016). Consequently, it is primarily the widespread use of new technology that includes high resolution cameras fitted to unmanned aerial vehicles (UAVs) which has resulted in an increased adoption of RS on a farm scale at local level (Messina and Modica 2020). Moreover, recently, the importance, capability, and possibilities to use the RS data for agricultural water stress monitoring are well established, including using them in machine learning algorithms (Virnodkar *et al.*, 2020). Nonetheless, aerial RS has the disadvantages of being difficult and expensive to operate. The advantages of low cost, simple structure, reliable transport, high flexibility, short operating cycles and excellent spatial resolution make UAVs capable of collecting crop data to achieve the desired spatiotemporal resolution (Zhang, Zhang, *et al.*, 2019). This makes UAVs more suitable for rapid and effective monitoring of crop moisture stress on an agricultural scale (L. Zhang, Zhang, et al. 2019a; Zhang et al. 2022). For the purpose of implementing effective irrigation systems for small farms, adequate indicators should be laid down to monitor maize water levels at farm level (Alvino and Marino 2017).

The use of remotely acquired data for the estimation of agricultural moisture stress parameters was investigated in a literature. Leaf area index (LAI) (Matese et al. 2018; Wijesingha et al. 2021), leaf water content (LWC) (Song *et al.*,2021), crop stress index (CWSI) (Alordzinu et al. 2021; Matese et al. 2018; Testi et al. 2008) and canopy water content are examples of water stress parameters examined. Alvino and Marino (2017) reviewed literature on the relationship of surface temperatures and remote sensing vegetation indices in relation to water-use efficiency (WUE) and evapotranspiration while Yan *et al.* (2006) reviewed literature on the advances in RS applications in mapping soil moisture, With a focus on methodology, issues relating to the estimation of soil moisture from remote sensing data have been discussed. Greco *et al.* (2012) limited their review of literature to the utilisation of ground-based thermal remotely sensed data excluding satellite and airborne techniques. In addition, a literature study has focused on the potential for UAV remote sensing data to predict crop water stress (Awais *et al.*, 2021), Also, use of remotely sensed temperature information from unmanned aerial vehicles to assess the water stress on crops (Messina and Modica, 2020; Ahmad *et al.*, 2021). Although, a review on cereal crops' water footprint estimation using RS and other methods (Feng *et al.*, 2021) included maize, little to no research efforts have been exerted towards reviewing literature on the utilisation of RS data in estimating maize crop water stress at local scales. It is therefore difficult to provide an efficient, reliable, responsive, practical, and appropriate RS options to estimate maize water stress on smallholder agricultural land due to this lack of summarised knowledge.

Therefore, considering the dearth of knowledge in RS application on maize water stress, in order to evaluate literature related to progress, challenges and evolution in the field of use of RS for maize water stress monitoring, this study carried out a systematic review. An understanding of the progress made in RS will provide insights on the needs and areas of expansion required in maize water stress detection, such as various methods available. This will be beneficial to role players in the agricultural and water sectors research at large to effectively determine maize needs and further direct irrigation plans. The study aims to achieve this by establishing advances made in monitoring maize water stress using RS technologies, and identify problems and opportunities linked with the use of RS technology for monitoring maize CWSI.

2.3. Methods

The aim of this study was to carry out a systematic review of the use of RS for maize water stress assessment. To carry out this review, the recommended Reporting Items for Systematic Reviews (PRISMA) guidelines were complied with (Albeha *et al.*, 2020). Two sections are set out in the review. The first section outlines progress made in the adoption of RS for the estimation of maize water stress, the last segment provides summary of challenges, and the way forward in the application of RS application in maize water stress monitoring. The literature review and analysis were conducted in four stages with a view to addressing these sections. These stages cover the criteria for selecting articles, searching strategy, eligibility criterion, data extraction and analysis.

2.3.1. Stage 1: Literature Search

A systematic search with no limitation on the year of publication was conducted in four electronic databases: Scopus, Web Science, Science Direct and Google Scholar. Using the string in Table 2-1, the keyword combination was used to obtain data from the SCOPUS, Web of Science, Science Direct and Google Scholar databases was searched.

Table 2-1: The main search words used for this study.

Search Database	Search Criterion	Total No. Articles	No. of articles
SCOPUS	TITLE-ABS-KEY (("Maize" AND "Water stress") AND "RS" OR "GIS")	114	95
Web of Science	("Maize" AND "Water stress") AND ("RS" OR "GIS") ; ("Corn" AND "Water stress") AND ("RS" OR "GIS"); ("Maize" AND "Water stress") AND "RS" OR "GIS" AND ("smallholder farms" OR "smallholder agriculture") (All Fields)	392	180
Google Scholar	("smallholder farms" AND ("maize" AND "RS" AND "water stress" OR "Leaf moisture" OR "stress" OR "water content*"OR "moisture content") AND "unmanned aerial vehicles*" OR "drones") and (("maize" AND "water stress") AND "RS" OR "GIS" AND "smallholder farms" OR "smallholder agriculture")	1092	50
ScienceDirect	("maize water stress" OR "corn water content" AND "RS" AND "farmers")	574	14
Articles considered before screening after removing duplicates = 169			

2.3.2. Stage 2: Screening and Eligibility Criteria

The following criteria must have been met for the articles which were eligible for analysis:

- peer-reviewed article in an accredited journal,
- research papers written in English,
- studies focusing on other crops and/or maize water stress and,
- studies focusing on RS techniques to detect maize water.

For screening purposes the bibliographic information of each article was obtained and stored on Mendeley's desktop.

From the Scopus, Web of Science, Google Scholars, and Science Direct databases an aggregate of 100, 180, 50 or 14 articles were retrieved which is broken down into Table 2-1. For the purposes of determining whether a study is eligible for inclusion, titles and abstracts have been evaluated based on these criteria. The first screening process took place and consisted in the erasure of duplications resulting in a consolidated figure of 169 articles. Following that, irrelevant articles have been removed from the database by an average of 17, including articles which were not written in English, resulting in a total of 152 articles. In line with the PRISMA and meta-analysis statements, included and excluded articles have been recorded (Figure 2-1). All studies not available in portable document format (pdf) were excluded, resulting in a total of 138 studies. In order to prepare additional screening, the PDF data of these articles have been retrieved and compiled in *Mendeley's desktop*. The length of the selected articles, as well as the number of retained articles after examination were then downloaded and recorded at 100. After this, a *Microsoft Excel* spreadsheet was set up with the aim of gathering data on each study and then using them for quantitative assessment.

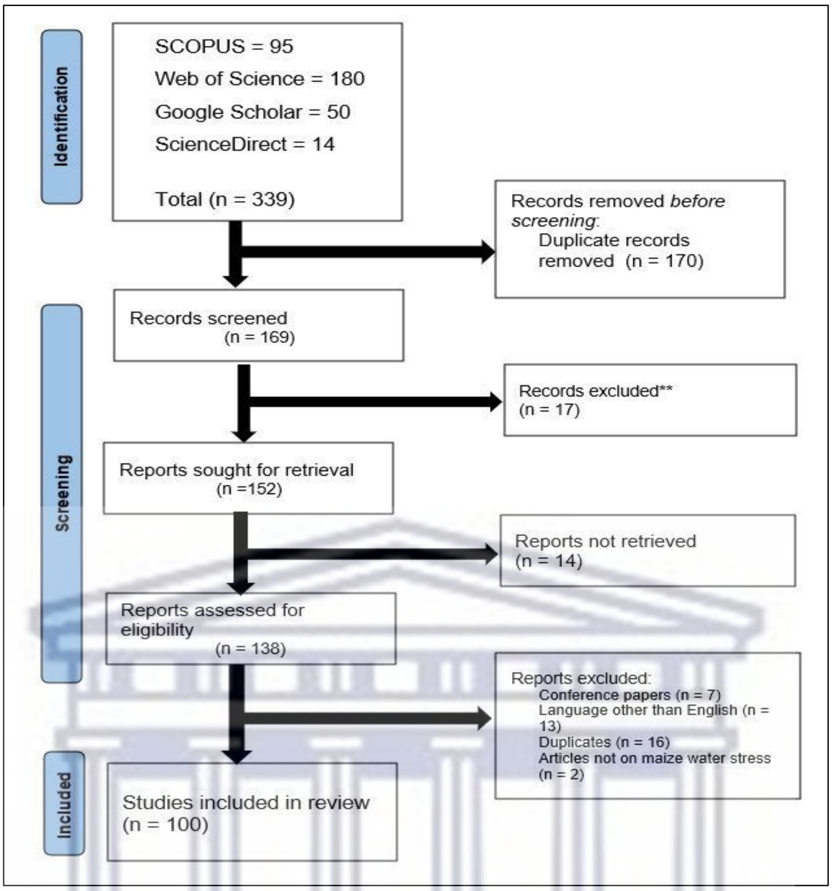

Figure 2-1: The results and filter process of articles that meet the search keywords used.

2.3.3. Stage 3: Data Extraction

Bibliographic information of selected articles, for example authors' names, article titles, year they were published, journal name, keywords, and the abstract digital object identifier (DOI), and uniform resource locator (URL) was exported from *Mendeley* into *Microsoft* Excel. In addition, the information on the study was collected with regard to the country, type of platforms, sensors, and instruments used, type of RS method used, the sensors' spectrum coverage, various vegetation indices, type of a water stress indicator studied, and prediction method used, after each of the articles has been searched, they've also been captured. In addition, coefficient of determination (R^2) in each study, source of water for the studied maize, and validation methods were recorded. To prepare for data analysis, the categorical data were then converted into two numerical variables of zeros (No) and ones (Yes).

2.3.4. Stage 4: Data Analysis

Qualitative and quantitative analysis has been carried out on the data obtained from the recovered articles. In particular, to visualize networks of occurrences and cooccurrences of major terms in literature, a bibliometric analysis was carried out. A bibliometric analysis is a quantitative method of assessing published articles that have shown to be useful for evaluating peer reviewed studies in specific areas of study (Han et al. 2020). The analysis was carried out by *VOSviewer* software (van Eck and Waltman 2010). The *VOSviewer* is designed to display the main terms associated with linked clusters on a network. Creating a map using the VOSviewer included selecting a counting method, selecting minimum number of occurrences for a term, calculating the relevance score for the co-occurrence terms and based on this score, display most relevant items, display a map depending on the selected items, consecutively (Masenyama et al. 2022). The features of *VOSviewer* for bibliometric mapping are described in detail by van Eck and Waltman (2010). The final database's titles and abstract was divided into two groups of studies using UAVs and studied using satellite and airborne (collectively) then they were imported as text information on *VOSviewer* for generating a map based on key terms used to monitor and map maize water status occurrence and co-occurrence (van Eck and Waltman 2010) by different sensors. In order to explore trends of concepts and subjects relating to mapping and monitoring maize water stress, the final database article titles and abstracts were used in VOSviewer.

Graphs of each study characteristics for which data were recorded have been created using the *Microsoft Excel* programme and are reported in the results section. The review has then been divided into 2 parts, which serve as the basis for the study. The first section outlines previous advances in maize moisture stress mapping and modelling using RS data. This section presents and details trends in the literature for quantitatively assessing maize water stress. The last stage provides an overview and discussion on the challenges and opportunities related to knowledge generation of maize water stress mapping and modelling using remote sensing data. In both stages the literature search characteristics, plant biological parameters, earth observation sensors, sensor platforms, algorithms and earlier use of optimal spectrum settings have been considered. This study assessed only the frequencies but did not conduct bias tests.

2.4. Results

2.4.1. Literature search characteristics.

The network map in Figure 2-2 show identified concepts divided into four clusters, red, green, blue, and yellow, in order to evaluate the development of topical concepts for predicting and mapping the water stress of maize crops on *VOSviewer* based on the information from the titles only. The first cluster in red has words “day”, “RMSE” (root mean square error), “stage”, “water”, “eta” (actual evapotranspiration), “WUE” (water use efficiency), “irrigation”, “accuracy”, “reflectance”, and “water deficit”. This cluster links the application of airborne and satellite data in maize water stress detection; maize is grown at different “irrigation” and “water deficit” levels, the spectral “reflectance” is measured during the “day” in all the different phenological stages. Thereafter, the airborne and satellite data is analysed to model maize “wue” and the model is then validated by comparing with ground data using “RMSE” as a statistical measurement indicator. The second cluster in green is comprised of words “impact”, “relationship”, “drought stress”, and “growth”. The words “impact” and “relationship” denotes the purpose of the study which determines “drought stress” on maize “growth”. There are key terms in the third cluster of blue, including “soil”, “NDVI” (normalised difference vegetation index), “vegetation indices”, “VWC” (vegetation water content). This cluster links the input data in the models predicting maize water stress; “soil” reflectance or moisture, “NDVI” (normalised vegetation index), and other “vegetation indices”, and “VWC” measurements. The last cluster in yellow has key term’s “ability”, “precipitation”, “maize”, and “yield”. This cluster denotes satellite and airborne sensors my pose the “ability” to estimate “maize” “yield” while “precipitation” is a water source.

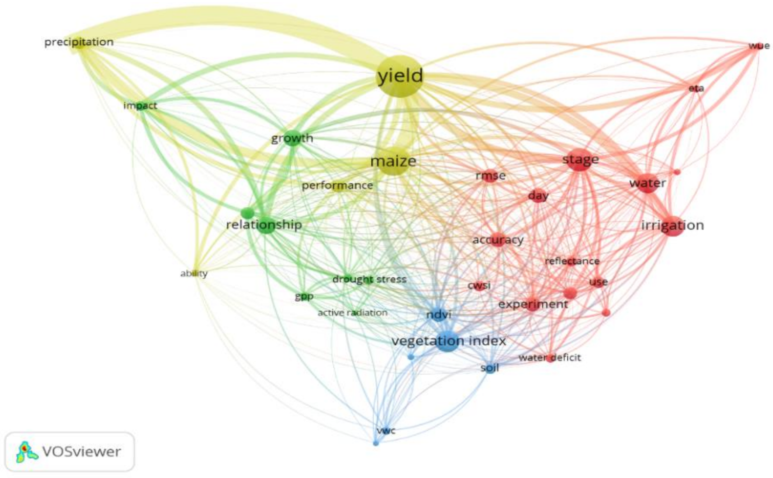

Figure 2-2:Concepts of satellites and airborne sensors application in maize water stress detection from studies' abstracts.

Similarly, results from the co-occurrence of concepts on studies that utilised UAVs to monitor and assess maize water stress in Figure *2-3*, show 4 different cluster categories. The first cluster in red, has the concepts "temperature", "UAV", "CWSI" (crop water stress index), "LST" (land surface temperature), "rmse", "value", and "ground". This cluster signifies "temperature" data obtained using "UAV" has been utilised to estimate "LST" and "CWSI", the relationship between UAV data and "ground" acquired "values" is compared and presented in "rmse" values. The second cluster (green) has terms "data", "crop", "NDVI" and "season". This cluster denotes the use of maize "crop" "reflectance" data has been utilised to develop "NDVI" for the growing "season" of the crop. The third cluster (blue) connects "chlorophyll fluorescence" and "pri" as the indicators of "maize" "water stress". The last cluster link the potential of UAVs to "model" maize water stress at a "field" scale using "cdi" (crop drought index) as a proxy.

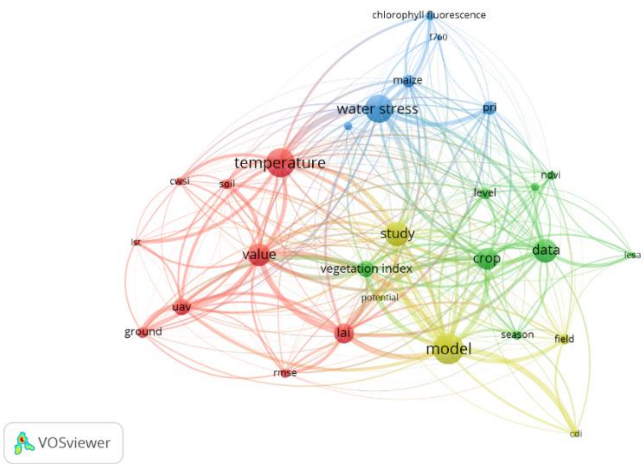

Figure 2-3:Concepts of UAVs application in maize water stress detection from studies' abstracts.

In assessing the titles and abstracts the co-occurrence analysis resulted in four clusters similar to the only abstracts analysis (Figure *2-2*) shown in Figure 2-4. Cluster 1 (Red) has key terms "soil", "vegetation index", "VWC", and "rmse". This cluster denotes the relationship between measured and estimated "vegetation index" and "VWC" has been determined using "rmse" values. The second cluster (green); has terms such as "satellite", "drought", and "growth", "impact", "relationship", and "response". This cluster links the prospects of utilising "satellite" for assessing "response" of maize "growth" to "drought" stress. Also, the inclusion of the words "impact" and "relationship" represents the specific study focus thus informing remote sensing model applied. The third cluster(blue); " WUE", "eta", "irrigation". This cluster denotes the measurements of maize " WUE" and "eta" at different irrigation levels during the changing phenological "stages". Cluster 4 has "precipitation", "maize" and "yield", this cluster links "precipitation" levels with increase or decrease of "maize" "yield".

The UAV used in monitoring and analysing maize water stress in Figure 2-5, shows that there are 4 cluster categories. The first cluster in Red has key terms "CWSI", "LST", "soil", "value", "lay", "vegetation index", "ground" and "rmse". It links the indicators of maize water stress "soil" moisture, "LST", "lay", and "cwsi" and other "vegetation indices", they are compared with "ground" measurement using "rmse" for accuracy assessment. The second cluster in green has keywords; "data", "season", "NDVI", "crop", and "level". This cluster denotes that "NDVI" data collection procedures, "data" is collected during maize "crop" growing "season" at different water stress "levels". The blue cluster, which is the third reveal key terms "pri", “maize”, “canopy temperature”, “water stress detection”. This cluster links proxies used to determine “maize” “water stress detection” which include “canopy temperature” reflectance, and “pri”. The last cluster in yellow links the potential of UAVs “model” maize water stress at a “field” scale.

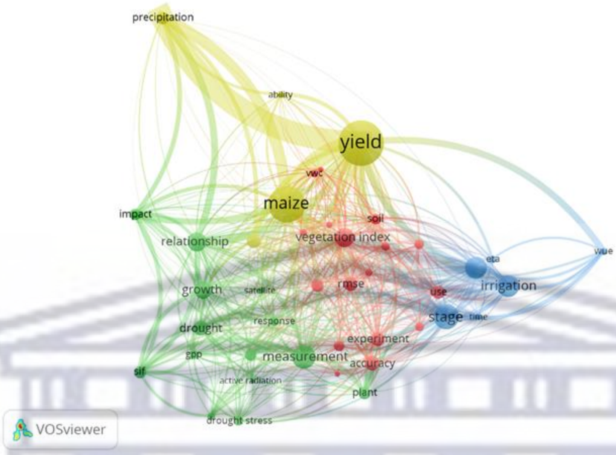

Figure 2-4:Concepts of satellites and airborne sensors application in maize water stress detection from studies’ titles and abstracts.

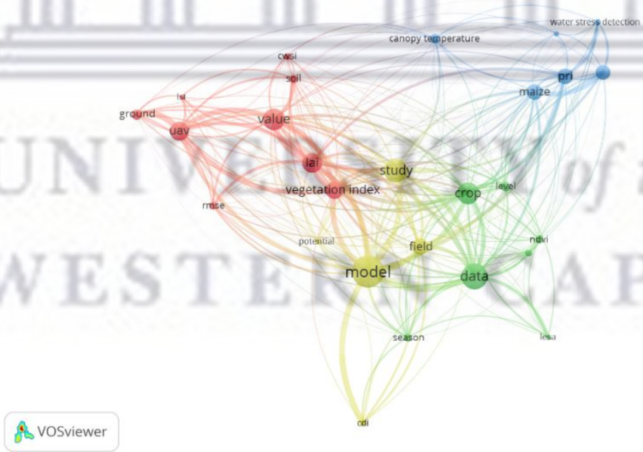

Figure 2-5:Concepts of UAVs application in maize water stress detection from studies’ titles and abstracts.

2.4.2. Trends in publications.

Recently, there has been a lot of focus on the assessment and modelling of maize water stress using remotely sensed data. This is demonstrated by the constant rise in the number of research that evaluated and modelled maize water stress using RS techniques. The study results reveal that the earliest publication of maize water stress was in 2002 (Figure 2-6). Since then, there has been constant publication rate with an increase from 2011. The year 2011 shows a drastic increase of 15 more publications compared to the beginning, of 2002. Overall, results show that RS applications for understanding maize water stress significantly increased from the year 2011 to date. As a result, a total of 100 articles have been published from 2002 to mid-2022. Overall, 38 countries around in the world remotely sensed maize water stress. Regarding spatial distribution of these studies, the United States of America (USA) (n = 37) has been shown to be at the forefront, globally, in on the utilisation of remotely sensed to estimates maize water stress followed by China (Figure 2-7). Nonetheless, less research efforts were observed from Africa contributing only 12% of the studies and South Africa contributed only 1%.

Figure 2-6:The number of studies that utilised remote sensing to assess maize water stress.

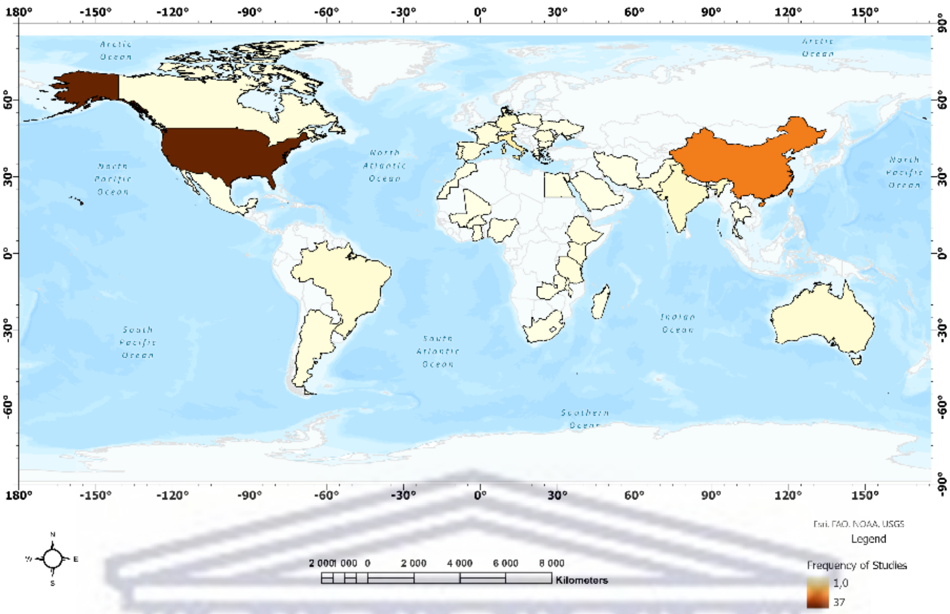

Figure 2-7: The spatial distribution of remote sensing studies related to the maize water stress.

2.4.3. Maize water stress indicators.

Four groups of maize water stress indicators were captured in this study (Figure *2-8*). These were categorized as plant, soil, temperature, and water-based indicators were recorded in this study. Out of 4 identified groups of maize water stress indicators, highest frequency of publication was noted on plant-based indicators (56%), water-based indicators (24%), temperature-based indicators (12%), and the least, soil-based indicators (8%) in that order. In total 25 indicators were identified in literature with soil water content being the single most frequently studied indicator (16%). This may be due to the fact that the amount of soil water available to plants is influenced by variables such as the quantity and timing of precipitation, the physical characteristics of the soil, and soil horizonation, in the case of water stress (Brogi et al. 2020).

The second indicator with most frequencies is the leaf area index (LAI) (14%) Figure 2-8a). Canopy temperature also has a notable frequency of publication record of (12%) (Figure 2-8c) followed by evapotranspiration (11%) (Figure 2-8b).

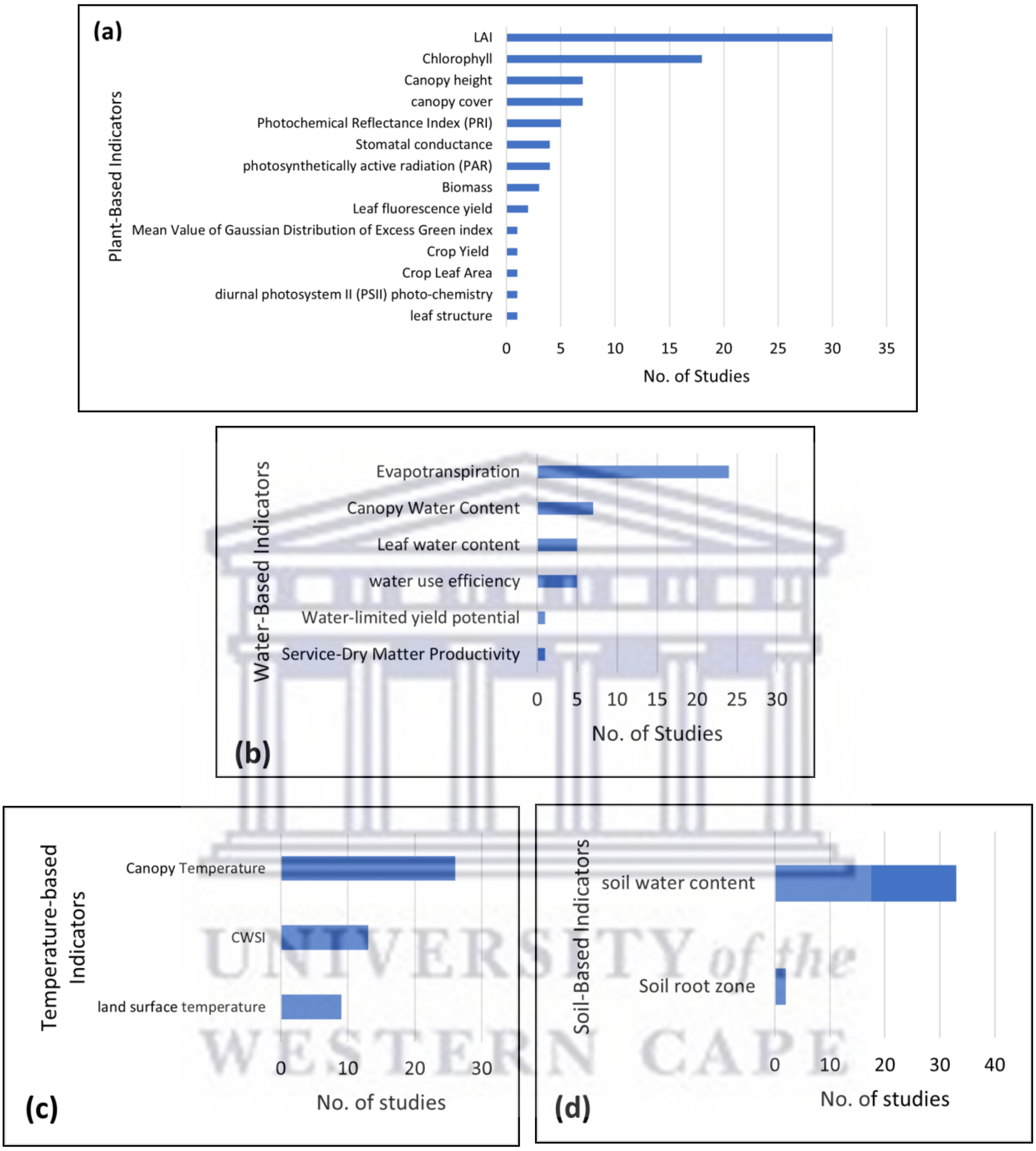

Figure 2-8:Plant (a), water(b), temperature(c) and soil (d) based maize water stress proxies utilised in studies to determine maize water stress.

2.4.4. Platforms and sensors.

Overall, 17 different satellite and airborne sensors were recorded from the literature collectively (Figure 2-9a). The highest frequency for publication in the Moderate Resolution Imaging Spectroradiometer (MODIS) (n = 21) is followed by Landsat 7 ETM (n = 11), then

Landsat 8 (n = 8) and finally Landsat 5 (n = 6). Meanwhile, a total number of 6 different UAV models were recorded and 11 studies explored the potential of utilising drones in mapping maize crop water stress (Figure 2-9b). Studies that utilised UAV-captured data for maize water stress mapping are significantly lower than those that use satellite and airborne captured data. Collectively, out of the 85 studies that utilised satellite, airborne and drone-captured data, only 18,8% used drone-captured data.

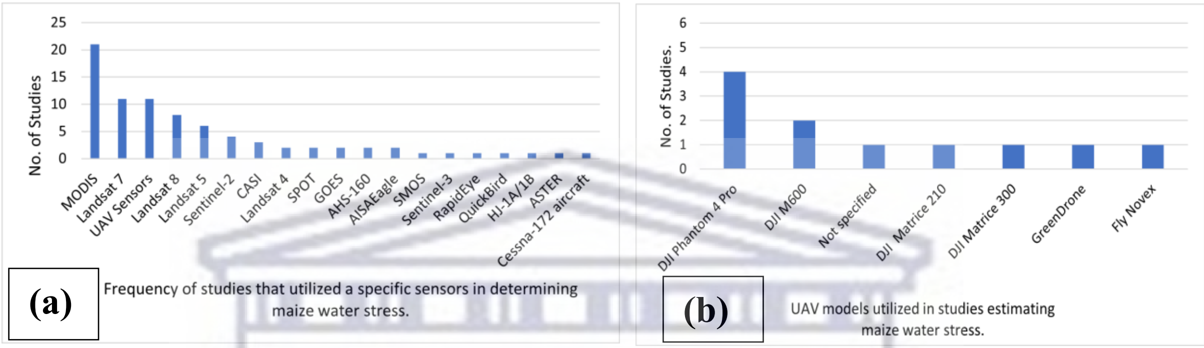

Figure 2-9: UAV, Airborne and Satellite sensors used in studies estimating maize water stress (a) and UAVs model type (b).

Meanwhile, results show that 16 different spectroradiometers and infrared thermal radiometers (IRTs) have been utilised for measuring spectral and canopy temperature reflectance, collectively (Figure 2-10a). ASD Field spectroradiometer is the single most frequently utilised amongst the 16 (38,89%), followed by S1-11 and S1-121 IRT sensors (8,33% each) (Figure 2-10a), low frequently utilised spectrometers are QE65Pro and the type of spectroradiometers which were not specified in the literature with the frequency of 8,33% each. Overall, the rest of the spectrometers and IRTs have the lowest same frequency of 2,78% each. Therefore, the result in Figure 2-16 reveal that energy balance models are a very widespread type of RS model used in maize water stress, their dependence on the measurement of red and Near Infrared surface reflectance data which serve as an input for these models may be attributed to this large number of spectroradiometers.

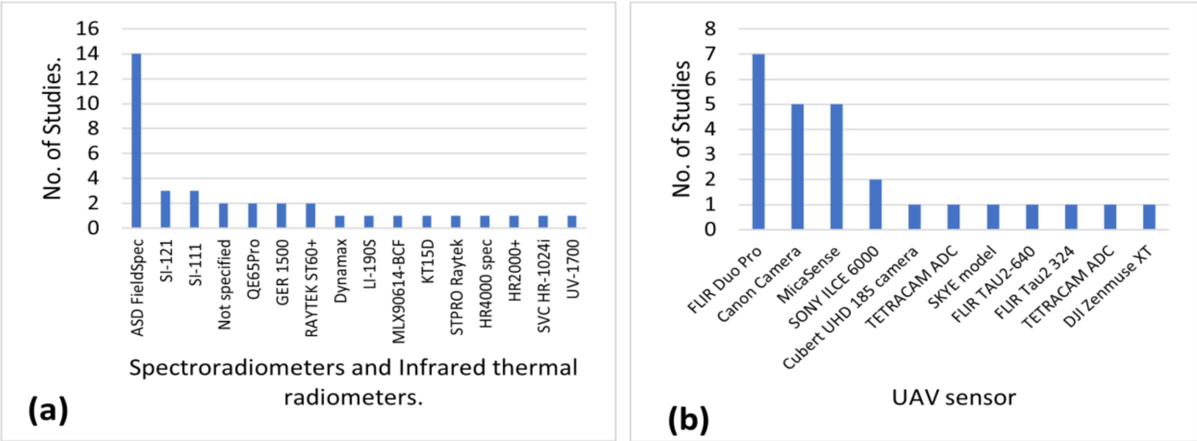

Figure 2-10:Spectroradiometer and Infrared Thermal Radiometers (a) and UAV sensors (b) used in studies using remote sensing to determine maize water stress.

Generally, FLIR Duo Pro followed by MicaSense then Canon cameras were the dominant UAV sensors recorded in this study (Figure *2-10*b). High usage of MicaSense RedEdge could be attributed to the fact that it covers wide range of electromagnetic spectrum from the Red to thermal infrared sections. With the exception of the thermal infrared range, the other bands on this sensor are comparable with the high spatial resolution Sentinel 2, which likewise reaches nearly same regions of electromagnetic spectrum (Sibanda et al. 2021). On the contrary, Hyperspec VNIR (37,5%) and Tetracam Multi-Camera Array (MCA) (25%) are the most frequently used airborne sensors found in this study (Figure 11a), whilst least utilised airborne sensors are FLIR A320 (12,5%), Hyperspec Fluorescence (12,5%), and AVIRIS (12,5%). Furthermore, there are studies that utilised camera sensors without embedding them on a sensor platform, Tamarisk 320 has been utilised in more than one study whereas other cameras have only been utilised in one study each (Figure *2-11*b).

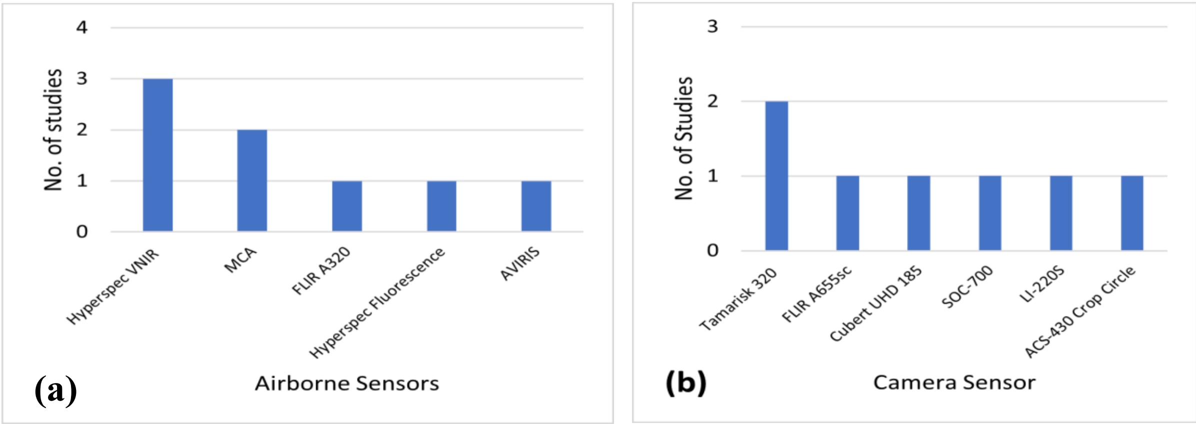

Figure 2-11: Airborne (a) and camera ground sensors (b) utilised in studies determining maize water stress.

Upon assessing whether there were significant differences in the performance (R^2) of these sensors in estimating maize crop water stress, the findings showed that there were significant variations in all satellite and airborne sensors ($p = 0.05$) (Figure *2-12*). The highest R^2 averaged value was obtained from QUICKBIRD with an average prediction accuracy of 91% followed by Cessna-172 aircraft (88%). Meanwhile, the freely available and commonly utilised sensors including Landsat 8, 7, 5 and 4 have average R^2 of 70%, 70%, 63% and 34%, respectively. In addition, Sentinel-2, MODIS, GOES and SPOT have yielded a low average prediction accuracy (R^2) of 46%, 44%, 47%, and 41% respectively. On the contrary, the utility of UAVs reveals averagely high estimate precisions with R^2 from 82% to 93%. But similarly, to Quickbird, UAVs average R^2 is high.

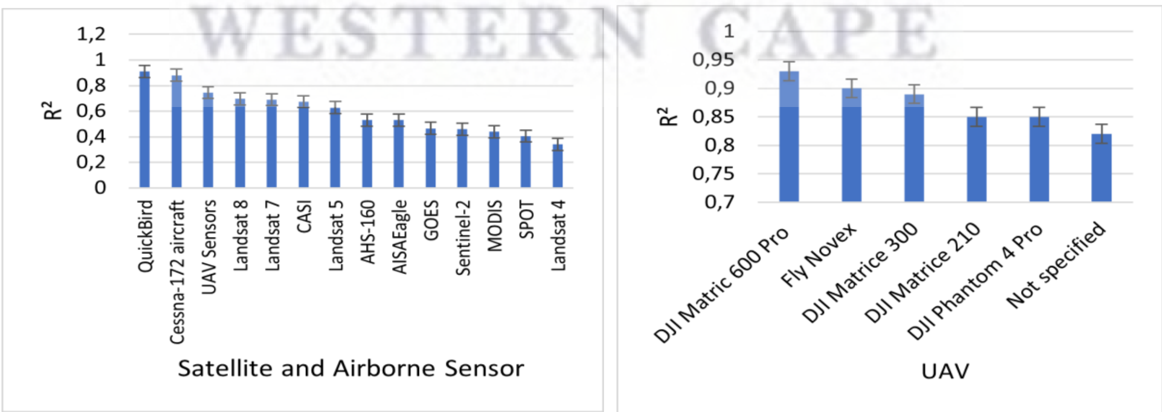

Figure 2-12: Average correlation coefficients values for Earth observation sensors used in the maize water stress studies.

2.4.5. Vegetation indices and spectral characteristics.

Numerous vegetation indices (VIs) derived from satellite and UAV borne sensors, field spectrometers, and cameras (incomplete sentence). Although there were numerous VI identified in the literature, only those that were utilised in more than two studies were considered in this review (

Table 2-2). As a result, 14 different VIs were recorded in this study. NDVI was the most widely used VI with a frequency of 41% (Figure *2-13*). NDVI was followed by OSAVI and GNDVI both utilised in 8% of the retrieved literature. Other indices included TCARI (7%), SR (7% each), EVI (6%), SAVI, PRI, NDRE (4% each), NDWI and RDVI (3%), LCI, DVI, VTCI (2% each). Even though SAVI is amongst the least used VIs, it has the highest average r^2 value. Red and near-infrared were the most commonly used electromagnetic spectrum segments for the generation of these VIs. Results show that analysis of maize water stress has been done using the provided wavelength spectra: the visible wavelength spectra in the blue range (450–495 nm), the green range (495–570 nm), the red range (620–750 nm), and the near-infrared wavelength spectra (850–1700 nm). Moreover, there is also the use of red-edge band reflectance.

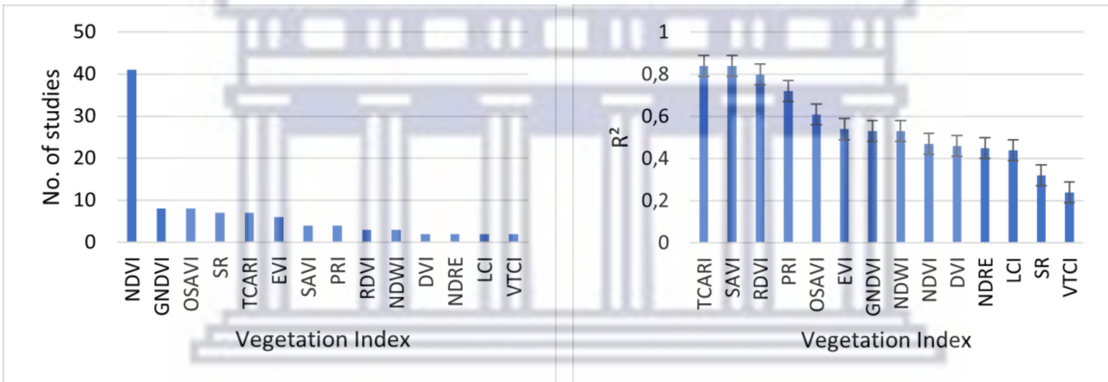

Figure 2-13: Vegetation indices used in studies analysing maize water stress using remote sensing data.

Table 2-2: Spectral indices commonly utilised for dictating maize crop water stress.

Indices	Acronym	Equation	Reference
Normalised difference vegetation index.	NDVI	(R800 − R670)/ (R800 + R670)	(Zhao et al. 2018)
Optimized soil adjusted vegetation index.	OSAVI	(1+0.16) *(r800-r670)/ (r800+r670+0.16)	(H. Zhou et al. 2022)
Green NDVI	GNDVI	(R800 − R550)/ (R800 + R550)	(Zhao et al. 2018)
Normalised Difference Red-Edge Index	NDRE	(R750 – R705)/(R750-R705)	(Liu et al., 2018)
Enhanced vegetation index.	EVI	2.5 × (R800 − R690)/ (R800 + 6.0 × R690 − 7.5 × R490)	(Liu and Huete 1995)
Transformed chemical absorption reflectance index.	TCARI	3((R700−R670)-0.2(R700-R550) R700/R670)	(Liu et al. 2010)
Simple Ratio.	SR	r900/r680	Gitelson and Merzlyak, (1996)
Soil Adjusted Vegetation Index	SAVI	(1 +L) NIR – RED/NIR+RED+L	(Huete 1988)
Photochemical reflectance index.	PRI	(R570−R530)/(R570+R530)	(Suárez et al. 2009)
Renormalised difference vegetation index	RDVI	(R800-R670)/(√R800=R670)	(L. Zhang, Zhang, et al. 2019b)
Difference vegetation index	DVI	r900 − r680	(M. Li et al. 2021)
Normalised Difference Water Index	NDWI	(R860−R1240)/(R860+R1240)	(H. Zhou et al. 2022)
Leaf chlorophyll index	LCI	(R850 -R710)/ (R850 +R680)	(Ramachandiran and Pazhanivelan 2017)
Vegetation temperature condition index	VTCI	LSTmax(NDVI)-LST(NDVI) /LSTmax(NDVI) – LSTmin(NDVI)	(L. Wang et al. 2018)

Results show that multispectral sensors (67%) that cover NIR and Red electromagnetic spectrum regions, have been the most explored sensors (Figure *2-14*). This is concurrent with the high utilisation of satellite sensors with freely available data such as Landsat and MODIS for the study of maize water stress (Figure *2-8*). Even some of the UAV sensors that have caught researchers' attention are multispectral; For example, the MicaSense family of multispectral cameras can record data in greater spatial resolution not only from visible wavelengths but also red edges and near infrared areas during electromagnetic spectrum. Hyperspectral sensors are the second most utilised sensors (17%) followed by the Thermal infrared sensors (16%) (Figure 14). SAR is the least utilised sensor type.

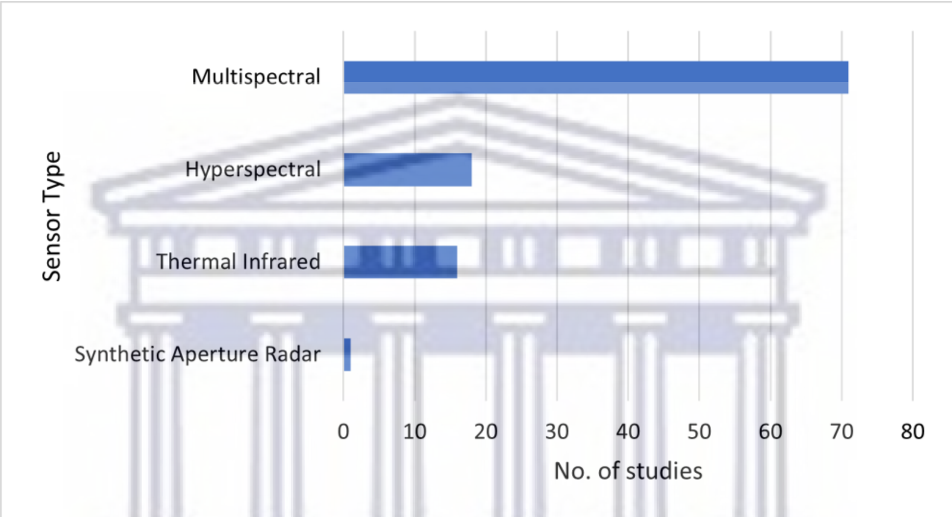

Figure 2-14:Spectrum coverage of sensor technologies used to in Remote sensing.

2.4.6. Machine learning algorithms utilised in remote sensing maize crop water stress.

Nine algorithms were utilised in maize crop water stress detection (Figure *2-15*). Linear regression was the most frequently utilised algorithm (30%) followed by the least squares regression (20%), and random (11%). Meanwhile, support vector machine was among the least adopted algorithms (6%). Figure *2-16* shows the average coefficient determination accuracies derived using different machine learning algorithms ranging between 97% and 30%. The optimum prediction accuracy was achieved through the Multi-Layer Perceptron network, followed by a simple algorithm (88%).

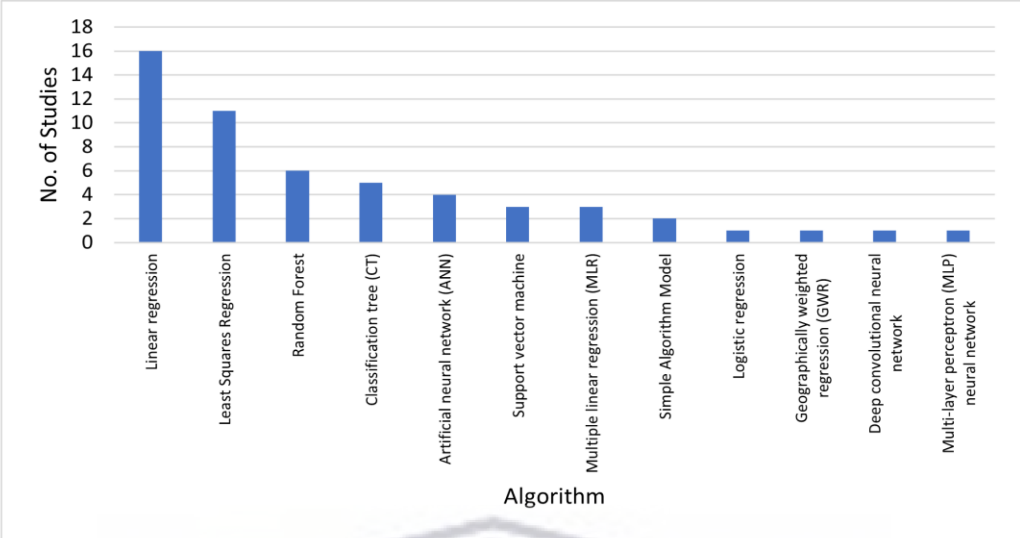

Figure 2-15: Machine Learning Algorithms and regression models utilised in studies using the application of remote sensing in maize water stress.

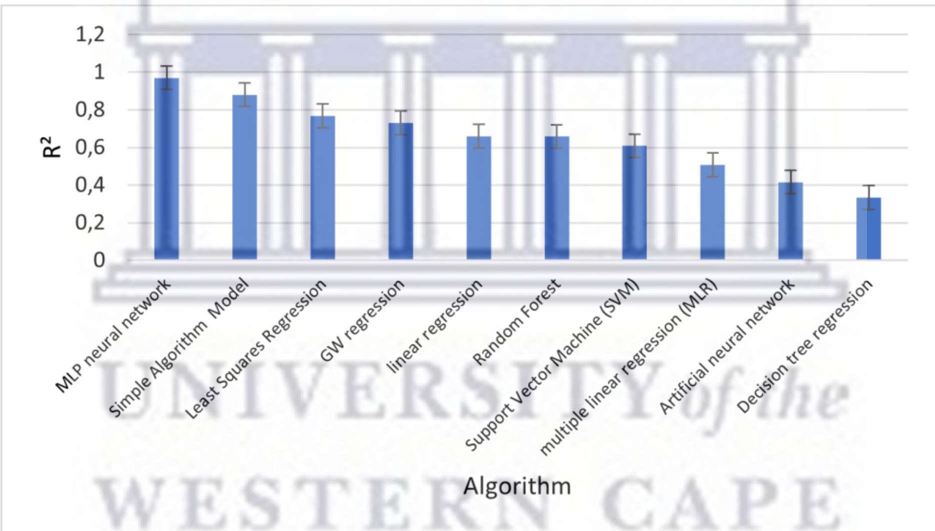

Figure 2-16: Average coefficient of determination (R^2) values produced by machine learning algorithms applied in the studies.

2.4.7. Models utilised in Remote Sensing maize crop water stress.

Only 39% of the studies followed a specific method for estimating or modelling maize crop water stress. Specifically, surface energy models were utilised in 25,64% of the studies, followed by FAO-56 (20,51%), AquaCrop (7, 69%), CERES (5,14%). Each of the remaining 16 models were adopted in 2, 56% of the studies. These results show that surface energy models (Figure *2-17*) are the most utilised in maize water stress which could mean they are best suited determining of maize CWS. However, WOrld FOod Studies (WOFOST), Soil-Canopy-Observation of Photosynthesis and Energy fluxes (SCOPE), and Mapping Evapotranspiration at high Resolution using Internalized Calibration (METRIC) model (s) were least utilised in retrieved literature.

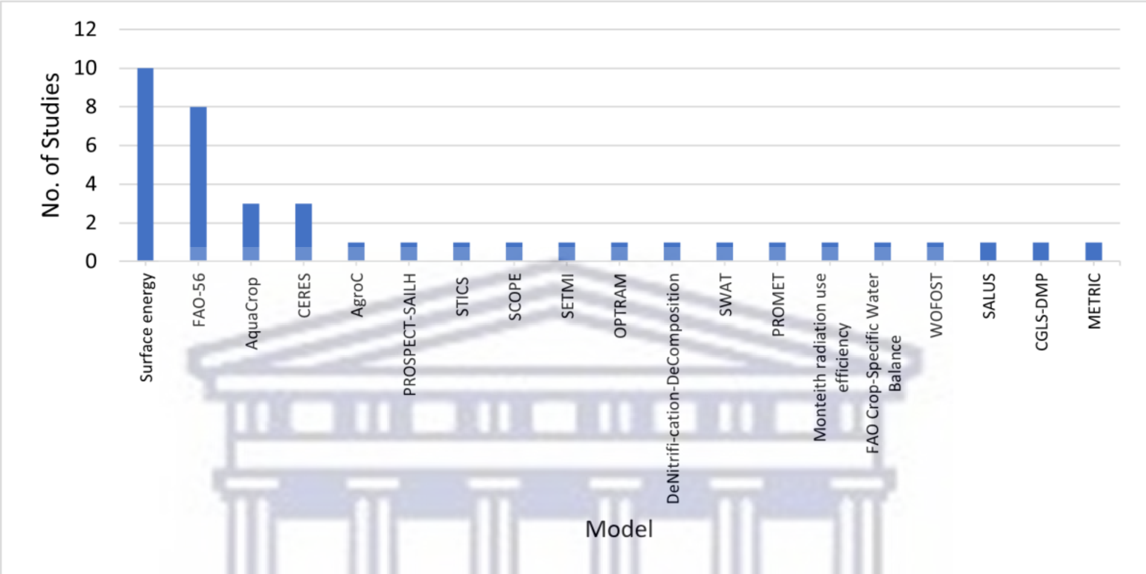

Figure 2-17:Models followed in determining maize water stress.

The most frequently used methods for model validation to analyse the water stress of maize are statistical accuracy assessment models such as root mean square errors (RMSE) or coefficient of determinations (R^2), from the retrieved literature. Results show that 69% of the reviewed studies have relied on statistical accuracy assessment such as RMSE, the R^2, the mean absolute error (MAE), and normalised root mean square error (NRMSE) for model validation (Figure 2-18). While a large number of researchers are leaning towards statistical validation meaning that they have to acquire ground measured data to compare with estimated, there is also few that have preferred dataset from another data source (26%) and very few have used data available from literature, that is, referencing work that has already been published (5%).

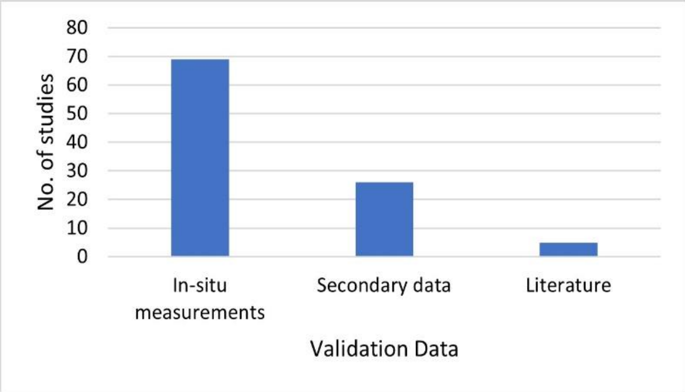

Figure 2-18: Validation data for the studies using remote sensing in determining maize water stress.

2.5. Discussion

2.5.1. Progress made in monitoring maize water stress using remote sensing technologies.

2.5.1.1. Changes in the key terms in literature.

In terms of assessing the evolution of key terms from literature, results revealed that utilised UAV captured data has been utilised to determine maize water stress from the years 2014 and 2015 until recently (Figure *2-19* and Figure *2-21*). “Chlorophyll fluorescence” and “pri” (photochemical reflectance index) are the earliest proxies of maize water stress determination followed by “temperature” from 2017 (Figure *2-19*). Figure *2-21*reveals similar results, however “canopy temperature” focus here is shown to have begun in 2015. Both Figures also show that the recognition of the UAV “potential” to monitor maize water stress gained popularity following the years 2019. Concurrently, “ground” measured data usage increased in the same years to validate UAV captured data using “rmse” (Figure *2-19* and Figure *2-21*). In addition, Figure *2-21* reveal that the recognition of UAVs ability to determine maize water stress at “field” increased from the year 2017. From as early as 2013 and 2014, satellites and airborne sensors had already been increasingly utilised in maize water stress (Figure *2-20* and Figure *2-22*). Both Figures reveal that from 2016 the research community became increasingly aware that maize spectral “reflectance” changes with different phenological stages during its “growth”. Following then “experiments” became increasingly important in monitoring maize water stress at different “irrigation” levels and “drought stress” (Figure *2-20*). From 2019 until recently “WUE” and “VWC” have become most adopted maize water stress indicators using satellites and airborne captured data.

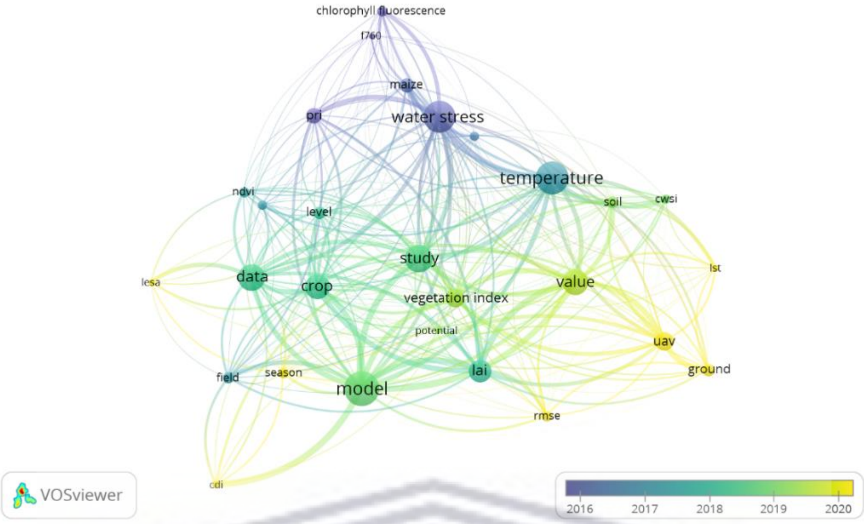

Figure 2-19: Topical concepts in mapping maize water stress using UAV sensors from studies' abstracts.

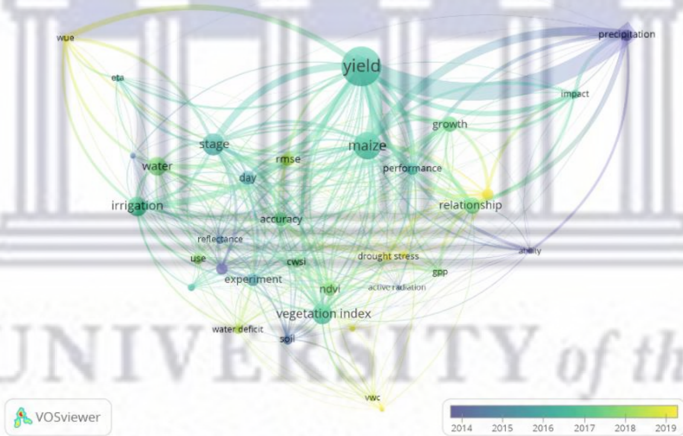

Figure 2-20: Topical concepts in mapping maize water stress using satellite and airborne sensors from studies' abstracts.

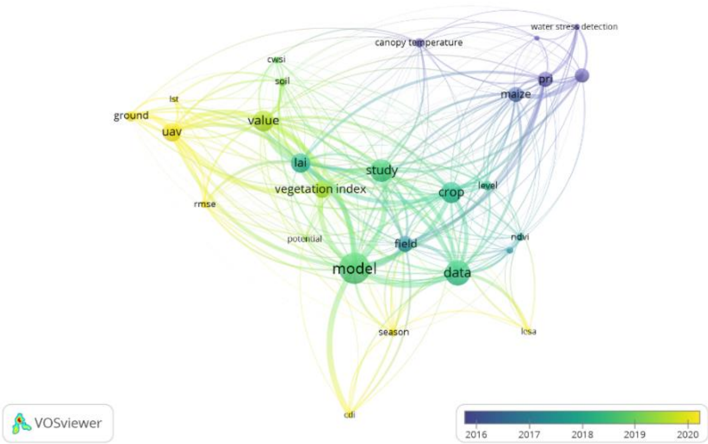

Figure 2-21: Topical concepts in mapping maize water stress using UAVs from studies' titles and abstracts.

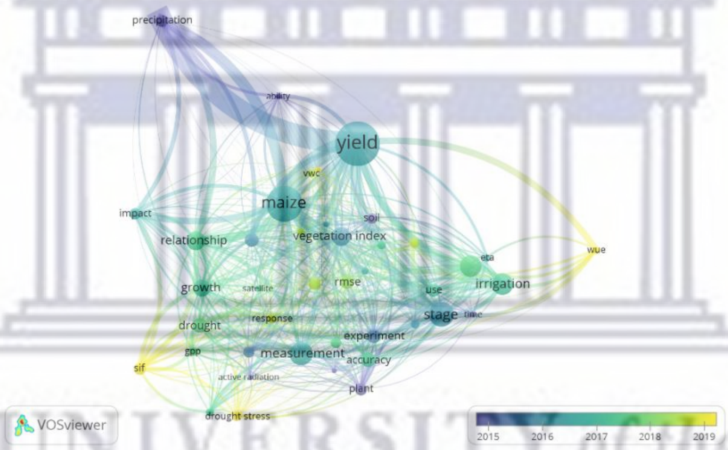

Figure 2-22:Topical concepts in mapping maize water stress using satellite and airborne sensors from studies' titles and abstracts.

2.5.1.2.Remote sensing platforms are playing an important role in determining the water stress of maize.

Generally, using RS to determine maize water stress has considerably increased in recent years (Figure *2-6*). In reality, the increase of RS use in maize water stress detection has been necessitated by the need to reduce agricultural water losses in order to transfer water resources into other uses in a society where demand is increasing (Rossini *et al.*, 2015). Additionally, many academics are concentrating on discovering alternatives and methods to boost agricultural productivity while using less irrigation water because of the knowledge that the world's water deficit is worsening alongside the rise in demand for food. Particularly for a commodity like maize, that is intensively farmed but also calls for a lot of irrigation (Rossini *et al.*, 2015). Results revealed that the first article on RS of maize crop water stress from retrieved literature was published in 2002. Then after, one article per year was published until 2010. Then from 2011 the number of published articles increased significantly to above 15 only by 2020 (Figure *2-6*). It is shown that, in particular because of better access to remote sensing data and the progress made with RS technology, what was originally described as a potential and beneficial tool for studying crop characteristics, particularly maize, has been transformed into a well-established water status study instrument. The capacity to examine the relationship between geographical variability in crop development and water stresses is provided by the analysis of crop phenology using remotely sensed datasets (Wang, Cherkauer, and Bowling 2016).

Results also showed that more than 17 different satellite and aircraft platforms, 7 types of Unmanned Aerial Vehicles used to capture remotely sensed data for the evaluation of maize crop water stress at a range of geographic coordinates, spatial resolution or temporal resolutions (Figure *2-9* and Figure *2-10*a). fact that some of the satellite images are freely available adds an advantage to their utilisation in agriculture (Kyere et al. 2019). In addition to being the oldest earth observation platform in space, Landsat also provides global satellite data of 30m resolution for over 47 years (Kyere et al. 2019). In fact, results revealed that Landsat is the most utilised RS data source for monitoring maize water stress. In particular, since 1999 and since 2008, the most widely used Landsat sensor, the Landsat 7 Enhanced Thematic Mapper Plus (ETM+), has been commercially available, followed by Landsat 8 Operation Land Manager (OLI), which was launched in 2013 (USGS 2013). In addition, Landsat 4 and 5 Thematic Mappers which were launched in 1982 and 1984, respectively (Butcher, Owen, and Barnes 2019), have also used in studies that determine maize water stress. For instance, Wang, Cherkauer and Bowling (2016) utilised Landsat 5 (Thematic Mapper) data to evaluate trends of maize leaf growth under climate stress in the St. Joseph River Watershed, in USA, using NDVI retrieved from 2000–2010. While all Landsat missions provide data at 30m resolution, the launch of each mission has been to provide better temporal and spectral coverage, spatial and radiometric resolution, than its predecessor (USGS 2013). For instance, Thematic Mapper (TM) provides data at 30m resolution, has 7 spectral bands including thermal infrared band (120m resolution) (Masina *et al.*, 2020). As compared to its predecessor, ETM+ has increased the resolution of the temperature band from 120m to 60m that can be used as a parameter for estimating surface temperatures related to crop water stress (Masina *et al.*, 2020). When Reyes-González *et al.* (2019) utilised the thermal band from ETM+ to estimate surface temperature, they found a good correlation between estimated and measured surface temperature with R^2 of 0.87. Padilla *et al.* (2011) used red and near infrared band of TM and ETM+ to compute SAVI as an input in the FAO-56 model for the estimation of maize evapotranspiration (ET). With the r^2 of 0.89, there is good comparison between daily estimated and measured ET. The significant increase in the utilisation of Landsat 8 (OLI and TIRS) can be attributed to the fact that compared to its predecessor, it has an improved radiometric performance to the 12-bit radiometric resolution (Butcher et al. 2019) thus has high sensitivity to very slight difference in electromagnetic energy. In nutshell, Landsat, with the new mission better than its predecessor, provides consistently improved remotely sensed data quality available in archives from 1972 (USGS 2013).

Apart from Landsat, MODIS was the second most widely sensor platform in mapping maize water stress. Unlike Landsat, MODIS has coarse resolution at these scale of ≥250m, thus limiting its application over heterogeneous agricultural systems since crops and fields are frequently mixed (Wulder et al. 2019). In fact, the results revealed that due to the low spatial and temporal resolution of the MODIS, when compared with Landsat, (Berni et al. 2009), Landsat-obtained map better preserves spatial detail at field scale (Ren *et al.*, 2021). Nonetheless, according to Ren *et al.* (2021) an excellent indicator of non-irrigation and irrigation, for instance, is the time-series NDVI produced from MODIS . In fact, MODIS provides variety of phenology products that authors have used to assess maize water status; leaf area index (Ines *et al.*, 2013), enhanced vegetation index (Holzman et al. 2018), vegetation temperature condition index (Wang *et al.*, 2018). Moreover, evapotranspiration, vegetation, albedo, and land cover products provided by MODIS (Javadian et al. 2020) have all been contributing to the study of maize water stress. It is because of these variety of data products available from MODIS that are utilised to determine maize water stress and therefore giving MODIS high number of frequency of publications. In particular, Wan *et al.* (2021) utilised Terra MODIS 8-day global land surface temperature (LST)/emissivity products (MOD11A2) with spatial resolution of 1 km to calculate the LST and Terra MODIS 8-day global surface reflectance products (MOD09A1) at 500 m spatial resolution to calculate the vegetation indices (including NDVI and EVI). Whereas, Li *et al.* (2021) assessed the ability of MODIS LST/Emissivity product (MOD11A1 and MYD11A1), and MODIS/Aqua LST/3-Band

Emissivity product (MYD21A1) to estimate daytime LST and found that MOD11A1 and MYD11A1 products underestimated daytime LST with a RMSE < 2.9°C. whereas MYD21A1 LST achieved an overall RMSE < 3.6 °C regarding daytime LST. Even though MODIS offers many data products including LST data its low spatial and temporal resolution makes it unfeasible for application in small holder plots which are small in size.

On the other hand, users may have access to high resolution images with pixels as large as 10m on Sentinel, a new platform which is still-emerging (Rivera-Marin, Dash, and Ogutu 2022). It also provides an opportunity for better assessment of a range of variables at higher spatial resolution in the determination of maize's water status. The program's introduction in 2015 (Mananze, Pôças, and Cunha 2018) may have influenced the increase in publications following that year (Figure *2-6*). According to Weiss and Jacob (2019) Sentinel-2 has unprecedented capacity to provide spectral sampling that allow the identification of crop types and varieties. In addition, many of the literature has recognised that Sentinel can be used to measure spatial temporal variability in crop water status. For example, in order to estimate the water content of the soil in a spatially heterogeneous agricultural landscape, Ambrosone *et al.* (2020)used sentinel-2 data through the Optical Trapezoid Model (OPTRAM) (Figure *2-17*) and found that estimations by OPTRAM are close to in situ measurement value. Also, Mananze, Pôças and Cunha (2018) used sentinel-2 images to retrieve maize LAI at small scale fields (<5ha) in Mozambique and found that Sentinel-2 can accurately estimate LAI at field scale. Perhaps Sentinel's ability to account for spatial heterogeneity thus giving a viable option of remotely sensed data applied in small scale field, will increase the RS data usage in determining maize water status.

While the medium resolution of Landsat (30m) to coarse resolution of MODIS (250- 1000m), have restricted their use at the small farm scale, UAV is a cutting edge field phenotyping platform for spatial data in agriculture (L. Zhang, Niu, et al. 2019). Even though satellite platforms like Sentinel provide highest spatial-temporal resolution of the freely available spaceborne data, UAVs can offer higher-quality data at the user determined scale and time. For instance, Cheng *et al.* (2022) used UAVs data obtained at the height of 30m and 6 day temporal resolution, whereas Zhang *et al.* (2019) obtained UAV multispectral data at a flight height of 70m with spatial resolution of 4.7 cm and fourteen flights from 2017.06.26 to 2017.08.29. UAVs are suitable for the quantification of maize water stress at a field level because they can fly over an area of interest and take aerial photographs at lower altitudes, thereby facilitating more accurate land sampling. As a result, it has been noted that research on the use of UAVs to map and monitor maize water stress has increased significantly. For instance, in their study, Zhang *et al.* (2019) mapped the maize crop coefficient (Kc) using UAV obtained data under various deficit irrigation levels, and found that when compared to on-site measurement Kc calculate from UAV data was able to capture field variability of crops and soil. When also estimating Kc, similarly to Zhang *et al.* (2019), Shao *et al.* (2021) found UAV-based VIs effectively correlate with ground-based data ($R^2 = 0.65$). In addition, while estimating maize CWSI, Zhang, *et al.* (2019a) found that CWSI values from UAV data retrieved by VI-CWSI regression models had more capabilities for evaluating field variations between the soil as well crops. The increased adoption of UAVs in agriculture research can be demonstrated by the fact that, compared to satellite imagery, they can produce data with incredibly high spatial and temporal resolution which improves their ability to predict maize water stress at local level.

For many crops water requirement inventories and monitoring needs, RS data and techniques have been shown to be useful, however, these are not limited to satellite and airborne platforms. Literature reveals that radiometric ground-based RS data has also been established to be a reliable RS data acquisition method. Camera sensors have been used as sources of ground remotely sensed data especially in field experiments (DeJonge, Mefford, and Chávez 2016), even though other authors have found it difficult to obtain maize phenology measurement for the entire growth cycle, it has been deemed feasible source of remotely sensed data. Tsakmakis, Gikas and Sylaios (2021) captured the green canopy cover (CC) An image was then processed using an RGB camera attached to a selfie stick approximately 3 metres above ground, via GIMP and Photoshop software. In addition, An *et al.* (2019) captured maize drought stress RGB images in the field and found that for the total dataset, classification and identification accuracy of drought stress from the captured images was 95.95% and 98.14%, respectively. A feasibility study was carried out on the use of thermal cameras to quantify high quality spatial canopy temperature in relation to soil moisture (Mangus, Sharda, and Zhang 2016). In their study, Mangus, Sharda and Zhang (2016) found that the thermal infrared system maintained an accurate measurement while adapting to changing ambient greenhouse conditions at precision of ±0.62 °C.

2.5.1.3.Remote sensing models as the basis for estimation of water stress in maize.

The numerical relationship between the measured biophysical variables on the ground and the remotely sensed spectral reflectance is calibrated by empirical approaches, also known as regressions (Weiss and Jacob 2019). For instance, nonlinear or linear relationships were established between: VIs and LAI (Micol Rossini et al. 2015; Shao et al. 2021), chlorophyll content (Behmann et al. 2014), or water content (Zhou *et al.*, 2022). Most of the algorithms applied were multivariate analysis techniques, especially linear regressions, because they are simple and straightforward to use (Figure *2-15*). However, linear regression can be significantly limited by not being able to see that the response and environmental variables have a nonlinear relationship (Xie et al. 2021). Therefore, results indicate the use of more advanced techniques for machine learning like SVM, RF (Filgueiras et al. 2020), PLS (Elmetwalli et al. 2021) and NN have been utilised as complimentary tools in maize water stress studies (Figure *2-15*).

Machine learning algorithms are effective because they do not rely on any assumptions about data distribution due to the fact that they are nonparametric (Barrett et al. 2014). In addition, machine learning techniques can give an indication of linear and nonlinear relationships among responses and the environment variables based on its easy structure, strong approximation capacity as well as excellent accuracy estimation (Deng et al. 2021; Guo et al. 2015). This offers a convenient and new technique for evaluating and estimating maize crop physiological parameters. Algorithms such as PLS can effectively reduce spectral response complexity and multi-collinearity by performing simple vector space projection operations, thereby reducing over-fitting (Krishna et al. 2019). In fact PLS has been successfully implemented to with spectral data to estimate leaf stomatal conductance (Sobejano-Paz *et al.*, 2020), LAI (Elmetwalli et al. 2021), and water content (Mirzaie et al. 2014). Also, the RF model can model high non-linear dimensional relations; resist "overfitting"; relative robustness of noise in data; establish an independent measurement of error rates; and determine the relevance of variables used (Xie et al. 2021). The model has therefore been effectively implemented in i) predicted agricultural data including maize crop coefficient for crop evapotranspiration assimilation (Shao et al. 2021), and ii) classified irrigated and non-irrigated maize (Ren *et al.*, 2021). Nonetheless, machine learning and multivariate algorithms proves to be able to estimate crop water stress parameters, thus their usage in maize water stress studies.

In addition, models that diagnose current maize water status and predict possible impacts for imminent management methods have also been utilised in maize water stress monitoring (Figure *2-17*). The results of such techniques may provide information about recommendations for the scheduling of irrigation in order to control maize water levels. Results reveal the widely used models comprise the surface energy, CERES Acquacrop, and FAO-56 model which is included in the Decision Support System for Agrotechnology Transfer (DSSAT) (Ahmad et al. 2018; Ines et al. 2013), the STICS model (Jégo, Pattey, and Liu 2012), the WOrld FOod Studies (WOFOST) model (Guissard, Lucau-Danila, and Defourny 2005) (Figure 2-18). Based on the energy balance, RS techniques have been developed to estimate ET from satellites and provide estimates of actual evapotranspiration. University of Idaho (USA) created the METRIC model to estimate ET, which is based on the Surface Energy Balance Algorithms from the Land (SEBAL) model (Alvino and Marino 2017). METRIC calculates evapotranspiration from Landsat imagery by calculating the available energy using the surface temperature of the earth from satellite imagery thermal bands and then calculates latent heat as a residual heat to the surface energy balance to constrain the heat flux for one or more layers of the canopy and soil (Alvino and Marino, 2017). In fact, Reyes-González *et al.* (2019) found that the METRIC model is good estimator of surface temperature with a r^2 of 0.87. METRIC model has also been found to be adopted in studies using remote sensing data for maize water stress modelling (Figure *2-17*). According to Claverie *et al.* (2012), these models initially were constructed to model crop growth in agricultural fields with well recognized soils, climate and farming practices that are not spatially homogeneous. In agriculture and the environment, they have been applied in a variety of ways. STICS for instance, which will simulate nitrogen, water and energy in addition to the WOFOST's focus on carbon and water while ignoring its balance of nitrogen. For some agricultural applications the description of crop growth over large areas may also require a multiplication of multiple simulations which would need to take place in a spatially distributed manner. It is therefore necessary to develop simple methods with a lower number of parameters, such as AQUACROP (Steduto *et al*., 2009), which examine crop biomass production in relation to water availability. A range of combined phenology and physiology processes, such as photosynthesis, respiration, evapotranspiration & nitrogen uptake used to simulate a large number of agricultural environmental variables is described in the STICS and CERES models. Nevertheless, large number of input data and parameters is significant for these models. Although input information for these models is mainly acquired in local setting from farmers or scientific experiments it is not available across large extents thus, they best perform in small-scale fields.

2.5.1.4. The use of wavebands and selection of spectral indices in determining maize water stress.

Application of RS in determining maize water stress has focused on electromagnetic spectrum from 0.4 µm to 2.5 µm, literature reveal variety of existing hyper- and multispectral sensors mounted on ground (e.g., ASD FieldSpec), airborne (e.g., drones, AVIRIS, Aisa), and spaceborne-level (e.g., Landsat, MODIS, Sentinel, SPOT) (Figure *2-9*). These optical sensors have been adopted for their spectral properties with particular regard in canopy, leaves and soil (Gerhards et al. 2019). The opportunity to develop narrowband vegetation indices has been opened especially by the available remotely sensed data, by making the interpretation of vegetation reflectance signatures and plant physiology and structure simple, such as photosynthetic activity, greenness or fractional vegetation cover, and canopy water content. Therefore, VIs have been considered indicators of the maize water stress. Results revealed that the most commonly used VI, the NDVI (Figure *2-13*) relies on near-infrared and red bands. NDVI serves as a quantitative gauge of the greenness of the vegetation (Ihuoma and Madramootoo 2017). Even though the absorption of chlorophyll during photosynthesis results is low in the blue and red electromagnetic spectrum regions, the green band is maximum thus giving rise to green vegetation colour (Yue et al. 2018). However, photosynthesis effectiveness declines with the leaves senescence increase during the reproductive stage, the correlation between red-NIR based VIs (such as NDVI) and measured maize water stress indicator is reduced during this stage (Yue et al. 2018). Sobejano-Paz *et al.* (2020) further elaborates that NDVI usually saturates at high vegetation coverage. Because of this, in their study, Chakraborty, Khot and Peters (2020) added new VIs in their analysis; GNDVI and NDRE and discovered that the crop vigour grew in the early development phases, peaked in the mid growth stages, and then fell in the late growth stages. Furthermore, Haboudane *et al.* (2002) empirically determined that the dependence of NDVI products on soil reflectance and sun view geometry leads to their instability. Nevertheless, NDVI is employed in irrigation studies for crop cover mapping as a way to calculate crop coefficients (Kc) for use in the standard FAO-56 approach (Figure *2-17*) (Rossini et al., 2013), to track changes in LAI (Suárez et al., 2009; Rossini et al., 2015; Sobejano-Paz et al., 2020), among others, in order to inform irrigation planning. In fact, the shortcomings of NDVI are remedied through the adoption of chlorophyll and structure-based indices that are derived from the visible (RGB), red-edge and NIR bands. OSAVI, for minimizing soil background effects on surface reflectance readings (Costa-Filho et al. 2020; Elmetwalli et al. 2021; Rossini et al. 2013; Verónica Sobejano-Paz et al. 2020) , SAVI, TCARI, because of its sensitivity to chlorophyll content (Rossini *et al.*, 2015; Zhang, *et al.*, 2019a), and RDVI. Overall, these indices aim to decrease the spectral noise generating from various non-photosynthetic materials presence and reduce brightness of the soil influenced by Near-Infrared and red derived spectral vegetation indices. OSAVI, GNDVI, NDRE, SAVI, RDVI, and TCARI were all recorded in the findings of the study with OSAVI being the most frequently published among them all.

On the contrary, as a consequence of short term changes in xanthophyll pigments when induced with water stress, PRI is directly linked to the photosynthetic process (Gerhards et al. 2019). Calculated at reflective wavelengths 530 and 570 nm (Suárez et al. 2009), PRI is referred as pre-visual index for water-stress detection (Gerhards et al. 2019). In fact, Panigada *et al.* (2014) found that contrary to traditional greenness indices (e.g. NDVI, OSAVI), PRI has been able to monitor the development of plant water stress, which gives rise to a higher degree of potential for early detection from where only physiological changes occur at an initial stage and subsequently in later stages when plants structure begins to be affected. Similar to NDVI, concerns over PRI's sensitivity to pigment levels, structural changes, illumination effects, soil background, and viewing angles, has led to its improvements to ensure more effective results (M Rossini et al. 2015). The resulting modifiedPRI (570–515nm) has proven to overcome PRI's demerit and thus proved to be more effective in detecting water stress (Verónica Sobejano-Paz et al. 2020). Furthermore, modifiedPRI has been found to best relate with other maize water stress indicators; canopy temperature, photosynthetic efficiency, and relative water content (Rossini et al. 2013). Nonetheless, results reveal that PRI ability to determining maize water stress has been recognized and utilised in literature.

The Normalised Difference Water Index (NDWI) tracks variations in the leaf water content through Short Wave Infrared (SWIF) and NIR at wavelengths of about 1240 nm and 860 nm (Zhang and Zhou, 2019; Ndlovu *et al.*, 2021; Zhou *et al.*, 2022). The SWIR reflectance is reflected in the changing water content of plants and spongy mesophyll structures on vegetation, however, NIR reflectance differ between leaf internal structure and dry matter content but are not influenced by water content. The combination of SWIF and NIR improves accuracy of determining the water content of vegetation by removing variations brought on by variations on leaf internal structure as well as dry matter content (Ihuoma and Madramootoo 2017). Studies have found NDWI a dependable estimator of water content since it presented the highest sensitivity to CWC (Zhang and Zhou, 2019), similarly, Zhou *et al.* (2022) demonstrated that maize water content was better estimated using the NDWI than the NDVI and OSAVI.

2.5.2. *Challenges and way forward in the use of RS technologies in mapping and monitoring maize water stress.*

The number and distribution of research utilising RS to examine maize water stress varied significantly around the globe. The ability of RS application in monitoring maize water stress has been adequately exploited by developed nations such as the China and the United States of America (USA). Specifically, America had most publications followed by Asia, then Europe and Africa. In total, over 74 countries have examined maize water stress using RS, with the USA contributing most research efforts and studies (Figure *2-7*). This shows that there is an uneven distribution of studies using RS data for maize water stress in the world, which may distort the international community's understanding and dynamics with regard to cereal water requirements. Consequently, the capacity to increase production while conserving water and policies to plan irrigation technologies as well as timely scheduling to address maize water irrigation requirements globally, may also be skewed.

In the meantime, there have been less than 5 published studies assessing the usefulness of remotely sensed information in Africa and global south (Figure *2-7*). Surprisingly, the countries with the lowest numbers of publications are those where maize is a staple crop grown commercially and in smallholder croplands that are more susceptible to crop water stress. Despite the widely acknowledged potential of RS in mapping and monitoring agricultural crops using freely accessible earth observation-data products, the application of the RS method, especially those aimed at the global north, is difficult due to complex interaction between weather and geography, highly diverse rainfall patterns with lack of ancillary data.

Since small-scale farmers predominate in Africa and grow rainfed maize, there is no data to support and validate these models. In brief, the dominant rainfed crop monitoring technologies suitable for the African cropping systems is severely hampered by excessive cloud cover during the rainy season, which restricts cloud free remotely sensed data (Sun et al. 2019). Most freely-available remotely sensed data's temporal resolution of the sensors as well as higher spatial resolution is not sufficient to record significant changes in maize phenology, compounded by frequent cloud cover, resulting in a lack of data (Chivasa, Mutanga and Biradar, 2017). In their study Javadian *et al.* (2020) articulated that MODIS ET product coverage has limit to North Africa and thus the region was excluded in their study. In addition, there is a need to revisit the period of 1 to 3 days in August and obtain an 8 day image composite over 70% agricultural land under clear sky conditions in sub-Saharan Africa (Bégué et al. 2020).

Perhaps the challenge faced by African countries in accessing high resolution freely available data is reinforced by the technological resources strategy that is mainly driven by the Global North institutions or funded through international organisations thus resulting in products as well as datasets that only partially meet the demand in Africa (Bégué et al. 2020). As a result, in African agricultural systems which are more diverse and yet have fewer documented records than those of industrialised countries, the data processing method used by applicants is often limited. Thus, research focusing on the application of RS dataset for determining maize water stress is required in Southern Africa and Africa as a whole. Fortunately, technological advances in sensor technologies have opened the opportunity for obtaining remotely sensed data of vegetation using the UAV technology with high spatial resolution at a user determined temporal resolution. However, its use in small scale farmers of Africa still needs to be further examined. In order to explore the heterogeneity of agricultural systems in Southern Africa, the use of UAV in the collection of data is essential, contributing to the detailed testing of the available high-resolution sensors to discriminate maize from other crops and to improve the accuracy of water stress estimates.

Apart from water stress different stresses that are rarely but sometimes accounted for, like pest and disease infestation, age of the crop, edaphic factors, local weather, and landscape affect maize reflectance properties (Chivasa, Mutanga and Biradar, 2017). While using maize canopy temperature measurements, Kullberg, DeJonge and Chávez (2017) acknowledged that other stresses that may have contributed to higher canopy temperature such as diseases may exist and therefore to remedy this, Degrees Above Canopy Threshold (DACT) method was used in their study. Other studies did not consider the influence of factors that might have altered the spectral reflectance of maize other than water stress (Rattalino Edreira et al. 2018; Rojas 2007). However, it suffice to note that considerable amount of publications considered change in spectral reflectance brought by different stages of maize growth and therefore obtained data measurements at different phenological stages (Bahir et al. 2017; Marinella Masina et al. 2020; Ndlovu et al. 2021; Shuai and Basso 2022). Nevertheless, it is worth noting that, despite these restrictions, RS data may still play an important role in accurately determining the water stress levels of maize in a disaggregated farming system. Which can be achieved by means of use of large spatial, wavelength and time resolution measurements such as UAVs in conjunction with the appropriate analytical techniques to train model using ground-truth data.

Particularly in Africa, where susceptibility to shocks from climate variability and unpredictable precipitation is significant, research activities need to be encouraged to investigate the value of RS in monitoring maize water stress. The opportunity to use UAVs as a method of gathering spatial data is presented by the dearth of data that might be restricting the usage of RS data in maize water stress monitoring on these regions. In light of the 4th Industrial Revolution, and in order to increase farming productivity, UAVs are becoming a cutting-edge source of precision data on crop water requirements which can be derived from near real-time spatial data. Compared to the widely adopted satellites data shown in the results section, the data provided by UAVs are highly likely to provide accurate, rapid, and spatially coherent models for the identification of maize water needs and irrigation schedules.

2.6.Conclusions.

In determining the water stress target, it is definitely feasible to use remotely sensed systems. Digital image techniques for leaf and canopy phenotypic classification to detect crop water stress using digital imagery data shall be used in addition to applications such as crop growth assessment, irrigation level, and crop yield. To improve image collection, the effective use of ground sensors and UAVs will become essential. In the immediate estimation of water stress in crops, which cannot be predicted by using a visual and thermal infrared image system or RedEdge, it is important to consider various symptoms. However, remote sensing data to predict water stress of maize in Africa is not widely used. In addition, the review confirmed that in applying RS to maize water stress estimation intrinsic limits caused by low resolution sensors and medium resolutions should not be ignored when transferring these methodologies to fragmented agricultural systems. The relevant spatial, time and spectrum resolution to be used are defined by the spatial patterns in these heterogeneous farming systems such as field size and shape. With sensor resolution levels low to medium, the problem of mixed pixel in scattered agricultural systems will continue. Nevertheless, with high resolution sensors such as UAVs whose pixels size are several times smaller than the field sizes that commonly occur in heterogenous crop systems, a significant improvement of water stress estimation is expected. The results of studies on detecting crop water stress through remote sensing systems, show potential in opening up new perspectives for research concerning the management of irrigation water in African countries thus further increasing the scope of remote sensing technologies, management & technology as well as new perspectives. In view of improving our understanding of African agriculture and the safety of food by means of early warning systems, it concludes that additional studies are necessary in order to determine whether high resolution multispectral RS will be used for a maize water stress estimation on heterogeneous farming systems.

2.7.Reference

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Lead to Chapter 3

The systematic review in chapter two identified numerous machine learning algorithms suitable for estimating crop water stress, these algorithms included the support vector machine (SVM), random forest (RF) and partial least squares (PLS) among others. In addition, the findings from this chapter highlight a gap in knowledge concerning optimal regression models suitable for estimating CWSI. As such, the proceeding chapter evaluates the performance of SVM, RF, and PLS in combination with spectral variables (Bands, Vegetation Indices, and combination thereof) in the estimation of CWSI. The optimal prediction algorithm for estimating CWSI in Chapter 3 will forecast CWSI across various phenological stages in Chapter 4.

3. Comparing machine learning algorithms for estimating maize crop water stress index (CWSI) using UAV-acquired remotely sensed data in smallholder croplands.

This chapter is based on a paper currently under review in the MDPI journal of *Drones*.

3.1. Abstract

Monitoring and mapping crop water stress and variability at a farm scale for cereals such as maize, one of the most common crops in developing countries with 200 million people around the world, is an important objective within precision agriculture. In this regard, unmanned ariel vehicle-obtained multispectral and thermal imagery has been adopted to estimate crop water stress proxy (i.e. crop water stress index) in conjunction with algorithms machine learning techniques; partial least squares (PLS), support vector machines (SVM), and random forest (RF) on a typical smallholder farm in Southern Africa. This study addresses this objective by determining the change between foliar and ambient temperature (Tc-Ta) and vapor pressure deficit to determine the Non-Water Stressed Baseline for computing the maize crop water stress index. Findings revealed a significant relationship between vapor pressure deficit and Tc-Ta ($R^2 = 0.84$) during the vegetative stage between 10:00 am and 14:00 pm South Africa Standard Time. Also, findings revealed entire stage maize endured low (CWSI < 0.5) water stress levels overall, thereafter, the best model for predicting crop water stress index was obtained using the random forest algorithm ($R^2 = 0.85$, RMSE = 0.05, MAE =0.04) using NDRE, MTCI, CCCI, GNDVI, TIR, Cl_RedEdge, MTVI2, Red, Blue, Cl_Green as optimal variables, in order of importance. Results indicated that NIR, Red, RedEdge derivatives and thermal band were some of the optimal predictor variables for crop water stress index. Finally, using unmanned aerial vehicle data to predict maize crop water stress index on a southern African smallholder farm has shown encouraging results when evaluating its usefulness regarding using machine-learned techniques. This underscores the urgent need for such technology to improve crop monitoring and water stress assessment, providing valuable insights for sustainable agricultural practices in food-insecure regions.

Keywords: Crop Water Stress Index (CWSI), UAV, Smallholder Farms, Maize, Machine Learning, Precision Agriculture.

3.2.Introduction

\Maize (*Zea mays L.*) is one of the most crucial crops and a primary food source for approximately 4.5 billion people in 95 developing countries, including southern African countries (Simanjuntak et al. 2023). Meantime, maize is one of the globe's crops affected by drought and heat stress because of a lack of precipitation due to climate change (Grote et al. 2021). In particular, the limited availability of water adversely affects maize metabolic activities, limiting biomass accumulation and decreasing photosynthetic rates due to reduced chlorophylls in leaves, ultimately leading to lower yields (Gerhards et al. 2018). Risks linked with precipitation variability could threaten national food security in developing southern African countries, considering the significance of maize production for local supply in these regions (Bradshaw et al. 2022). As a result, water stress quantification has become an essential issue for agricultural production, in particular precision farming. In order to support the design and adaptation of climate change mitigation and adaptation measures, it is particularly important to unravel spatiotemporal patterns and severity of water stress at different scales (Ferreira et al. 2023). Soil-based methods have traditionally been the primary means of assessing crop water stress, however, there has been an increasing preference for plant-based methods. The indirect assessment of the actual plant water status, as highlighted by (Pradawet et al. 2022) makes this method less preferred. Plant-based methods offer a more direct proxy for crop water's actual state than soil-based methods (Ahmad et al. 2021).

Evaluating crop canopy temperature variations as a proxy for water status is one of the most widely used plant-based methods. Researchers have investigated canopy temperature as a water stress indicator based on their inverse relationship with the rate of water loss and stomatal behaviour (Berni et al. 2009). This is because when the heat is absorbed into the crop, the temperature of the crop canopy increases, but it cools when the heat is used to evaporate water or transpire. The stomata close in response to soil water depletion, leading to decreased water uptake, gas exchange, and photosynthesis (Pradawet et al. 2022). Thus, water-stressed plants would generally have less transpiration and thus higher temperatures than those not affected by the stress (Berni et al. 2009; Buckley 2019; Kögler and Söffker 2019).

Canopy temperature variations are often quantified using imagers and thermal infrared thermometers (Ramírez-Cuesta et al. 2022). Hand-held thermometers were developed and gained popularity in the 1970s and 1980’s (Idso *et al.*, 1981; Jackson et al., 1981), leading to the establishment of the Crop Water Stress Index (CWSI). This normalised index has been developed to overcome the effects of other environmental parameters that significantly alter the relationship between plant stress and plant temperature (Berni et al. 2009). CWSI ranges between 0 and 1, representing a continuum from no water stress to water stress (Idso *et al.*, 1981; Jackson et al., 1981). The premise behind the index computation is detailed in the work of Idso *et al.* (1981). To provide an early intervention in increasing crop production, the CWSI could be used to identify water-stressed crops. In this regard, the CWSI, based on the surface temperature of the canopy, is now considered the preferred index for quantifying water stress in crops (Poblete-Echeverría et al. 2018). Literature shows that this range is consistent with stress levels in many crops (Berni et al. 2009) which include grapes (Ru et al. 2020), olive (Berni et al. 2009; Egea et al. 2017), nectarine (Park et al. 2021), peach (Gonzalez-Dugo et al. 2021), potatoes (Ekinzog et al. 2022; Rud et al. 2014), sunflower (Nouraki et al. 2021; Orta, Erdem, and Erdem 2002), African eggplant (Mwinuka et al. 2021), and wheat (Qin et al. 2021).

Furthermore, the empirical CWSI approach makes it necessary to use a Non-water-stressed baseline (NWSB) generated from the linear relationship between canopy and air temperature difference (Tc-Ta) for well-watered crop and vapor pressure deficit (VPD) to calculate the lower limit. For a given combination of crop and environmental conditions, this relationship is consistent (Pradawet et al. 2022). It is important to highlight that the CWSI has been effectively implemented in determining maize water stress across various climatic conditions. Studies in China (Zhang *et al.*, 2019; Gu *et al.*, 2021), the United States of America (Carroll *et al.*, 2017; Zhang *et al.*, 2023), and Thailand (Pipatsitee et al. 2023; Pradawet et al. 2022) have successfully implemented the CWSI for this purpose. While CWSI has been widely utilised globally to assess maize water stress, there is still a need to further explore its applicability in Africa, especially in Southern Africa, where a decline in maize production has been observed (Tandzi and Mutengwa, 2020; Akanbi et al. 2021). Above all, very few studies have explicitly assessed maize CWSI in smallholder croplands of southern African environmental conditions.

Meanwhile, incorporating remote sensing techniques into precision agriculture has revealed numerous methods conducive to characterizing CWSI spatially explicitly for critical crops such as maize. Remote measurement capability eliminates the need for labour-intensive and time-consuming techniques traditionally used to detect water stress at the field or farm level. This efficiency in data collection and stress assessment is a significant advantage and a driving force behind the interest in utilising CWSI for optimising crop production. However, the utility of remote sensing, particularly in regions like Southern Africa, has been hindered by the scarcity of data suitable for field-scale applications. Freely available satellite remotely sensed data (i.e., Landsat TM, ASTER, MODIS) are typically characterized by coarse spatial resolutions, which are not suitable for accurately capturing canopy temperature variations of different crops against the soil background in heterogeneous smallholder croplands (Zhang *et al.*, 2019).

Furthermore, cloud cover remains an important challenge with the use of satellites relaying remote sensing data (Mulla 2013). Recently, UAVs, to create a highly spatiotemporally precise platform to specifically detect and monitor water stress in crops, have evolved a popularly functioning system that delivers remotely sensed data that is relevant for spatial awareness (Berni et al. 2009; Bian et al. 2019). Particular, temperature-based imagery acquired through UAV-borne platforms can efficiently capture crop water stress by analysing canopy temperature concerning the physiological parameters of a crop at a field scale (Zhang *et al.*, 2019). Several studies have shown a strong relationship between CWSI data derived from UAVs and physiology parameters, e.g. transpiration rates, stomatal conductance, leaf water potential or stem water potential, in crops like maize (Gu et al. 2021; Ru et al. 2020).

Furthermore, regarding the aspect of UAVs remotely sensed data's spatial resolution, several studies have illustrated that spectral derivatives exhibit superior performance than conventional bands in mapping crop attributes (Lee, Wang and Leblon, 2020; Aldubai *et al.*, 2022). In the plant canopy, vegetation indexes can detect minute changes (Giovos et al. 2021) because they significantly correlate with water stress indicators such as stomatal conductance (Baluja, *et al.*, 2012,Gago, *et al*., 2015). In the case of (Baluja et al. 2012), a large correlation between NDVI and stem water potential was identified with an R2 value of 0.68. On the other hand, results obtained by (Espinoza et al. 2017) revealed a significant relationship between stomatal conductance and GNDVI ($p < 0.01$). (Zarco-Tejada et al. 2013) found a correlation of $R^2 = 0.77$ between the normalised photochemical reflectance index (PRInorm) and CWSI. (Zhang and Zhou, 2019) developed CWSI inversion models based on vegetation indices that showed the best relationship with CWSI, TCARI/RDVI and TCARI/ SAVI (both r^2 greater than 0.80). More efforts are required to document the relationship between UAV multispectral vegetation indices and CWSI, particularly for the maize crops in smallholder croplands.

Moreover, various machine learning methods, RFs, SVMs, and ANNs were widely employed and demonstrated to be accurate and effective in detecting and mapping various crop attributes, including water stress (Raczko *et al.,* 2017; Cai *et al.*, 2018; Mochida *et al.*, 2019, Singhal *et al.,* 2019; Lee *et al.,* 2020). Because they use sophisticated statistical techniques, machine learning methods are the most precise and effective method to learn complex non-linear functions between spectral data and biophysical parameters (Alabi et al. 2022). For instance, Ndlovu *et al.* (2021) established that the RF algorithm was best for estimating maize's specific leaf area, equivalent water thickness, and fuel moisture content to rRMSEs of 3.48%, 3.13%, and 1%, respectively. RF has been applied to predict CWSI for crops other than maize (Guo *et al*., 2020; Ma *et al.,* 2021; Yang *et al.,* 2021). For instance, (Yang, Gao, Chen, et al. 2021) demonstrated that RF could optimally estimate the CWSI of *B. chinensis var. parachinensis* (R^2 = 0.86). Guo *et al.* (2020) observed that RF outperformed SVM in estimating chlorophyll content, with average RMSEs of 2.90, and 3.11, respectively. However, SVM has also shown promising results in predicting relative water content, achieving an R^2 of 0.72 and RMSE of 6.22% (Ma et al. 2021). Nonetheless, literature also shows that, despite the optimum performance of these Machine Learning algorithms, no algorithm has been exhaustively tested to enable accurate and effective identification and mapping of plant characteristics in a variety of environments (Adam *et al.,* 2012; Masenyama *et al.,* 2023). Additionally, very limited studies have sought to characterise maize CWSI using UAV-acquired data. Therefore, the efficiency of different commonly used machine learning approaches in predicting CWSI needs to be further assessed.

Therefore, the objective of this study was to conduct a comparative assessment of the performance of PLSR, SVM and RF in estimating maize CWSI using UAV-acquired remotely sensed data in smallholder croplands typically found in Southern Africa. To address this objective, the relative contribution of bands, vegetation indices, and both datasets combined was evaluated. This research sought to provide a reference to accurately capture the spatiotemporal characteristics of CWSI in the typical small-scale agricultural areas of developing countries in Southern Africa. The study has established a maize crop water stress index based on field temperature data to achieve this overall objective. The significance of this study lies in its addressing of a critical aspect of precision agriculture, which is leveraging advanced technologies and analytical methods for near-real-time monitoring and mapping of the staple crop, maize's crop water stress, in the context of smallholder farms in developing countries, specifically for optimising food production. The findings of this study will have implications for sustainable agriculture and food security in regions facing water-related issues.

3.3.Material and Methods

3.3.1. *Study Site*

This study was conducted at rural area of Swayimane, uMshwathi Local Municipality, approximately 55 km north-east of Pietermaritzburg, in the KwaZulu-Natal Province, South Africa (-22,125031° to -34,834171° S and 16,451891° to 32,891122° E,) (Figure 3-1). The area is dominated by the smallholder farming systems with dominant rainfed crops such as sugarcane, maize, sweet potato, and amadumbe (*taro*). The climate is mainly warm and wet in summer and dry in winter. The mean annual temperature is 17 °C, with temperature ranging between 11.8 °C and 24 °C. The mean annual rainfall varies between 600 and 1200 mm, with most of it coming during the summer. During the study period the study area received an average of 242.8 mm rainfall of, 82.81 % humidity of and maximum average air temperature of 24 °C (Figure 3-2). These measurements were taken using an Automatic Weather Station installed at as school. following the World Meteorological Organization's standards, proximal to the study area. This research was carried out in an area of 0.28 hectares farmed by smallholder maize (Figure 3-1).

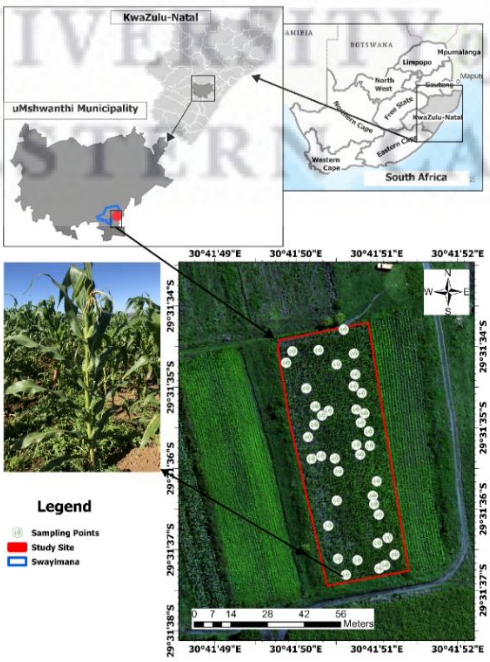

Figure 3-1: Location of the Swayimane study area, study site, and smallholder maize field.

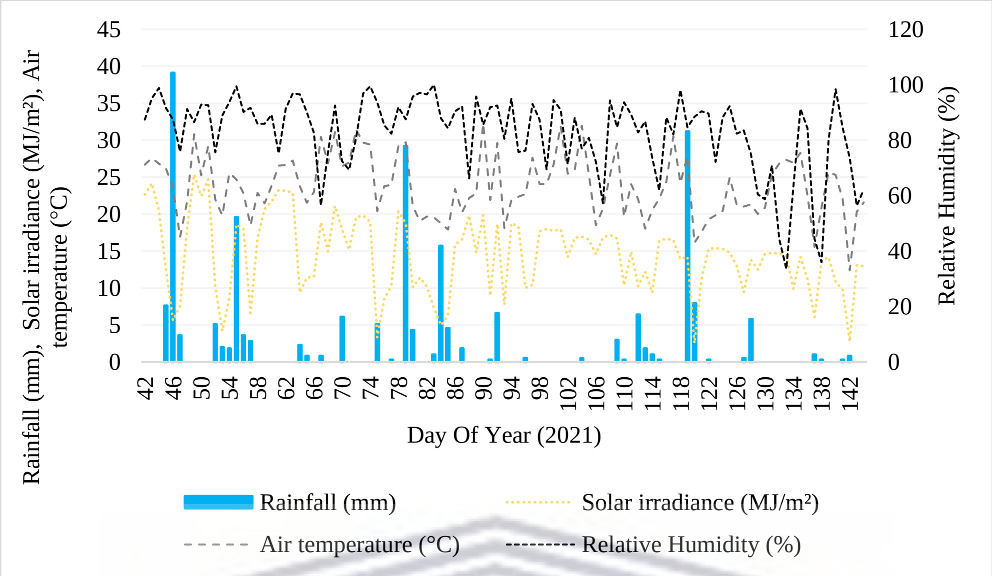

Figure 3-2: Weather conditions, including, rainfall, solar irradiance, air temperature, and relative humidity, recorded over the study period.

3.3.2. *Maize canopy temperature measurement.*

The maize has been sown on 8 February 2021 and harvested on 26 May 2021. At the centre of the maize field, two infrared radiometers (IRR), (SI-111, Apogee Instruments Inc., Logan, Utah, USA), mounted on a four-meter meteorological tower, were installed (Figure *3-3*). These sensors have been extensively used in the literature are increasingly used as a non-destructive method to monitor canopy temperature (Berni et al. 2009; DeJonge et al. 2015; Han et al. 2018; Morales-Santos and Nolz 2023). In the range of -60 °C to 110 °C, the sensor measured the target temperature at 8–14 m. The surface temperature was measured in a 23 and 45 half angle field of view (FOV) perpendicular to the direction of the row. Using the CR1000 datalogger (Campbell Scientific, Logan, Utah, USA), temperatures were measured 10 seconds apart and averaged to: 5 minutes, 10 minutes, 30 minutes, and 60 minutes (Figure *3-3*c). The 10:00 am – 14:00 pm (South Africa Standard Time) 60-minute foliar temperature data was used in this study to develop the daily vapor pressure deficit (VPD) and vapor pressure gradient (VPG), and ultimately the non-water stressed baseline (NWSB) and non-transpiring baseline (NTB).

A temperature-controlled room with blackbody cones has been used for the radiation source calibration of IRR sensors. To do so, sensors were placed within the fitting when the blackbody cone was opened. Thermal isolation of IRR sensors from the cones was used to ensure that each one could measure its temperature. The IRRs did not change, while the cone was monitored and noted to be at temperatures under 12 °C and above 18 °C in addition to a temperature level equal to or less than that of the IRR. From every 10 °C, measurements of the IRRs and blackbody cones were taken until they reached constant temperatures. IRR measurements on maize temperature were carried out to calibrate hand-held IRT measurements to develop CWSI.

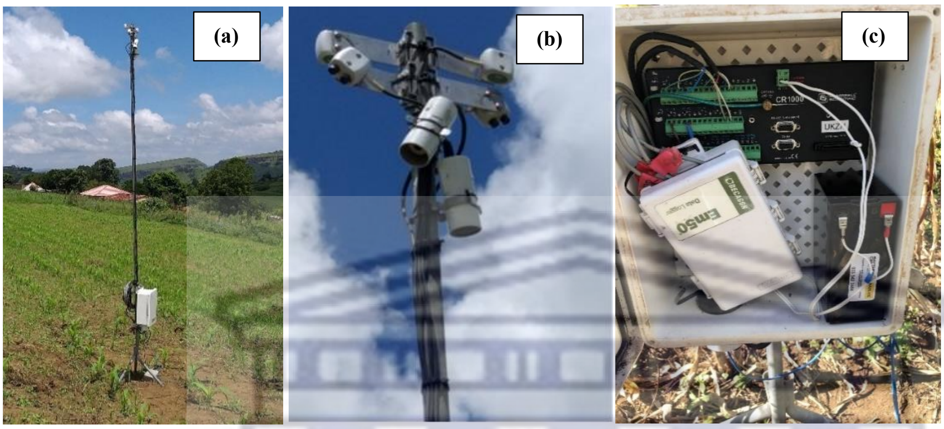

Figure 3-3: (a) Automated in-field meteorological tower in the maize field, (b) meteorological tower mounted infrared radiometers (IRR), (c) CR1000 data logger, Em50 datalogger and 12 V battery (Brewer et al., 2022).

A polygon in the experimental field was digitised in the Google Earth Pro domain and imported into ArcGIS 10.5 to generate sample points. In the digitised field boundary, a total of 50 sample points were generated based on stratified random sampling. These points were then uploaded into a hand-held Trimble Global Positioning System (GPS) with sub-meter accuracy. These GPS points were used to navigate to the actual sampling point in the field. Maize plants that coincided with or were within proximity to the point were considered for temperature measurements in this study. For consistent biweekly measurements, maize plants were marked at each sampling point. Specifically, 50 maize points were sampled four times across the growing season.

The temperature of the maize, from the early vegetative growth stage to the late reproductive growth stage, was measured with a hand-held infrared GM320 IRT thermometer, using a digital laser, at two weekly intervals. Infrared thermometers (IRT) with the capability of recording temperatures ranging from approximately -50 °C to 330 °C were used to measure maize canopy temperatures in the field. These measurements were carried out concurrently with the UAV image acquisition, between 10:00 am to 14:00 pm (South Africa Standard Time). Measurements were carried out during this time period since the VPD is maximum for the day, therefore water stress is likely to be highest during this time(Gardner *et al.*, 1992). IRT values from the vegetative and tasselling stages have been obtained from the most recent completely grown leaf with an open collar. After that, measurements were taken at the same node as the primary ear shank, where an ear leaf is attached (Costa et al., 2003). At each sampling point, the IRT was held at about 2 meters (m) above the ground and approximately 50 cm from the canopy. Three subsequent temperature measurements were taken to ensure that a maize canopy dominated the fields of view. The temperature measurements were captured along with each plant's location. Subsequently, a point map with this information was produced in a GIS and later used to extract the crop spectral signatures for statistical analysis.

3.3.3. *Meteorological data collection.*

The automatic weather station (AWS) was used for the meteorological data. Hourly averaged meteorological data comprised of air temperature (°C), wind speed (m/s), solar radiation (Wm-2), and relative humidity (%) were used. The following temperature and relative humidity sensors were used to observe meteorological variables above ground: CS215 Temp/RH probe (temperature and relative humidity) and Licor LI2005 pyranome-ter (solar radiation).

3.3.4. *Crop Water Stress Index (CWSI) Calculation*

While alternative approaches, such as soil moisture methods and the measurement of temperature and stomatal conductance demonstrated by (Brewer et al. 2022), exist, the Crop Water Stress Index (CWSI) stands out as one of the proxies that can be effectively correlated with the direct detection and mapping of water stress in maize crops. CWSI was calculated using calibrated foliar temperature data measured using a hand-held infrared thermometer (IRT) detailed in section 3.3.2 and data measured using the AWS. The CWSI was calculated by using Equation 1:

$$\mathrm{CWSI} = \frac{\Delta\mathrm{T} - \mathrm{Twet}}{\mathrm{Tdry} - \mathrm{Twet}} \qquad \text{Equation 1}$$

where ΔT, *Twet* and *Tdry* are the actual measurement of the difference between the canopy and air temperature (Tc -Ta), lower limit, and upper limit of baselines estimated, respectively. The upper and lower limits are also respectively referred to as non-water-stressed baseline (NWSB) and non-transpiring baseline (NTB) and are calculated as follows (Equation 2 and Equation 3):

$$\text{Twet} = \text{m} * \text{VPD} + \text{b} \qquad \text{Equation 2}$$

$$\text{Tdry} = \text{m} * \text{VPG} + \text{b} \qquad \text{Equation 3}$$

where *m* and *b* represents the slope and intercept, respectively. VPD represents vapor pressure deficit, is calculated using Equation 4 - Equation 6, by relating it to air temperature (Ta) and relative humidity (RH) collected in the field, following the description of Allen *et al.* (1998):

$$e_s = 0.6108 * \exp\left[\frac{17.27\text{T}}{\text{T}+237.3}\right] \qquad \text{Equation 4}$$

$$e_a = e_s * \left(\frac{RH}{100}\right) \qquad \text{Equation 5}$$

$$\text{VPD} = e_s - e_a \qquad \text{Equation 6}$$

where T, RH, e_s, e_a are air temperature, relative humidity, saturated vapor pressure (kPa) at the air temperature Ta, and actual vapor pressure (kPa), respectively. As, aforementioned, the weather data was measured using the AWS. To calculate *Tdry* values, the vapour pressure gradient (VPG) is determined. VPG is the change in the pressure of the air-saturated water vapour at the temperature (Ta) and the pressure of the air-saturated water vapour at the temperature (Ta + b) (Gu et al. 2021).

The first step to determine CWSI involved determining functions for Twet and Tdry for rainfed maize in Swayimane environmental conditions. This was achieved by following the procedure outlined by (Taghvaeian, Chávez, and Hansen 2012). After two significant rainfall days, maize ΔT was collected by IRT sensors in the field and plotted with their respective VPD values. This assumes that the soil water deficit has been remedied because of these wet spells, which led to maize having access to adequate soil water. Therefore, conditions existed that were not water stressed. This was determined for 2 hours before and 2 hours after midday, as recommended by (Jackson et al. 1981). The resulting equation from this linear segment was extracted to obtain the coefficients of Equation 2 and Equation 3. By using simple linear regression a three-step moving average was followed to plot the relationship between ΔT and VPD, as (Idso et al. 1981) suggested. According to (Taghvaeian et al. 2012), the CWSI method is valid only when the conditions of clarity are met, to ensure that all the days selected to calculate the CWSI correspond to the field visits days. CWSI values range from 0 to 1, with 0 indicating no water stress and 1 indicating the most severe stress. In addition, a relationship between foliar temperature and stomatal behaviour has been observed during the maize phenological cycle (Brewer et al. 2022). To illustrate the relationship between water consumption and the foliar temperature used to calculate CWSI in this study. Additionally, CWSI was computed for 4 phenological stages.

3.3.5. *UAV multispectral-thermal system.*

A DJI Matrice 300 (DJI Inc., China) quad-rotor UAV and Micasense (MicaSense, Inc., WA, USA) multispectral sensor covering RGB (Red, Green, and Blue), NIR (Near Infrared), RedEdge, and thermal sections of the electromagnetic spectrum was used to collect images in this study (Figure 3-4b). The MicaSense has a Downwelling Light Sensor 2 (DLS-2) and MicaSense Altum camera to capture images from a platform of low-altitude UAV camera system over the smallholder farms. The MicaSense Altum camera has a high-resolution five-band multispectral narrow bands (blue, green, red, red-edge, NIR) and a radiometric longwave infrared thermal camera. The spectral characteristics of the MicaSense are detailed in Table 3-1 (Ndlovu *et al.,* 2021; Brewer *et al.*, 2022).

Table 3-1:MicaSense Altum camera specifications (Brewer et al. 2022).

Spectral colour	Band range	Ground sampling distance at a flying height of 120 m
Blue	475 nm	5.2 cm per pixel
Green	560 nm	5.2 cm per pixel
Red	668 nm	5.2 cm per pixel
RedEdge	717 nm	5.2 cm per pixel
Near-infrared	842 nm	5.2 cm per pixel
Thermal Infrared	8000-14000 nm	81 cm per pixel

3.3.6. *Image acquisition and processing.*

A kml file representing the boundary of the maize field digitised in Google Earth Pro was used to develop the flight plan. This has been transferred into the DJI controller's intelligent console and used to create flight plans (Figure 3-4c). The MicaSense Altum sensor was calibrated before and after the flight using a calibration reflectance panel (CRP) (Figure 3-4d). Users had to manually take an unshaded picture directly over the CRP to determine the illumination conditions for a particular flight day, time and location. The UAV was flown in the clearest air conditions every two weeks., between 10:00 am and 14:00 pm. This period is concurrent with canopy temperature measurements. Detailed flight conditions are presented in the works of Ndlovu *et al.*, (2021) and Brewer *et al.*, (2022).

After 3576 images were acquired, mosaiced, and radiometrically corrected using Pix4Dfields software (Pix4d Inc., San Francisco, CA, USA). While the exact details of radiometric correction in Pix4d may be proprietary, the general workflow involves utilising CRP images captured before and after flight to administer radiometric and atmospheric correction to a MicaSense multispectral image. It applies sensor-specific calibration parameters to normalise the digital number values. It then implements dark object subtraction (DOS) to identify and subtract the dark objects based on the CPR images. This corrects for sensor biases and atmospheric scattering. Then, histogram matching is implemented to standardise the distribution of pixel values across the bands. The CPR images are also used as a white reference for adjusting potential variations in illumination conditions, ensuring pixel values are normalised to a standard reflectance scale. After processing, Pix4d generates a complete orthomosaic and digital elevation model (DEM) as GeoTiff images. Using Google Earth Pro, ground reference points were digitised to core-register the orthomosaic image in ArcGIS 10.5. Images were referenced to the Universal Transverse Mercator (UTM zone 36S) projection after attaining RMSE less than half a pixel (3.5 cm). The image was then used to compute vegetation indices.

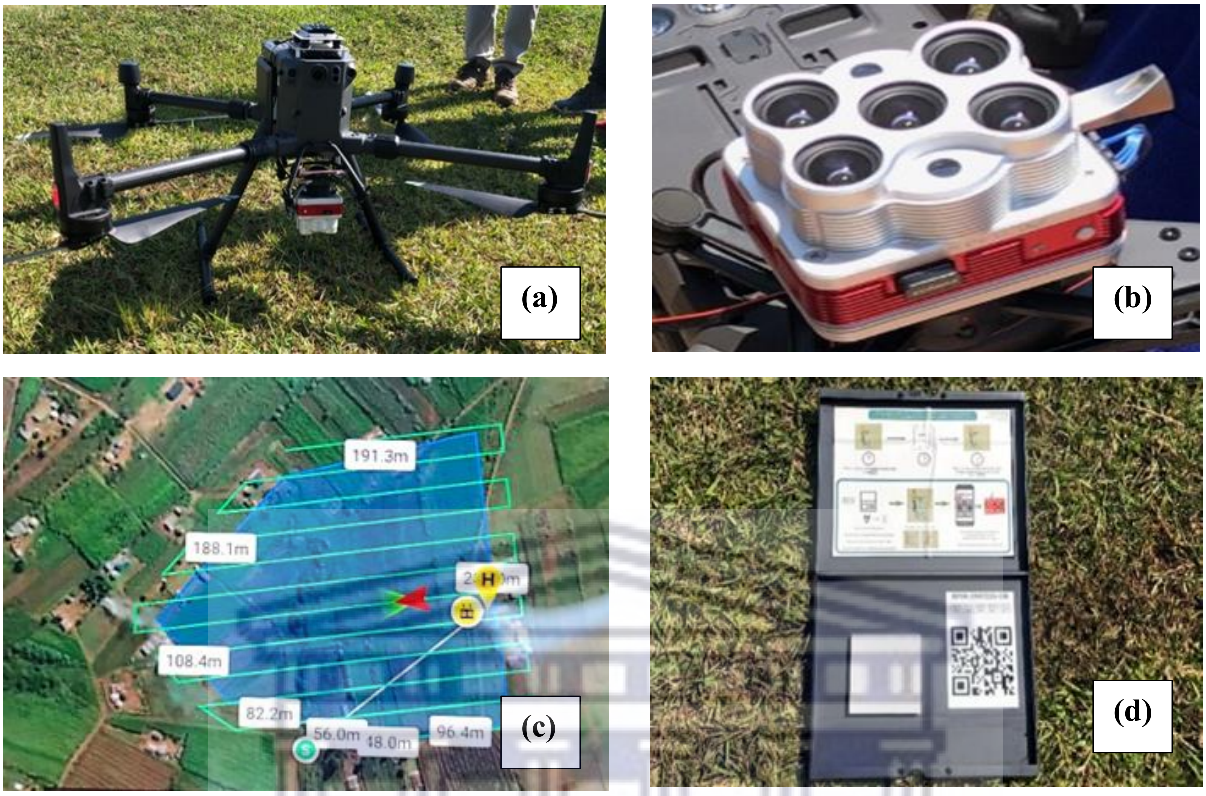

Figure 3-4:(a) UAV system, DJI Matrice 300 and, (b) MicaSense Altum camera. (c) DJI M-300 flight plan, (d) MicaSense Altum calibration reflectance panel.

3.3.7. *Vegetation Indices' Selection.*

The GPS co-ordinates of the ground sampled temperature readings were used to extract reflectance values of the multispectral bands. To calculate vegetation indices as indicated in *Table 3-2*, surface reflectance values were then used. The selected vegetation indices are commonly used to relate to canopy physiological parameters (Yue *et al.*, 2018). Furthermore, these indices are intended to improve vegetation optical characteristics as part of the whole spectrum response in trees' canopy. Consequently, VIs are applied to minimise unpredictability factors such as background noise on soils and particularly during the first stages of growth cycle, particularly during the growth cycle's first stages (Zhang and Zhou, 2015). To establish a regression model between UAV-based data and CWSI, multispectral and thermal bands, and VI were generated and employed (Table 3-3). In addition to the indices in Table 3-2, TCARI/NDVI, TCARI/SAVI, TCARI/OSAVI, TCARI/RDVI, and NDVI/REDEDGE were also calculated. The points with the CWSI information were then overlaid with the acquired and pre-processed multispectral bands and the derived vegetation indices (Table 3-2). The spectral signatures extracted in a table format were then used for statistical analysis in this study.

Table 3-2:List of vegetation indices (VIs) used for modelling crop water stress index.

Vegetation index	Equation	Reference
Normalised difference vegetation index (NDVI)	$\frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED}}$	Rouse *et al.*, 1974
Green normalised difference vegetation index (GNDVI).	$\frac{\text{NIR} - \text{GREEN}}{\text{NIR} + \text{GREEN}}$	Gitelson *et al.*, 1996
Normalised difference red-edge index (NDRE)	$\frac{\text{NIR} - \text{RED EDGE}}{\text{NIR} + \text{RED EDGE}}$	Fitzgerald *et al.,* 2010
Soil adjusted vegetation index (SAVI)	$\left(\frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED} + \text{L}}\right) * (1 + \text{L})$ L is a constant between 0 and 1.	Xue and Su., 2017
Optimized soil adjusted vegetation index (OSAVI)	$\frac{\text{NIR} - \text{RED}}{\text{NIR} + \text{RED} + 0.16}$	Xue and Su., 2017
Green chlorophyll index (Cl_green)	$\frac{\text{NIR}}{\text{GREEN}} - 1$	Zhang and Zhou., 2015
Red-edge chlorophyll index (Cl_RED_EDGE)	$\frac{\text{NIR}}{\text{REDEDGE}} - 1$	Zhang and Zhou., 2015
Red Edge NDVI (RENDVI)	$\frac{\text{NIR} - \text{REDEDGE}}{\text{NIR} + \text{REDEDGE}}$	Gitelson and Merzlyak, 1994
Modified Soil Adjusted Vegetation Index (MSAVI)	(1/2) * (2 * (NIR +1) – sqrt ((2 * NIR + 1)2-8(NIR - RED)))	Bannari *et al.,* 1995
Simple Ratio (SR)	$\frac{\text{NIR}}{\text{RED}}$	Baret and Guyot, 1991
Modified Triangular Vegetation Index (MTVI2)	(1.8(NIR-GREEN)-3.75(RED-GREEN))/(√((2NIR+1)^2)-6(NIR-5√RED)-0.5)	Liu et al., 2010
Canopy Chlorophyll Content index (CCCI)	NDRE /NDVI	Varco et al., 2013
MERIS Terrestrial Chlorophyll Index (MTCI)	$\frac{\text{NIR} - \text{RED EDGE}}{\text{RED EDGE} - \text{RED}}$	Dash and Curran, 2004
Normalised Difference Water Index (NDWI)	(GREN-NIR)/(GREEN+IR)	Özelkan, 2020
Ration Vegetation Index (RVI)	$\frac{\text{RED}}{\text{NIR}}$	Jordan, 1969
Transformed Chlorophyll Absorption in Reflectance Index (TCARI)	3[REDEDGE – RED - 0.2(REDEDGE/GREEN) (REDEDGE/RED)]/OSAVI	Haboudane *et al.*, 2004

3.3.8. *Statistical analysis*

To assess the performance of support vector, radio frequency and PLS regression algorithm in forecasting CWSI a comparative analysis has been carried out. These are the most widely applied machine learning algorithms when sensing different characteristics of a plant crop (Lary et al. 2016). In view of their optimum performance which has been shown in the literature, these algorithms have been selected and used in this study. All the algorithms were implemented as detailed below.

The R statistical environment was used to statistically estimate CWSI using remotely sensed data. Before conducting the estimations, a Pearson product-moment correlation test was employed to explore the relationship between CWSI and the derived spectral variables after testing data for normality. The correlation coefficient denoted "r" was used to determine the strength and direction of the relationship between CSWI and the predictor spectral variables. A correlation coefficient 'r' ranges between -1 and 1, with -1 as a total negative linear correlation, 0 as no correlation, and + 1 as a total positive correlation. To estimate maize CWSI, a comparative analysis of the performance of support vector, radio forest and PLS regression was conducted in this study. These algorithms were chosen and used based on their optimal performance in remote sensing different optical phenotypical crop elements (Cai et al. 2018; Mochida et al. 2019). All the algorithms were implemented, as detailed below.

The Partial Least Square (PLS): is a multivariate regression technique to define linear relationships between sets of response variables and predictor variables (Haaland and Thomas 1988), which in this study is CWSI and spectral reflectance, respectively. It is beneficial to deal with data that has a wide range of independent variables because it allows a reduction in correlation coefficients between the datasets for noncorrelated latent variables (Geladi and Kowalshi, 1986; Martens and Naes, 1992; Wold *et al.,* 2001; Krishna et al., 2019). PLS was performed using the "pls" function and optimised based on the number of components ('*ncomp'*) with a minimal error in R. Generally, PLSR groups predictor variables into latent variables (components) based on their influence in predicting the predicted variable. Then, the optimal number of components that exhibit a lower error (root mean square error (RMSE)) is selected. In this study, three components yielded optimal results; hence, '*ncomp'* was set to 3.

The Support Vector Machine (SVM): splits classes with a decision surface that increases the margin between the classes. The surface is deemed an optimum hyperplane, and data points near the hyperplane are support vectors (Krishna et al. 2019). Lee *et al.,* (2020) defines a hyperplane as a flat affine subspace of a dimension (p-1), where p indicates the number of dimensions. The hyperplane is a straight line in the two-dimensional plot, breaking training data into individual sections. The SVM uses a Non-linear Kernel function for situations with a linear correlation to the data. The Radial Basis Kernel was used in performing SVM, which can trick the data into a more dimensional space to classify it in different spatialities by exploiting the radiative distance across observations. Thus, the "svmRadial" method was used for this model in R. To determine the optimal model parameters *'sigma'* was held constant at a value of 0.084 while 'C' was set to 0.5 for the final model.

The Random Forest (RF): The algorithm randomly selects several samples from the training dataset. The most important independent variables of the randomly selected samples are used to develop a decision tree. After that, trees are split at each node dependent on the most contributing explanatory variable to the response variable. For each prediction of the response variable, an average value of a multitude of decision trees and outputs is built. The parameter *mtry* in RF accounts for the number of variables used for splitting at each tree node for decision tree learning. R defines the *mtry* parameter for RF by default as one-third of the number of predictor variables (Kuhn and Johnson 2013). This study set the ntree to a default value of 500 (Mashiane *et al.*,2023). Then the '*tuneRF*' function, which performs a grid search over the specified '*mtry'*, was employed by selecting the combination that optimised the errors. Specifically, '*mtry'* for the final model was set to 2.

3.3.9. *Accuracy assessment*

The overall performance and robustness of the predictive models were appraised by the coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute error (MAE). A K-fold cross-validation technique was employed since all the regressions used in the study had different hyperparameters for optimal performance. Also, the K-fold cross-validation was chosen because it is a robust approach for tuning hyperparameters, which has been demonstrated to be superior in accurately estimating errors (Eugenio et al. 2020). The K-fold cross-validation technique precludes overfitting in the case of prediction models. Therefore, in this study, the overall process of developing predictive models involved 10-fold cross-validation repeated three times on the training data, using the '*train ()'* function from the '*caret*' package in R. Cross-validation provided the best components to retain the lowest RMSE in all the three models. The PLS, SVM and RF analyses were performed using UAV-acquired bands and vegetation index (VI) as predictor variables for predicting CWSI. The field data in this study was divided into 70% for training and 30% for testing samples, respectively, following (Nguyen et al. 2021) that the 70/30 approach is optimal for splitting training and testing data.

3.4. Results

3.4.1. *Determining Baselines for Crop water stress index.*

Figure 3-5 shows the slope and intercept of the NWSB from 2 days in the vegetative stage of maize, resulting in the equation shown in the TcTa vs VPD scatterplot. The same coefficients developed for NWSB determines NTB and using VPG instead of VPD. The relationship between the Tc-Ta and VPD was significant ($R^2 = 0.84$). The Tc-Ta decreases with increase in VPD.

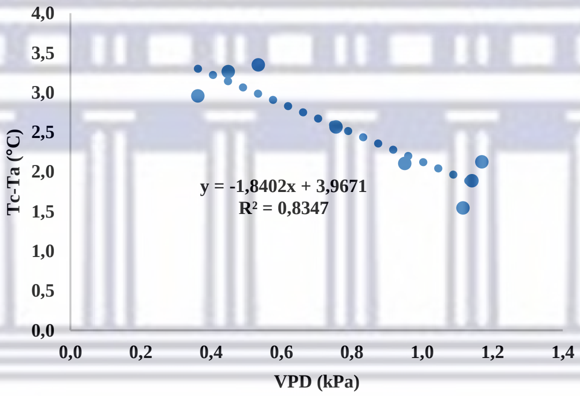

Figure 3-5:Non-water-stressed baselines used to calculate the CWSI for maize at vegetative growth stage (DOY 93 and 97).

Figure *3-6* shows patterns of CWSI obtained on four different days representing different maize growth stages. Averagely there has been low crop water stress, with peak on DOY 89 (31 March 2021). The lowest CWSI was recorded on the DOY 75, showing almost no stress. Maize water stress increases as maize grows and decreases towards the end of the vegetative stage. Figure *3-6* shows that the entire stage maize endured low (< 0.5) water stress levels overall.

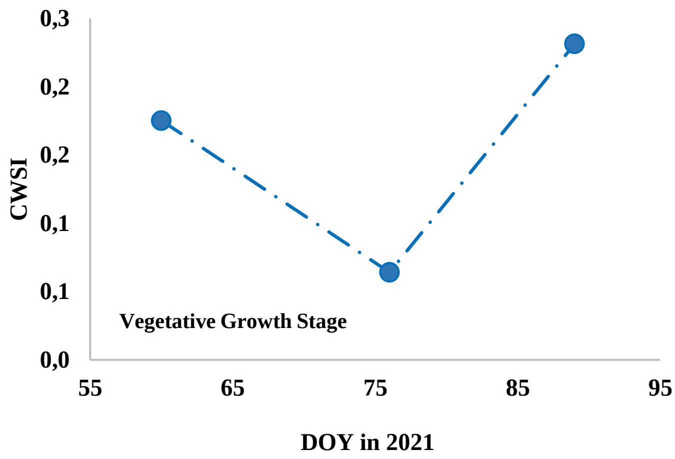

Figure 3-6:CWSI for maize in vegetative stage.

3.4.2. *Exploring the relationship between CWSI and Spectral variables*

Table *3-3* shows the correlation coefficients between the CWSI and the spectral reflectance. The results indicate a link between all the data measured by a UAV and water stress index. Of the 6 different bands investigated, the strongest relationship, which was also positive, was observed between the TIR band and CWSI (r = 0.59). Meanwhile, the rest of the 6 bands showed a negative relationship with CWSI. The Red band showed the strongest negative relationship among them all. Similarly, the 21 investigated VI showed a negative relationship with the CWSI, except for TCARI_OSAVI (r = 0.19) and NDWI (r = 0.35). OSAVI yielded the strongest negative relationship with CWSI (r = -0.62). All these VI were derived from the Blue, Green, Red, RedEdge, and NIR Bands, which also showed a similar relationship with CWSI. These findings suggested that the relation between vegetation indices and CWSI was slightly higher than that of bands only.

Table 3-3: Correlation coefficients r between CWSI, bands and VIs.

No	Bands	r	No.	Vegetation Index	r	No	Vegetation Index	r
1	BLUE	-0.41	1	MSAVI	-0.51	12	TCARI_OSAVI	0.19
2	GREEN	-0.51	2	SR	-0.19	13	TCARI_RDVI	-0.55
3	RED	-0.54	3	MTVI2	-0.52	14	CCCI	-0.43
4	RED_EDGE	-0.52	4	Cl_RED_EDGE	-0.55	15	MTCI	-0.50
5	NIR	-0.53	5	Cl_GREEN	-0.41	16	RVI	-0.19
6	TIR	0.59	6	RDVI	-0.48	17	NDWI	0.35
			7	TCARI	-0.53	18	NDVI	-0.14
			8	NDRE	-0.45	19	GNDVI	-0.54
			9	OSAVI	-0.62	20	RENDVI	-0.33
			10	TCARI_NDVI	-0.55	21	SAVI	-0.50
			11	TCARI_SAVI	-0.54			

3.4.3. *Comparing the performance of Spectral feature in estimating maize Crop Water Stress Index across all algorithms.*

Figure 3-4 shows model accuracies obtained using PLS, SVM, and RF regression algorithms in predicting maize CWSI based on bands, indices and both datasets combined. The most optimal model, which exhibited a relatively higher R^2 (0.85) and lower RMSE (0.05), was derived using a combined dataset of bands and vegetation indices (Figure 3-4). This was followed by a model derived using bands-only with a RMSE of 0,09. The least accurate model in this study was obtained using vegetation indices-only data. Specifically, vegetation indices yielded an R^2 of 0.53 and a RMSE of 0.1. Generally, when the bands were combined with indices, lower RMSE were attained across all models (Table 3-4).

Overall, there was a significant ($p = 0.05$) difference between the performance of bands, vegetation indices and combined datasets Specifically, the mean RMSE exhibited by vegetation indices was significantly higher than that exhibited by bands-only and combined datasets. This implied that the vegetation indices did not significantly improve the estimation of CWSI across all algorithms. Nonetheless, bands only exhibited a relatively lower average RMSE when compared to vegetation indices. However, their mean RSME was extensively higher than that yielded by the combined dataset (Figure 3-4). This implied that the combined datasets significantly improved the model accuracies across all algorithms compared to bands and vegetation indices (Figure 3-4).

Table 3-4: Prediction accuracies of CWSI derived using optimal models based on the PLS, SVR, and RF regression models.

	Bands			Vegetation Indices			Combined		
	R^2	RMSE	MAE	R^2	RMSE	MAE	R^2	RMSE	MAE
Partial Least Squares	0.5	0.1	0.078	0.45	0.11	0.088	0.44	0.1	0. 09
Support Vector Machine	0.55	0.1	0.073	0.5	0.1	0.065	0.67	0.07	0.04
Random Forest	0.88	0.06	0.049	0.63	0.08	0.054	0.85	0.05	0.04

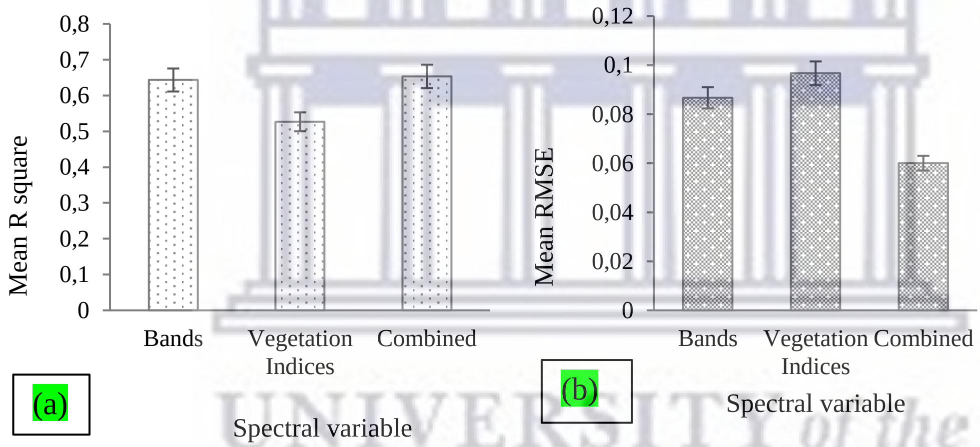

Figure 3-7: Comparative performance of Bands, Indices and Combined datasets in predicting CWSI based on (a) mean R-squares and (b) average RMSEs.

3.4.4. *Comparing the performance of Machine Leaning algorithms*

Figure 3-8 shows the findings from a comparative assessment of the performance of algorithms based on all datasets used in this study. It was observed that RF had the highest mean R^2, and lowest mean RMSE and MAE (R^2 = 0,79, RMSE = 0,06, MAE = 0,05). This implied that RF outperformed SVM and PLSR in estimating maize CWSI in smallholder croplands. SVM attained the second highest mean R^2, second lowest mean RMSE and mean MAE (R^2 = 0.57, RMSE = 0.09, MAE = 0.06). Meanwhile, PLS had the lowest mean R^2, and the highest mean

RMSE, and MAE (R^2 = 0.46, RMSE = 0.1, MAE = 0.08) (*Figure 3-8*). Overall, there was a significant difference between the mean RMSE exhibited by PLS, SVM and RF (*Figure 3-8*c). Based on *Figure 3-8*, RF emerged as the optimal algorithm for predicting maize CWSI in smallholder croplands exhibiting the highest R^2, lowest RMSE and MAE among all the models.

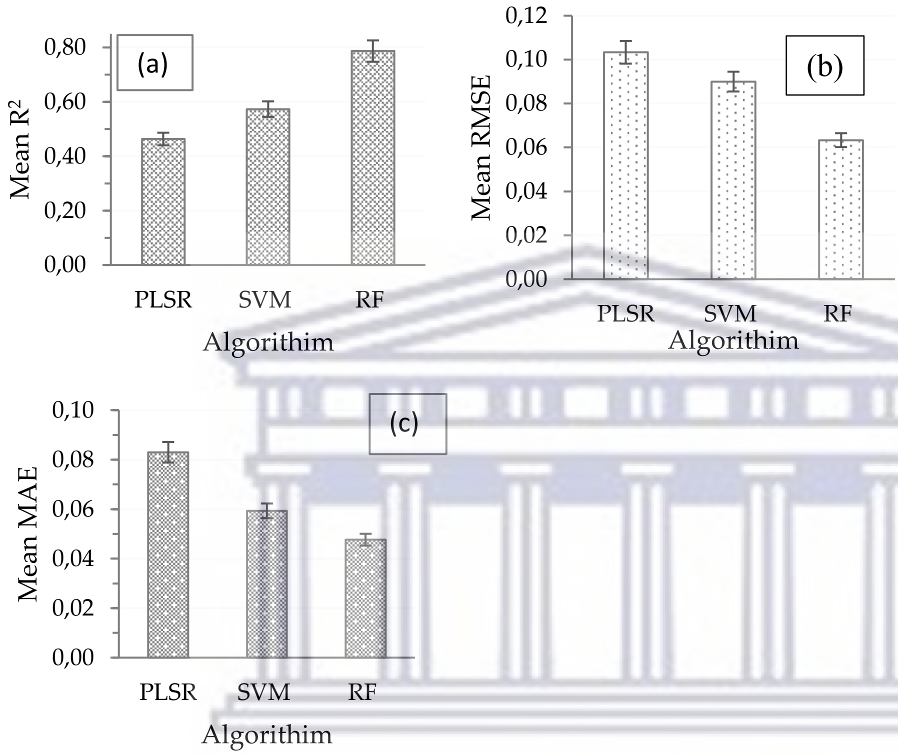

Figure 3-8: Average RMSE (c), MAE (b) and R^2 (a) derived using Random Forest, Support vector machine and Partial Least Squares region algorithms.

3.4.5. *Optimal models for Estimating Maize Crop Water Stress Index.*

The most important variables in the PLS, SVM and RF model are shown in Figure 3-9(aii-cii). Ultimately the PLS model attained an RMSE of 0.1 based on CCCI, MTCI, NDRE, Cl_RedEdge, MTVI2 including other variables (Figure 3-9a), in that order of importance. Meanwhile SVM exhibited a RMSE of 0.07 based on TIR, TCAR_SAVI, TCARI_OSAVI, CCCI, and TCARI_RDVI amongst others, in importance order. The RF model achieved an RMSE of 0.05 using variables including NDRE, MTCI, CCCI, GNDVI, and TIR in order of importance (Figure 3-9c).

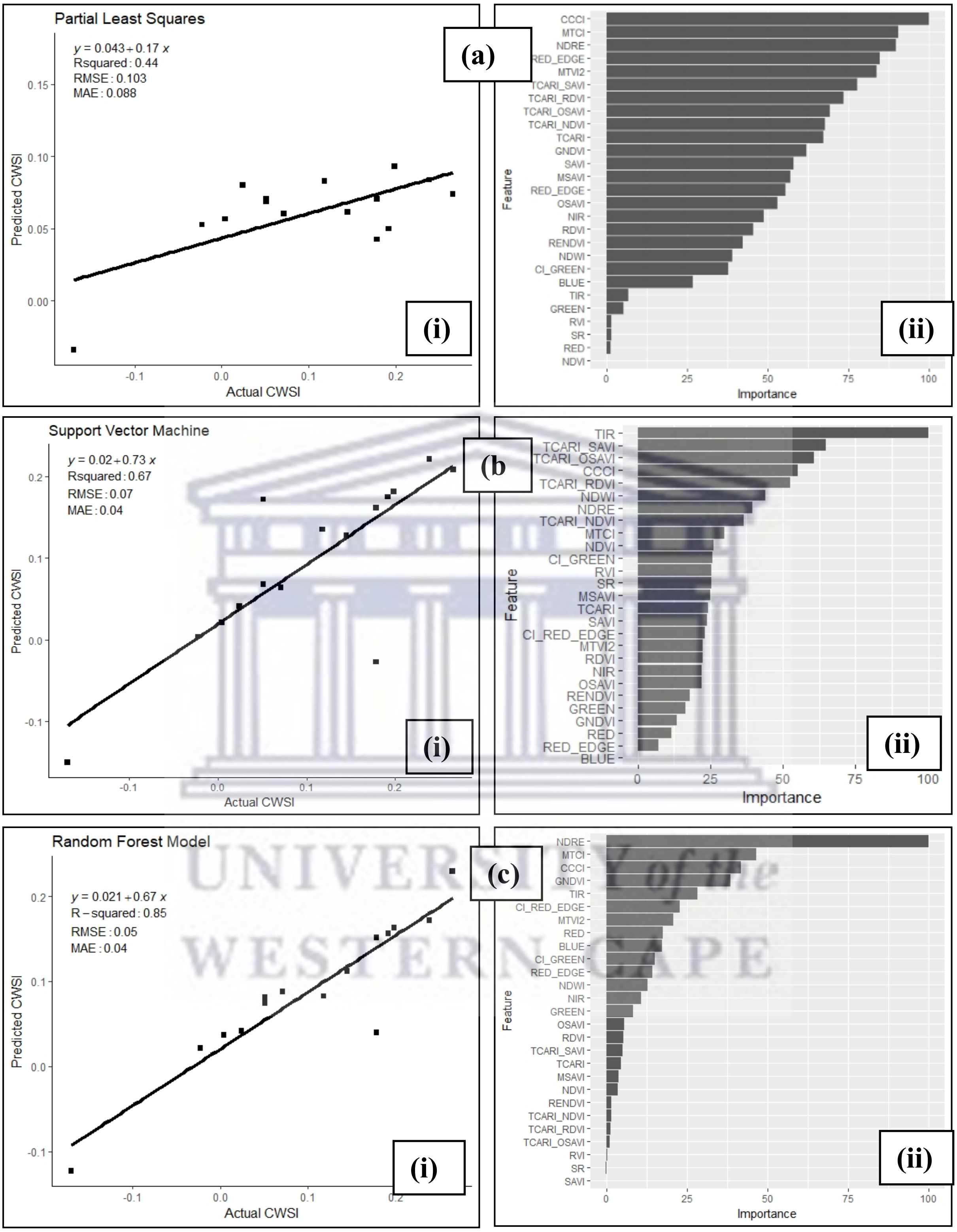

Figure 3-9: Relationship between the predicted and observed CWSI derived using combined spectral bands and vegetation indices (i) in conjunction with (a) PLR, b) SVM, and c) RF), as well as associated variable importance (ii) models and the model variable importance scores.

3.4.6. *Mapping the Spatial Distribution of Maize Crop Water Stress.*

The spatial variation of maize water stress was modelled using the optimal variable in each model. Figure 3-10 illustrates the spatial variations of maize stress determined by PLS (a), SVM (b) and RF (c). Results indicate that the maize water stress is relatively low throughout the field and increased towards the north and east of the plot (Figure 3-10b) and west to south of the field (Figure 3-10c) for the PLS SVM and RF models, respectively. On the contrary, the PLS (Figure 3-10a) modelled map showed little to no spatial variability for crop water stress in the maize plot. The RF-modelled map showed relatively low water stress levels across the field, with significant spatial variation in the entire field. Therefore, the results show that the PLS model was the poorest performing model in the prediction of CWSI, thus showing very low spatial variability in the field. On the other hand, RF model best performed in the prediction of CWSI, thus indicating the high spatial variability of maize water stress in the field, which was relatively low across the field.

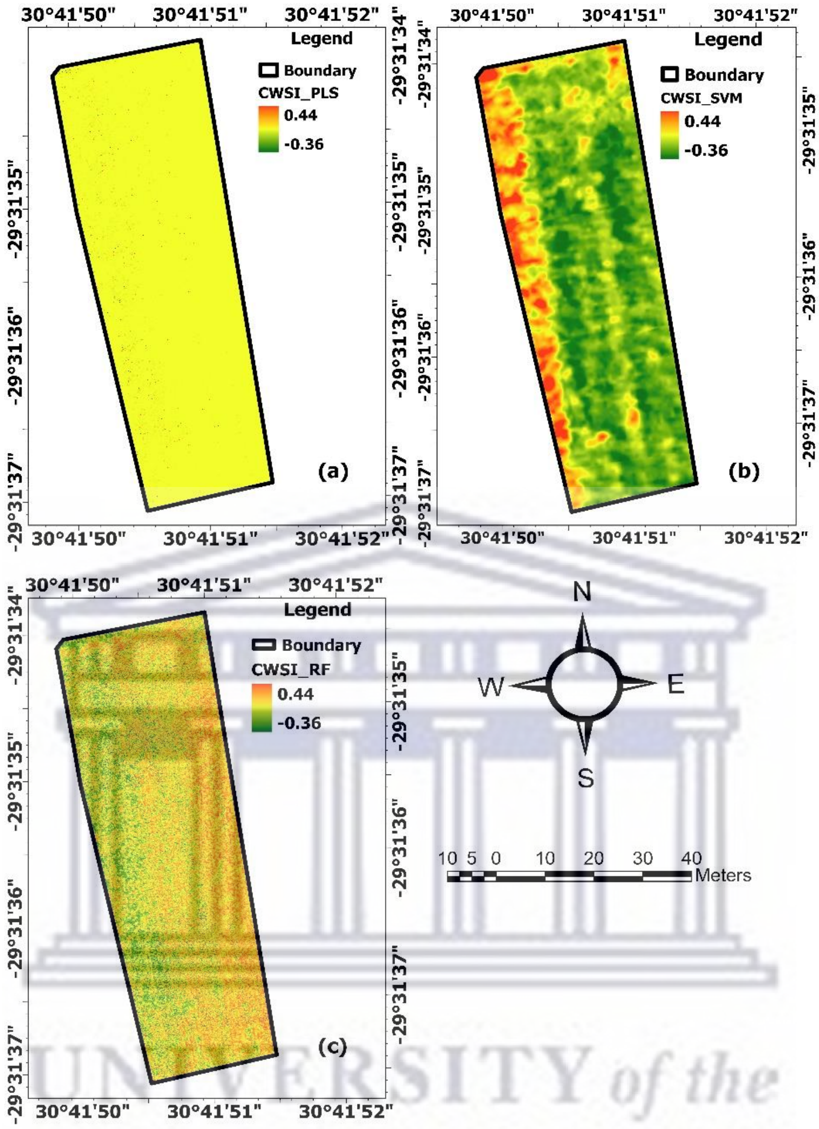

Figure 3-10: Spatial distribution of CWSI developed using (a) PLS, (b) SVM, and (c) RF algorithms.

3.5.Discussion

The study's objective was to compare PLSR, SVM and RF performance in estimating maize CWSI using UAV-acquired remotely sensed data in smallholder croplands typically found in Southern Africa. To address this objective, the relative contribution of bands, vegetation indices, and both datasets combined was evaluated.

3.5.1. *Estimating Crop water stress index.*

Determining NWSB at each maize growth stage is necessary for determining CWSI, therefore, NWSB was determined for the vegetative growth stage of maize. Results showed a strong relationship between Tc-Ta and VPD with R^2 of 84. This may be due by the changes in photosynthesis and transpiration during the vegetative stage of maize (Ru *et al.,* 2020). Similar relationship were found for maize (Zhang *et al.,* 2019; Zhang *et al.*, 2023). Furthermore, results showed that CWSI was relatively low during this growth stage (CWSI <0.3). This could be attributed to the rainfall in the area received during this period, which could have replenished the soil with water. According to Jamshidi *et al.* (2020) a significant yield reduction occurs when the CWSI values are greater than 0.40. Moreover, Kacira, Ling and Short (2002) revealed that CWSI can detect stress levels 24 to 48 hours before the manifestation of visible signs of stress on plants. Therefore, the results of the CWSI could provide a timelier insight into the adaptation to climate change and the management of agricultural water resources, which could be a valuable option for smallholder farmers.

3.5.2. *Mapping of Maize CWSI Using optimal model*

Results showed that maize CWSI was optimally estimated to an RMSE of 0.05, and MAE of 0.04, based on the spectral reflectance of NDRE, MTCI, CCCI, GNDVI, TIR as the most significant variables, in order of importance (Figure 3-9 c). The optimal performance of the chlorophyll-based VIs such as NDRE, MTCI, CCCI, and GNDVI could be explained by the fact that the image was acquired during the late vegetative stage characterised by high canopy closure, leaf area index, and chlorophyll content concentrations, indicative of highly photosynthesising maize plants which indirectly alters the temperature and stomatal conductance of the crop. This explains why chlorophyll-based VIs were influential in this study. The TIR, red and blue bands also demonstrated good performance in the RF model (Figure 3-9cii). The significance of the TIR to the model could be attributed by the fact that the leaf temperature is primarily determined by the plant's ability to photosynthesise and the efficiency of the internal leaf structure such as cavities, chloroplasts, and mesophyll cells, compared to ambient temperature. Therefore, when a plant is undergoing water stress, molecules in the leaf tissue show signals that induce physiochemical change which leads to increased foliar temperature with respect to air temperature which explains why it was related to a temperature derive CWSI in this study (Bonada et al., 2013; Ustin and Jacquemoud., 2020).

In addition, the blue band has been selected as one of the important variables estimating CWSI, which is directly related to leaf chlorophyll content, due to its strong correlation with chlorophyll in green maize crop pigments due to absorption for photosynthesis (Zhu et al. 2020). This explains how important this plant was at the end of the vegetative season, when the maize crop canopy had entirely covered the ground (Nandibewoor, Hebbal, and Hegadi 2015), consistent with the low CWSI values obtained.

On the contrary, the NIR band was not very influential in optimally estimating CWSI. The changes in the leaf structure of maize in the study site were likely not captured well by the MicaSense NIR range camera. As a result, our results do not agree with several other studies which demonstrated that NIR regions of the electromagnetic spectrum are also influential in detecting and mapping crop water stress at the canopy level (Berni et al. 2009). Subsequently, NDVI was not among the best-performing indices. This is aligned with results from other studies, where NDVI exhibited a low correlation with stomatal conductance (Baluja et al. 2012; Gago et al. 2015; Zarco-Tejada, González-Dugo, and Berni 2012). The high spectral saturation of NDVI under high vegetation coverage could contribute to this observation. Meanwhile, the impact of the RedEdge Band-derived indices could be attributed to their effectiveness in mitigating saturation effects at higher crop foliage density and coverage (Naidoo et al. 2022; Sun et al. 2020). For example, to increase the performance of the RF model, it was found that a combination of traditional vegetative and red edges-based indices could be used at the late stage.

3.5.3. *Comparative performance of bands vegetation indices and combined data sets.*

The prediction of CWSI was conducted using three different data sets (bands only, vegetation indices only, and the combination thereof) based on SVM RF and PLSR algorithms. The combined dataset outperformed the bands and VIS models in all three modelling scenarios. Specifically, combined data exhibited a mean RMSE of 0.05 in relation to RMSE of 0.06, and 0.08 for Bands, and VIs, respectively. Using the combined data modelling resulted in the most optimal prediction accuracy based on NDRE, MTCI, CCCI, GNDVI, and TIR, as important predictor variables, in order of importance. This indicates that the combination of indices and spectral bands improved the performance of variables that could have saturated under high canopy cover. This could be explained by combining bands and vegetation indices, providing a broader spectral range coverage. Bands capture spectral information in a single section of the electromagnetic spectrum, which is sensitive single plant health element or feature, while vegetation indices are derived from combinations of Bands from different sections of the electromagnetic spectrum. Subsequently, VIs derives their strength from more than one section of the electromagnetic spectrum, making them sensitive to more features.

Furthermore, VIs tends to reduce the impact of noise on the crop spectral signatures. Therefore, combining bands and VIs ensures sensitivity to various aspects of plant health and physiological conditions such as water stress. Above all, combining these datasets offers a synergistic effect of capturing both structural and physiological aspects of water-stressed crops, enhancing the overall sensitivity and accuracy of the estimation process. Also, health VIs were the most selected estimation features for crop water stress in relation to traditional indices such as NDVI. The optimal performance of VIs such as NDRE, MTCI, and CCCI could be explained by the ability to circumvent spectral saturation when a crop's canopy is fully covering the ground. For instance, at high canopy density, the NDVI becomes spectrally saturated (Li et al. 2018). Thus, the results reveal that combining wavelengths with VIs such as NDRE, MTCI, and CCCI improved the estimation accuracies.

However, when VIs only were used, the prediction accuracies were significantly reduced (RMSE = 0.08). This indicates that the traditional indices combined with the chlorophyll-based indices could not detect crop water stress. This is despite indices such as TCARI's usefulness in reducing non-photosynthetic background noise (Li et al. 2018). Generally, VIs improve estimation accuracies, as water stress accumulates (Zhang and Zhou, 2019). However, this study was conducted during the vegetative stage when water stress was limited due to the frequent precipitation in the study area.

Contrary to the findings of this study, (Zhang and Zhou, 2019) and (Baluja et al. 2012) demonstrated a strong correlation between VIs and water stress indicators during the late reproductive and maturation stages of the crops. Similarly, (Baluja et al. 2012) found that TCARI/OSAVI improved from R^2 of 0.58 to 0.84 during the late vegetative and maturation stages, respectively. Their results demonstrated that as water stress accumulates, VIs become more sensitive. Our results are supported by those of (Zhang *et al.*, 2019), which also demonstrated relatively low-performance VIs-only data in predicting maize CWSI.

Meanwhile, Bands only demonstrated a significant relationship with the maize CWSI. In particular, the TIR band was the most optimal in the RF model. This could be attributed to the fact that there was full vegetation cover, and the lack of soil background disturbance allowed the measurement of canopy temperature and stomatal conductance resulting from water utilisation (Poblete-Echeverría et al., 2017). This shows that bands were able to capture the changes in canopy temperature. This is supported by the literature where water stress in agricultural plants was detected using remote canopy temperature measurements on a TIR basis (Jackson et al., 1981; Jones and Callow, 2004; Costa, Grant, and Chaves, 2013).

3.5.4. *The Performance of Machine Learning Algorithms in Predicting Maize crop water stress index (CWSI).*

The findings of this study demonstrated that RF optimally outperformed SVM and PLSR at single analysis stages (*Table 3-4*) and across all stages when findings were pooled (*Figure 3-8*). Specifically, RF optimally predicted CWSI to a RMSE of 0.05, MAE of 0.04 and R^2 equivalent to 0.85 across all datasets. The optimal performance of RF could be attributed to its ease of optimisation and execution compared to other algorithms. Additionally, RF can tolerate highly correlated variables, such as bands combined with vegetation indices (Breiman, 2001; Loggenberg et al., 2018; Ndlovu et al., 2021; Xie et al., 2021). RF, being a non-linear method, offers high simulation accuracy and a very flexible model-building process, making it robust in comparison to other algorithms (Wang et al. 2021).

Furthermore, the RF excels in modelling non-linear dimensional relationships while preventing overfitting. Importantly, RF demonstrates relative robustness regarding noise detection in data, the establishment of an impartial estimate of error rate, and the capacity to determine the relevance of optimal predictor variables for modelling (Krishna et al. 2019; Xie et al. 2021). Similarly, the algorithm has been proven optimal in predicting crop water stress for crops such as rice (Wu et al. 2023) and wheat (Liu et al. 2016). Consistent with these studies, RF outperformed SVM and PLS.

SVM produced the second-best results in the prediction of CWSI (RMSE = 0.067, MAE = 0.07). Its strength lies in handling outliers, showcasing substantial generalization capability when dealing with unseen patterns (Liang et al. 2018). This model is reliable for the regression of small linear and high-dimensional samples (Yuan et al. 2017), which may explain its superior performance compared to PLS. Another advantage of the SVM is its effective processing of data acquired with few samples, as demonstrated in this study, without compromising resultant accuracies (Mountrakis, Im, and Ogole 2011). In contrast, PLS performed least in effectively in estimating CWSI across all dataset scenarios (RMSE = 0.086, MAE = 0.073).

PLS cannot handle data conditions such as high dimensionality and correlation of predictor variables, which may explain its poor performance (Naidoo et al. 2022). In addition, due to PLS's tendency to struggle with collinear variables, as observed in this study, non-linear relationships between predictor variables and certain crop parameters could have contributed to poor performance (Atzberger et al. 2010). Moreover, the literature notes that PLS is best suited for large training datasets (Wang et al. 2016). Future considerations may involve exploring a larger sample size to enhance the accuracy of PLS prediction for maize crop water stress in smallholder farms. Furthermore, exploring other machine learning algorithms could be beneficial in finding an optimal model to substitute PLS.

3.6.Conclusions

This study sought to assess the performance of PLSR, SVM and RF in estimating maize CWSI using UAV-acquired remotely sensed data in smallholder croplands typically found in Southern Africa. To address this objective, the relative contribution of bands, vegetation indices, and both datasets combined was evaluated. Grounded on the results of this study, it can be concluded that:

- RF proved to be the most suitable algorithm for predicting maize CWSI in smallholder croplands, utilising NDRE, MTCI, CCCI, GNDVI, and TIR, as important predictor variables, listed in order of importance. Specifically, RF was optimal compared to the PLS and SVM, resulting in the highest R^2 (0.79) and the lowest MAE (0.06) and RMSE (0.05) on average in three different data groups (bands only, VI only, and combined data).
- Combining bands and vegetation indices resulted in the best prediction of maize CWSI compared to using these variables separately. Specifically, the two models, SVM and RF, improved when the analysis was performed with the combined data compared to when performed with bands only and/or indices only, resulting in the lowest RMSE of 0.07 and 0.05 for SVM and RF, respectively.

Overall, these results demonstrate that the UAV data could be used optimally to forecast the water stress of maize crops on a smaller scale. These results indicate that the UAV multispectral camera could capture the spatial variation of maize crop water stress at a field scale. This further concurs with the notion that adopting cutting-edge technologies, e.g., machine learning, remote sensing, and UAVs, plays a crucial role in the future of smallholder agricultural systems. Findings from this study indicate that using UAV technologies in smallholder farms in conjunction with machine learning algorithms such as the RF model holds promise for improving the management of agricultural crops for improved production. Moreover, UAV provides near-real-time information beneficial to farmers for early preparedness and response to improve crop productivity. These findings contribute to precision agriculture, involving advanced technologies and analytical methods for the near-real-time monitoring and mapping of crop water stress in staple crops such as maize. This is particularly relevant in developing regions where food and nutrition insecurity have been reported. The implications extend to sustainable agriculture and food security in regions facing water-related issues.

3.7.References

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Lead into Chapter 4

The findings from preceding chapter demonstrated that when compared to support vector machine and partial least squares, random forest was suitable for optimally predicting crop water stress index. In this regard, random forest algorithm has been adopted in the proceeding chapter to further predict CWSI in different maize phenological growth stages. Specifically, the next chapter will utilize UAV-acquired spectral variables in conjunction with the random forest regression throughout the vegetative and reproductive growth stages in a typical smallholder farm in Southern Africa. The results from this chapter will also identify the optimal phenological stage to determine CWSI, as well as optimal spectral variables.

4. Assessment of Maize crop water stress index (CWSI) using unmanned Ariel vehicle (UAV) acquired data across different phenological stages.

This chapter is based on a paper submitted for review to the Journal of Applied Remote Sensing.

4.1. Abstract

The temperature-based Crop Water Stress Index (CWSI) stands out as a robust metric among precise techniques for assessing the severity of crop water stress, particularly in susceptible crops like maize. This study used UAVs to collect remotely sensed data in combination with random forest regression ensembles to detect maize CWSI spatially and explicitly in smallholder cropland. Specifically, this study sought to predict foliar temperature derived-maize CWSI as a proxy for crop water stress, using UAV-acquired spectral variables in conjunction with the random forest regression throughout the vegetative and reproductive growth stages in a typical smallholder farm in Southern Africa. CWSI was derived after computing the non-water-stress-baseline (NWSB), non-transpiration-baseline (NTB) using the field measured canopy temperature, air temperature and humidity data during the vegetative growth stage (V5, V10, and V14) and reproductive growth stage (R1 stage). Results showed that CWSI (CWSI < 0.3) could be estimated to a R^2 of 0.86, RMSE of 0.12, and MAE of 0.10 for the 5th vegetative stage; R^2 of 0.85, RMSE of 0.03, and MAE of 0.02 for the 10th vegetative stage; R^2 of 0.85, RMSE of 0.05, and MAE of 0.04 for the 14th vegetative stage; R^2 of 0.82, RMSE of 0.09, and MAE of 0.08 for the first Reproductive stage. The Red, RedEdge, NIR and TIR UAV-bands and their associated indices (CCCI, MTCI, GNDVI, NDRE, Red, TIR) were the most influential variables across all the growth stages. The vegetative V10 stage exhibited the most optimal prediction accuracies (RMSE = 0.03, MAE = 0.02), with Red band being the most influential predictor variable. The results of the study show that, on small, fragmented farms, UAVs remote sensing data can monitor maize water stress using. Also, the findings valuably contribute to the significance of determining water stress at different phenological stages to develop timeous response measures at each stage and therefore contribute to the smallholder farming adaptation and resilience.

Keywords: CWSI, Random Forest, Smallholder farming, UAV.

4.2. Introduction

Maize (*Zea mays L.*) is a multisystemic crop that can adapt to various weather conditions very well (Sa et al. 2022). For example, this is a basic crop to the most vulnerable and plays an essential role in ensuring that food requirements are met especially for subsistence farmers of regions such as Southern Africa (Chivasa et al. 2017). However, a foremost environmental challenge that hinders the production of maize, worldwide is water stress (Zhuang et al. 2017). Water stress affects maize crops at different stages thereby impacting both the vegetative and reproductive growth of the crop (Zhuang et al. 2017). Maize requires more water during the reproductive stage (Kranz et al. 2008). Consequently, maize yield can be significantly reduced due to water stress during vegetative and reproductive growth stages. Cakir (2004) demonstrated that water stress during rapid vegetative growth led to up to 40% grain yield loss, which was indicated physiologically by a reduction in plant extension and a drop in leaf size. Similarly, Li *et al.* (2012) noted that water scarcity resulted in a decrease in leaf growth rates, leaf numbers, leaf area and plant height which ultimately led to significant losses in terms of crop production. In this regard, there is an urgent need to exert efforts towards detecting and understanding the tolerance of crops to abiotic stresses. This is particularly true for rainfed agriculture in countries receiving less than 500 mm precipitation, as this amount is below the critical levels required for obtaining good yields (Sa et al. 2022). Therefore, it is necessary to determine water stress levels in maize crop fields at different crop developmental stages to implement appropriate response measures and mitigate its impacts on crop production.

This has led to a great interest in research on plant physiology parameters relating to leaf water potential and stem water potential, which can be used for indicators of water stress (Park et al. 2021). Recently, however, there have been reports of a search for plant based water quality indicators that would be an alternative to the stem water potential and are seen as standard criteria for assessing groundwater stress levels (Garcia-Tejera et al. 2021; Shackel et al. 2021). In this context, the temperature of the canopy has been generally accepted as a non-invasive and reliable alternative crop water stress indicator (Ramírez-Cuesta et al. 2022). The use of canopy temperature as an indicator of water stress relies on the biophysical link between canopy temperature and the opening and closing of stomata in response to water availability (Poblete-Echeverría et al. 2018). Plants tend to close their stomata when there is moisture stress. This then facilitate an increase in foliar temperature as there will be no water released to cool the plant (DeJonge *et al*., 2015). Meanwhile when there is a lot of water available the plant opens the stomata to release vapour to cool the leaves which results in reduced temperatures ((Zarco-Tejada *et al.*, 2013; Pou *et al.*, 2014; Gonzalez-Dugo *et al.*, 2015). In this regard, the opening and closing of stomata due to the water availability influences canopy temperature. This interaction then serves as a key indicator which is easily detected as a proxy for assessing crop water stress (Zarco-Tejada, González-Dugo and Berni, 2012; Gonzalez-Dugo *et al.,* 2020).

Moreover, in addition to water supply, canopy temperature is also affected by micro-meteorological conditions such as canopy, air temperature (Ta), relative humidity (RH), and vapor pressure deficit (VPD). Thus, an effort has been made to reduce the influence of these climatic conditions and a wide range of temperature based indices have emerged in recent decades (Gerhards et al. 2018). The indices included the CWSI, an index that measures crop water stress based on canopy temperature and therefore reduces the need for ground surveys (L. Zhang, Zhang, et al. 2019b). There are two widely used CWSI models: the theoretical model proposed by Jackson *et al.* (1981), and the empirical model proposed by Idso *et al. (*1981). Empirical approaches are often preferred and adopted because they are relatively cheap and easy to implement. They require few variables, such as canopy temperature and relative humidity (Ta and RH, respectively) (Zhang *et al.*, 2019).

The computation of CWSI takes into account the influence of meteorological parameters on canopy temperature that have been explored as an effective method for monitoring the crop water status for maize (Han et al. 2018; Irmak, Haman, and Bastug 2000; Zia et al. 2013), , peaches (Wang and Gartung 2010), grapevine (Agam et al. 2013; Pou et al. 2014; Zarco-Tejada et al. 2013), olives (Berni et al. 2009), and cotton (Ballester et al. 2019; González-Dugo et al. 2006). A good correlation between CWSI and the other crop water stress indicators, such as soil water content (DeJonge et al. 2015; Taghvaeian et al. 2012), leaf water potential (Gonzalez-Dugo, Zarco-Tejada, and Fereres 2014), and stomatal conductance (Gonzalez-Dugo et al. 2015; Pou et al. 2014; Zarco-Tejada et al. 2013) have been established. However, the aforementioned studies utilised CWSI to assess crop water stress were point based approaches which did not take into consideration spatial variability of crops.

Space borne remotely sensed datasets have also been implemented in characterising CWSI as a proxy for crop water stress (Cetin et al., 2023; Jamshidi et al., 2021; Sayago et al., 2017).

However, space borne platforms (i.e., Landsat and Seninel-2 MSI) have a coarse spatial resolution which often masks out information on crop temperatures when it comes to small fragmented and heterogeneous smallholder croplands (Zhang *et al.,* 2019). In the meantime, a widespread adoption of remote sensing thermal data by unmanned aerial vehicles for monitoring agricultural water stress has been achieved at field level (Bellvert et al. 2016; Bian et al. 2019). In this context, the introduction of high resolution thermal cameras on board by emerging technologies such as unmanned aerial vehicles and thus their widespread use in monitoring crop water stress has been a significant factor (Berni et al. 2009; Zarco-Tejada et al. 2013). However, much of these aforementioned studies have been conducted using CWSI and UAVs acquired multispectral remotely sensed data have been conducted in controlled environments such as experimental plots in developed countries. There is therefore a need to assess these techniques in typical smallholder croplands of Southern Africa, where there is data scarcity, for timely assisting in circumventing impacts of crop water stress.

Other than the application of fine spatial resolution UAV-acquired images, the integration of robust machine learning algorithms and vegetation indices (VIs) in predicting crop water stress indicators has been proven to be effective in mapping crop water stress in a spatially explicit manner (Zhao et al., 2018). In the quantification of water stress in plants, numerous VIs have been identified which are particularly useful for both direct and indirect quantification (Zarco-Tejada et al. 2012; Zhang and Zhou 2019; Zhao et al. 2018). Such indices include the renormalized difference vegetation index (RDVI), normalised difference vegetation index (NDVI), soil-adjusted vegetation indices (SAVI), transformed chlorophyll absorption in reflectance index (TCARI), and optimization of soil-adjusted vegetation index (OSAVI), which are based on visible, near-infrared (NIR) and RedEdge bands (Zhang *et al.*, 2019). These VIs are significant in providing vital vegetation information because of their sensitivity to vegetation density and biomass (e.g., NDVI and SAVI), as well as leaf water content (e.g., NDWI) (Giovos *et al.,* 2021). These VIs are used to monitor and predict leaf area, leaf chlorophyll absorption, crop water stress, and for other applications. However, when these indices are used to predict the crop characteristic, they are influenced by the soil background, to reduce this impact, indices including TCARI/OSAVI are used to (Zhang *et al.,*2015). The use of machine learning techniques has been encouraged because they are able to predict trends and accurately anticipate major crop parameters in the multitemporal collection of many spectral bands and VIs, generating highly dimensional data (Naidoo et al. 2022).

In particular, a commonly utilised machine learning algorithm is the Random Forest (RF), which operates by obtaining predicted values from combined decision trees (Breiman 2001). Compared to other machine learning algorithms, RF has been found to be easy to execute, more robust, and has been known to be resistant to overfitting issues (Breiman 2001; Loggenberg et al. 2018; Ndlovu et al. 2021; Xie et al. 2021). Moreover, the RF model is a non-linear method that provides high simulation accuracy as well as easy model development process (Wang *et al.,* 2022). The RF has been extensively used for crop monitoring because of its rapid computational speed, as well as a good degree of stability in comparison with linear regression and Neural Network algorithms (Xie *et al.*, 2021). RF may consider multiple variables, is highly stable with changes in the parameter values of a classification model and can average tree forecasts for each forest. As a result, in terms of classification and prediction, the RF has an advantage. RF regression algorithm was used to predict maize CWSI from spectral bands and VIs because it is able to develop a multicollinear and multidimensional analyses on large databases (Breiman 2001),

In light of the potential of utilising multispectral data obtained from UAVs with machine learning in mapping crop water stress, this study aimed to assess the feasibility of using UAV sensed data for predicting maize crop water stress indices through random forest regression across all vegetative and reproductive stages of maize in a smallholder farm.

4.3. Materials and Methods

4.3.1. *Study Site*

The research was conducted on a 0.28 hectares smallholder maize field (Figure 4-1). This study field (-22,125031° to -34,834171° S and 16,451891° to 32,891122° E) is located 55 km north-east of Pietermaritzburg, in the rural area of Swayimane, uMshwathi Local Municipality, in the KwaZulu-Natal Province of South Africa (Figure 4-1). The area is dominated by the smallholder farming systems which are mainly rainfed. Dominant cultivated crops in the area include such as sugarcane, maize, sweet potato, and amadumbe (*taro*). Furthermore, crop production in the area thrives due to the favourable environmental conditions in the region, in which summers are mainly warm and wet whilst winters are dry. The annual temperatures range between 11.8 °C and 24 °C with mean annual temperature of 17 °C. The average annual rainfall is between 600 mm and 1200 mm, the area receives most of its rain in summer. The area has received an average humidity of 82.81 %, 242.8 mm rainfall and the highest air temperature of 24 °C over the study period (Kapari *et al.*, 2024). An automatic weather station mounted at Swayimane Primary school nearly 2 km from the maize plot continued to monitor weather conditions. Weather data was downloaded from Swayimane weather website.

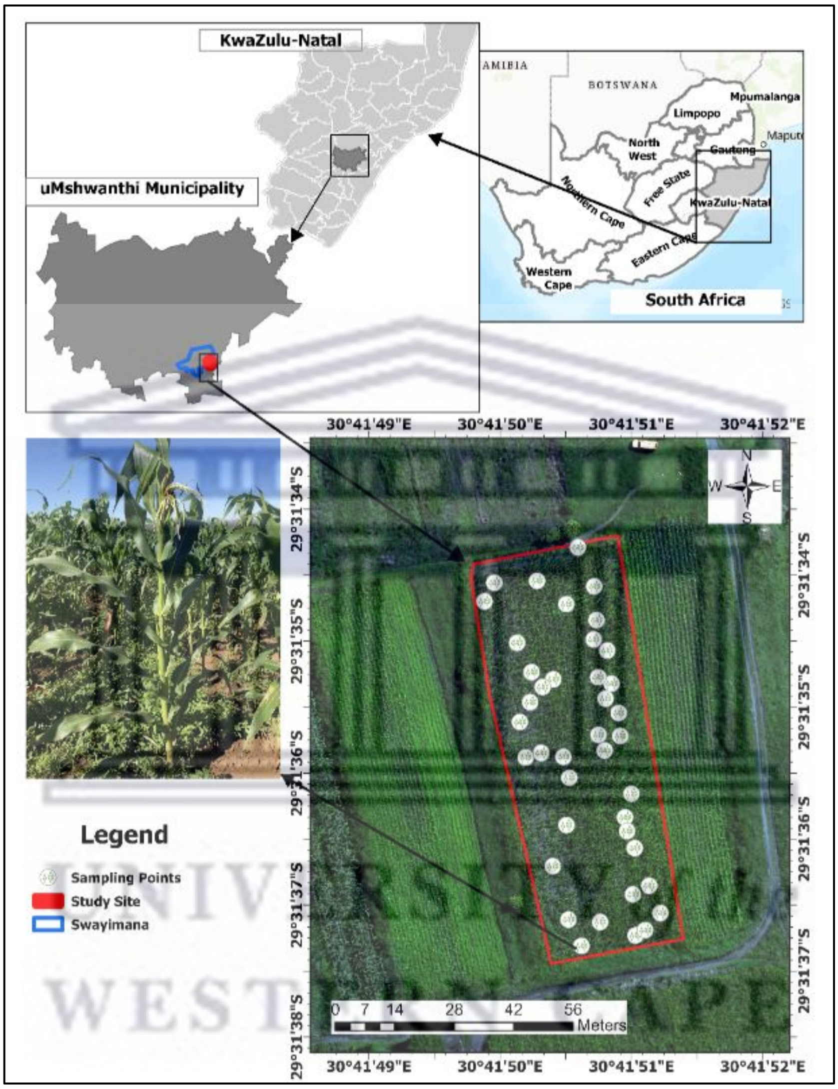

Figure 4-1: Location of the Swayimane study area, study site, and smallholder maize field.

4.3.2. *Maize phenotyping.*

The maize seeds were planted on 8 February and harvested on 26 May 2021 with an overall growth rate of 108 days. Maize growth is divided into vegetative stages and reproductive stages as outlined by Cakir (2004). Within each stage, maize growth, and development encounter certain transitions as a function of environmental conditions under which it is grown as well as the crop's genetic potential. These are significant to deduce for monitoring and informing smallholder farmers, just so the farmers can manipulate the growth environment at the right time to increase yields. Although these stages are outlined in the work of Du Plessis (2003), the below Table 4-1 only outlines stages that were examined for the purpose of this study (Table 4-1). These stages were chosen due to data availability as well as their significant characteristics to the maize growth and development.

Table 4-1:Assessed maize growth stages and their characteristics.

Days after emergence	Growth stage		Description	Pictures
21 - 31	V5	Vegetative stages.	Plant population is established at this stage as potential cobs and tassel forms. Thus, the yield potential is determined. A growth point of 20 to 25 mm below the surface.	
38 - 43	V10		Early cob development and ear initiation.	
49 - 55	V14		Tassel begins to grow fast at the growth point. From the sixth to eighth node above the surface, active development of lateral shoots and cobs. Brace root development. Highly sensitive to heat and drought stress, thus farmer should avoid any nutrient and water shortages to ensure maximum cod and kernels development.	
63 - 69	R1	Reproductive stage.	Pollination takes over for 5-10 days period. Maize is sensitive to stress during this period, thus, if leaves are already wilted from moisture stress in the morning, possible crop loss of about 7% per day is experienced. Maize begins to translocate nutrients from other parts of the plant to the cob.	

4.3.3. *Maize canopy temperature measurement.*

The temperature of the canopy has been measured using two infrared radiometers (IRR) (Apogee SI-111, Apogee Instruments Inc., Logan, UT, USA) located on a four meter meteorological tower at the centre of the maize field (Figure 4-2). The temperature measurement readings form these sensors ranged from -60 °C to 110 °C, in the 8–14 µm. Additionally, the field of view (FOV) was set at a 23° and 45° half-angle perpendicular to the row direction to obtain canopy temperature data. The canopy temperature was obtained every 10 seconds then later averaged to: 5-minutes, 10-minutes, 30-minutes, 60-minutes by means of datalogger CR1000 (Campbell Scientific, Logan Utah, USA) (Figure 4-2). This study used the 60-minutes interval foliar temperature data to develop the NWSB and non-transpiring baseline (NTB) for vegetative and reproductive stages.

The calibration of IRR sensors was carried out by a chamber that is temperature-controlled with blackbody cones for radiation source, where the sensors were held at an opening on the blackbody. Thermal isolation from the cones was used for each of the IRR sensors, which were monitored at their respective temperatures. The IRR was maintained at a continuous temperature and the cone has been controlled at temperatures of less than 12 °C, higher than 18 °C and in line with the IRR. For every 10 °C measured, measurements of IRR and black body cones have been performed until they reach at least constant temperature. IRR measurements on maize temperature calibrated hand-held IRT measurements for the development of the CWSI.

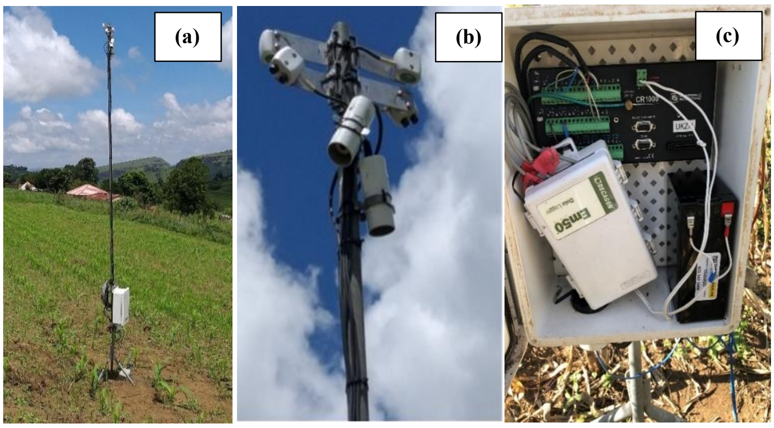

Figure 4-2: (a) Automated in-field meteorological tower in the maize field, (b) meteorological tower mounted infrared radiometers (IRR), (c) CR1000 data logger, Em50 datalogger and 12 V battery.

The experimental field polygon was digitized using Google Earth Pro thereafter used in ArcGIS 10.5 for generating sampling points. For the purpose of obtaining a total of 50 sample points within the digitized field perimeter, systematic random sampling was carried out. The coordinates have since been transferred to the handheld GPS unit of Trimble Global Positioning System with submeter accuracy. To navigate the sampling zones, these locations have been used. A maize plant closer to the sample site was selected and considered for this study upon its arrival at the sampling point. Maize plants at each sampling site have been marked in order to achieve consistency with the measurements made once a week. A handheld infrared GM320 thermometer (IRT) with digital laser was used to measure foliar temperature data during the early vegetative growth to late reproductive growth stages of maize at two-week intervals.

Temperature measurements were recorded at each sampling point/plant from 10:00 a.m. until 14:00 p.m. (South Africa Standard Time). Temperature measurements of maize canopy were captured simultaneously with the image acquisition using the drone across all field sampling dates. Foliar (IRT measured) temperature readings were conducted from a fresh fully expanded ear leaf with an exposed collar during the vegetative stage. Thereafter, foliar temperature was then measured from the ear leaf (i.e., the leaf attached at the same node as the primary ear shank) (Brewer *et al.,* 2022). Temperature measurements from IRT have been carried out and averaged three further times. Each temperature measurement was then captured in spreadsheet along with other measured crop attributes such as stomatal conductance. The SC-1 leaf porometer (Decagon Devices, Inc., Pullman, WA, USA) was used to measure stomatal conductance in mmol m^{-2} s^{-1} for period of 30 seconds. The multispectral and thermal UAV imagery was combined with all the field measured samples to create a point map.

4.3.4. *Meteorological data collection.*

The automatic weather stations (AWS) installed at Sayimana Primary School following the World Meteorological Organization's standards was used to obtain meteorological data (Brewer *et al.,* 2022). Hourly averaged meteorological data, including, relative humidity (%) and air temperature (°C), were utilised to estimate vapour pressure deficit (VPD) for the determination of NWSB and ultimately CWSI.

4.3.5. *UAV multispectral-thermal system.*

A DJI Matrice 300 (DJI Inc., China) quad-rotor UAV and Micasense (MicaSense, Inc., WA, USA) multispectral sensor system was used to collect images in this study (Figure 4-3b). The Micasense camera system was characterised by a Downwelling Light Sensor 2 (DLS-2) integrated with a GPS module (RedEdge, MicaSense Inc., Seattle, WA, USA) that captures high-resolution five-band multispectral narrow bands (blue, green, red, red-edge, Near-Infrared (NIR)) and a radiometric longwave infrared thermal camera as specified in Ndlovu *et al*. (2021) and Brewer *et al*. (2022).

4.3.6. *Image acquisition and processing.*

The flight plan was designed using field boundary digitised on Google Earth Pro and imported into the UAV's smart console as a keyhole markup language format (Kml) (Figure 4-3c). The flight controller was used to generate a flight plan which the aircraft followed in capturing the images. After the flight plan was generated, the flight specific details are illustrated in Table 4-2. Data acquisition was conducted under clear skies, between 10:00 hrs and 14:00 hrs, as this timeframe represented the optimal period when solar radiation was at its maximum. Prior to image acquisition, the MicaSense Altum calibrating reflectance panel (CRP) was used to calibrate the sensor before and after the flight (Figure 4-3d). This included the pilot manually taking an unshaded image directly over the CRP to determine the illumination before and after the flight. The remotely sensed data was acquired using the UAV at 2-week intervals. and simultaneously with the other crop elements.

Table 4-2:UAV flight specifications.

Parameters	Specifications
Altitude	100 meters
Ground sampling distance.	7 cm
Speed	16 m/s
Flight duration	14 minutes 36 seconds
Composite images	321
Image overlap	80 %

After images were acquired, they were mosaiced and radiometrically corrected using Pix4Dfields software (Pix4d Inc., San Francisco, CA, USA). The images of the CRP acquired before and after acquisition the flights were utilised to calibrate the capture reflectance values from possible variabilities imposed by changes in the atmospheric conditions. A complete orthomosaic GeoTiff image was generated after pre-processing. Reference points identified in Google Earth Pro were used to orthorectify the image in ArcGIS 10.5. Images were referenced to the Universal Transverse Mercator (UTM zone 36S) projection to a root mean square error (RMSE) of less than half a pixel (3.5 cm).

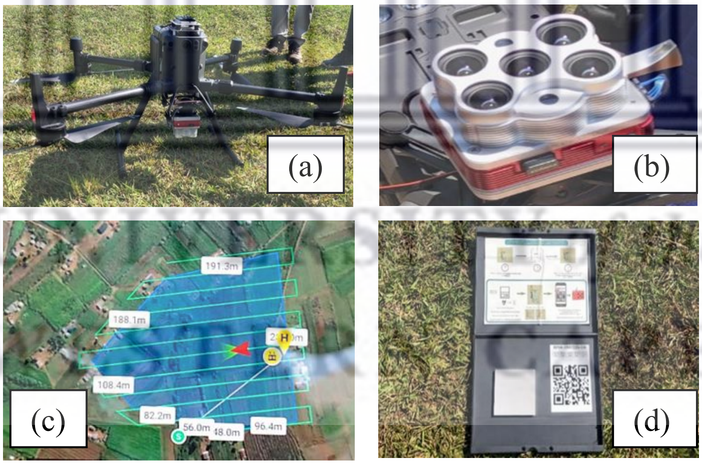

Figure 4-3: (a) UAV system, DJI Matrice 300 and, (b) MicaSense Altum camera. (c) DJI M-300 flight plan, (d) MicaSense Altum calibration reflectance panel.

4.3.7. *Selection of Vegetation Indices*

The point map with temperature readings generated as explained in *section 4.3.6* was used to extract reflectance values of the multispectral bands. The surface reflectance values were then used to compute vegetation indices using formulars shown in *Table 4-2*. The selected vegetation indices are commonly used to relate to canopy physiological parameters (Yue et al., 2018). In addition, these indices aim to improve the contribution of vegetation optical characteristics to the total spectral response of the canopy (Yue et al., 2018). Vegetation indices also attempt to correct any confounding factors such as soil bottom reflectivity in the crop, especially in the early stages of the growth cycle (Zhang and Zhou, 2015). To establish a regression model between UAV collected data and CWSI, multispectral and thermal bands, and VIs in work of Kapari *et al.,* (2024) were selected.

4.3.8. *Crop Water Stress Index (CWSI) Calculation*

The CWSI was calculated by using Equation 7, Equation 8, and Equation 9:

$$\mathrm{CWSI} = \frac{\Delta \mathrm{T} - \mathrm{Twet}}{\mathrm{Tdry} - \mathrm{Twet}} \quad \text{Equation 7}$$

where ΔT is the actual measurement of the difference between the canopy and air temperature (Tc -Ta), *Twet* is the lower limit, and *Tdry* is upper limit of the estimated baselines. Herein, *Twet* and *Tdry* are also respectively referred to as non-water-stressed baseline (NWSB) and non-transpiring baseline (NTB) which are determined as follows:

$$\mathrm{Twet} = \mathrm{m} * \mathrm{VPD} + \mathrm{b} \quad \text{Equation 8}$$

$$\mathrm{Tdry} = \mathrm{m} * \mathrm{VPG} + \mathrm{b} \quad \text{Equation 9}$$

where *m*, *b* in both equations represents the slope and intercept, respectively. VPD is obtained using Equation 10 to Equation 12, following the description of Allen *et al.* (1998):

$$e_s = 0.6108 * \exp\left[\frac{17.27\mathrm{T}}{\mathrm{T}+237.3}\right] \quad \text{Equation 10}$$

$$e_a = e_s * \left(\frac{RH}{100}\right) \quad \text{Equation 11}$$

$$\mathrm{VPD} = e_s - e_a \quad \text{Equation 12}$$

where T is air temperature, RH is relative humidity, e_s is saturated vapor pressure (kPa) at the air temperature Ta, and e_a is actual vapor pressure (kPa). To calculate *Tdry* values, vapour pressure gradient (VPG) is determined. VPG is the change in the air-saturated water vapor pressure at temperature (Ta) and the air-saturated water vapor pressure at temperature (Ta + b) (Gu et al. 2021).

Specifically, the first step to determine CWSI involved determining functions for *Twet* and *Tdry* for rainfed maize under Swayimane environmental conditions. This was achieved by following steps articulated by Taghvaeian *et al.* (2012). Maize ΔT was calculated by IRT measurements in the field after two significant rainfall days and were plotted with their corresponding VPD values. This is under the assumption that after these wetting events, soil water deficit was replenished therefore maize had access to sufficient soil water. Therefore, non-water stressed conditions existed. This was determined for 2 hours before and 2 hours after midday, as recommended by Jackson *et al. (*1981). The resulting equation from this linear segment was extracted to obtain the coefficients of Equation 8 and Equation 9 by using simple linear regression. A three-step moving average was followed to plot the relationship between ΔT and VPD for the vegetative and the reproductive stages, as suggested by Idso *et al.* (1981). According to Taghvaeian, Chávez and Hansen (2012), CWSI method is only valid under clear-sky conditions, to ensure this all the days selected to calculate the CWSI were corresponding to the field visits days in all the assessed stages. The CWSI values ranges from 0 to 1, where 0 indicates no water stress, while 1 indicates most severe stress.

4.3.9. *Statistical analysis*

The RF implementation was in the RStudio software version 1.4.1564, and the outputs were a set of decision trees. Thereafter, trees were split at each node dependent on the most contributing explanatory variable to the response variable (López-Calderón et al. 2020). For each prediction of the response variable, an average value of a multitude of decision trees and outputs are built. The models developed included spectral variables (bands and VIs) as independent variable and CWSI as the dependent variable. Furthermore, all the regression models developed for each growth stage in the study have different hyperparameters for optimal performance. The parameter *mtry* in RF accounts for the number of variables used for splitting at each tree node for decision tree learning. In R the default value of *mtry* is defined by dividing predictive variables by 3 (Kuhn and Johnson 2013). Meanwhile, the other parameter, *ntree*, which indicates the generated number of trees, has default value of 500 (Mashiane *et al.,* 2023).

The K-fold cross-validation technique was used in this study considering it optimal performance in literature (Eugenio et al. 2020). In this study, the overall predictive model development process involved the 10-fold cross-validation repeated three times on the training data, using the '*train ()*' function from the '*caret*' package in R. Cross-validation provided the best components to retain that lowest RMSE in all the models. The field data in this study was split into a 70% for training and 30% for testing samples.

4.3.10. *Accuracy assessment*

The overall performance and robustness of the RF predictive models were appraised by coefficient of determination (R^2), the root mean square error (RMSE), and the mean absolute error (MAE).

4.4.Results

4.4.1. *Non-water stressed baselines (NWSBs) and Maize crop water stress index (CWS) for vegetative and reproductive stages.*

Figure 4-4(a) shows the relationship between Tc-Ta and VPD that was used to derive the slope and the intercept of the NWSB. The same coefficients developed for NWSB determines NTB and using VPG instead of VPD, while Figure 4-4(b) shows the relationship between the Tc-Ta and VPD was significant for vegetative ($R^2 = 0.84$) and reproductive ($R^2 = 0.95$) stage. The Tc-Ta decreases with increase in VPD.

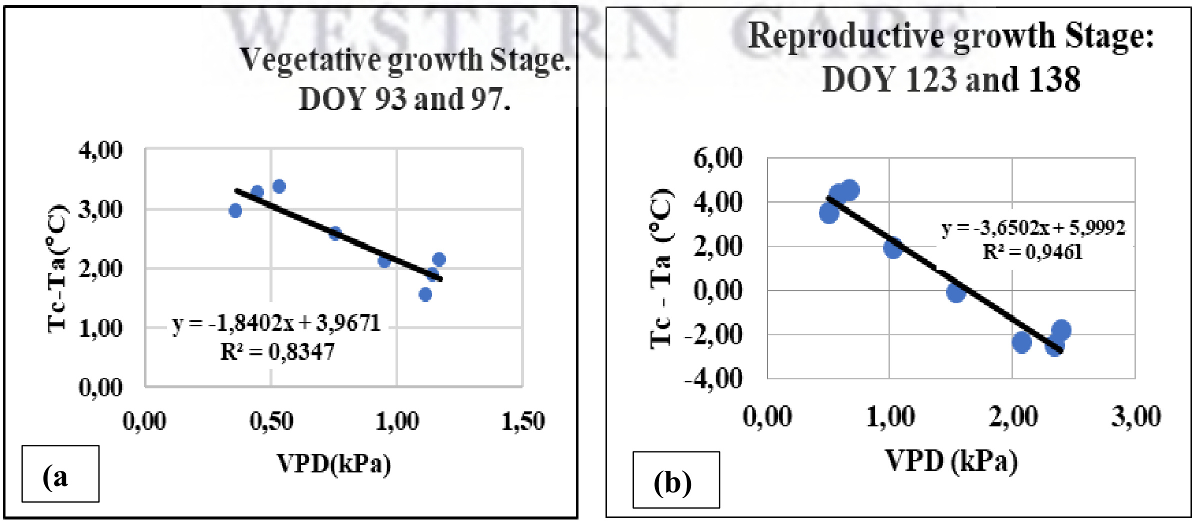

Figure 4-4:Non-water-stressed baselines used to calculate the CWSI for maize growth stages.

Patterns of CWSI obtained on four different days for the maize growth stages can be observed in the Figure 4-5. The results show that values of CWSI close to zero for the two growth stages. The lowest CWSI value was determined on DOY 76, whilst the highest value was determined on DOY 89. On average, there was low crop water stress during the study period. Generally, these findings show that maize water stress levels varied at different stages as maize grows from vegetative to reproductive stage. Figure 4-5 depicts that overall, for both stages when maize incurred low water stress levels.

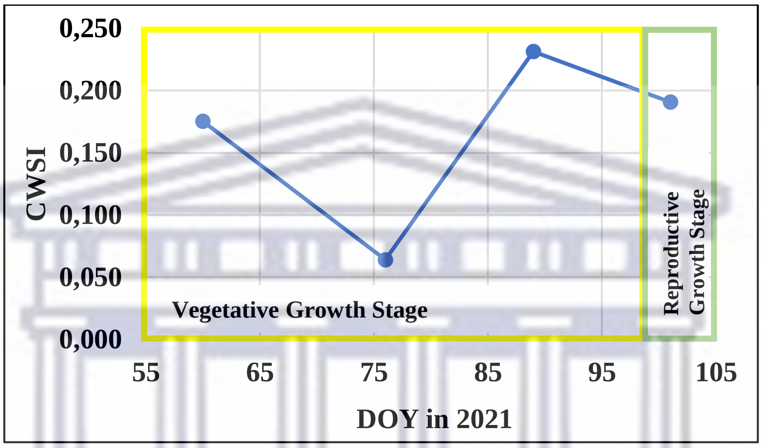

Figure 4-5: CWSI for maize.

4.4.2. *Predicting crop water stress index (CWSI) of maize during the vegetative and reproductive growth stages using random forest.*

CWSI was predicted to a RMSE of 0.12 and R^2 of 0.86 during the vegetative stage (V5) based on NDWI, SAVI, TCARI_RDVI, RedEdge, TIR, GNDVI and MTCI as optimal predictor variables in order of importance (Figure 4-6a). During the V10 growth stage CWSI was estimated to a RMSE of 0.03 and R^2 of 0.85 based on Red, TIR, GNDVI, TCARI, Cl_GREEN, CCCI, and NIR, in order of importance (Figure 4-6b). During the final vegetative stage (V14), CWSI was estimated to a RMSE of 0.05 and R^2 of 0.85 based on NDRE, MTCI, CCCI, GNDVI, TIR, Cl_RedEdge, and MTVI2 as optimal variables in order of importance (Figure 4-6c). Meanwhile during the reproductive stage CWSI of maize was estimated to a RMSE of 0.09 and $R^2$of 0.82 based on TIR, TCARI, RedEdge, Red, RDVI, RVI, Green as optimal variables in order of importance.

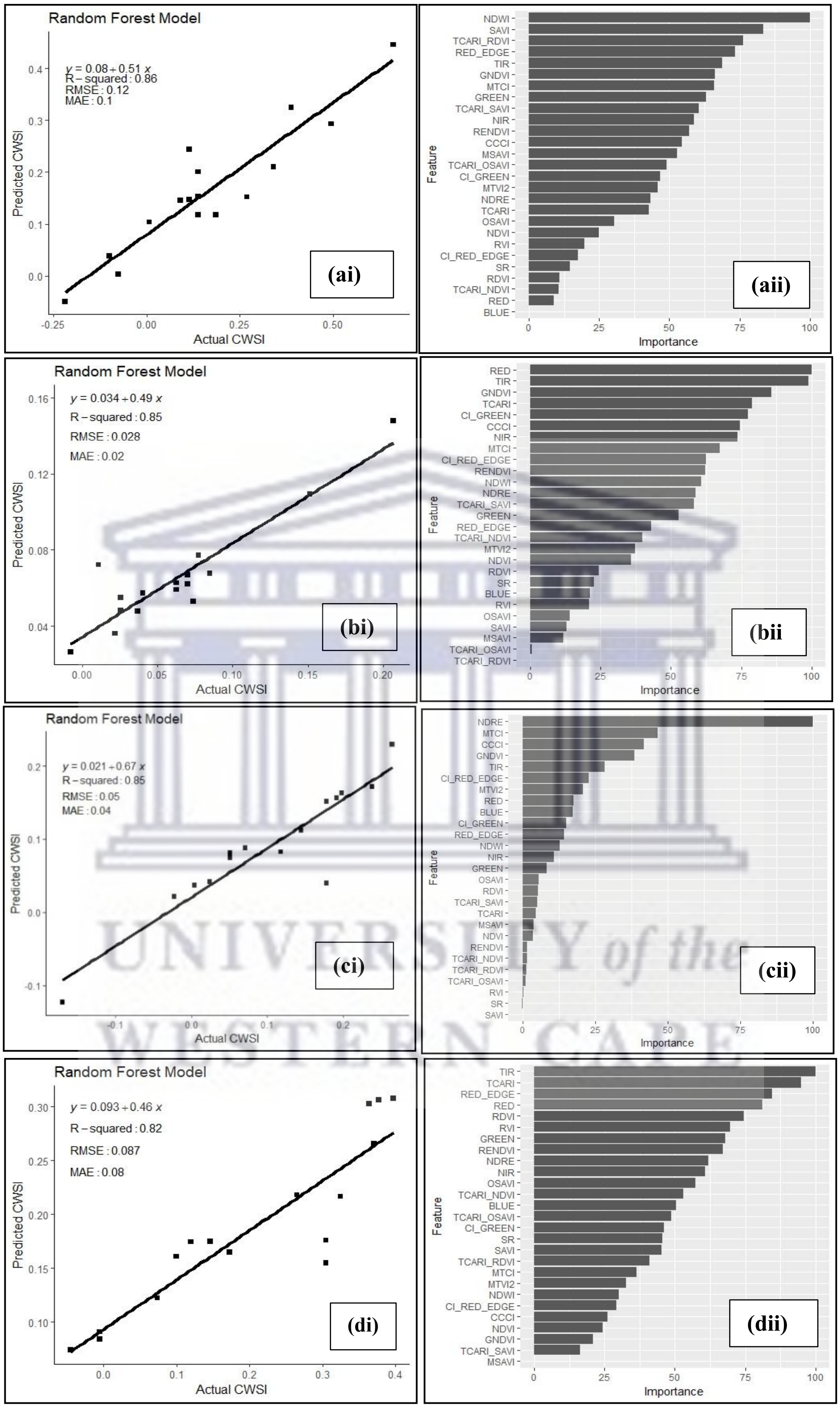

Figure 4-6:Linear relationships between actual and predicted CWSI (i) for maize crop's vegetative stages (a) V5, (b) V10, (c) V14, and (d) reproductive stages (R1) as well as the corresponding variables' importance (ii).

4.4.3. Spatial distribution of Maize crop water stress index (CWSI) at different phenological stages.

Figure 4-7 are maps showing the spatial distribution of CWSI in the experimental field at different growth stages. Figure 4-7 indicates that, on average, there has been consistently low water stress levels throughout the stages. However, CWSI increased as maize grew, and growth stages changed. The early reproductive (R1) growth stage the exhibited the highest CWSI ranging from 0.05. Subsequently, CWSI was low during the vegetative stage (V5, V10, and V14). Nonetheless, during the late vegetative stage and early reproductive stage (V10 and R1), results on Figure 4-7 show that the western portion of the field showed signs of water stress (Figure 4-7 c and d).

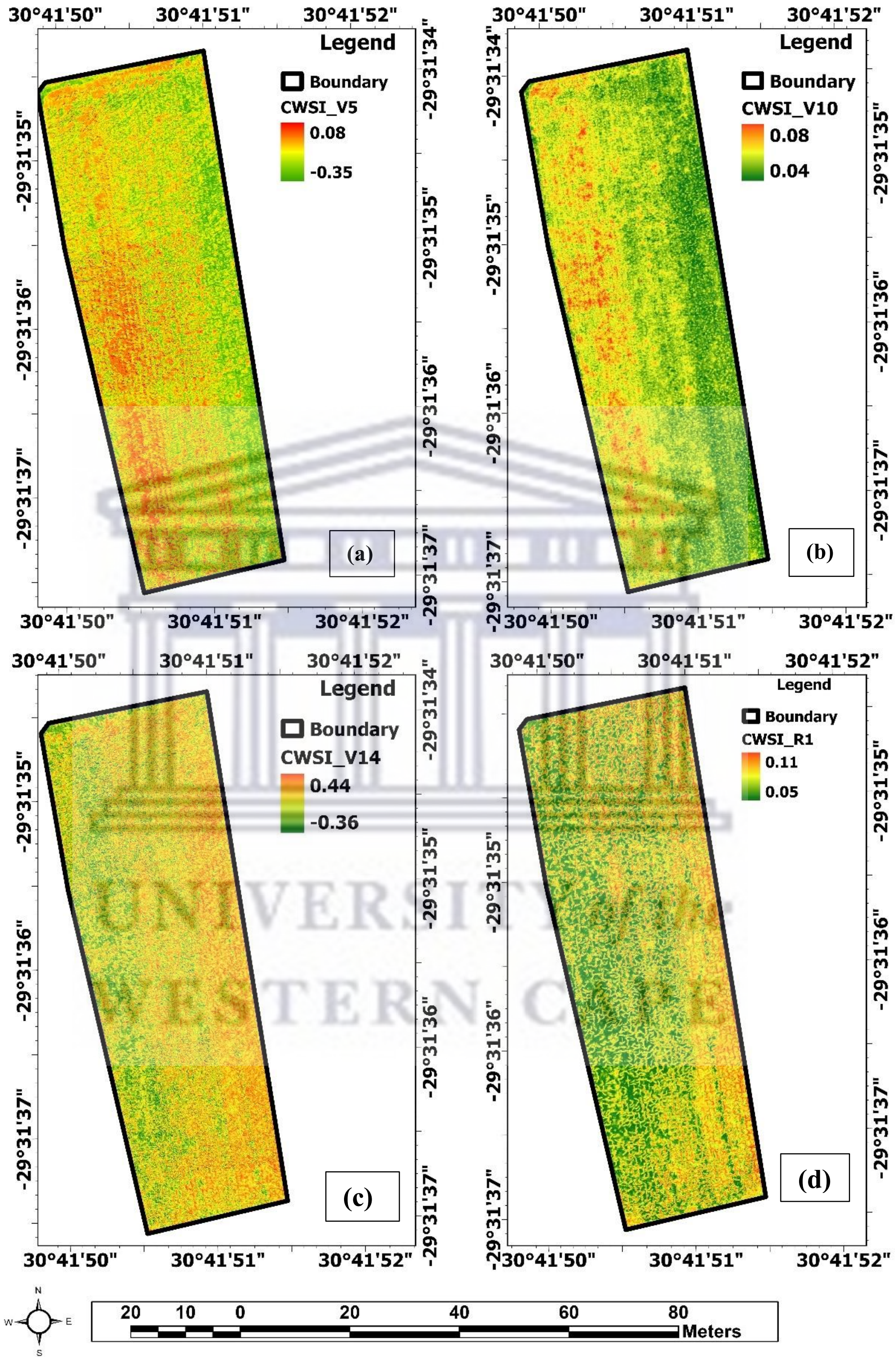

Figure 4-7:Maize CWSI over the smallholder field for vegetative stages (a) V5, (b) V10, (c) V14, and reproductive stages (d) R1.

4.5. Discussion

4.5.1. Determination of the baselines and maize CWSI for the vegetative and the reproductive stages.

According to results, the NWSB slope during reproductive stage was more pronounced than at vegetative phase. Because of the NWSB's slope reflecting crop transpiration capacity (Gu et al. 2021), results reveal that the transpiration of maize varies due to change in microclimatic conditions at each stage (i.e. vegetative and reproductive growth stages), leading to Tc decrease due to growth from the vegetative to the reproductive stage, thus leading to Tc-Ta decrease in similar changes of VPD and, concurrently, NWSB slope declined.

Furthermore, results also revealed the intercept of NWSB in the vegetative was lower than in reproductive, showing that as maize continued to grow, the gap gradually increased. This further indicates that under vegetative stage, maize canopy temperature was lower than in reproductive stage, and their Tc-s were different. Nonetheless, studies have reported slope and intercept ranging from (−1.79 to 3.35) and (1.06 to 3.43), respectively (Taghvaeian, Chávez and Hansen, 2012; Taghvaeian *et al.,* 2014; DeJonge et al., 2015; Han *et al.,* 2018). Findings revealed that the slope and intercept values were not outside the range of the existing NWSB intercept and slope. This variability could be attributed to differences in climatic conditions, given that these values were determined under Mediterranean climate, which differs from the tropical climate experienced in the KwaZulu-Natal province. To the best of our knowledge, maize baselines have not been identified in this region, resulting in a lack of literature for comparison.

The NWSB results were able to determine CWSI for both vegetative and reproductive stages. Results reveal that CWSI was relatively low during these stages (CWSI < 0.3) this may well be due to the study location receiving rainfall that could have been replenishing moisture in the soil, availing it for photosynthesis. Previous studies found that under well irrigated conditions, the CWSI values were less than 0.5 (Berni *et al.*, 2009; Bellvert *et al.*, 2016; Zhang *et al.*, 2019). Notable results are that the CWSI values began to decline in reproductive stage. Similarly, Zhang *et al.* (2019) and Han *et al.* (2018) noted that CWSI was lowest during the maize reproductive stage. Meanwhile, Jamshidi *et al.* (2020) found that CWSI values over 0.40 led to substantial reduction in yield. CWSI adoption as water stress indicator is further recommended by Tanriverdi *et al.* (2016), Ihuoma and Madramootoo (2017), Sharma *et al.*

(2018), and Kumar, Shankar and Poddar (2020), who alluded that when related to methods such as soil moisture-based indicators, CWSI offers a relatively more straightforward indicators of water stress detection.

4.5.2. Comparative estimation of CWSI in maize across different growth stages.

Based on the RF results, V5 stage yielded the maximum RMSE of 0.12 using NDWI, SAVI, TCARI_RDVI, and RedEdge band as significant variables in order of importance. These results indicate CWSI sensitivity to the RedEdge, Red, Green, and NIR bands as well as their associated derivatives. This has been corroborated by literature that shows a statistically representative correlation between leaf reflectance across the spectrum and water quantity in crop leaves (Wijewardana et al. 2019). Specifically, the RedEdge section has been related to crop water stress (Ballester et al. 2019; Niu et al. 2019). This is due to the RedEdge's capability to record the changes in chemical and physiological processes generated by photosynthetic activities, stomatal conductance and crop foliar temperature (Zarco-Tejada et al. 2003). Additionally, because of its sensitivity to high foliar reflectance due to pigment concentrations within plants' canopy structure, the Red and NIR regions have been largely related chlorophyll concentration (Sankaran *et al.*, 2013; Singhal *et al.*, 2019). Red, RedEdge and NIR bands and associated VIs significance in this early vegetative stage indicates strong chlorophyll concentrations due to low leaf area values, leading to a higher dynamic crop's photosynthesis rate and enabling high reflectance in RedEdge and NIR sections (Singhal *et al.,* 2019). Furthermore, in the V5 stage, NDWI was able to explain the variations of maize CWSI owing to its strong correlation for plant water stress (Zhang and Zhou 2015). Overall, results indicate that low canopy coverage in the V5 stage was impacted by soil background reflectance during image acquisition, thus RedEdge and NIR bands led to highest RMSE achieved thus poor performance of CWSI prediction.

The lowest RMSE of 0.03 was attained when predicting CWSI during the middle vegetative stage (V10) using Red band, TIR band, GNDVI, TCARI, Cl_Green, and CCCI as optimal variables, in the order of importance. Meanwhile the late vegetative stage (V14) yielded a RMSE of 0.05 using NDRE, MTCI, CCCI, GNDVI, TIR band, Cl_RedEdge, MTVI2, and Red band as optimal variables, in order of importance. Generally, the late vegetative stages are characterized by high LAI and stronger chlorophyll concentrations that are sensitive to these spectral derivatives (Ustin and Jacqueemoud 2020). In addition, the high levels of chlorophyll due to maize reaching photosynthetic maturity and requiring a high degree of productivity for fruit production, associated with later vegetative stages (Rostami et al., 2008). Results reveal that the chlorophyll-based VIs and bands (such as Red band, Cl_Green, CCCI, Cl_RedEdge) have been significant to the estimation of CWSI. Perhaps dense canopy coverage which presents homogenous scene of green pigment reflectance during image acquisition, has led to optimal prediction of CWSI in the smallholder field due too little to no soil background disturbance. Similar observations were made by Xie and Yang, (2020), Chivasa, Mutanga and Burgueño (2021), and Espinoza *et al.* (2017) also noted that there was high chlorophyll concentration in the late vegetative growth stages of maize which was susceptible to water stress indicators.

During R1, the model prediction resulted in the RMSE of 0.09, with TIR, TCARI, RedEdge, Red, RDVI, RVI, and Green as optimal variables, in order of importance. From the 1970s, thermal remote sensing became a possible instrument detecting early plants water stress (Gerhards et al. 2019). TIR band has been linked to biophysical parameters such as canopy temperature and stomatal changes resulting from water availability (Poblete-Echeverría et al. 2017). Plants close stomata when they experience water stress, thus reducing the loss of water and consequently lead to reduction in evaporative cooling. Therefore, leading to equilibration between the temperature of the plant's canopy and ambient temperature. On the other hand, well hydrated plants allow transpiration and evaporative cooling to be maintained which leads to a lower temperature of the canopy (Zarco-Tejada et al., 2012). For that reason, it is plausible to directly detect plant water stress through canopy temperature. Water stress presence in crops is detected with remote measurements of canopy temperature on a TIR basis (Costa, Grant, and Chaves 2013; Jackson et al. 1981; Jones and Callow 2004). Specifically, canopy temperature, that is strongly determined by TIR can record released radiant energy (Zarco-Tejada et al. 2012). This stage (Maize R1) is characterized by dense canopies, results show that the accuracy of estimating CWSI through TIR region was improved. Thus, crop surface temperatures were strongly detected in the reproductive stage (RI) when TIR was the optimal variably for the RF model at this stage.

4.5.3. Implication of the Findings.

As the commercial agricultural practices become a focal point of modern innovation and development, smallholder farmers often do not have necessary resources needed for adopting effective agricultural practices and optimise agricultural production. Therefore, the findings from this study suggest a potential advantage for UAVs, as they may be capable of profoundly conducting investigation for near real-time crop water stress detection using CWSI as a proxy, incorporating multispectral and thermal imaging technology. Therefore, the findings from this study are valuable as source of information pertaining agricultural water management of smallholder farmers since it provides information pertaining water stress levels at critical phenological stages (V5, V10, V14, R1). The results also suggest the potential adoption of climate smart practices during these stages that are susceptible to water stress. Notably, the UAV data revealed optimal periods for CWSI prediction, particularly at the V10 stage. The effective determination of crop water stress during this vegetative stage is crucial, as it can significantly impact crop development and productivity. Implementing water management climate-smart practices at this stage could help smallholder farmers achieve desired yields and prevent crop loss.

4.6. Conclusions

This study's overall objective of this study focused on assessing the utilisation of UAV obtained data in determining maize CWSI for vegetative and reproductive stages using RF regression. Findings reveal, the RF algorithm when applied to UAVs remotely sensed data, can effectively predict maize CWSI during both the vegetative and reproductive growing stages. The Red, RedEdge, NIR and TIR UAV-bands and their associated indices (CCCI, MTCI, GNDVI, NDRE, Red, TIR) were significant in the predictors of CWSI. The optimal RF model was identified at the V10 growth stage, with Red band being the most influential variable. Notably, the RF regression model demonstrated high predictive for CWSI in all the investigated maize growth stages (i.e., V10, V14, and R1) with $R^2 > 0.80$, and RMSE <0.1. The successful quantification of CWSI using the UAV technology provides valuable information for smallholder farmers, enabling them to take precautionary measures and make informed decisions with regarding farm management. This positions technology of UAV as a credible and promising remote sensing data acquisition tool for precision farming.

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5. Chapter 5: Synthesis and conclusions.

5.1. Introduction and overview of the objectives

Smallholder farmers largely impacts majority of the rural population livelihoods (Aaron 2012). Unfortunately, these farmers continue to face challenges that negatively impact their production, thus threatening household food security. This is particularly true for those smallholder farmers that cultivate maize, a staple crop for majority of Southern Africans. Majority of these smallholder farmers grow maize under rainfed conditions, thus making them susceptible to crucial threats that are related to water stress due to changing climate that results in erratic weather events eventually leading to loss of yields (Adisa *et al*., 2018). In this regard, this study assessed the UAV acquired data application in combination with machine learning algorithms on quantitatively characterising maize water stress in smallholder croplands. To achieve this overarching objective the following objectives were addressed.

1. To conduct a systematic review on the application of remote sensing in the assessment of maize water stress.
2. To compare three machine learning algorithms (Partial Least Squares (PLS), Support Vector Machine (SVM), and Random Forest (RF)) in estimating maize crop water stress in smallholder croplands
3. To estimate maize CWSI across different phenological stages using UAVs acquired data in smallholder croplands.

5.2.Summary of the findings

Results indicated that there is an increase on the publication of articles with focus on remote sensing technology application on maize water stress assessment since 2002. Remote sensing use for maize water stress assessment has been adequately established and the Landsat alone was found to be the most utilised remote sensing sensor. However, despite the proven efficiency of remote sensing applications in maize water stress over the years, its application has been centred on the developed nations i.e., United States of America (USA) and. Research efforts on drone based remote sensing applications mapping maize crop water stress have been generally limited in Africa particularly southern Africa. These results indicated that more research efforts are required on assessing maize water stress of heterogeneous agricultural systems and consequently enhance our comprehension of agricultural systems dominating Africa thus progress food security by early response to water demands in smallholder croplands. Especially, because the majority of rural population in Africa, even Southern Africa depends on smallholder faming for their livelihoods. One of the factors hindering the remote sensing application in Africa remains the data unavailability in this region. This is because freely available data such as the one provided by Landsat, offers low spatial resolution that does not meet the demand for monitoring fragmented agricultural systems dominating Southern African region. Perhaps one such sensor that was found to be utilised is Sentinel sensor. Although still emerging, Sentinel offers high resolution images with pixels as large as 10 meters (Rivera-Marin et al. 2022) that are better suited to monitor fragmented small croplands. However, UAVs can offer higher-quality data at the user-determined scale and time and without cloud interference. Results from the literature search revealed that even though UAVs have developed cutting-edge field phenotyping platforms that offer spatial data in agriculture (Ballester et al. 2019; Siegfried, Longchamps, and Khosla 2019), their use on monitoring maize water stress still needs to be further explored. These findings further justified this study's aim to evaluate the application of UAV acquired data in quantitatively characterising maize water stress in typical southern African smallholder croplands.

This study's second objective intended to compare three machine learning algorithms (PLS, SVM, and RF) in estimating maize crop water stress in smallholder croplands. The CWSI was adopted as a proxy for maize water stress. Results revealed that when compared to PLS and SVM, RF was the optimal model in predicting CWSI using bands, vegetation indices and combined data. The RF estimated CWSI at a R^2 of 0.85 RMSE of 0.05, and MAE of 0.04 based on NDRE, MTCI, CCCI, GNDVI, TIR, Ci_RedEdge in order of importance. RF was then selected and used to address the last objective based on its optimal performance.

The third and last objective was to predict CWSI at vegetative and reproductive maize growth stages. Precisely, four stages were compared: three in the vegetative growth stage (V5, V10, and V14 stages) and one on the reproductive stage (R1 stage). Results showed that CWSI was optimally estimated during the maize V10 stage (RMSE of 0.03, MAE of 0.02). Thereafter the V14 (RMSE = 0.05, MAE = 0.04) stage then R1 (RMSE = 0.09, MAE = 0.08), whilst the V5 (RMSE = 0.12, MAE = 0.10) stage performed the worst. Nonetheless, the determined CWSI showed that maize was under low water stress during the all the examined stages (CWSI < 0.3).

The most optimal or influential estimation spectral variables were RedEdge, Red, thermal and NIR and their associated derivatives.

5.3.Specific conclusions

Conclusions that can be derived from this study's findings are:

- CWSI can be optimally predicted using UAV obtained remotely sensed data. Particularly the variables derived from the NIR, Red, RedEdge and TIR derived spectral variables.
- The RF model is more robust in predicting CWSI when compared with SVM and PLS models.
- The optimal maize developmental stage to determine CWSI in concert with RF model was the V10 stage.

5.4.General conclusion

Overall, results demonstrated UAV obtained data is reliable to estimate maize water stress in small croplands. Also, RF was identified as the optimal model to predict CWSI. Nevertheless, the use of UAV technology in smallholder farming systems can provide crucial information that farmers can use to mitigate or even avoid yield losses through informed decision making.

5.5. Limitations of the study and recommendations for future work.

In this study, data was collected using the UAV six bands multispectral camera (RGB, RedEdge, NIR, and TIR band) to calculate VIs. An additional shortwave infrared waveband could have been useful in computing water sensitive VIs recommended for detecting foliar moisture variations. These could have improved the prediction of CWSI. Although costly, future works can consider a multispectral sensor with wavebands including shortwave infrared band. Even more so, future studies can explore the use hyperspectral cameras, since they have an advanced high spectral resolution and are better suited to detect minute variations in canopy structures and leaf pigments (Zarco-Tejada et al. 2018).

NWSB in this study were determined from the data collected on days after a rainfall event. This was done under the assumption that on these days soil water deficit was fully replenished thus providing sufficient water to the maize crop. Soil moisture data would have been useful to deduce exact days when the maize crop was under non-water stress conditions. Alternatively, *Twet* and *Tdry* reference temperatures' readings could be collected from the field using method such as the one suggested by Padhi et al. (2009). These methods of determining Twet and Tdry were not followed in this study due to data unavailability of equipment. However, these methods could be further adopted in future works. Overall, baselines at different location, with different climatic conditions can also be explored in Southern Africa.

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