

UAV-BASED REMOTE SENSING ASSESSMENT OF TARO-WEED COMPETITION WITHIN SMALLHOLDER FARMING SYSTEMS

Report to the
Water Research Commission



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EXECUTIVE SUMMARY

Global agricultural food production systems are challenged by an expanding population and climate change, leading to concerns regarding food insecurity and malnutrition. To enhance the resilience of these systems, there is a recognized need to diversify food production by promoting Neglected and Underutilized Crops (NUCs), such as taro (*Colocasia esculenta*). NUCs are crucial for resource-poor and marginalized communities, particularly in sub-Saharan Africa (SSA), as they are nutrient-dense, climate-resilient, and suitable for low-input agriculture.

However, poor weed management is often the primary contributing factor to low NUC yields and inferior product quality in smallholder farms. Weeds are deleterious because they compete with crops for primary resources like sunlight, nutrients, and, critically, water. Since many smallholder farms in SSA rely on rainfed agriculture and face water scarcity, quantifying the impacts of weed water use is also essential.

This project sought to improve weed management by moving away from inefficient conventional control methods and adopting a site-specific approach. Precision Weed Management (PWM), also referred to in the literature as Integrated Weed Management (IWM) or Site-Specific Weed Management (SSWM), uses advanced data collection and geospatial analysis to map weed distribution and quantify resource competition. In this report, the term PWM is used consistently to describe these data-driven, spatially explicit weed management approaches, while IWM and SSWM are treated as equivalent concepts for clarity and consistency.

The core aim of this project was to accurately identify and map the spatial distribution of weeds and quantify the impacts of weed water use on crop health, quality, yield, and available water resources. The specific objectives achieved included: (1) to provide a literature review on crop-weed competition and the potential of PWM to mitigate these impacts, (2) to develop a trial to quantify crop-weed interactions using traditional and UAV (Unmanned Aerial Vehicle)-based approaches, (3) to map and identify weeds during the various NUC growth stages, and (4) to quantify the water use of NUCs and weeds using UAV imagery.

The research encompassed three distinct study sites in KwaZulu-Natal, South Africa: Site A, a commercial farm monitoring irrigated cannabis (*C. sativa* L) to validate water use models; Site B (Fountainhill Estate) focused on validating models for rainfed taro; and the central field experiment, Site C (Swayimane), featured distinct management plots (weeded, unweeded, and intermediate taro) designed to quantify the impacts of crop-weed competition on water use and yield in a smallholder farming context. The study also identified dominant weed species affecting taro production at the Swayimane site, including Jimsonweed (*Datura stramonium*), Black Jack (*Bidens pilosa*), nut grass (*Cyperus rotundus*), and selected grass species, highlighting the need for targeted and efficient weed management strategies.

The following key findings emerged from the project:

Precision Weed Mapping and Technology Suitability: The systematic literature review confirmed that UAVs are the most frequently utilized remote sensing platform for PWM and are suitable for mapping weeds in the spatially heterogeneous areas characteristic of smallholder farms. The study thereafter went on to develop a cloud-based supervised classification algorithm leveraging UAV multispectral imagery and the Google Earth Engine (GEE) platform.

The Best Classification Method was found to be the Object-Based Image Classification (OBIC) technique, combined with textural properties derived from the Gray Level Co-occurrence Matrix (GLCM), which proved to be the best-performing approach. In terms of accuracy, using the Gradient Tree Boost (GTB) classifier, this method achieved a high overall accuracy (OA) of 98.82% (with 300 training points). In terms of temporal relevance, weed detection and mapping are most effective

during the Early Vegetative (EV) growth phase of the crop, as reliability decreases later when the crop canopy obscures the weeds.

Quantifying Water Use (actual evapotranspiration - ET_a): The potential of empirical models derived from multispectral UAV vegetation indices (VIs) was assessed to reliably estimate actual evapotranspiration (ET_a). When it came to model suitability, the ET_a-NDVI model was identified as the most suitable approach for reliably estimating the water use of taro under rainfed, sparse conditions (sites B and C), showing consistent alignment with measured data. In terms of the consumption of water, applying the model to different management plots (site C) revealed clear differences in water consumption, such as, the unweeded plot accumulated the highest ET_a (407.3 mm), the unweeded plot used 23.97% more water than the intermediate (farmer-managed) plot (328.6 mm), and the weeded plot accumulated the lowest ET_a (256.9 mm), consuming 21.8% less water than the intermediate plot. From an impact perspective, this confirms that the presence of high weed biomass significantly elevates evapotranspiration rates due to increased transpiring surfaces, thus wasting critical water resources.

Economic Impact Assessment: Effective weed management directly correlated with improved profitability, as it was observed that the unweeded plot yielded the lowest net profit of R3,083 (\$171), the weeded plot (which minimized resource competition) resulted in the highest net profit of R16,339 (\$908) and the weeded plot generated 19.82% higher profit than the intermediate field (R13,639).

The findings presented in this report emphatically underscore that poor weed management significantly limits NUC yields and increases water waste. UAV technology, coupled with cloud computing platforms like GEE and appropriate analytical techniques (OBIC-GLCM and ET_a-NDVI), provides a practical and valuable resource for developing reliable, high-resolution maps essential for early weed detection and water use monitoring.

However, the widespread adoption of these technologies by smallholder farmers is restricted by the digital divide, high initial investment costs for equipment, and the need for specialized skills. The report recommends: (a) Strategic collaboration- regarding research institutions and government agencies that must strategically collaborate to establish capacity-building infrastructure that addresses the digital divide and operational challenges, and (b) Future research should focus on refining the empirical relationships between vegetation indices and crop coefficients (K_c) across different growth stages and agroecological zones to enhance model scalability and adaptability.

Lastly, capacity building was identified as a core mandate of the Water Research Commission (WRC) and was integrated throughout the project's implementation to ensure post-project sustainability. The project focused on developing the competencies of postgraduate students and early-career researchers, as well as enhancing institutional capacity. The project formally supported two full-time MSc students and provided ongoing technical, mentoring, supervisory, and partial financial support to two additional postgraduate students, totalling four students engaged in capacity development. These students achieved significant technical and research competencies, including the installation and operation of specialized equipment such as the eddy covariance (EC) flux tower and automatic weather station, pre-processing and analysis of UAV multispectral and RGB imagery, and advanced programming skills using GEE and R statistical software. Professionally, students successfully completed their degrees and they actively disseminated their research findings through numerous presentations at major conferences (e.g., SRI 2024, UKZN Postgraduate Research & Innovation Symposium), where they received awards for their work.

The project also enhanced institutional and early-career researcher capacity. Project leaders, Dr Mahomed and Dr Gokool, exemplified the progression from WRC postgraduate students to leading WRC-funded research projects. Furthermore, Dr Mahomed secured an AfOx catalyst grant, enabling a study visit to the University of Oxford to focus on scaling up UAV research and developing an open-access decision support tool for smallholder farmers. Institutional capacity was also strengthened through access to advanced infrastructure, including multiple UAV Systems and in-situ monitoring

instrumentation. Crucially, the research was operationalized for community benefit: project members engaged continuously with the Swayimane community and farmers. Following the research trial, the project recorded a particularly encouraging outcome: farmers adopted key research recommendations, shifting from sporadic to more frequent weekly weeding practices, resulting in reported improvements in crop growth and demonstrating the early uptake of research-driven best practices by smallholder farmers.

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LIST OF ACRONYMS AND ABBREVIATIONS

asl	above sea level
AUC-ROC	Area Under the Curve Receiver Operating Characteristic Curve
BSc Hons	Bachelor of Science Honours
CA	Conservation Agriculture
CART	Classification and Regression Tree
CBDV	Colocasia Bobone Disease Virus
CHM	Canopy Height Model
CIVE	Colour Index of Vegetation
CNN	Convolutional Neural Network
CRP	Calibrated Reflectance Panel
CWRR	Centre for Water Resources Research
DAP	Days After Planting
DJI-M-300	DJI Matrice 300
DL	Deep Learning
DLS-2	Downwelling Light Sensor 2
EC	Eddy Covariance
ET	EvapoTranspiration
EV	Early Vegetative
EVI	Enhanced Vegetation Index
ExR	Excess Red
ExGR	Excess Green-Red
FAO	Food and Agriculture Organisation
GCI	Green Chlorophyll Index
GEE	Google Earth Engine
GLCM	Gray Level Co-occurrence Matrix
gNDVI	Green Normalized Difference Vegetation Index
GPS	Global Positioning System
GSD	Ground Sampling Distance
GTB	Gradient Tree Boost
IWM	Integrated Weed Management
KML	Keyhole Markup Language
LAI	Leaf Area Index
LST	Land Surface Temperature
LULC	Land Use Land Cover
LV	Late Vegetative
MAE	Mean Absolute Error
MAV/s	Manned Aerial Vehicle/s
METRIC	Mapping Evapotranspiration at High Resolution with Internalized Calibration
ML	Machine Learning
MSc	Master's in Science
MV	Mid Vegetative
NDVI	Normalized Difference Vegetation Index
NDVIre	Normalized Difference Vegetation Index Modified by Red-Edge bands
NGRDI	Normalized Green-Red Difference Index
NIR	Near-infrared
NIRG	Near Infra-Red Green Ratio
NUCs	Neglected and Underutilized Crops
OA	Overall Accuracy
OBIA	Object-Based Image Analysis
OBIC	Object-based Image Classification

PA	Precision Agriculture
PB	Pixel-Based
PBIA	Pixel-Based Image Analysis
PBIC	Pixel-based Image Classification
PRISMA	Preferred Reporting Items for Systematic Reviews and Meta-Analyses
PRISMA-ScR	Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews
PWM	Precision Weed Management
QADI	Quantity and Allocation Disagreement Index
RF	Random Forest
RGB	Red, Green, and Blue
RMSE	Root Mean Square Error
ROI	Region of Interest
RS	Remote Sensing
RTK	Real Time Kinematic
RVI	Ratio Vegetation Index
SAST	South African Standard Time
SAVI	Soil Adjusted Vegetation Index
SBRE	Simple Ratio of Blue and Red-Edge
SEBS	Surface Energy Balance System
SEBAL	Surface Energy Balance Algorithm for Land
SNIC	Simple Non-Iterative Clustering
SNIR-R	Simple Ratio of Near-infrared and Red
SNRE	Simple Ratio of Near-infrared and Red-Edge
SSA	Sub-Saharan Africa
SSWM	Site-Specific Weed Management
SVM	Support Vector Machine
TaBV	Taro Bacilliform Virus
TLB	Turcicum Leaf Blight
TMAX	Maximum Air Temperature
TMIN	Minimum Air Temperature
UA	User Accuracy
UAV/s	Unmanned Aerial Vehicle/s
UKZN	University of KwaZulu-Natal
UWC	University of Western-Cape
VF	Vegetation Fraction
V/Is	Vegetation Index/s
WRC	Water Research Commission
YOLO	You Only Look Once

LIST OF SYMBOLS

$^{\circ}\text{C}$	degree Celsius
Δ	Slope of the saturated vapour pressure curve ($\text{kPa } ^{\circ}\text{C}^{-1}$)
γ	Psychrometric constant ($\text{kPa } ^{\circ}\text{C}^{-1}$)
λET	latent heat flux ($\text{Wm}^{-2}/ \text{MJ.m}^{-2}.\text{day}^{-1}$)
ETr	Reference evapotranspiration ($\text{mm day}^{-1}/ \text{W.m}^{-2}$)
ETa	Actual evapotranspiration ($\text{mm day}^{-1}/ \text{W.m}^{-2}$)
G	soil heat flux ($\text{W.m}^{-2}/ \text{MJ.m}^{-2}.\text{day}^{-1}$)
H	sensible heat flux ($\text{W.m}^{-2}/ \text{MJ.m}^{-2}.\text{day}^{-1}$)
Kc	Crop coefficient (Dimensionless)
L_v	latent heat of vaporization ($L_v = 2.45 * 10^6 \text{ J.kg}^{-1}$)
R^2	Coefficient of determination (Dimensionless)
RH	Relative Humidity (%)
RHavg	average relative humidity (%)
R_n	Net radiation ($\text{W m}^{-2}/ \text{MJ.m}^{-2}.\text{day}^{-1}$)
e_s	Saturated vapour pressure (kPa)
e_a	Actual vapour pressure (kPa)
$e_s - e_a$	vapor pressure deficit (kPa)
TMAX/TMIN	Maximum/minimum air temperature ($^{\circ}\text{C}$)
u_2	Wind speed at 2 m (m.s^{-1})

REPOSITORY OF DATA

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1. INTRODUCTION

1.1 Background and Rationale

Globally, agricultural food production systems are unable to keep pace with existing food demands. With this demand for food increasing as a result of the expanding population, there are growing concerns that food insecurity and malnutrition will be amplified, particularly in the face of climate change (Segarra et al., 2020). Despite these concerns, there remain only a select few crop species that are grown for the purposes of food production throughout the world, which is largely a consequence of the green revolution paradigm that has dominated agricultural food production activities (Chivenge et al., 2015; Mabhaudhi et al., 2017b; 2019). While the green revolution has undoubtedly contributed to an increase in food security, there is a growing consensus that declining agro-biodiversity has contributed to modern food production systems being more vulnerable to stressors, which will likely impact their ability to meet future food and nutrition targets due to their lower resilience (Mabhaudhi et al., 2017a). Subsequently, there is a need to diversify the agricultural food production system by shifting away from the intensification and overreliance on a select few crop species (Mayes et al., 2011; Chivenge et al., 2015).

The increase in the cultivation of neglected and underutilized crops (NUCs) is one of the most promising approaches to address current and future food and nutrition security challenges. This is largely due to these crops being well-suited for production in low-input agricultural systems, their nutrient density, as well as their tolerance to both biotic and abiotic stresses (Mayes et al., 2011; Chivenge et al., 2015; Modi and Mabhaudhi, 2016; Li et al., 2020). In regions such as sub-Saharan Africa (SSA), where the prevalence of food insecurity and malnutrition remains high, the promotion and prioritization of NUCs takes on added significance as local growing conditions are often unfavourable for most staple crops. Subsequently, NUCs can play an important role as a supplementary or alternate source of food and nutrition (Chivenge et al., 2015). Considering that NUCs are climate-resilient and their larger-scale cultivation possesses immense potential in contributing to alleviating food insecurity, malnutrition and poverty, particularly in resource-poor and marginalized communities, there is a need to optimize and incentivize their production (Iyagba 2010; Mabhaudhi et al., 2019; Li et al., 2020).

NUCs are typically characterized by lower yields in comparison to staple crops; however, they are generally able to compensate for this through their ability to withstand adverse climatic and environmental conditions (Padulosi et al., 2013). Nevertheless, it is of critical importance to ensure that optimal yields of NUCs can be attained so that the potential of these crops to alleviate the aforementioned socio-economic challenges can be realized. Furthermore, by improving their yield potential, this may contribute to their production becoming more appealing as there will be improved profitability associated with their cultivation (Padulosi et al., 2013). In SSA, root and tuber crops (such as cassava, orange-fleshed sweet potato and taro) are one of the main sources of food consumed by the population and therefore achieving good, high-quality production levels of these crops takes on added significance (Iyagba et al., 2010; Mabhaudhi et al., 2017b).

While there are several factors that may contribute to low yields and inferior product quality in many farmer's fields, poor weed management is often the primary contributing factor (Iyagba, 2010; Ekeleme et al., 2021). This can be attributed to the initial slow growth of these crops, which results in them being poor weed competitors, particularly during the early stages of crop development (Iyagba, 2010; Nedunchezhiyan et al., 2013; Soares et al., 2016; Ekeleme et al., 2021; Kumar et al., 2020; Omeje et al., 2022). In smallholder taro systems, weed pressure from species such as Black Jack (*Bidens pilosa*) and other annual grasses can significantly reduce crop growth, water use efficiency, and yields, necessitating the need for more effective and targeted weed management strategies.

Weeds adversely affect crop performance by competing directly for essential resources, including water, sunlight, nutrients, and physical space, and may further impair crop growth through allelopathic interactions that inhibit physiological development (Nedunchezhiyan et al., 2013; Kumar et al., 2020; Esposito et al., 2021). Given that weed control is often labour-intensive, costly, and resource-demanding, particularly for smallholder farmers, quantifying the magnitude of weed impacts is critical for designing efficient management strategies that enhance crop productivity while minimizing the inefficient use of limited resources (Esposito et al., 2021; Kawamura et al., 2021).

Conventional weed control or management approaches typically involve uniformly spraying the entire field with herbicide. However, weeds are usually unevenly distributed within these fields; therefore, this is inefficient from both a labour and economic perspective. Furthermore, this approach also adversely impacts the health of the surrounding environment and workers applying the herbicide (Esposito et al., 2021; Kawamura et al., 2021).

Precision weed management (PWM), often referred to as integrated weed management (IWM) or site-specific weed management (SSWM), has been promoted as a more sustainable alternative to conventional weed control. This approach focuses on improving the understanding of crop–weed competition dynamics and using this knowledge to develop customised management strategies, thereby reducing the harmful environmental impacts associated with blanket control methods (Esposito et al., 2021; Mohidem et al., 2021).

PWM aligns with the broader precision agriculture (PA) paradigm, which has gained prominence in the agricultural sector over the past decade (Boursianis et al., 2020; Sishodia et al., 2020). PA involves the targeted application of management interventions informed by advanced data collection, analysis, and communication technologies to enhance productivity, conserve critical resources such as water and nutrients, and mitigate negative environmental impacts (Huang et al., 2018; Boursianis et al., 2020; Sishodia et al., 2020).

For clarity and consistency, this report uses the term **Precision Weed Management (PWM)** to describe site-specific, data-driven weed management approaches that utilise spatial information from remote sensing technologies. The terms IWM and SSWM are treated as equivalent concepts within this report.

The use of remotely sensed data acquired from satellites, manned or unmanned aerial vehicles (UAVs) has often been used to guide and inform weed management. However, the use of satellite and manned aerial vehicle (MAV) data may be less attractive for widespread PA applications. This is largely due to the spatial, spectral and temporal trade-offs that are characteristic of freely available datasets and the large cost implications of more advanced satellite and manned-aerial systems (Huang et al., 2018; Mohidem et al., 2021). The unique characteristics of UAVs, such as their ability to provide cost-effective spatially representative data at user-defined intervals, have seen this technology emerge as an important tool to facilitate PA applications such as IWM (Huang et al., 2018; Singh et al., 2020; Esposito et al., 2021; Kawamura et al., 2021; Mohidem et al., 2021; Roslim et al., 2021). Considering the versatility and potential of UAV technologies for PWM in concert with recent advancements in machine learning (ML) and big data geospatial processing platforms, this study aims to accurately identify and map the spatial distribution of weeds as well as understand and quantify the impacts of weed water use on crop available water resources. It is envisaged that this information will then serve to guide more effective weed management in the future.

1.2 Project Aims and Objectives

The main aim of this project is to accurately identify and map the spatial distribution of weeds as well as understand and quantify the impacts of weed water use on crop health, quality, yield and available

water resources. It is envisaged that this information will then serve to guide more effective weed management in the future. Subsequently, the following specific objectives have been identified, forming the basis of the project;

1. To provide a literature review on the impacts of crop-weed competition on crop yields and quality, as well as the potential of PWM to mitigate these impacts.
2. Develop and set up a trial that will enable the impacts of crop-weed interactions to be quantified through traditional and UAV-based approaches.
3. Map and identify weeds during the various NUC growth stages.
4. Quantify the water use of NUCs and weeds using UAV imagery.

1.3 Project Scope

This project aimed to build upon and enhance the past and ongoing research conducted on the Water Research Commission-funded projects, namely, (i) "Water use of indigenous root and tuber food crops" (completed in 2024) and (ii) "Leveraging the Google Earth Engine to analyse very-high spatial resolution unmanned aerial vehicle data to guide and inform precision agriculture in smallholder farms". In doing so, this project demonstrated how UAV technologies and big-data geospatial cloud computing can be used for various PA applications by quantifying crop-weed dynamics. This allowed for the implementation of PWM, which has the potential to improve the quality and quantity of NUC yields. Subsequently, this project undertook investigations that primarily centred around the (i) collection of ground truth data to develop and assess the accuracy of the crop-weed maps that were produced and the (ii) measurement and estimation of weed and NUC water use (during the different growth phases) to quantify the impacts of weeds.

1.4 Structure of the Report

The report is structured into seven chapters, followed by appendices. The specific focus of a particular Chapter or Chapters is structured and organized according to the objectives identified in the project.

Chapter 1 introduces the project, reiterating its core focus, which is the mapping and assessment of crop-weed competition impacts in neglected and underutilized crops. By establishing this foundational need for advanced agricultural interventions in NUC production, the report proceeds to **Chapter 2**, which provides a systematic review of existing remote sensing literature to identify the most effective PWM strategies. This is done to provide a foundational understanding of crop-weed competition and the potential role of PWM to mitigate its impacts, particularly within the context of smallholder farming systems (**Objective 1**).

Chapter 3 presents an overview of the methodology used to quantify the impacts of crop-weed interactions. It includes an assessment of UAV imagery and cloud computing tools for precision crop-weed mapping, along with preliminary results. Subsequently, this chapter addressed **Objective 3** of the project, which was to "Map and identify weeds during the various NUC growth stages". Furthermore, this technical chapter operationalized the theoretical findings of the literature review (Chapter 2) by setting up a trial (**Objective 2**) and using UAV technology to produce actual weed maps.

Chapter 4 discusses the preliminary results of quantifying water use by NUCs and weeds (**Objective 4**). This is achieved by validating a Vegetation Index (VI)-based empirical model derived from multispectral UAV imagery to estimate actual evapotranspiration (ET_a) under various weed management practices.

Chapter 5 of the report synthesizes the research findings from the technical chapters (Chapters 2, 3, and 4) and provides a comprehensive reflection on the project as a whole.

Chapter 6 provides a final summary of the project's achievements and formally concludes the report. This chapter transitions from the detailed technical discussions (Chapters 2, 3, 4) and synthesis (Chapter 5) to outlining the forward-looking strategy based on the research outcomes.

The References section (Chapter 7) provides a comprehensive list of all the sources cited throughout the report.

Appendices A, B and C, collectively comprise the first set of appendices, focusing on the non-technical but mandated aspects of the research: Capacity Building, Knowledge Dissemination and the timeline of project activities and deliverable milestones.

Appendices D and E, respectively, contain the abstracts from the dissertations derived from studies conducted by postgraduate students involved in the project, which complement the main findings of the report.

Overall, the report is designed to move systematically from the general context (Chapter 1) to the literature basis (Chapter 2, focusing on PWM methodology), through the primary technical findings on weed mapping (Chapter 3) and water use (Chapter 4), culminating in synthesis, reflection, and dissemination (Chapters 5–7).

2. LITERATURE REVIEW

2.1 Introduction

Building on the study context and objectives outlined in Chapter 1, this chapter presents a structured review of the literature on weed management strategies in smallholder and PA systems. The review emphasizes the development of PWM, the remote sensing platforms commonly used, and vegetation indices applied for weed detection and crop–weed discrimination, with particular attention to applications in resource-constrained and smallholder farming contexts.

Given the fragmented and heterogeneous nature of smallholder systems and their unique socio-economic constraints, it is critical to identify remote sensing–based approaches that are both practical and feasible for PWM. To address this, a systematic scoping review and attribute analysis were conducted with the specific objectives of identifying: (i) common remote sensing platforms, (ii) sensor characteristics, and (iii) data analysis procedures used to support PWM, while contextualizing these findings within the challenges and opportunities characteristic of smallholder agriculture.

The review is organized into five sections. Section 2.1 provides the background and rationale for the review. Section 2.2 outlines the methodology used to identify and evaluate the literature. Section 2.3 presents the results of the attribute analysis, including influential publications, prominent authors, and leading journals. Section 2.4 discusses the findings in relation to the review objectives, and Section 2.5 concludes with the key insights drawn from the literature.

2.2 Materials and Methods

This systematic literature review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) approach. The literature database for the bibliometric analysis was compiled by first searching for articles within the Scopus abstract and citation database. The choice of keywords and variants used in the search string was informed by a subset of the literature identified through Google Scholar and the authors' experience in this subject area. A structured query string consisting of the following keywords and variants ("Remote sensing" OR "satellite" OR "UAV" OR "drone" OR "Unmanned aerial vehicle" AND "agriculture" OR "farm*" OR "crop" AND "Integrated weed management" OR "precision weed management" OR "site-specific weed management") was used to source the literature on 5 September 2023.

The search results were first filtered by selecting full-length articles written in English and published in accredited journals. Thereafter, the remaining articles were screened for eligibility based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) framework (Tricco et al., 2018). Only those articles that met the following eligibility criteria were retained in the final literature database: (i) the study must utilize at least one of the remote sensing platforms to implement PWM, (ii) the study applied remote-sensing-based techniques to guide and inform PWM decision making, and (iii) the study provided a methodological description of how the remotely sensed data were used to detect and map weeds.

The structured query search in Scopus yielded 111 potentially relevant studies. Twenty-one of these studies were excluded as they were not written in English or published in accredited peer-reviewed journals. The remaining 90 articles were then manually screened for eligibility by their titles and abstracts, and a further 19 articles were excluded. The authors then sought the remaining 71 articles, and a further 18 articles were removed after being assessed against the eligibility criteria defined for the study by examining the full text of each article. The final literature database containing 53

publications was then exported into the Biblioshiny and VOSviewer (version 1.6.20) software applications for further analysis (Van Eck and Waltman, 2010; Aria and Cuccurullo, 2017). An overview of the article selection process is provided in Figure 2.1. Additional attributes were added to the literature database to perform the attribute analysis by extracting specific information from each selected study. These include remote sensing platforms, sensor type, spatial resolution, classification method, classification algorithms, extracted bands and features, geographic location, and crop type.

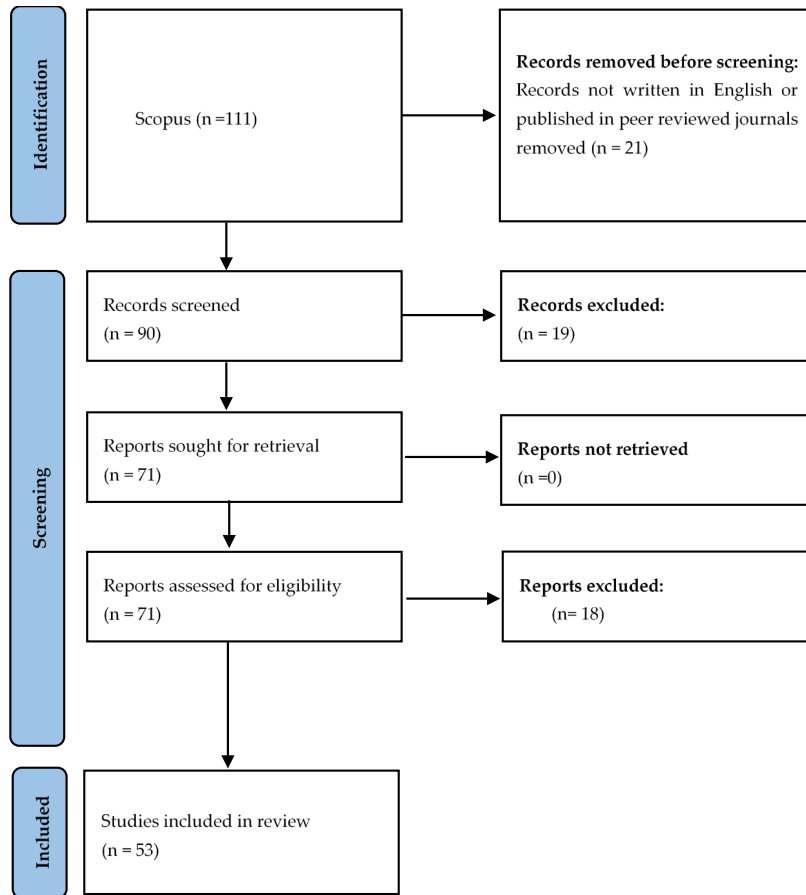


Figure 2.1 A conceptual flow diagram depicting how the final literature database was compiled using the PRISMA guidelines

2.3 Results

2.3.1 General characteristics

Research on RS-based techniques to detect and map weeds to facilitate PWM has been ongoing for almost two decades. It has steadily increased annually by approximately 14% (Table 2.1). Of the 53 publications selected for further evaluation, more than 80% have been published in the last decade, of which approximately 53% have been published in the past three years (Figure 2.2). This may result from advancements in sensor capabilities, data accessibility, data processing, and computational power (Bahrami et al., 2022).

Table 2.1 A summary of the general characteristics of the selected studies included in the final literature database

Description	Results	Description	Results
Timespan	2006-2023	Keywords plus (ID)	410.00
Number of journals	24.00	Author keywords (DE)	192.00
Number of publications	53.00	Authors	186.00
Annual growth rate	13.80%	Single-authored articles	0.00
Document average age	4.91	Co-authors per article	4.94
Average citations per doc	50.11	International co-authorships	15.09%

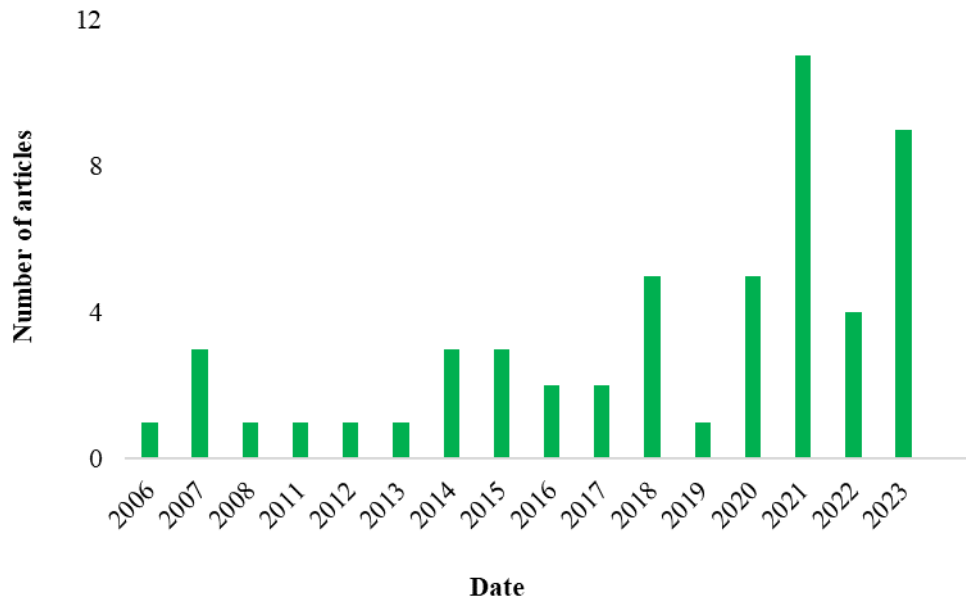


Figure 2.2 Annual distribution of published articles (years without published articles have been omitted)

The 53 publications contained within the final literature database were published across 24 journals, with *Computer and Electronics in Agriculture* ($n = 8$), *Remote Sensing* ($n = 8$), and *Precision Agriculture* ($n = 7$) accounting for approximately 43% of published articles. According to Bradford's Law, articles published within these journals on remote sensing to facilitate PWM are among the most influential and of greatest interest (Figure 2.3). *Computer and Electronics in Agriculture* and *Precision Agriculture* also retain their position among the top 3 most influential journals when ranked according to the total number of citations and h-index values (Table 2.2).

A total of 186 authors contributed to the 53 publications on using remote sensing to facilitate PWM. Of these 186 authors, 14 published 3 or more articles (Table 2.3). Francisca López-Granados can be considered the most influential author in this research focus area, ranking highest for 4 out of the 5 author performance metrics (listed in Table 2.3). Torres-Sánchez et al. (2014) received the highest number of citations and average citations per year. In their study, the authors investigated using an UAV equipped with a low-cost commercial-grade camera for vegetation fraction (VF) mapping to facilitate early-season PWM in wheat fields. Several visible spectral indices were derived to quantify VF, and the influence of flight altitude and image acquisition dates on classification accuracy was also evaluated. Overall, the study's results demonstrated that using visible spectral indices derived from a low-cost commercial-grade camera onboard a UAV flying at low altitudes can satisfactorily distinguish VF in wheat fields and thus has potential for early PWM applications. The most highly cited article based on the normalized TC metric was by Gallo et al. (2023). These authors employed the latest version of the You Only Look Once (YOLOv7) deep learning algorithm to detect weeds among chicory

using red, green, and blue (RGB) imagery acquired from a UAV. The study's results demonstrated that the YOLOv7 algorithm performed satisfactorily for weed detection and outperformed previous versions. However, the need for large-scale datasets to develop and test the model may limit its suitability for operational applications.

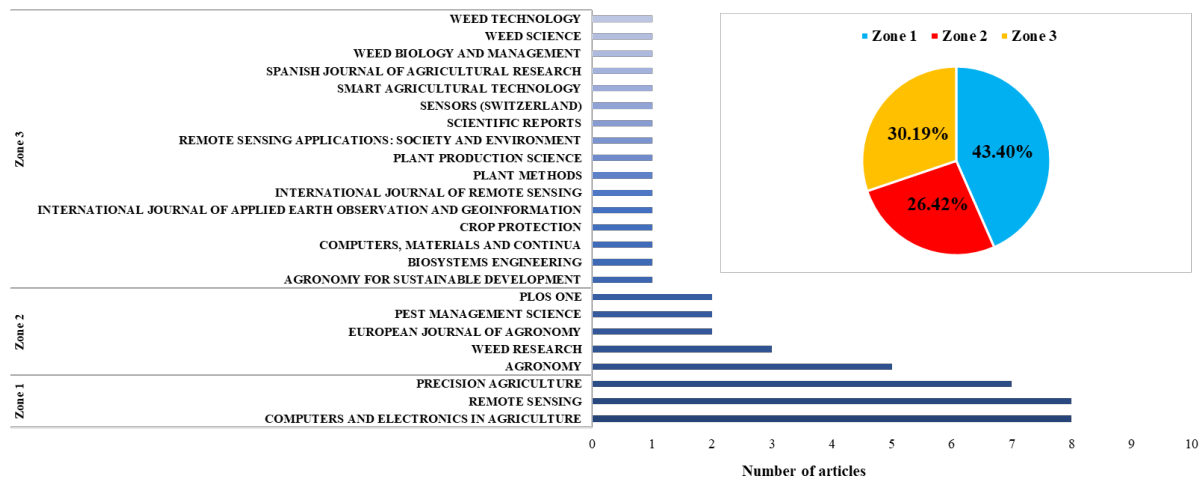


Figure 2.3 Number of publications per journal and journal ranking according to Bradford's Law

Table 2.2 Journal publication metrics listed in chronological order

Journal	Number of publications	TCs	h-index	Publication year start
Weed Science	1	70	1	2006
Weed Research	3	81	3	2007
Weed Biology and Management	1	21	1	2007
Weed Technology	1	12	1	2007
Computers and Electronics in Agriculture	8	705	6	2008
Crop Protection	1	13	1	2011
Precision Agriculture	7	506	7	2012
Plos One	2	363	2	2013
European Journal of Agronomy	2	67	2	2014
Biosystems Engineering	1	26	1	2015
Sensors (Switzerland)	1	133	1	2015
Agronomy for Sustainable Development	1	68	1	2016
Remote Sensing	8	349	7	2018
International Journal of Applied Earth Observation and Geoinformation	1	85	1	2018
International Journal of Remote Sensing	1	44	1	2018
Pest Management Science	2	42	1	2020
Spanish Journal of Agricultural Research	1	4	1	2020
Agronomy	5	44	3	2021
Plant Production Science	1	18	1	2021
Scientific Reports	1	2	1	2022
Remote Sensing Applications: Society and Environment	1	2	1	2023
Smart Agricultural Technology	1	1	1	2023

Table 2.3 Author-level citation metrics for authors with 3 or more publications

Author	h-index	g-index	m-index	TCs	Number of articles	Publication start year
LÓPEZ-GRANADOS F	14	18	0.78	1833	18	2006
DE CASTRO AI	10	11	0.83	1397	11	2012
TORRES-SÁNCHEZ J	9	12	0.82	1393	12	2013
JURADO-EXPÓSITO M	7	7	0.39	282	7	2006
PEÑA JM	7	7	0.70	1114	7	2014
JIMÉNEZ-BRENES FM	5	5	0.83	244	5	2018
PEÑA-BARRAGÁN JM	5	5	0.29	444	5	2007
MESAS-CARRASCOSA FJ	4	5	0.40	265	5	2014
RASMUSSEN J	3	4	0.33	48	4	2015
SERRANO-PÉREZ A	3	3	0.33	326	3	2015

The top 10 keywords and words that frequently appear in the titles of references but not in the titles or keywords of articles (Keywords plus) are shown in Table 2.4, whereas the co-occurrence of keywords that appear three times or more are shown in Figure 2.4. The results suggest that UAVs feature quite prominently in PWM practices. Furthermore, UAV-acquired or -derived (vegetation indices) data are often used with machine and deep learning (DL) techniques to aid with image analysis and classification to detect and map weeds, which can serve as a precursor to implementing weed control interventions. It should be noted that some of the keywords and keywords plus also formed part of the search query string used to identify the pool of literature that was reviewed and analyzed. Subsequently, there is an element of bias that may exist in the aforementioned finding.

Table 2.4 Top 10 author keywords and keywords plus

Keywords	Frequency	Keywords plus	Frequency
Site-specific weed management	16	Weed control	31
Precision agriculture	15	Precision agriculture	24
Remote sensing	12	Crops	17
Unmanned aerial vehicles (uav)	9	Remote sensing	17
Deep learning	8	UAV	17
Machine learning	7	Weed	17
Vegetation indices	5	Deep learning	15
Weed detection	5	Image analysis	14
Weed mapping	5	Unmanned vehicle	14
OBIA	4	Antennas	11

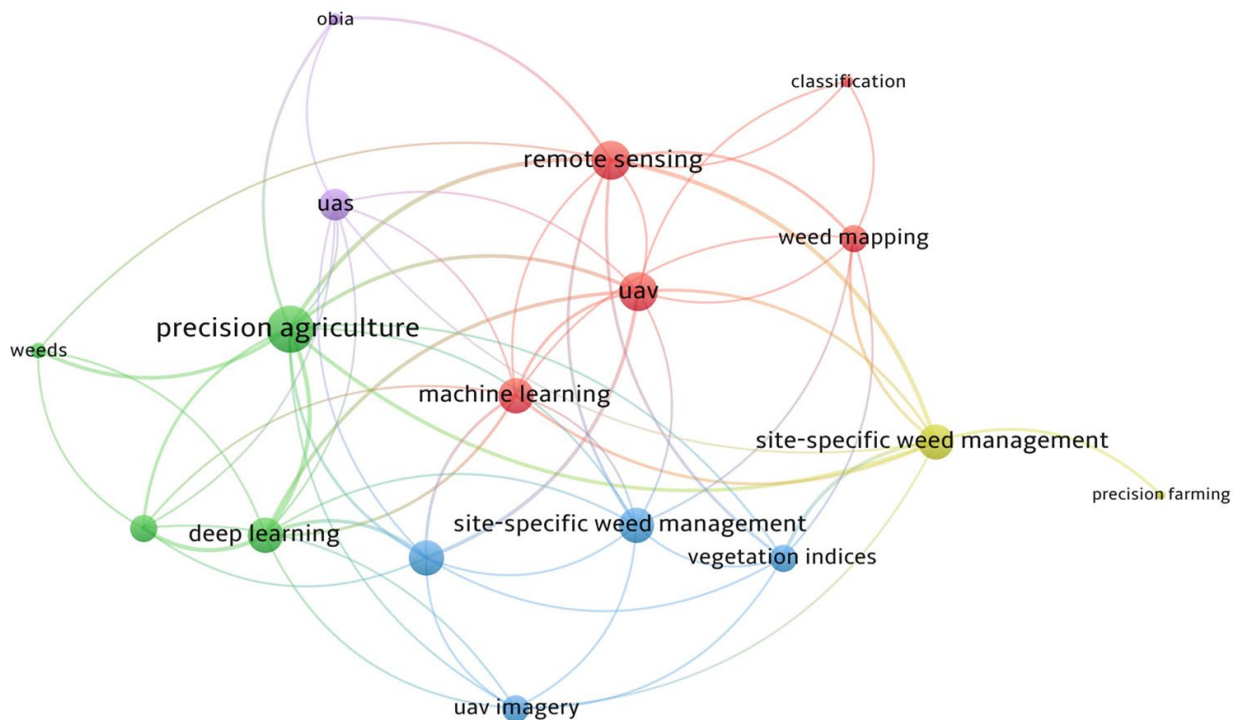


Figure 2.4 Co-occurrence network of author keywords

2.3.2 Key attributes

2.3.2.1 Remote sensing technologies

Satellites, MAVs, and UAVs have all been utilized to collect data to aid in weed detection for PWM applications. The earliest reported study by López-Granados et al. (2006) involved the acquisition of aerial imagery in southern Spain over a winter wheat crop with natural weed infestations using an MAV. MAVs featured almost exclusively during the formative years of this particular research focus area (Figure 2.5). However, as UAV technologies began to emerge, they quickly dominated this research space and have remained the preferred platform for weed detection to facilitate PWM.

This may be due to the unique characteristics of UAVs and their associated sensors that enable them to acquire very-high-spatial-resolution data at user-defined intervals in near-real time for most weather (Esposito Crimaldi et al., 2021; Roslim et al., 2021). UAVs further possess fewer limitations imposed by weather conditions, with the ability to fly even on cloudy days; greater flexibility in acquisition scheduling and payload options; reduced costs of vehicles and sensors; and access to difficult-to-reach areas, amongst others (Torres-Sánchez et al., 2014; Stroppiana et al., 2018). The spatial resolution of the satellite sensors (Quickbird and Sentinel-2) used in various studies ranged from 2.4 to 10 m, whereas the spatial resolution of the sensors onboard MAVs ranged from 0.12 to 0.30 m. Although acceptable-to-good accuracies were attained at these spatial resolutions, detecting and differentiating weeds from crops necessitates very-high-spatial-resolution imagery (Mohidem et al., 2021; Roslim et al., 2021). UAVs are typically equipped with sensors that can provide images with centimeter-to-sub-centimeter spatial resolution. Furthermore, the added flexibility of easily flying at various altitudes allows for optimizing flight planning and data capturing at the most appropriate spatial resolution (Mohidem et al., 2021; Roslim et al., 2021).

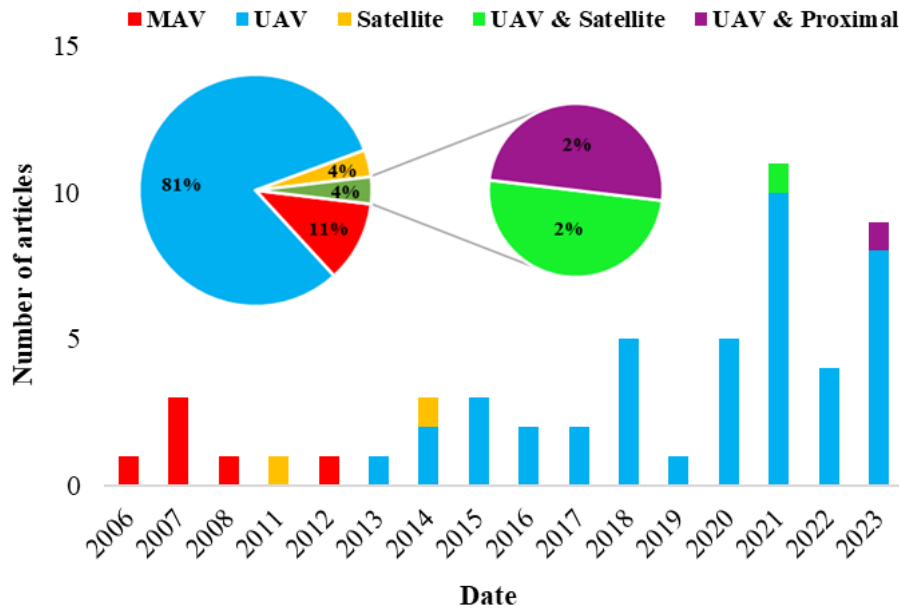


Figure 2.5 Historical evolution and percentage contribution of articles per sensing platform

While very-high-spatial-resolution imagery is paramount to accurately detect weeds, the spectral resolution of the imaging sensor is equally important, as it influences the ability to differentiate between weeds and crops based on their unique spectral properties (Mohidem et al., 2021). Several types of sensors can be used for RS-based PWM applications, of which RGB and multispectral sensors feature most prominently. RGB sensors are among the most popular and widely utilized sensors as they provide high-quality images, can be used for several applications, are relatively inexpensive, possess minimal operational requirements, and do not require radiometric and atmospheric corrections (Mohidem et al., 2021; Roslim et al., 2021). While multi-spectral sensors are accompanied by, *inter alia*, higher costs and additional image processing requirements, their use remains quite popular due to their ability to acquire information across more than three bands (RGB), allowing for a wider range of potential applications beyond crop and weed mapping (Mohidem et al., 2021; Rosle et al., 2021).

2.3.2.2 Algorithms and Methodologies

Machine-learning (ML)-based approaches have been widely used to detect and differentiate weeds from crops. These approaches typically involve the use of nonparametric methods to identify and learn complex relationships between target (e.g., weeds) and predictor (e.g., spectral bands, indices, or physical characteristics) variables (Bahrami et al., 2022). In most instances, all spectral bands captured by a sensor will be used as predictor variables when training and applying a classification algorithm. However, the sensor type and classification approach influence the choice of spectrally derived indices or physical characteristics that may be used. For RGB sensors, simple ratios between the RGB bands, excess green (ExG), excess red (ExR), excess green–red (ExGR), color index of vegetation (CIVE), shape, texture, and canopy height are often used. While many of the aforementioned predictor variables are also used for multi-spectral sensors, some of the commonly used multi-spectral-specific indices include the normalized difference vegetation index (NDVI), ratio vegetation index (RVI), normalized green–red difference index (NGRDI), soil adjusted vegetation index (SAVI), and near–infrared–green ratio (NIRG).

Several machine-learning-based algorithms have been used to detect and map weeds (Mohidem et al., 2021), with the random forest algorithm being the most extensively applied. According to Bahrami et al. (2022), this may potentially be due to (i) the robust nature of the algorithm, (ii) its ability to

perform efficiently even on large volumes of data, (iii) it uses relatively few hyperparameters, and (iv) is less sensitive to noise and overfitting. In addition to the choice of predictor variables and classification algorithms, another important factor to consider when detecting and differentiating weeds from crops is the classification approach, i.e., pixel- or object-based.

Pixel-based (PB) approaches have traditionally been the go-to method for land cover classification studies and involve using the attributes of individual pixels to perform a classification (De Giglio et al., 2019; Tassi et al., 2021). This approach is appropriate when the spatial resolution of the pixel is similar in size to the object that is being classified. However, with very-high-resolution imagery such as that used for crop and weed mapping, the size of the pixels can be significantly smaller than the object being classified. It may lead to greater classification inaccuracies (Whiteside et al., 2011). Object-based methods overcome this limitation by performing a pre-classification, whereby a segmentation algorithm is used to generate objects by grouping pixels based on their spectral properties, shape, size, or texture. The attributes of these objects are then used to perform a classification (De Giglio et al., 2019; Tassi et al., 2021). Although object-based methods overcome some of the limitations associated with pixel-based approaches, they do possess limitations of their own, such as the impact of the choice of segmentation algorithm, over- or under-segmentation, and computational effort that is required (Liu and Xia, 2010; Tassi et al., 2021). Subsequently, the strengths and limitations of each of these approaches will need to be considered before deciding which method to adopt. However, pixel- and object-based approaches have been shown to perform well for crop and weed mapping (Castillejo-González et al., 2014; Torres-Sánchez et al., 2022; El Immani et al., 2023).

DL is a subset of ML that has also featured quite prominently in weed mapping studies and has often produced superior results to traditional ML-based approaches (Rosle et al., 2021). DL is centered on a far more complex image analysis process whereby meaningful features are automatically extracted from the raw input data, requiring relatively limited user input to develop, train, and evaluate the model to perform classifications. DL models for weed mapping are usually based on some form of convolutional neural network (CNN), with the most popular example among the reviewed studies being the YOLO model (Ettiene et al., 2021; Dutta et al., 2022; Ajayi et al., 2023; Gallo et al., 2023). Despite their ability to produce highly accurate results and requiring relatively minimal user intervention, these models are complex, computationally demanding, and data-intensive, which may limit their feasibility for widespread crop and weed mapping applications.

2.3.2.3 Studies on Crops Association with Weeds

The geographic distribution and frequency of studies by country are shown in Figure 2.6. Research on the use of RS data to aid in detecting and mapping weeds for PWM applications has been conducted in 18 countries, with Spain being the leading nation in this research focus area. Most of this research has been conducted in European nations, accounting for approximately 70% of the studies undertaken globally. Contrastingly, limited studies have been conducted within nations that form part of the Global South. Regarding the detection and mapping of weeds among crops, crops that have featured most frequently (Figure 2.7) in the reviewed studies were wheat ($n = 13$), sunflower ($n = 8$), and maize ($n = 7$). This is potentially due to their status as major grain and oilseed crops. Consequently, these crops generally attract greater interest as the impacts of weeds can significantly affect global grain and oilseed supplies, which in turn threatens food security.

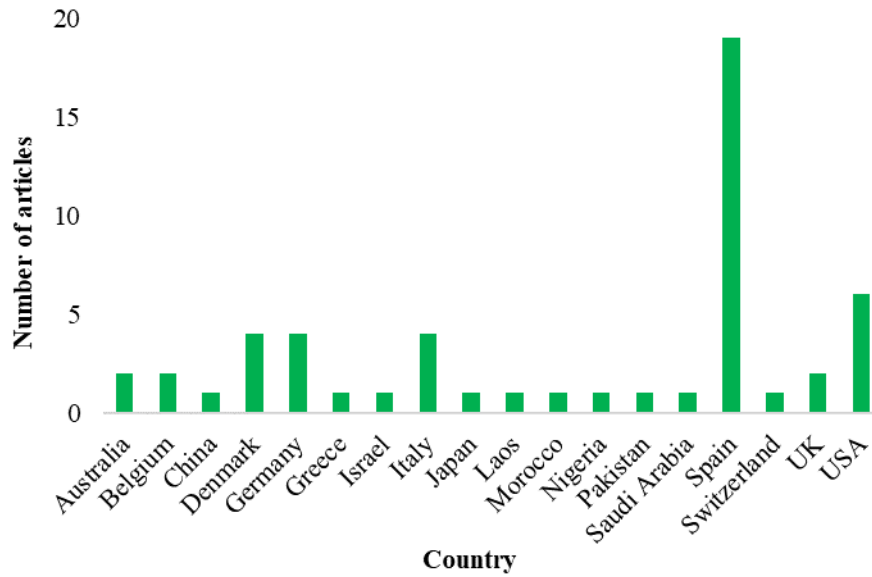


Figure 2.6 Geographical distribution and frequency of studies by country

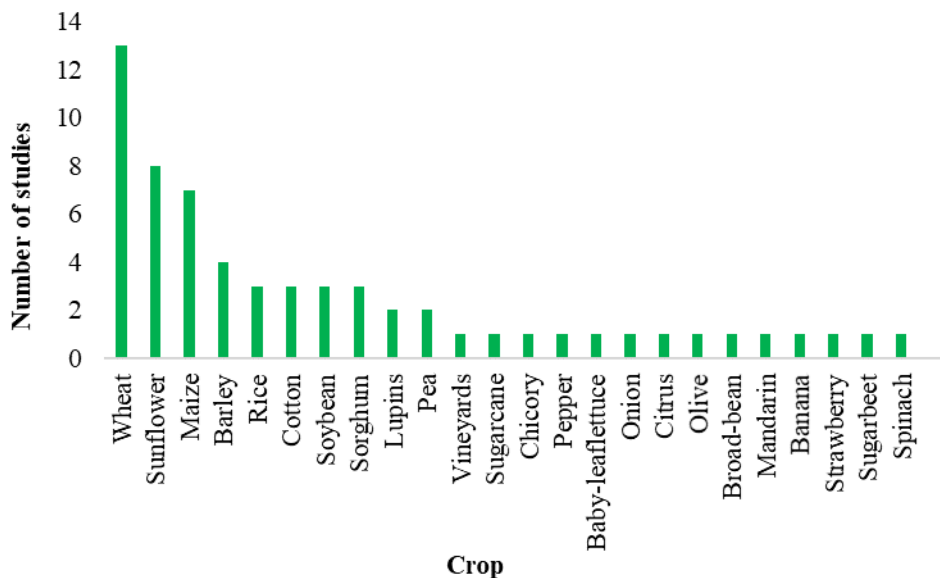


Figure 2.7 Number of articles per crop type

2.4 Discussion

To our knowledge, there has been no standard approach for systematically identifying an RS platform and considering sensor characteristics and data analysis procedures to facilitate PWM for smallholder agriculture. The information presented in the results section is extracted and synthesized from 53 studies published in various journals. This review highlights RS approaches as the focus of most of the studies discriminating weeds from cultivated systems, which are also considered one of the most important technologies for PA (López-Granados et al., 2006). In past decades, MAVs and satellites were used to capture images for PA applications (Huang et al., 2018). However, satellites and MAVs may be less attractive for widespread PWM applications (Huang et al., 2018; Mohidem et al., 2021), particularly in smallholder farm settings.

Considering the often fragmented and heterogeneous nature of smallholder farming systems, freely available satellite earth observation datasets are generally unsuitable for these environments due to the spatial, spectral, and temporal trade-offs that are characteristic of these datasets (McCarthy et al., 2023). In addition, the large cost implications of more advanced satellite and manned aerial systems render these options unfeasible for many of these farmers (Huang et al., 2018; Mohidem et al., 2021). The unique characteristics offered by UAVs, such as their ability to provide cost-effective spatially representative data at user-defined intervals, have seen this technology emerge as an important tool to facilitate PA applications such as PWM and are promising for smallholder farm applications (Torres-Sánchez et al., 2014; Gao et al., 2018; Huang et al., 2018; Stroppiana et al., 2018; Singh et al., 2020; Esposito Crimaldi et al., 2021; Kawamura et al., 2021; Mohidem et al., 2021; Roslim et al., 2021; Gokool et al., 2023).

As previously indicated in Section 2.3, very-high-spatial-resolution imagery is preferential to accurately detect and map weeds (Esposito Crimaldi et al., 2021; Mohidem et al., 2021), which restricts the types of sensors and RS platforms suitable for this task (Fernández-Quintanilla et al., 2018). While several sensors exist, of which RGB and multi-spectral sensors feature more prominently than others, UAV-mounted RGB sensors remain the most widely used sensor for PWM (Esposito Crimaldi et al., 2021; Mohidem et al., 2021). Although the purchase of UAVs and associated ancillary resources requires a substantial upfront investment, it provides higher-resolution images compared to other RS systems. Furthermore, this initial investment is compensated by the repeatability of flights, which increases the frequency of derived datasets, thus minimizing the costs of labour and critical resources. Additionally, UAVs equipped with a relatively cheap RGB sensor may represent the most feasible option for smallholder farmers concerned with PWM applications, since images from these sensors require less additional processing, which reduces the need for purchasing additional processing software, thereby reducing overall operational costs (Rosle et al., 2021).

A variety of classification methods can be implemented to detect and map weeds using UAV imagery and can be performed using proprietary or open-source software. Recently, ML algorithms implemented within cloud computing environments are being implemented more frequently as they offer many advantages over traditional methods, particularly for processing and analyzing large complex datasets (Bahrami et al., 2022). Furthermore, with cloud-based platforms such as Google Earth Engine (GEE) being freely available and easily accessible, many of the barriers that have restricted users (particularly those in developing countries) from exploiting technological advancements to guide agricultural operations have now been removed (Torres-Sánchez et al., 2022). While the availability and accessibility of such a powerful data processing platform have opened up many new and exciting avenues to a wide range of users interested in utilizing RS to guide and inform PA applications, users will require good internet connectivity. They may also be restricted with regards to (i) the amount of data that can be stored and processed, as well as by (ii) the choice of techniques that are available to them (Navarro, 2017). For example, users can only choose from selected ML algorithms when performing image classifications within the platform.

Similarly, while DL has shown a great deal of promise for producing very accurate maps, these techniques are not directly available within GEE. Furthermore, when considering other major limitations of these techniques for weed detection, such as computational resources and large datasets for training that are expensive and time-consuming to acquire, as well as the specialized skills required to implement them, these requirements typically limit their application for smallholder farmers (Huang et al., 2018; Rosle et al., 2021; Sapkota et al., 2022; Xu et al., 2022; Gallo et al., 2023). Subsequently, users interested in adopting these approaches will require high-powered computational resources and a large volume of data to successfully implement these techniques; neither are readily available nor easily accessible in resource-constrained regions.

According to the geographic distribution and frequency of studies (Figure 2.6), using RS for weed management is mainly concentrated in the Global North (Hunter et al., 2022). Considering that the demand for agricultural products will increase globally, owing to the rapidly growing population and rising incomes, and since a majority of food is also produced within SSA, research to determine cost-effective ways of maximizing the use of technologies like UAVs for use in the Global South is equally crucial and required.

While past studies mainly focused on three major food staples, namely wheat, sunflower and maize, a need to diversify our agri-food systems with more climate-resilient and nutrient-rich crops. In this regard, NUCs can complement the cultivation of staple crops, along with the potential to improve the sustainability and resilience of food systems, which in turn can enhance food and nutrition security (Mabhaudhi et al., 2017a; Mabhaudhi et al., 2019). Furthermore, with the cultivation of NUCs mainly being confined to smallholder farms, there exists an opportunity to improve the socio-economic circumstances of poverty-stricken and marginalized smallholder communities and improve food sovereignty by enabling smallholder farmers to exert a greater influence in food production systems (Chivenge et al., 2015; Mabhaudhi et al., 2017a; Mabhaudhi et al., 2019). Subsequently, research on PWM using UAVs for NUC and weed combinations is required, with techniques and findings from studies conducted on major crops used as guides. Considering the limited literature on the use of UAVs for weed detection within smallholder farms and on NUCs, a review of such calibre was both necessary and important to undertake.

Studies conducted on crop-weed competition using UAVs were mainly limited to assessing crop yield losses, overlooking the significant uptake of soil water by weeds, which also threatens crop productivity and exceeds the global water constraints (Singh et al., 2022). Since farming is not solely driven by yield and considering the global threats of climate change, environmental degradation, and an ever-growing population exerting pressure on over-constrained water resources, the water use of weeds also represents a critical component of assessing and managing weeds in the agricultural sector (Singh et al., 2022). For example, several smallholder farms in SSA are reliant on rainfed irrigation and challenged by water scarcity concerns. Therefore, if weeds are not properly managed, or their water use is not adequately accounted for, weeds may deprive crops of an already limited water supply, which can eventually result in lower crop productivity (Biazin et al., 2012). Furthermore, insufficient rainfall during crop production periods and periods of dry spells could lead to food insecurity issues. Hence, in addition to crop yield and crop status monitoring, research on the use of UAV technologies for water use estimation is required, given that these technologies possess the capabilities for several applications, including water use applications.

With the development of UAVs, monitoring both early- and late-season weeds provides unprecedented opportunities for cost-effective near-real-time mapping with high spatial, spectral, and temporal resolutions (López-Granados, 2011). Early-season weed monitoring is generally found to be more suitable and preferred for weed identification as it is critical for safeguarding the productivity of the growing crop, as weeds compete with the crop for a longer period and can cause higher yield losses if allowed to produce seed (Dobbs et al., 2022; Anderegg et al., 2023). This is particularly true for an NUC crop such as taro, which can take up to 49 days to emerge (Mabhaudhi, 2012). Furthermore, taro is relatively slow-growing, taking up to 300 days to reach physiological maturity. Hence, it is important to keep the site weed-free. Furthermore, performing early discrimination of the types of weeds growing in the crop field provides the added advantage of selecting the correct type of herbicide treatment to be applied, thus avoiding using a wide-spectrum herbicide (Torres-Sánchez et al., 2022). For smallholder farmers, this could result in reduced costs, and given that manual weed removal is often practiced, it presents the best time to manage weeds, as they are easier to control (Xu et al., 2023).

Compared to early-season weeds, late-season weeds do not directly affect crop yield as they do not compete for resources during the crop's critical growth stage (Sivakumar et al., 2020). However, weeds that survive early weed management methods due to herbicide resistance or incorrect herbicide selection or application can persist, thus resulting in a higher weed seedbank that affects subsequent growing seasons (López-Granados, 2011; Sivakumar et al., 2020; Rozenberg et al., 2021; Dobbs et al., 2022; Rai et al., 2023). Therefore, mapping of late-season weeds can provide information for developing long-term weed management strategies and for farmers to evaluate the efficiency of their previous weed control methods (Sivakumar et al., 2020; Rozenberg et al., 2021). For smallholder farmers, these late-season weed maps can be useful in reducing herbicide use and crop management costs. Considering the merits of mapping both early- and late-season weeds for smallholder farmers, the two approaches can complement each other, with a useful application being to combine them to determine the effectiveness of the management decisions made in such farm settings.

Despite the economic and environmental advantages that PA techniques can potentially bring, adopting geospatial information technologies is lagging in the developing world, with the biggest gap in PA adoption for smallholder farms (Mattivi et al., 2021). The hesitancy of these farmers is due to feasibility considerations, being less high-tech-oriented, and the high initial investment costs, and they still prefer traditional practices that are no longer practical (Mattivi et al., 2021). Consequently, it is very important to develop cost-effective tools and utilize open-source software where possible to address the specific issues faced in such countries, and thus its adoption worldwide, especially in weed management, to control and increase yield production, leading to a better economy for the country and farmers. While UAV technology may remain unaffordable for many small-scale farmers, specialists can leverage innovative UAV-based business enterprises to offer a more affordable option where the investment cost is shared across multiple farms by a UAV service provider (UNDP, 2021).

Other key barriers that have not been identified through the bibliometric and attribute analysis but will significantly influence the adoption of UAV technologies by smallholder farmers include a lack of awareness and digital skills among farmers, requiring co-learning and participatory approaches among the public and private sectors, civil society, and academia (Navarro, 2017; UNDP, 2021). The public and private sectors can partner with non-governmental organizations and leverage their on-ground presence (e.g., agricultural extension workers) for delivering hands-on training, building digital capacities of farmers (UNDP, 2021), and creating decision support systems that offer advisory services to the farmers. Further addressing these barriers requires creating solutions within a user-centered framework that accounts for local contexts, such as language and societal barriers, and enabling policies to support the digitalization of the sector. For example, with supportive policy frameworks and subsidies for purchasing UAV models, China has become one of the most UAV-friendly countries, possessing over 50,000 agricultural drones in operation (UNDP, 2021). Considering these favourable policies and technological support mechanisms, it is envisaged that at least 80% of the future UAV market will be in the PA segment (UNDP, 2021).

2.5 Conclusion

Neglected and underutilised crops (NUCs) have considerable potential to address food and nutrition insecurity, particularly in smallholder farming systems, due to their adaptability to low-input agriculture, high nutrient density, and resilience to biotic and abiotic stresses. Given that approximately 80% of food production in Asia and sub-Saharan Africa is generated by smallholder farmers, and that NUCs often constitute the primary food sources for these populations, there is a pressing need to support smallholder farmers in achieving higher productivity and improved crop quality.

However, poor weed management remains a major constraint to achieving desirable yields and quality in NUC production. Conventional weed control techniques are often unfavourable due to cost, labour intensity, and potential environmental harm. PWM, therefore, offers an alternative approach, combining multiple control strategies to reduce reliance on chemical inputs and improve sustainability—particularly in smallholder contexts.

The literature review identified several key findings that directly inform this study. First, PWM has been shown to enhance weed detection accuracy and improve resource-use efficiency compared to traditional blanket management, especially when high-resolution UAV imagery is used. Vegetation indices such as NDVI and NDRE, along with texture-based metrics, have been effective in distinguishing crops from weeds under controlled conditions.

Second, the majority of PWM research has focused on large-scale commercial farming systems in developed regions, with limited application in the smallholder and mixed-cropping environments typical of sub-Saharan Africa. Studies addressing NUCs such as taro are particularly scarce, highlighting a significant research gap.

Third, although UAV-based PWM demonstrates strong technical potential, few studies integrate weed management outcomes with crop water use or evapotranspiration dynamics. This represents a critical knowledge gap, particularly for smallholder systems where water availability and efficiency are central concerns.

These gaps underscore the need for an integrated PWM framework that combines high-resolution UAV imagery, vegetation indices, and water-use analysis within smallholder taro systems. This study, therefore, aims to address these gaps by developing and evaluating a UAV-based PWM approach tailored to smallholder taro production, contributing to improved weed management, water-use efficiency, and overall crop productivity. The findings of this literature review guided the selection of remote sensing data, vegetation indices, and analytical methods used in the methodology presented in Chapter 3. Moreover, the identified research gaps—particularly the limited application of PWM in smallholder NUC systems—directly motivated the field trials and technical procedures described in Chapter 3.

3. ASSESSING WEED MAPPING TECHNIQUES FOR PRECISION MANAGEMENT IN A SMALLHOLDER FARMING CONTEXT USING UAV MULTISPECTRAL IMAGERY AND GEOSPATIAL CLOUD COMPUTING

3.1 Introduction

To address the research gaps identified in the preceding literature review, this chapter operationalizes PWM by testing various UAV-based classification algorithms within the specific context of a smallholder taro farm.

Selecting the appropriate supervised classification algorithm is crucial for producing reliable crop-weed interaction maps. There are two main approaches commonly used in image processing: the traditional pixel-based image classification (PBIC) and the more recent object-based image classification (OBIC) (Liu and Xia, 2010; Liu and Abd-Elrahman, 2018; Šiljeg et al., 2022). PBIC uses individual pixels to identify each class, while the OBIC utilizes segmentation and textural properties to group pixels that represent an object based on its spatial, spectral and geometric properties (Tassi and Vizzari, 2020). Although this approach is associated with producing higher classification accuracies, it introduces a degree of complexity. ML and DL models are typically used to train and validate the supervised classification algorithms. Common ML classifiers include maximum likelihood, random forest (RF), support vector machine (SVM), gradient tree boost (GTB), and classification and regression tree (CART) (Tassi and Vizzari, 2020; Qu et al., 2021; Técher, 2022). Although there are many DL packages that have been developed over the years, convolution neural networks (CNNs) and YOLO are among some of the most popular ones (Gallo et al., 2023; Xing et al., 2024). Generating a reliable classification algorithm is time-consuming and often requires computation efficiency and an experienced user (Sattar et al., 2024). These challenges often hinder the development of classification algorithms with many input features, especially in areas with limited resources.

In recent years, Google Earth Engine (GEE), a cloud-based open source platform, has demonstrated the potential of addressing these challenges by simplifying workflows using JavaScript, enabling automation of repetitive tasks that require multiple functions and iterative processes to improve algorithm performance (Mutanga and Kumar, 2019; Ghosh et al., 2022; Yang et al., 2022). The environment also enables the adoption of workflows generated by other developers for similar investigations. Although many GEE-based studies have focused on long-term satellite image collections (e.g. Landsat 8-9 and Sentinel-2) at regional and national scales. Very few studies have used UAV imagery and the cloud-based platform at local spatial scales (Tassi and Vizzari, 2020; Qu et al., 2021; Yang et al., 2022). Drawing on the key findings and identified gaps from the literature reviewed in Chapter 2, this chapter outlines the study area, data collection procedures, and analytical methods used to assess PWM in taro systems.

Considering the challenges of distinguishing weeds from taro in smallholder fields and the potential of UAV imagery and GEE for PA, this study aimed to develop a pragmatic cloud-based supervised classification algorithm capable of producing reliable weed distribution maps to support PWM. To achieve this aim, the study had three objectives: (1) to identify the most suitable mapping algorithm between PBIC and OBIC; (2) to evaluate the performance of classifiers available in GEE, including SVM, RF, CART, and GTB; and (3) to assess the effect of training point datasets on classification performance during different growth phases.

3.2 Materials and Methods

3.2.1 Study site description

This study was conducted in Swayimane, a rural community situated 56 km northeast of Pietermaritzburg within the uMshwathi Local Municipality (29°31'33.2"S; 30°41'51.8"E) in KwaZulu-Natal, South Africa (Figure 3.1). This community has a population of approximately 6856 (53% females), of which many families in Swayimane are mainly reliant on subsistence farming to support their livelihoods (Mthethwa et al., 2022). Over the years, the community has built strong relations with active agricultural organizations that have been assisting them by encouraging farmers to adopt sustainable farming practices through the sharing of research findings. The area receives a mean annual precipitation that ranges between 600 and 1200 mm, with an elevation of approximately 840 meters above sea level (asl) (Brewer et al., 2022). Among commercially viable crops like maize and sugarcane, the community is also known for growing NUCs, such as taro and sweet potato (Ndlovu et al., 2021; Thothela et al., 2023). Since the majority of the agricultural land in this community is rainfed, the majority of the farming occurs during the summer rainfall period (October to February) (Mthethwa, 2023). The boundaries of the study site were demarcated to cover an area of approximately 2,276 m². The site consisted of three plots: (1) a weeded plot, where weeding was conducted biweekly; (2) an unweeded plot, where no weeding was carried out throughout the growing season; and (3) an intermediate plot, where the farmer employed multiple weed control methods including cattle cultivation, herbicide application, and manual labor using hoes during the first three months of the growing season, as depicted in Figure 3.1.

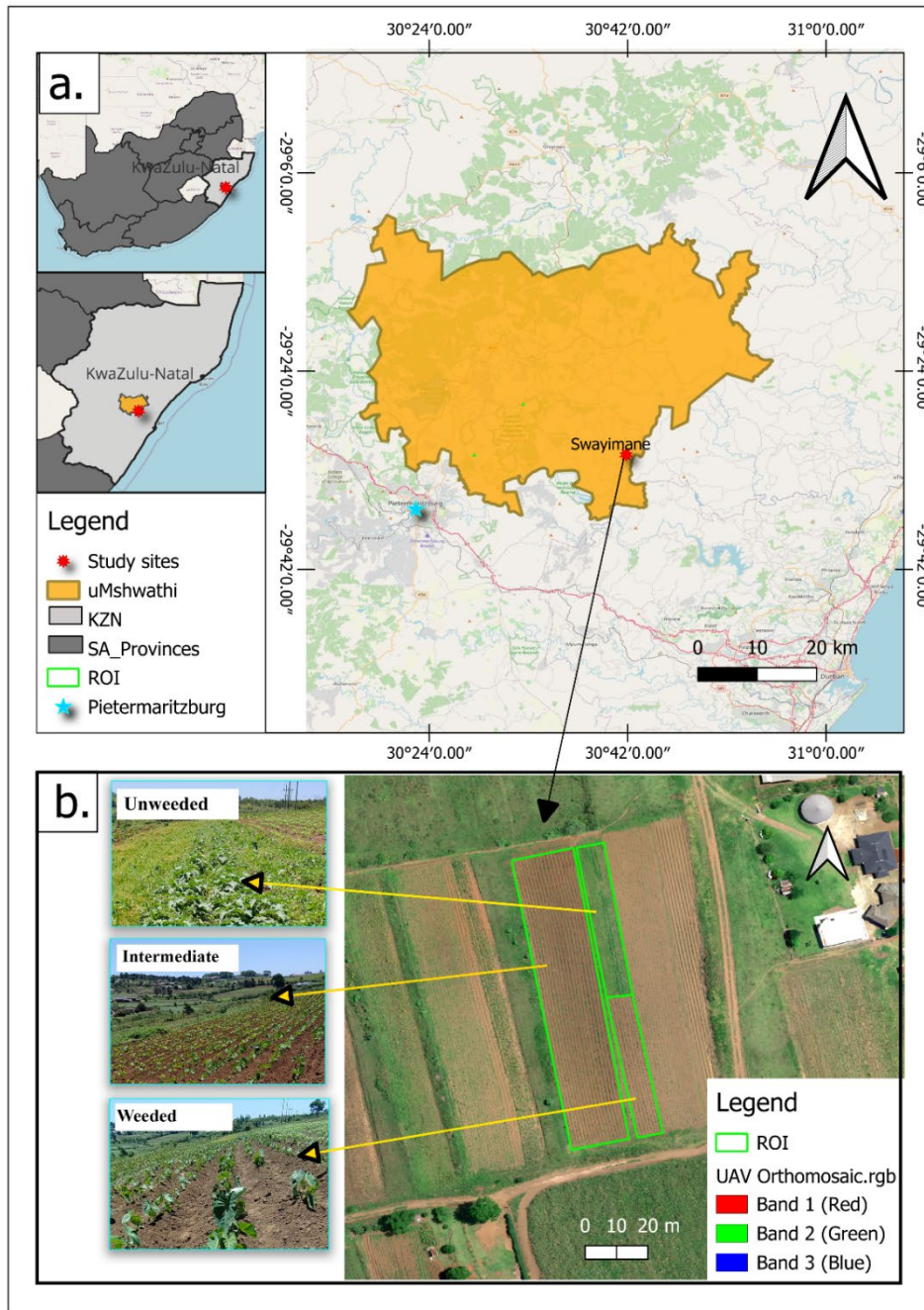


Figure 3.1 Study area location showing (a) the study site in Swayimane, and (b) the boundary demarcations of the taro plots. The RGB UAV image was captured on November 22, 2023.

3.2.2 Field design of the different weed management practices

The characteristics of the taro grown in this study matched those of the landrace referred to as Umbumbulu by Mabhaudhi and Modi (2013) (Figure 3.2a). Bulbs in the intermediate field were sown on September 4th, 2023, while the weeded and unweeded plot was planted 18 days after (September 22nd, 2023). The inter-row spacing was approximately 1 m, while the average distance between each crop in a row was 0.5 m, i.e., 20,000 planta ha⁻¹ (Fig. 3.2.b).



Figure 3.2 This illustration shows the Umbumbulu taro landrace, depicting (a) the field before the bulbs were sown and (b) the crop two months after sowing

The herbicide (farmag paraquat 200) was applied in the intermediate field on October 15th, 2023, using a knapsack spray. The first round of hand weeding took place on November 10th, 2023, which was three weeks after emergence, and this management practice was implemented every fortnight, throughout the growing season. The crops were in the field for approximately seven months and harvesting took place on April 15th, 2024.

3.2.3 Methodology

This section provides a detailed description of the steps that were followed to determine the best-performing supervised classification algorithm that can provide reliable weed distribution maps for smallholder farms.

3.2.3.1 Acquisition and processing of imagery

All the images utilized in this study were captured by a MicaSense Altum camera with a Downwelling Light Sensor 2 (DLS-2) mounted on a DJI Matrice 300 (DJI-M-300) UAV (Figure 3.3. a). The DJI-M-300 platform was configured to capture imagery at an altitude of 100 m, with a ground sampling distance (GSD) of 0.07 m. The camera is equipped with 6 spectral bands as highlighted in Table 3.1. Before flying the UAV, the boundaries of the region of interest (ROI) were demarcated using Google Earth Pro and imported as a keyhole markup language (KML) file into the DJI smart controller for flight planning (Figure 3.3 b). The MicaSense Altum camera had to be calibrated before and after each flight to ensure accurate reflectance values by accounting for the prevailing light conditions during image acquisition at the site (Figure 3.3c). The sensor was configured with a 70% side overlap and a frontal overlap of 80%, which are considered for minimizing geometric distortions (caused by environmental conditions such as wind, which can affect the sensor's stability, and variation in surface illumination due to terrain and aspect) and ensuring complete image coverage for accurate mosaicking and analysis. Images were acquired fortnightly on clear sky days during periods of optimal solar irradiance (between 10:00 a.m. and 12:00 p.m. South African Standard Time (SAST) throughout the growing season.

The scenes were captured under consistent lighting conditions and at low altitudes typical of UAVs flights (100 m), where atmospheric interference is minimal and often negligible. The Pix4D fields (version 2.4.3) Software was used to stitch all images captured by the UAV after each flight.

Corrections were applied during pre-processing using the software by selecting settings that account for weather conditions (clear sky or overcast) during the time of image acquisition. This was based on the protocol that has been followed by other published authors (Brewer et al., 2022; Gokool et al., 2023). An orthomosaic GEOTIFF image was generated as an output file. Ground truth data of the ROI boundaries were captured using a Trimble Juno handheld GPS (Global Positioning System) device with a sub-meter differential correction accuracy. To ensure all the stitched images are aligned and to account for potential errors introduced by minor shifts during preprocessing. The stitched image was imported into QGIS (desktop version 3.42.2) software to assess alignment with ground truth data. All the data layers were georeferenced using the WGS_1984_UTM_36S projection coordinate system. Following the pre-processing, image orthomosaics were subsequently uploaded into the GEE environment as GeoTiffs for further analysis.



Figure 3.3 UAV image acquisition equipment: (a) the DJI Matrice 300 drone alongside a calibration reflectance panel, (b) the DJI smart controller displaying the flight plan, and (c) the MicaSense Altum camera

A script was developed in the GEE code editor to (i) import and generate all the necessary inputs, (ii) create the image classification models using the PBIC and OBIC techniques and (iii) assess the performance of the algorithms. All the UAV images that were captured were then imported into GEE to create an image collection that was resampled to a spatial resolution of 7 cm. The boundaries for the 3 plots were demarcated in GEE and the training data that was used for the image classification was collected from within these boundaries.

Table 3.1 Spectral and Spatial Specifications of the MicaSense Altum camera bands

Band	Central Wavelength (nm)	Band number (m.pixel ⁻¹)
B1 - Blue	475	0.07
B2 - Green	560	0.07
B3 - Red	668	0.07
B4- Red-edge	717	0.07
B5 - Near- infrared (NIR)	842	0.07
B6 - Thermal infrared	8 000-14 000	1.09

The training datasets were generated via visual inspection (using prior knowledge acquired from multiple study site visits) due to the lack of a GPS device that had a sub-centimeter differential correction accuracy. In efforts to address the impact of training data on classification accuracy, three training datasets were generated and evaluated in the early vegetative (EV) growth phase. Each has a different number of total training points as depicted in Table 3.2.

Table 3.2 The number of training data points for each land class present in the study area

Class	Number of training points		
	Test 1	Test 2	Test 3
Taro	50	80	100
Bare soil	50	80	100
Weeds	50	80	100
Total	150	240	300

The vegetation indices (VIs) listed in Table 3.3 were derived from the images, after which all bands were combined to enhance vegetation features by increasing the spectral separability of different land cover classes while minimizing the influence of shadows and other potential sources of misclassification. Each VI applied in this study was selected to target specific plant properties:

This selection of indices, adapted from Gokool et al. (2024), was chosen to capture a comprehensive range of vegetation properties relevant for accurate land cover classification:

- NDVI (Normalized Difference Vegetation Index) enhances overall vegetation greenness and biomass.
- NDVIg (Green NDVI) improves detection of chlorophyll content in leafy vegetation.
- NDVIre (Red-Edge NDVI) is sensitive to subtle changes in chlorophyll and stress conditions.
- EVI (Enhanced Vegetation Index) corrects for atmospheric influences and canopy background signals. More sensitive to dense vegetation.
- SAVI (Soil-Adjusted Vegetation Index) minimizes soil brightness effects, especially in sparse vegetation areas.
- SNIR-R (Simple Ratio of Near-Infrared and Red) enhances vegetation reflectance differences.
- SBRE (Simple Ratio of Blue and Red-Edge) targets pigment concentrations related to plant health.
- SNIR-RE (Simple Ratio of Near-Infrared and Red-Edge) emphasizes chlorophyll absorption characteristics.
- GCI (green chlorophyll index) estimates chlorophyll content more precisely.

Table 3.3 The vegetation indices used to enhance the spectral signatures of the land cover classes in this study. This list was adapted from Gokool et al. (2024).

Data Extracted	Equation	Reference
Normalized Difference Vegetation Index (NDVI)	$\frac{NIR - Red}{NIR + Red}$	El Imanni <i>et al.</i> (2023)
Green Normalized Difference Vegetation Index (gNDVI)	$\frac{GREEN - Red}{GREEN + Red}$	Naito <i>et al.</i> (2017)
NDVI modified by red-edge bands (NDVI _{re})	$\frac{NIR - Red_{edge}}{NIR + Red_{edge}}$	Fitzgerald <i>et al.</i> (2010)
Enhanced Vegetation Index (EVI)	$2.5 * \left(\frac{NIR - Red}{NIR + 6 * Red - 7.5 * Blue + 1} \right)$	(Nouri <i>et al.</i> , 2020)
Soil Adjusted Vegetation Index (SAVI)	$1.5 * \left(\frac{NIR - Red}{NIR + Red + 0.5} \right)$	Richard <i>et al.</i> (2017); Da Silva <i>et al.</i> (2020)
Simple Ratio of NIR and Red (SNIR-R)	$\frac{NIR}{Red}$	Pepe <i>et al.</i> (2001)
Simple Ratio of Blue and Red-Edge (SBRE)	$\frac{Blue}{Red_{edge}}$	Gokool <i>et al.</i> (2024)
Simple Ratio of Near-infrared and Red-Edge (SNRE)	$\frac{NIR}{Red_{edge}}$	Sharifi and Felegari (2023)
Green Chlorophyll Index (GCI)	$\frac{NIR}{Green} - 1$	Brewer <i>et al.</i> (2022)

3.2.3.2 Classification and accuracy assessment

Within the study, there were three supervised classifications evaluated, namely: PBIC, OBIC without gray level co-occurrence matrix (GLCM), and OBIC with GLCM, as shown in Table 3.4. The PBIC simply utilized concatenated multispectral bands and vegetation indices listed in the Tables 3.1 and 3.3 (the combined bands were included across all three algorithms) to develop the training dataset. The OBIC employed the Simple Non-Iterative Clustering (SNIC) algorithm for segmentation, which was refined through iterative tuning of its parameters. The final SNIC parameters included: size (1), compactness (0.07), connectivity (4), and neighborhood size (3). The key distinction between investigations two and three (Table 3.4) is the addition of the GLCM,

which introduces textural properties to the clusters. The reason behind this distinction was to highlight the potential contribution of textural properties to enhancing classification accuracy. OBIC with textural features adopted the workflow from a similar study that was undertaken by Tassi and Vizzari (2020). Each image classification approach was tested using the ML algorithms available in GEE, namely, (i) SVM, (ii) RF, (iii) CART, and (iv) GTB. The dataset was split into 70% training and 30% validation.

The classifier performance was evaluated by generating a confusion matrix to calculate the following metrics: producer accuracy (PA), user accuracy (UA), overall accuracy (OA) and Kappa coefficient (Gu and Congalton, 2020). During the optimization process of determining a baseline classification algorithm, it was observed that tuning the classifier hyperparameters in GEE had a relatively minor contribution to improving accuracy compared to other inputs and parameters (e.g., VIs, spatial resolution, number of training data points). Therefore, the recommended values provided in GEE were used for each classification model. The rationale for this was to produce a potentially simpler and more computationally efficient workflow, which is particularly beneficial for machine-learning novices. Furthermore, it potentially avoids model overfitting and generally provides reasonable performance (Go and Park, 2024).

Table 3.4 Approaches that were adopted to determine the most reliable mapping technique

Classification Approach	Investigation number
Pixel based	1
OBIC without GLCM	2
OBIC with GLCM	3

The UAV image captured during the EV phase was used to identify the best approach. The OA and Kappa coefficient results from the three mapping techniques were assessed using datasets with different numbers of training points, and four classifiers (RF, SVM, CART and GTB) available in GEE.

The best mapping technique and the number of training data points were adopted to observe the classification accuracy in different growth phases, as shown in Table 3.5. Two trials were conducted to assess the impact of training datasets on the algorithm's performance. Trial one utilized the same training dataset that was used to identify the best image classification technique (to highlight the importance of early detection), while trial 2 used different training datasets at each growth phase (to assess the algorithm's ability to differentiate classes in dense vegetation and how the maps become unreliable when weed control methods are not implemented in time).

Table 3.5 UAV imagery acquisition dates selected to represent the different growth stages of taro at the Swayimane study site

Growth Phase	Development	Date of classified image	Months after planting
Early vegetative (EV)	Emergence after sowing	22-Nov-23	1-2
Mid vegetative (MV)	Maximum canopy cover	06-Feb-24	4-5
Late vegetative (LV)	Leaf senescence	15-Mar-24	6-8

A summarized flowchart depicting the methodology that was adopted for this study is illustrated below in Figure 3.4.

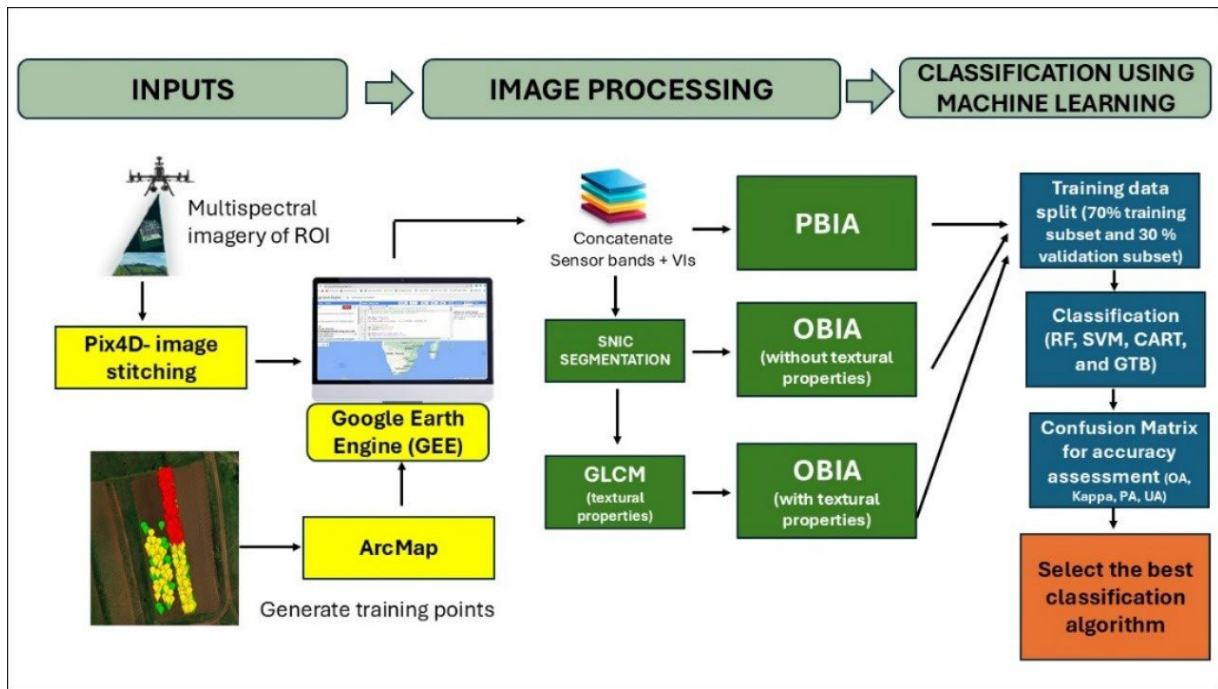


Figure 3.4 Flowchart illustrating the adopted methodology

3.3 Results

3.3.1 Analysis of image classification techniques

Based on the data obtained, it was observed that the best performing image classification technique was the object-based with GLCM, which managed to achieve an OA and kappa coefficient of 98.82% and 0.97, respectively, using the GTB classifier and 300 training data points, as shown in Table 3.6.

The classified maps in Figure 3.5 correlated with the results captured in Table 3.6. The classifiers generally performed well; most of the classification approaches achieved an OA above 80%. In our efforts to understand the influence of training datasets on the OA algorithm, a criterion to explore the relationship was established. The OA percentages highlighted in green represented instances when there was a positive correlation observed between an increase in training data points and a higher classification accuracy (150 points served as a reference baseline), and the instances where there was no correlation, the OA was highlighted in red. The percentages in bold are indicative of the best-performing classifier based on the selected training dataset. Overall, GTB and CART ranked the highest across more training datasets than the other classifiers. Both classifiers had an equal score of 5.

Table 3.6 Overall accuracy (OA) and Kappa coefficient statistic resulting from pixel-based (PB) and object-based (OB) image classification techniques at a spatial resolution of 0.07 m

Image Classification Technique	Training Dataset (points)	Classifiers							
		RF		SVM		CART		GTB	
		OA	Kappa	OA	Kappa	OA	Kappa	OA	Kappa
PB (multispectral)	150	88.64	0.83	70.45	0.56	93.18	0.90	88.64	0.83
	240	90.63	0.86	93.75	0.90	93.75	0.90	89.06	0.83
	300	88.78	0.83	88.78	0.83	91.84	0.88	93.88	0.91
OB (without GLCM)	150	89.74	0.85	79.49	0.69	89.74	0.85	87.18	0.81
	240	79.16	0.68	83.33	0.75	80.56	0.71	84.72	0.77
	300	91.17	0.87	82.35	0.73	98.52	0.97	95.58	0.93
OB (with GLCM)	150	93.18	0.90	93.18	0.90	97.72	0.97	97.72	0.97
	240	91.30	0.87	88.40	0.82	89.86	0.85	92.75	0.89
	300	95.29	0.93	83.53	0.76	95.29	0.93	98.82	0.98

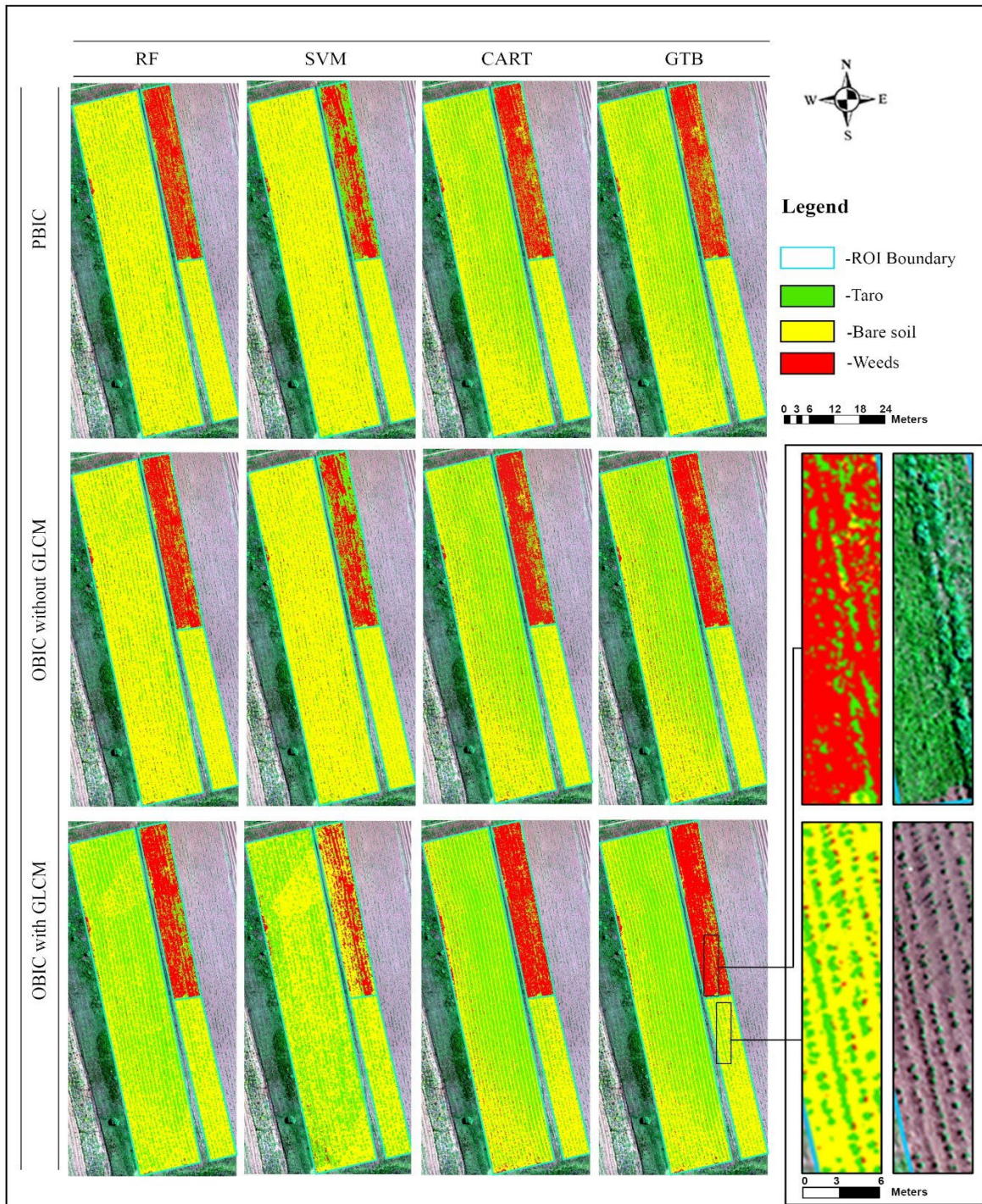


Figure 3.5 Visual representation of image classification results using different classifiers based on 300 training data points

3.3.2 Assessment of the OBIC-GLCM algorithm in different growth phases

The best-performing classification algorithm (OBIC with GLCM, using 300 training data points and the GTB classifier) was adopted and tested on three UAV images representing the different growth phases (EV, MV, and LV), as shown in Table 3.5. Two trials were conducted across the various growth stages to observe the impact of the training dataset on classification accuracy. The OBIC GLCM algorithm produced satisfactory results that agreed with the expected outcomes in both trials.

The OA in trial one was 98.82%, 43.10%, and 60.26% for the respective EV, MV and late vegetative (LV) stages. However, trial two had an excellent performance of 98.82%, 95.50%, and 92.68% during the same growth phases. In instances when weeds dominated the canopy cover, the underlying crop was obscured, making the map unreliable for studies requiring detailed information on crop development.

The classified maps supported by the images in Figure 3.6 were able to provide a more detailed overview of the land cover changes in the three plots. During the EV growth phase, the canopy cover of taro in the intermediate field was larger than that of the weeded field because the crop had more time to develop (it was sown earlier). Unlike the unweeded field, which had dense vegetation throughout the growing season. There was a significant increase in canopy cover (the maximum cover was during the MV stage) of taro as the crop matured in the weeded field, compared to the intermediate field, which was starting to increase in weed pressure because the farmer had stopped applying weed control practices. These findings in trial one highlight the importance of early weed detection. The decrease in classification accuracy throughout the season indicates that the maps become unreliable over time. They are more effective at identifying weeds during the EV growth phase.

Table 3.7 Performance metrics for the UAV imagery captured during the different growth stages of taro at the Swayimane study site using the best performing classification algorithm (OBIC with GLCM, GTB, and 300 training points)

Trial 1	Growth Phases					
	Early Vegetative		Mid Vegetative		Late Vegetative	
	OA (%)	Kappa	OA (%)	Kappa	OA (%)	Kappa
	98.82	0.98	43.10	0.16	60.26	0.40
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Taro	100.00	96.55	31.42	50.00	48.15	46.64
Bare Soil	100.00	100.00	34.37	36.64	48.00	48.00
Weeds	96.77	100.00	69.23	43.90	84.62	88.00
Trial 2	OA (%)	Kappa	OA (%)	Kappa	OA (%)	Kappa
	98.82	0.98	95.50	0.93	92.68	0.89
	PA (%)	UA (%)	PA (%)	UA (%)	PA (%)	UA (%)
Taro	100.00	96.55	93.10	96.43	90.00	93.10
Bare Soil	100.00	100.00	100.00	97.05	96.00	96.00
Weeds	96.77	100.00	92.59	92.59	92.59	89.29

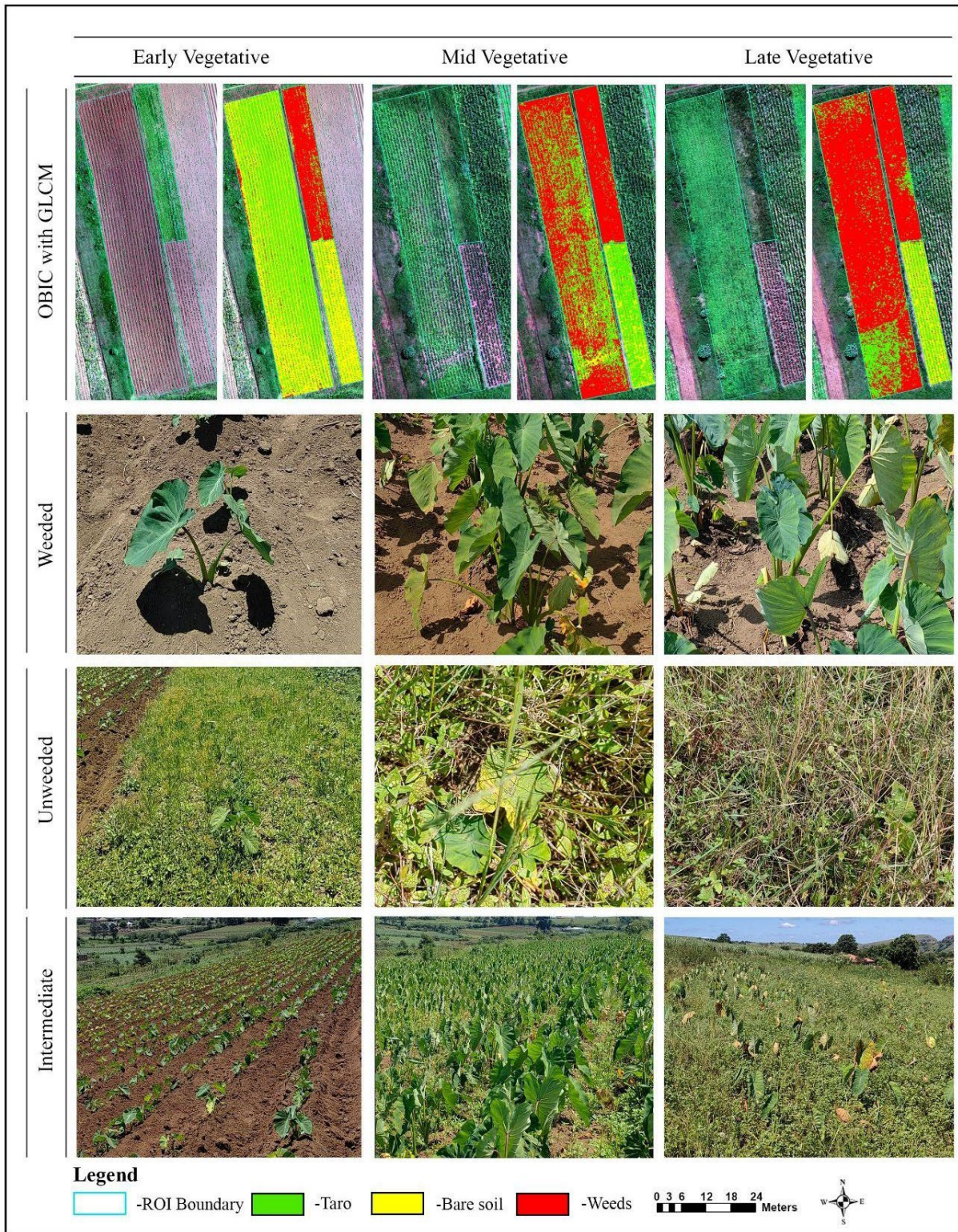


Figure 3.6 Visualization of the best-performing algorithm applied to taro fields at the Swayimane study site under different weed management practices across growth stages from 22 November 2023 to 15 March 2024

3.4 Discussion

3.4.1 Performance of the image classification algorithms

In recent years, the realm of RS has evolved quite significantly. The acquisition of high spatial resolution imagery from multispectral UAVs has improved the amount of data that can be extracted for various applications (El Imanni et al., 2023). This RS advancement, in conjunction with cloud computing platforms such as GEE, has enabled the possibility of exploring complex image classification techniques and processes that would require a lot of time and high-end computational capacity (Pham et al., 2023). This integration of RS and IoT in agriculture has the potential to bridge the gap between researchers and farmers.

The OBIC with GLCM using the GTB classifier emerged as the best-performing classification algorithm in this study, achieving an overall accuracy (OA) of 98.82%. This result aligns with the findings of Tassi and Vizzari (2020), who applied a similar workflow to classify satellite imagery from Landsat 8, Sentinel-2, and PlanetScope. They noted that while PBIC was more effective with medium-resolution imagery (e.g., Landsat 8), OBIC significantly enhanced the classification accuracy of high-resolution sensors, particularly PlanetScope (3 m spatial resolution). In their study, textural features derived from GLCM were most effective in distinguishing between spectrally similar land cover types, a trend that was also evident in our results. In particular, homogeneity and contrast textures help differentiate weedy patches from crop rows, which are often difficult to separate using spectral information alone.

This conclusion is supported by Khadka et al. (2025), who applied OBIA (Object-Based Image Analysis) with GLCM for landslide detection using Sentinel-2 imagery, and by Sattar et al. (2024), who compared PBIC, OBIC with GLCM, and OBIC using multi-resolution segmentation in eCognition software. Interestingly, Sattar et al. (2024) reported a contradictory outcome, where PBIC outperformed both OBIC variations (PBIC = 98%, OBIC+GLCM = 96%, OBIC+MRS = 89%), suggesting that algorithm performance may be data- and context-dependent, influenced by sensor type, spatial resolution, and landscape heterogeneity. Another factor that can significantly enhance the accuracy of UAV-based weed mapping is the use of a sub-centimeter real-time kinematic (RTK) GPS device.

Some of the poor performance observed in Table 3.7 can be attributed to a combination of data and method-related factors. On average, OBIC without textural properties performed worse than PBIC and OBIC with GLCM, highlighting the importance of properly configuring input features. The SVM classifier produced the lowest accuracies, likely due to its sensitivity to the kernel function, which was not adjusted in this study (Verma et al., 2020). Across all algorithms, a notable increase in OA was observed when the training dataset size increased to 300 points, indicating that small or imbalanced training datasets can limit the ability to capture class heterogeneity effectively. Overall, 77.8% of the tested classification combinations in Table 3.6 yielded OA values exceeding 85%, a threshold considered satisfactory in RS literature (McNairn et al., 2009; Rasmussen et al., 2021; Gokool et al., 2023). These findings underscore the utility of multispectral UAV imagery in generating accurate weed distribution maps and demonstrate the promising transferability of OBIC workflows to cloud-based platforms like GEE, provided that sufficient training data and appropriate classifiers are applied.

3.4.2 The success of the image classification technique in weed detection

This study successfully generated a cloud-based image classification algorithm using UAV imagery. The general trends agreed with other studies that adapted the workflow in GEE. However, they all used satellite imagery and the non-parametric ML models available on the platform.

Therefore, assessing other models is necessary. It will provide a deeper understanding of how the algorithms function and an opportunity for potential optimization. Šiljeg et al. (2022) used UAV imagery with SVM (non-parametric) and maximum likelihood (parametric) to assess PBIC and OBIC for mapping olive tree crowns. The results showed that SVM performed the best using OBIC. Huang et al. (2020) also used UAV imagery and found that the PBIC approach outperformed the OBIC technique (90.3% and 82.3%). In this case, a DL model contributed to the PBIC outperforming the OBIC, and Bao et al. (2024) observed similar findings on the classifier performance.

El Imanni et al. (2023) used the crop canopy height model (CHM) from UAV imagery to enhance a pixel-based approach for weed mapping in a citrus field. Adding this input feature enhanced the overall classification accuracy from 95.08% to 96.87%. Based on these findings, it is evident that there are other ways of obtaining a high classification accuracy apart from the complex OBIC (Qu et al., 2021; El Imanni et al., 2023). The observed trends infer that non-parametric models are preferred over parametric models in UAV-based weed mapping algorithms (Šiljeg et al., 2022). This inference is also supported by Shirzadifar et al. (2020), who used 6 classifiers to assess OBIA and PBIA (Pixel-based image analysis) on UAV imagery. The DL classifiers generally produce higher overall classification accuracies than ML (Verma et al., 2020; Haq et al., 2021).

3.4.3 The effect of the training dataset on classification accuracy

Although the aim of the research was achieved, it is important to note that other factors contributed to these findings. The high classification accuracy can be partially attributed to the low number of land cover classes, which influences the balance and quality of training datasets (Tyukavina et al., 2025). This view is further supported by the close agreement between the Kappa coefficient and OA shown in Table 3.6. However, increasing the number of classes will likely introduce greater class heterogeneity, affecting the distribution of training data points and resulting in a potential divergence between OA and Kappa. The influence of poor-quality training datasets on the two metrics was evident in trial one (Table 3.7). The poor results in trial one can be attributed to changes in the spectral reflectance and geometric properties of both taro and weeds as they developed during the growing season. These changes likely contributed to misclassification, as the auxiliary features used to develop the training dataset did not account for them, resulting in a lower OA (Kulithalai Shiyam Sundar and Deka, 2022) (Table 3.7). Although trial two was able to achieve high overall accuracies, the training data only captured objects that were visible above the canopy cover. In instances where weeds dominated the canopy cover, the crop beneath was obscured, rendering the map unreliable for studies requiring detailed information on crop development.

Despite this, many image classification studies still rely on Kappa-based metrics to assess an algorithm's validity. However, their use in thematic mapping has faced growing criticism. Other researchers have noted that Kappa is sensitive to class imbalance and fails to account for spatial allocation errors. Their findings considered the metric flawed and proposed the adoption of the quantity and allocation disagreement index (QADI) (Verma et al., 2020; Feizizadeh et al., 2022; Pontius Jr et al., 2025). The findings of this study suggest that while Kappa is a useful indicator of performance, it is insufficient on its own and should be complemented with additional metrics to provide a more comprehensive assessment of classification accuracy in heterogeneous agricultural landscapes.

3.4.4 Cloud-based classification algorithm in smallholder farms growing NUCs

Overall, the findings from this study serve as a resource for generating workflows that can be adopted in similar studies to produce reliable spatio-temporal maps. These maps can be used to assess the effectiveness of various agricultural management practices. Some of the examples include detecting weed distribution, diseases, crop phenotyping, yield prediction, and crop water use (Mattivi et al., 2021). There is evidence where UAV imagery was utilized to monitor taro blight using DL algorithms (Boonrang et al., 2024; Jie et al., 2025; Wang et al., 2025). These technological advancements have the potential to enhance agriculture in SSA. However, some challenges still contribute to the adoption rates remaining low. There is still a digital divide between researchers and smallholder farmers. Therefore, intentional collaboration between the research organizations and the government is essential for developing capacity-building infrastructure that can help with bridging the gap (Choruma et al., 2024).

3.5 Conclusion

The main aim of this study was to generate a cloud-based image classification algorithm that could produce reliable weed distribution maps to enhance PWM in smallholder farms. Through leveraging GEE and UAV imagery, we were able to identify the OBIC approach with textural properties as the best classification algorithm. The algorithm was tested in different growth phases and was able to detect land cover changes accurately. These maps can be utilized for early detection of weeds to ensure sustainable control methods are adopted. Furthermore, monitoring the temporal crop-weed changes and integrating these maps with other RS crop monitoring (maps) tools, such as ETa models, can strengthen the utility of these maps, as this enables one to gain insight into quantifying water uptake in the soil by weeds.

Finally, based on the current findings, one can infer that high spatial resolution imagery, good training data, and a cloud computing environment are essential when it comes to developing weed distribution maps efficiently. Adopting GEE as a processing platform has the potential to become a knowledge dissemination hub that connects researchers and farmers. While this chapter focuses on the spatial identification of weeds, the following chapter (Chapter 4) extends this analysis by quantifying the physiological impact of weeds on crop water use through evapotranspiration modeling.

4. ASSESSING THE POTENTIAL OF MULTISPECTRAL UAV-DERIVED VEGETATION INDICES FOR ESTIMATING WATER USE OF TARO (COLOCASIA ESCULENTA) UNDER DIFFERENT WEED MANAGEMENT PRACTICES

4.1 Introduction

Population growth trends require that there be an increase in agricultural productivity to address potential food security concerns. In recent years, diversification of food sources by promoting NUCs such as taro has been among the plausible solutions (Mabhaudhi et al., 2013; Chivenge et al., 2015; Mudau et al., 2022; Soumare et al., 2022). To date, taro is severely under-researched, and there has been a widely held perception that the crop has high water consumption, which may have contributed to low utilization. However, in recent years, scientific findings have acknowledged its high nutritional value and resilience to climate variability (Mabhaudhi et al., 2013; Hossain et al., 2021). As such, maximizing the productivity of such a crop is essential in an era where climate change and population growth are at the core of future thinking regarding sustainable development and innovation (Chowhan and Dayya, 2022).

Recent climate change studies have highlighted potential shifts in agroecological zones driven by the increasing frequency of extreme weather events, particularly in SSA (Mugiyo et al., 2022). At the national scale, much of South Africa falls within a semi-arid zone, receiving a mean annual precipitation of approximately 465 mm (Ullah et al., 2022). Future projections from Global Circulation Models indicate heightened susceptibility to drought, especially in already dry regions (Mahomed, 2017; Park et al., 2023). In response, various interventions have aimed to enhance water-use efficiency in agriculture through sustainable irrigation scheduling, improved monitoring systems, and the selection of climate-resilient genotypes (Ghiat et al., 2021). However, these efforts have largely concentrated on commercially dominant crops. There remains a critical need to extend similar research and investment toward NUCs to promote agricultural diversification and optimize productivity under changing environmental conditions (Modi and Mabhaudhi, 2020).

According to Gerrano et al. (2019), most taro producers in South Africa are smallholder farmers located in the Eastern Cape, KwaZulu-Natal, Mpumalanga, and Limpopo provinces. Taro serves as an affordable source of essential nutrients for resource-limited households. These farmers primarily depend on rainfall for crop production, making it crucial to quantify the water use of taro to support improved management practices and maximize yields (Berger et al., 2015).

Crop water use, commonly referred to as evapotranspiration (ET), is often estimated using crop coefficient (K_c) values (Kamble et al., 2013). ET is the combined process of soil evaporation and plant transpiration (Mthembu et al., 2024). The K_c is typically expressed as the ratio between actual evapotranspiration (ET_a) and reference evapotranspiration (ET_o). This value is influenced by crop type, growth stage, local climate conditions, and seasonal variations, which all contribute to its variability (Mhaweji et al., 2021).

To obtain accurate ET_a estimates, various ground-based techniques based on surface energy balance principles have been employed, including eddy covariance, Bowen ratio, and surface renewal methods (Anapalli et al., 2020; Singh et al., 2024). However, these point-based approaches are limited by high equipment costs, the need for specialized expertise, and their application over small, homogenous areas (< two hectares). Technological advancements have driven a transition toward RS and improved modeling techniques, which address many of these limitations. RS has become a valuable tool for acquiring data across larger and more diverse agricultural landscapes, especially in areas with limited resources and technical capacity.

When it comes to the application of RS in agriculture, the most common datasets were developed using open-source satellite imagery such as Sentinel, Landsat (7, 8, and 9), and MODIS at regional, national, and global spatial scales (Allam et al., 2021; Aliabad et al., 2022). However, these datasets have been beneficial for multi-temporal scales. The overpass time, spatial resolution, and cloud and dust interference in the atmosphere are some challenges that inhibit their suitability for smallholder farm studies. On the other hand, UAVs have demonstrated great potential to contribute towards PA that is more suitable for local spatial scales.

There is currently insufficient evidence to identify any single algorithm as the gold standard for estimating ETa in smallholder farm environments. However, the most common algorithms in ETa research are the surface energy balance system (SEBS), the surface energy balance algorithm for land (SEBAL), and mapping evapotranspiration at high resolution with internalized calibration (METRIC). They all rely on land surface temperature (LST) (captured by the thermal sensor) data in determining the wet and dry pixels that represent the range of evapotranspiration occurring at a given time in the ROI (Bastiaanssen et al., 1998; Allen et al., 2011; Allam et al., 2021). The main difference between these algorithms lies in the parameterization.

Over the last two decades, RS experts have been at the forefront of developing alternative workflows that can provide accurate ETa estimates using models with fewer input requirements. To date, one of the simplest ways of obtaining ETa data on record is through the use of empirical models that rely on VI, such as the NDVI and the EVI2 as proxies for Kc. So far, these methods have been validated in satellite imagery studies (Abbasi et al., 2021; Woldemariam et al., 2024). There is no evidence supporting the reliability of these models using UAV imagery in smallholder farms. Therefore, it is essential to address this knowledge gap. High computational efficiency and ample storage capacity are required when processing RS data. Cloud computing infrastructure, such as GEE, has made significant strides in ensuring that the environment is the solution and provides the opportunity for collaboration on the platform (Gxokwe et al., 2022). Having established a reliable method for mapping weed distribution in Chapter 3, this chapter assesses the resource competition dynamic by quantifying the actual water use (ETa) of taro under the different weed management practices previously mapped. This study evaluated the viability of a VI-based empirical model to estimate the ETa of taro under different weed management practices in a smallholder farm using multispectral UAV imagery.

To fulfill the research aim, the study pursued three specific objectives: (1) to evaluate the performance of VI-based ETa empirical models using in-situ data; (2) to determine the potential of the best-performing VI-based empirical model for estimating taro water use under different management practices; and (3) to assess the impact of various weed management practices on taro yield and economic value.

4.2 Materials and Methods

4.2.1 Study site description

The study was conducted across three sites within the uMshwathi Local Municipality, KwaZulu-Natal Province, South Africa (Figure 4.1): Site A – a commercial farm approximately 15 km northeast of Pietermaritzburg (29°31'38.7"S; 30°28'4.3"E; 812 m asl.); Site B – Fountainhill Estate (29°26'56.83"S; 30°32'48.80"E; 905 m asl.); and Site C – Swayimane (29°31'33.2"S; 30°41'51.8"E; 840 m asl.). The area is primarily used for agriculture, with sugarcane, maize, taro, and sweet potatoes being the main crops grown. The majority of the farming in the region is rainfed, which typically occurs in the summer rainfall period (between October and February). Various studies conducted within the local municipality have reported that the area experiences average minimum and maximum temperatures ranging between 11°C and 24°C (which correlates with the measurement meteorological data shown

in Table 4.1) and mean annual precipitation ranging between 800 and 1200 mm (Brewer et al., 2022; Mthembu, 2022; Dlamini, 2024).

Table 4.1 The cumulative rainfall, average relative humidity (RH avg), and minimum and maximum air temperatures (TMIN and TMAX obtained from eddy covariance (EC) systems located near the three study sites during the respective monitoring periods: site A (14 December 2022 to 12 April 2023), site B (1 January 2022 to 11 April 2022), and site C (22 November 2023 to 31 March 2024))

ROI	Measurement			Rainfall (mm)	RHavg (%)
	Period (days)	TMAX avg (°C)	TMIN avg (°C)		
Site A	135	25.55	15.86	294.60	73.68
Site B	100	26.57	16.31	292.60	67.41
Site C	115	24.93	16.60	250.50	82.35

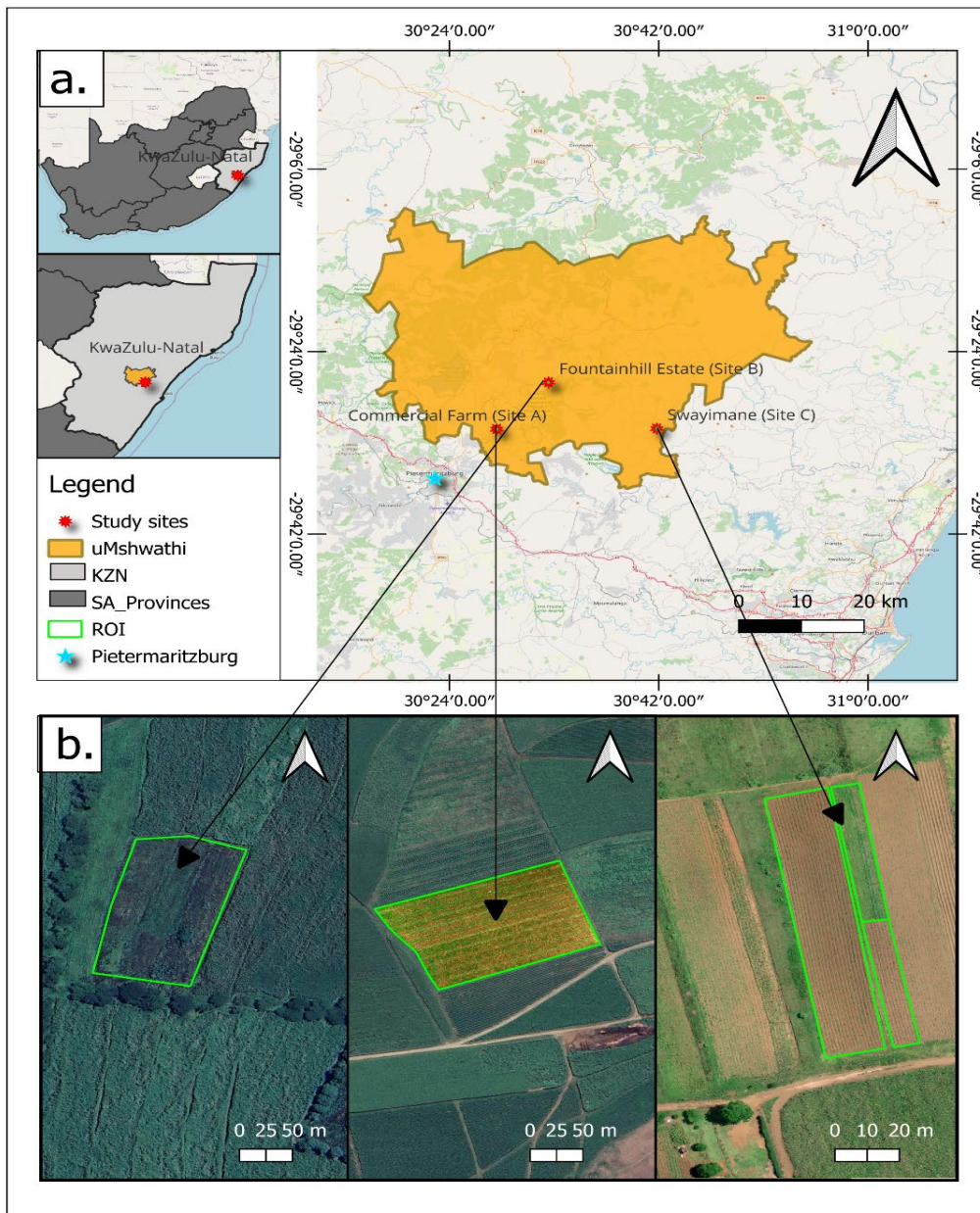


Figure 4.1 Map showing the locations and boundary demarcations of the study sites. RGB UAV imagery was captured for the Commercial Farm (Site A) on 18 January 2023, Fountainhill Estate (Site B) on 6 June 2022, and Swayimane (Site C) on 22 November 2023.

4.2.2 Field design

4.2.2.1 Site A (Commercial Farm)

The study site covered an area of approximately 25,880 m², and the crop that was being observed was cannabis (*C. sativa* L). The growing season for this trial was approximately 5 months between November 2022 and April 2023. Drip irrigation was implemented to ensure the plants had sufficient water available for optimal growth during periods of low rainfall. The fertilizer was dissolved for application using the same system. This irrigation system promotes efficient water use and better nutrient uptake, thus aiding in the sustainable use of resources while maximizing productivity. Manual labour was used in removing weeds, setting up the irrigation network, and during the harvesting

period. The inter-row spacing was 2.5 m, while the intra-row spacing (space between plants in a row) was 2 m, respectively. The texture of the soil samples was characterized as sandy clay loam (74% sand, 5% silt, and 21% clay at a depth between 0 and 0.2 m below the topsoil surface, with a pH between 4.12 and 5.54). The topography of the ROI had a gentle slope of 13.1%. The data for this trial were from a study conducted by Denton et al. (2025). The growth phases used in this study were based on information in Table 4.2.

Table 4.2 The crop development stages of Cannabis according to Mediavilla et al. (1998)

Growth Phase	Development	Duration (weeks after planting)
S0	germination and emergence	≈1-2 weeks
S1	vegetative stage	≈3- 8 weeks
S2	flowering and seed formation	≈9- 17 weeks
S3	senescence	≈18-22 weeks

4.2.2.2 Site B (Fountainhill Estate)

The study site was demarcated to cover an area of approximately 9750 m², and the crop being investigated in this trial was taro (landrace- Dumbe dumbe). The inter-row spacing was 1 m, while the intra-row spacing was 0.5 m. The duration of this experiment was between December 2021 and June 2022. This trial was purely rainfed. Workers from the nearby community (Swayimane) were contracted to assist with planting, weed management, application of fertilizer (gromo accelerator), herbicide (gramoxone), and harvesting. The soil texture for this area was characterized as sandy loam (80% sand, 4% silt, and 16% clay, at a depth ranging between 0 and 0.3 m). The data for this trial were from a study conducted by Reddy (2025).

4.2.2.3 Site C (Swayimane)

A workflow that could be adopted to observe the impact of different weed management practices on the water use and yield of taro was investigated in this trial. Initially, the study site was demarcated to cover an area of 980 m². The proposed field was designed to consist of 2 split plots, where one was weeded throughout the growing season, while the other was unweeded. After the bulbs were sown, we were notified that the farmer had planted the same crop in the field adjacent to our study area. This new field was added as the third plot to enhance the study by gaining insight into the effectiveness of current management practices used by the farmer. Thus, the study area was increased to 2276 m². The third plot was identified as the intermediate field because the farmer applied conventional weed management strategies. These include cultivating using cattle, applying herbicide (farmag paraquat 200), and manual labor during the first 3 months after planting. The soil texture for the ROI was characterized as sandy loam (75% sand, 7% silt, and 18% clay, at a depth ranging between 0 and 0.4 m). The study site had five species identified as weeds in the field (Figure 4.2).

It is important to note that manure was applied in all three plots. The inter- and intra-row spacing was the same as Site B (1 m and 0.5 m, respectively). However, the planting dates were different. The taro bulbs in the intermediate field were sown on September 4th, 2023, while the bulbs in the weeded and unweeded fields were sown on September 22nd, 2023. The first round of the weeding took place. On November 10th, 2023, for the weeded field. This process was repeated every fortnight. Harvesting

took place in early April 2024. The growth phases used in this study were based on information in Table 4.3.

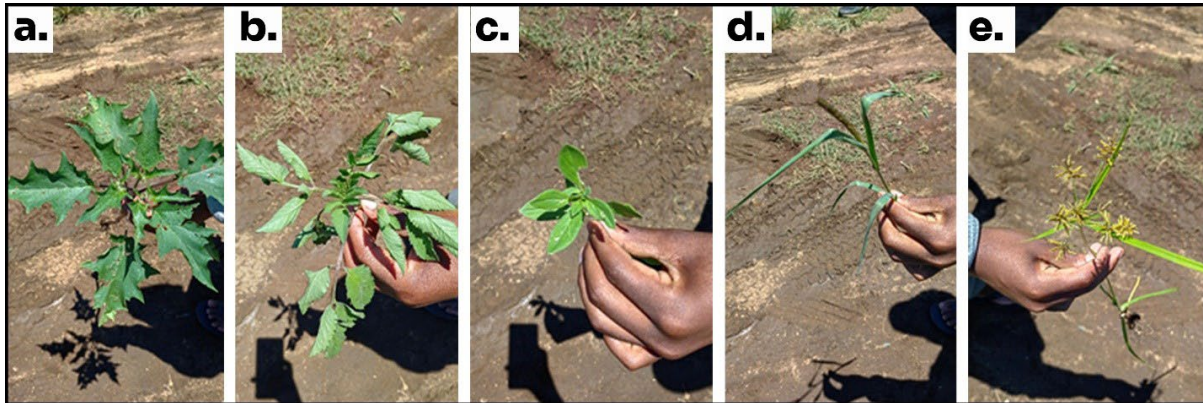


Figure 4.2 Types of weeds identified within the boundary of the taro field at the study site: (a) Jimsonweed (*Datura stramonium* L), (b) Black Jack (*Bidens pilosa*), (c) Spermacoe, (d) Wheat grass (*Poaceae*), and (e) Nut grass (*Cyperus rotundus*). Images were captured on December 8, 2023

Table 4.3 The crop development stages of taro relevant to the Swayimane study site (Site C). This information was supported by other studies (Mabhaudhi and Modi, 2013; Limisha et al., 2022; Kunz et al., 2024).

Growth Phase	Development stage	Months after planting
Phase I (crop establishment)	recovered plant after sowing	1-2 months
Phase II (grand growth)	maximum rooting depth, and canopy cover	4- 5 months
Phase III (Maturation)	leaf senescence, yield formation	6-8 months

4.2.3 Data acquisition

4.2.3.1 In-situ ETa data acquisition and preprocessing

An eddy covariance (EC) system was set up to monitor sites A and B's microclimatic conditions and crop water use. The flux tower comprised multiple sensors (shown in Figure 4.3 and listed in Table 4.4) that were connected to a Campbell CR3000 datalogger programmed to measure data at a frequency of 10 Hz, which was averaged at 30-minute intervals. All the components on the flux tower were powered by two 12 V direct current batteries connected to a solar panel that was mounted on the strong box (Figure 4.3 and Figure 4.4). Several factors had to be considered when deciding where the EC system was mounted in the respective fields. These included topography, flux footprint, and prevailing wind direction (the rule of thumb proposes that 1 meter above the crop canopy can provide a fetch of approximately 100 m). Failure to adhere to these guidelines can result in inaccurate in-situ measurements. The flux tower captures ETa data in two ways (direct and indirect). This study relied on ETa data captured using the direct approach. This method uses the sonic anemometer (CSAT3A, Campbell Scientific, Logan, Utah, USA) and the open path gas analyzer (EC150, Campbell Scientific, Logan, Utah, USA) functioning simultaneously to estimate the concentration of moisture content, also referred to as latent heat flux (λET) ($W.m^{-2}$) in the atmosphere within the footprint range. In sites A and B, these sensors were mounted at 2 m height and 1.5 m above the crop canopy. Adjustments were made throughout the growing season to ensure the height above the crop was constant in both fields. Furthermore, λET was determined utilizing Equation 1.

$$\lambda ET = L_v \cdot \overline{w' \rho'_w}$$

Equation 1

As shown in equation 1, λET ($W.m^2$) was calculated using latent heat of vaporization ($L_v = 2.45 \cdot 10^6$ $J.kg^{-1}$ at $20^\circ C$), and the mean covariance of fluctuation in vertical wind speed (w), and fluctuation in water vapour density (ρ_w) ($kg.m^{-3}$). The indirect method calculates λET as a residual of the energy balance model using Equation 2. Net radiation (R_n) was measured using the CNR4 Net Radiometer (Kipp and Zonen, Delft, Netherlands). The net radiometer was installed at a height of approximately 3 m above the crop canopy in both sites. Soil water content sensors (CS616 Water Content Reflectometers, Campbell Scientific, Logan, Utah, USA) were installed at different depths [in site A (0.2 m, 0.4 m, and 0.6 m), and B (0.15 m, 0.3 m, and 0.6 m)], and soil temperature thermocouples (TCAV Type E thermocouples, Campbell Scientific, Logan, Utah, USA) were deployed to determine soil heat flux (G) [in site A and B (2 cm, 5 cm, and 8 cm)]. Sensible heat flux density was measured using the sonic anemometer (Mbangiwa *et al.*, 2019).

$$\lambda ET = R_n - G - H$$

Equation 2

As shown in equation 2, λET ($W.m^2$) was determined as the difference between net radiation (R_n) ($W.m^2$), soil heat flux (G) ($W.m^2$), and sensible heat flux (H) ($W.m^2$). Daily ET_a was obtained using Equation 3, and the 86400 represents the number of seconds in 24 hours.

$$ET_a = \frac{\lambda ET}{L_v} * 86400$$

Equation 3



Figure 4.3 Installation of the Eddy Covariance flux tower at Site A

Table 4.4 The sensors mounted on the eddy covariance flux tower in sites A and B

Instruments	Measurement	Manufacturer
EC150 CO ₂ /H ₂ O Open-Path Gas Analyser	CO ₂ /H ₂ O flux	Campbell Scientific, Logan, Utah, USA
TE525mm Tipping Bucket Rain Gauge	Rainfall	Texas Instruments, Dallas, Texas, USA
HC2S3 Temperature and Relative Humidity Probe	Temperature; relative humidity	Campbell Scientific, Logan, Utah, USA
HFP01 Soil Heat Flux Plate	Ground heat flux	Huxflux, Delft, Netherlands

CSAT3A Three-Dimensional Sonic Anemometer	CO ₂ /H ₂ O flux	Campbell Scientific, Logan, Utah, USA
CNR4 Net Radiometer	Net solar radiation	Kipp and Zonen, Delft, Netherlands
FW1 Type E fine wire thermocouples	Air temperature	Campbell Scientific, Logan, Utah, USA
TCAV Type E thermocouples	Average soil temperature	Campbell Scientific, Logan, Utah, USA
CS616 Water Content Reflectometers	Volumetric soil water content	Campbell Scientific, Logan, Utah, USA

The remaining sensors recorded microclimatic variables used to calculate daily reference evapotranspiration (ET_r) via the FAO-56 Penman-Monteith method (Equation 4). Two reference surfaces are typically applied: short grass (0.12 m height) and alfalfa (0.5 m height), with the former generally used for low vegetation and the latter for taller crops (Mbangiwa *et al.*, 2019; Ramírez-Cuesta *et al.*, 2020). The calculation assumes that the reference crop is well-watered and not under stress. Under these conditions, ET_r is estimated using the following equation:

$$ET_r = \frac{0.408\Delta(R_n - G) + \gamma \left(\frac{900}{T + 273} \right) u_2 (e_s - e_a)}{\Delta + \gamma(1 + 0.34u_2)} \quad \text{Equation 4}$$

where reference evapotranspiration (ET_r) (W.m⁻²) was determined using the following variables: the slope of the saturation vapour pressure curve (Δ , kPa °C⁻¹), net radiation at the crop surface (R_n) (W.m⁻²), soil heat flux (G) (W.m⁻²), psychrometric constant (γ), mean daily air temperature at 2 m height (T) (°C), wind speed at 2 m (u₂) (m.s⁻¹), saturation vapor pressure (e_s) (kPa), actual vapour pressure (e_a) (kPa), vapor pressure deficit (VPD) (e_s - e_a) (kPa).

When ET_a and ET_r have been determined, the crop coefficient (K_c) can be calculated by using Equation 5 below. To obtain K_c on a daily or monthly temporal scale, it is essential to ensure that the other variables (ET_a and ET_r) also use the same timestamp.

$$k_c = \frac{ET_a}{ET_r} \quad \text{Equation 5}$$

To ensure the reliability of the dataset and minimize the influence of errors from malfunctioning sensors, several quality control measures were implemented. The steps outlined below were followed to improve data quality and ensure that only accurate and relevant information was used in the analysis:

- We focused on the 30-minute data captured between 07:00 and 17:00, because it represented a period when evapotranspiration (ET) normally occurs.
- Negative λET values were omitted, since they indicated potential malfunction of sensors that are often caused by exposure to condensation or power shortage. These values were interpolated by calculating the product of daily ET_r and the average monthly k_c value.
- The energy balance closure was determined in both sites (A and B). The method that was adopted was a ratio between (H + λET) and (R_n - G). A value closer to 1 indicates near-perfect energy balance closure (Jin *et al.*, 2022). The two sites had an energy balance closure above 75%.

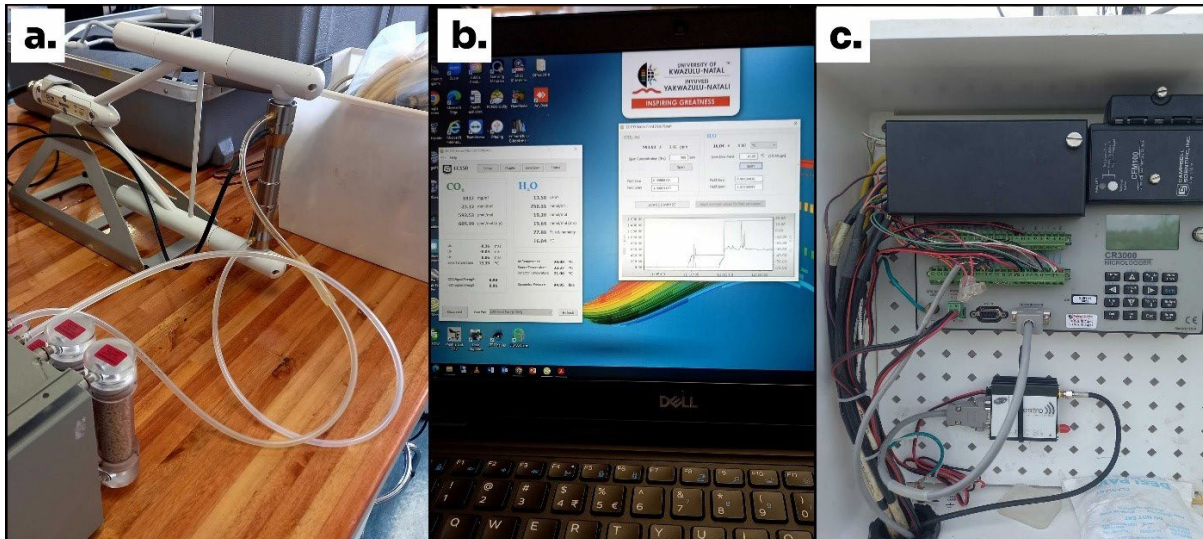


Figure 4.4 Calibration process components: (a) EC150 CO₂/H₂O Open-Path Gas Analyzer, (b) configuration using the EC100 Series Monitor software, and (c) the Campbell CR3000 datalogger in the field after all sensors were connected

4.2.3.2 Remotely sensed data acquisition and preprocessing

All the remotely sensed data were captured using a Mica Sense Altum camera and a DLS-2 mounted on a DJI-M-300 UAV in sites A and B. The same RS platform was used in Site C. However, there were a few instances where the DJI-M-300 was not available (in Site C).

The DJI Mavic 3 multispectral was employed as an alternative (band specifications presented in Table 4.5). The Mica Sense Altum camera imagery was captured at a GSD of 7 cm per pixel, with the UAV flying at an elevation of 100 m above the ground, while the Mavic 3 multispectral captured footage at a GSD of 0.7 cm per pixel, flying at an elevation of 15 m above the ground. A KML file containing the ROI demarcations was generated using Google Earth Pro and imported into the DJI smart controller for flight planning. The calibration reflectance panel (CRP) was used before each flight to ensure the camera was calibrated according to the lighting conditions on the day. The camera had an 80% frontal overlap, while the side overlap was 70%. To enhance image stitching accuracy that is often affected by geometric distortions resulting from environmental factors such as wind (which can destabilize the sensor) and uneven surface illumination due to terrain and slope. The process also minimizes the likelihood of data gaps occurring during flight.

Table 4.5 Specifications of the sensors that captured the imagery used in this study

Sensor	Band	Central wavelength (nm)	GSD (cm.pixel ⁻¹)
Mica Sense Altum Sensor	B1 - Blue	475	7
	B2 - Green	560	7
	B3 - Red	668	7
	B4- Red-edge	717	7
	B5 - Near-infrared (NIR)	842	7
	B6 - Thermal infrared	8 000-14 000	109
Mavic 3 multispectral	B2 - Green	560	0.7
	B3 - Red	650	0.7
	B4- Red-edge	730	0.7
	B5 - Near-infrared (NIR)	860	0.7

RS data were captured every fortnight on days with clear skies between 10:00 a.m. and 12:00 p.m. South African Standard Time (SAST) to ensure consistent lighting conditions. Image correction was performed during pre-processing using Pix4Dfields (version 2.7.2) by selecting settings that account for weather conditions. All images captured on each day were stitched together to form an orthomosaic. The same application was used to generate the ROI shapefiles. The RS dataset used in this study for site A was captured between January 2023 and April 2023, site B between February 2022 and June 2022, and site C between November 2023 and March 2024.

All stitched images and shapefiles containing the demarcation of the ROI in all three sites were uploaded to GEE. The image collection was resampled to a spatial resolution of 7 cm per pixel. A script was generated to extract the NDVI and EVI2 values for water use estimation using empirical models on the platform.

4.2.4 Methodology for generating VI-based ETa empirical model

In identifying an efficient approach to estimate water use in smallholder farms, resource availability was a key consideration. The multispectral sensors employed in this study lacked specific spectral bands (e.g., those needed to derive albedo, which requires shortwave radiation), limiting their suitability for most surface energy balance methods. This limitation led to the adoption of vegetation index (VI)-based workflows, which are better suited to smallholder contexts due to their lower input requirements (Abbasi et al., 2021; Abbasi et al., 2023a; Woldemariam et al., 2024). The empirical models developed in this study utilized NDVI and EVI2 as proxies for Kc. NDVI, a widely used indicator of crop health, captures vegetation greenness by reflecting chlorophyll content and canopy density (Equation 6) (Brewer et al., 2022).

$$NDVI = \frac{NIR - RED}{NIR + RED} \quad \text{Equation 6}$$

Some studies highlighted that NDVI is prone to errors in areas with low vegetation cover and high soil reflectance (Houborg and McCabe, 2016; El Imanni et al., 2023). According to Woldemariam *et al.* (2024), EVI was developed to address some of the limitations induced by using NDVI. However, in this study, EVI2 was utilized instead of EVI because the VI did not require the blue band, which is not available in the DJI Mavic 3 when capturing using multispectral mode (Equation 7) (Nouri et al.,

2020). To reduce the potential error that could be introduced by utilizing different UAVs, a percentage difference of NDVI and EVI2 values from imagery captured by the platforms during the same period in site C was calculated. The potential error was approximately 5.44%, which is within an acceptable range.

$$EVI2 = 2.5 * \frac{(NIR - RED)}{NIR + 2.4 * RED + 1} \quad \text{Equation 7}$$

Three empirical formulas were applied to both VIs (NDVI and EVI2). The first ETa estimation directly calculated the selected VIs and ETr, as shown in Equations 8 and 9.

$$ETa_NDVI = NDVI * ETr \quad \text{Equation 8}$$

$$ETa_EVI2 = EVI2 * ETr \quad \text{Equation 9}$$

The second formula was a scaled version based on the assumption that under well-watered and unstressed conditions, the maximum value for NDVI and EVI2 is 1, while the Kc value is 1.2 (Abbasi et al., 2023a), as shown by Equations 10 and 11.

$$NDVI_{scaled} = 1.2 * NDVI \quad \text{Equation 10}$$

$$EVI2_{scaled} = 1.2 * EVI2 \quad \text{Equation 11}$$

The ETa for the scaled VIs was calculated using Equations 12 and 13.

$$ETa_NDVI_{scaled} = NDVI_{scaled} * ETr \quad \text{Equation 12}$$

$$ETa_EVI2_{scaled} = EVI2_{scaled} * ETr \quad \text{Equation 13}$$

The third formula observed the linear regression between Kc and the respective VIs at different growth stages based on the assumptions stated by Woldemariam et al. (2024), as shown in Equations 14 and 15.

$$NDVI_{kc} = 1.25 * NDVI + 0.2 \quad \text{Equation 14}$$

$$EVI2_{kc} = 1.25 * EVI2 + 0.2 \quad \text{Equation 15}$$

The ETa for the Kc-based empirical formulas was calculated using Equations 16 and 17:

$$ETa_NDVI_{kc} = NDVI_{kc} * ETr \quad \text{Equation 16}$$

$$ETa_EVI2_{kc} = EVI2_{kc} * ETr \quad \text{Equation 17}$$

The fourth formula was a modified version of EVI2 generated by Abbasi et al. (2023a) based on findings from Nagler et al. (2013) and Abbasi et al. (2021), which incorporates the Beer-Lambert Law to express canopy light absorption and maximum, as shown in Equation 18.

$$\text{MEVI2} = 1.5125(1 - e^{-2.25 \cdot \text{EVI2}}) - 0.169$$

Equation 18

The ETa obtained from adopting MEVI2 as a proxy for kc was calculated using Equation 19.

$$\text{ETa_MEVI2} = \text{MEVI2} * \text{ETr}$$

Equation 19

4.2.5 Assessing the performance of the VI-based ET empirical model estimates

To identify a reliable model, daily estimates of seven empirical models were validated against in-situ daily measurements captured in sites A and B. Their performance was assessed based on three statistical metrics: the coefficient of determination (R²) (Equation 20), mean absolute error (MAE) (Equation 21), and root mean square error (RMSE) (Equation 22). These metrics were ranked using the hydrological ranking system (1 represented the best, and 7 represented the poorest performance), as shown in Table 4.6 (Rudraswamy et al., 2023). The results for the metrics were captured in Table 4.7. Each combination of metrics was summed up and ranked as shown in Table 4.8.

$$R^2 = 1 - \frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{\sum_{i=1}^n (y_i - \bar{y})^2}$$

Equation 20

$$\text{MAE} = \frac{\sum_{i=1}^n |y_i - \hat{y}_i|}{n}$$

Equation 21

$$\text{RMSE} = \sqrt{\frac{\sum_{i=1}^n (y_i - \hat{y}_i)^2}{n}}$$

Equation 22

The models that had the best combination for the overall ranking were adopted for comparison of temporal and cumulative graphs at all 3 sites. The comparison throughout the season consisted of ETa estimates generated from monthly averages of NDVI and EVI2 that were multiplied by daily ETr. After the best-performing models were identified, temporal graphs were generated for both sites. These graphs comprised daily in-situ measurements and remotely sensed ETa estimates, where monthly average values for the proxies were multiplied by the daily ETr.

Table 4.6 The ranking style used to validate the VI-based ETa models

Category	Ranking performance	Color code
1	Best	Blue
2	-	Green
3	-	Yellow
4	-	Orange
5	-	Light Red
6	-	Red
7	Poorest	Dark Red

4.2.6 Assessing the cost and benefit of implementing different weed management practices

The costs and benefits of the different weed management practices were assessed. The average corm mass per plant was measured at the end of the growing season across different plots. This allowed the estimation of the total yield per plot, assuming the average corm mass per plant remained constant within a particular field. The plot area and number of plants were standardized. The intermediate field was chosen as the reference for this investigation, covering approximately 1,300 m². It consisted of 17 rows, each with about 196 plants, allowing for a total capacity of 3,332 plants. Table 4.14 summarizes the inputs required for each management strategy. The price of taro per kilogram was estimated using yield data from the intermediate field and information provided by the farmer. According to the farmer, a 20 kg batch of taro was sold for R130.00 (approximately \$7.40), which is equivalent to R6.50 per kg, or approximately \$0.37 per kg (based on current exchange rates). To assess the impact of the management practices, the average mass of samples from all three plots was measured. In calculating yield per unit area, it was assumed that all plants interact uniformly with the environment across the field. A summarized flowchart illustrating the methodology adopted for this study is presented below in Figure 4.5.

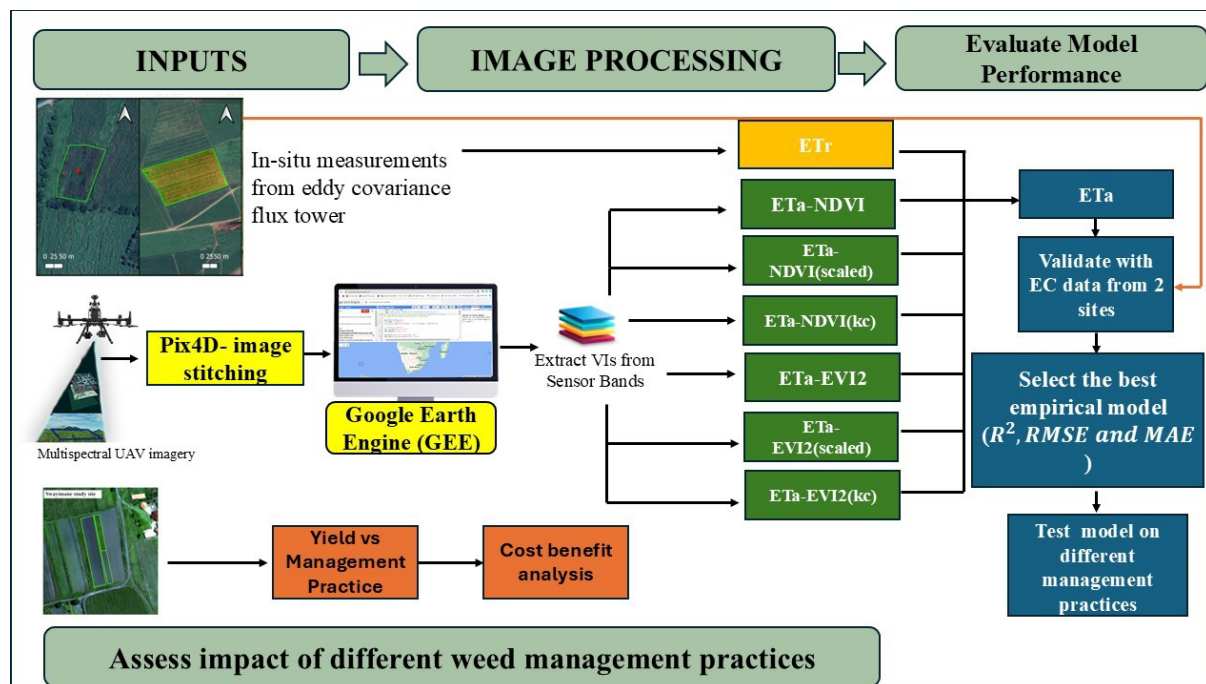


Figure 4.5 Flowchart outlining the methodological approach used in this study

4.3 Results

According to the final ranking scores, the best models were ETa-NDVI, ETa-EVI2(kc), and ETa-MEVI2, with a final ranking score of 5, 6 and 5, as shown in Table 4.8. The weakest models were ETa-NDVI (kc), ETa-EVI2, and ETa-NDVI (scaled). They shared a ranking score of 12 and the latter 11. Site A had strong R^2 values that ranged between 0.83 and 0.87 compared to site B, which had 0.49 and 0.57, respectively. The error metrics highlighted poor model performance in both sites. However, the statistics with the best combination were identified based on the multi-criteria decision-making process. This holistic assessment reduces the degree of bias associated with the tradeoffs of each metric and ensures the best models are robust and capable of providing reliable data extrapolation in areas without in-situ measurements.

Table 4.7 Accuracy metrics for observed and estimated evapotranspiration (ETa) of taro, derived from eddy covariance flux tower measurements and VI-based models at the study sites A and B

Site	Statistic	ETa-NDVI	ETa-NDVI scaled	ETa-NDVI (kc)	ETa-EVI2	ETa-EVI scaled	ETa-EVI2(kc)	ETa-MEVI2
Site A	R^2	0.83	0.83	0.84	0.83	0.83	0.86	0.87
	MAE	0.38	0.47	1.49	1.03	0.70	0.56	0.63
	RMSE	0.44	0.56	1.66	1.14	0.78	0.60	0.68
Site B	R^2	0.49	0.49	0.49	0.49	0.51	0.57	0.57
	MAE	0.58	1.20	0.79	0.66	0.59	0.76	0.58
	RMSE	0.76	1.36	0.95	0.83	0.79	0.95	0.80

Table 4.8 Model ranking based on the statistical performance using a combination of accuracy metrics at both sites (A and B)

Classification	Site	ETa-NDVI	ETa-NDVI scaled	ETa-NDVI (kc)	ETa-EVI2	ETa-EVI scaled	ETa-EVI2(kc)	ETa-MEVI2
Score (Sum of statistics based on ranking category)	Site A	8	9	17	18	16	8	9
	Site B	9	20	18	14	8	13	7
Rank	Site A	2	4	6	7	5	2	4
	Site B	3	7	6	5	2	4	1
Score based on rank		5	11	12	12	7	6	5

4.3.1 Validating the selected ETa-VI empirical models

The in-situ data that was used in site A was collected between 1 January 2023 and 30 April 2023. Overall, the magnitude of variation for observed and simulated ETa was comparable. The ETa-EVI2 and ETa-MEVI2 had a significantly close alignment with measured ETa between days 61 and 129. The two models overestimated towards the end of the season. Despite ETa-NDVI being more consistent, the simulated output was slightly underestimated compared to the observed data. Nevertheless, the accumulated ETa for the measured data during the observed period was 336.20 mm, while ETa-NDVI, ETa-EVI2(kc), and ETa-MEVI2 were 259.90 mm, 322.60 mm, and 333.10 mm. Overall, there was an underestimation of 22.67%, 4.04%, and 0.92%, respectively, when compared to the measured data (Figure 4.6b). Significant differences were noted between 47 and 53 days after planting (DAP). The ranges for measured ETa were 2.21 - 6.09 mm, while the ranges for the simulated were 0.73 - 2.54 mm (ETa-NDVI) and 0.74 - 2.58 mm for ETa-EVI2(kc), and ETa-MEVI2, respectively, as depicted in Figure 4.6a.

The in-situ data used in Site B were collected between 1 February 2022 and 24 June 2022. The simulated outputs generally overestimated ETa for most of the recorded period, although the temporal dynamics of all models were broadly consistent with the EC observations (Figure 4.7a). No unusual spikes were evident in the in-situ data; however, some pronounced peaks in ETa-EVI2(kc) and ETa-MEVI2 were observed between 142 and 166 DAP, aligning with rainfall events and increased crop water demand. These models captured fluctuations in ETa but tended to amplify the magnitude of responses, particularly during peak growth stages. Cumulative ETa estimates highlighted overestimation relative to EC measurements. The accumulated ETa for the observed period was 168.80 mm, while ETa-NDVI, ETa-EVI2(kc), and ETa-MEVI2 recorded totals of 189.30 mm, 236.60 mm, and 187.10 mm, respectively (Figure 4.7b). This represented overestimations of 12.84%, 40.22%, and 10.78% compared to the reference data. Among the models, ETa-EVI2(kc) showed the largest deviation, while ETa-MEVI2 was closest to the EC observations, and ETa-NDVI was more consistent. Climatic conditions during the same period (Figure 4.7c) indicated that ETa variability was strongly influenced by rainfall pulses, with peaks in ET following precipitation events.

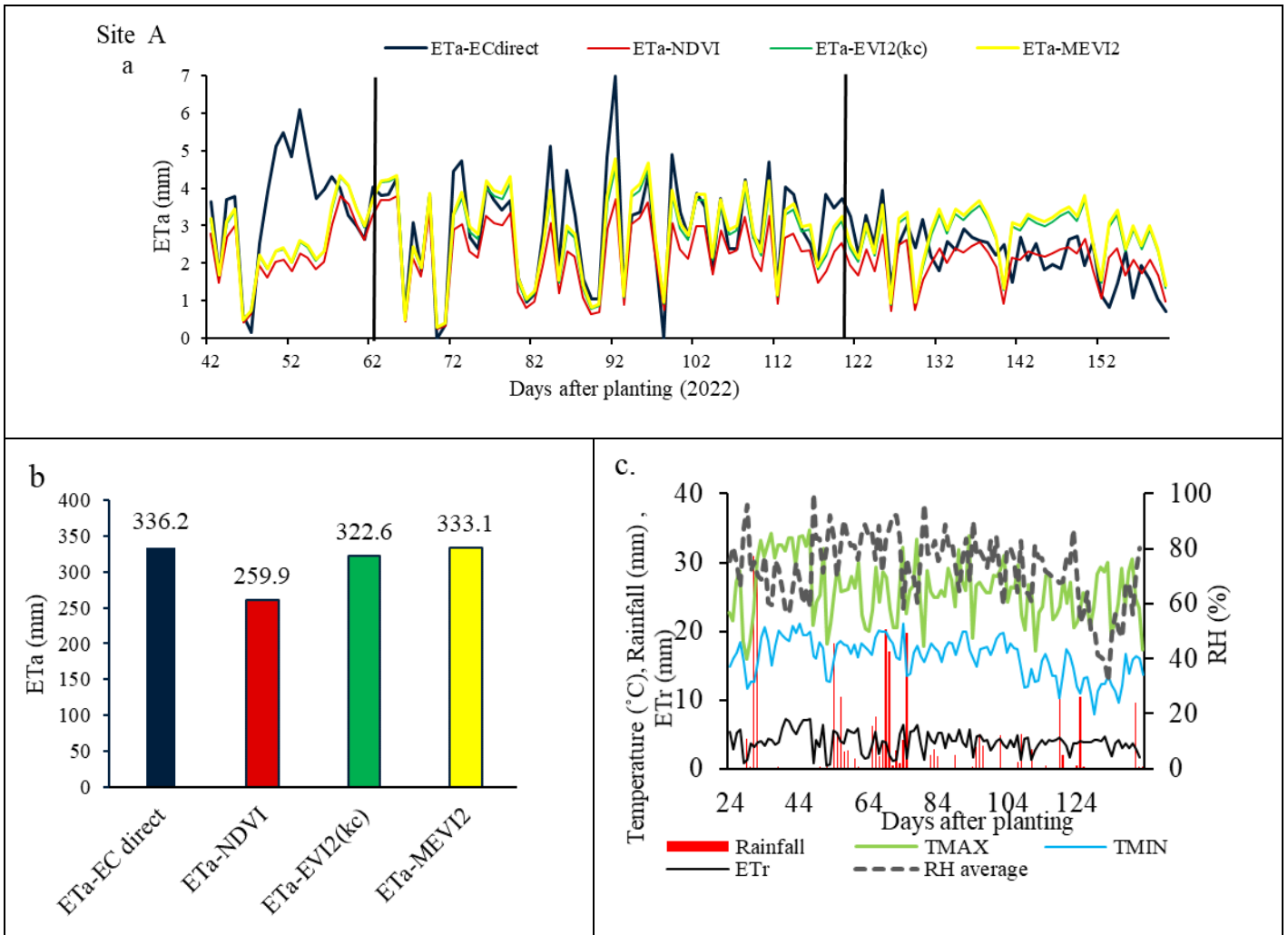


Figure 4.6 Graphs illustrating (a) temporal graph showing the relationship between daily measured ETa by the EC flux tower and estimates from the VI-based empirical models between day 42 and 160 after planting, (b) the accumulated ETa for the observed data captured by the EC flux tower and VI-based empirical models in site A, (c) daily temporal variations of the rainfall, reference evapotranspiration (ETr), average relative humidity (RH), average maximum and minimum air temperature (TMAX and TMIN) from 14 December 2022 to 12 April 2023, in site A

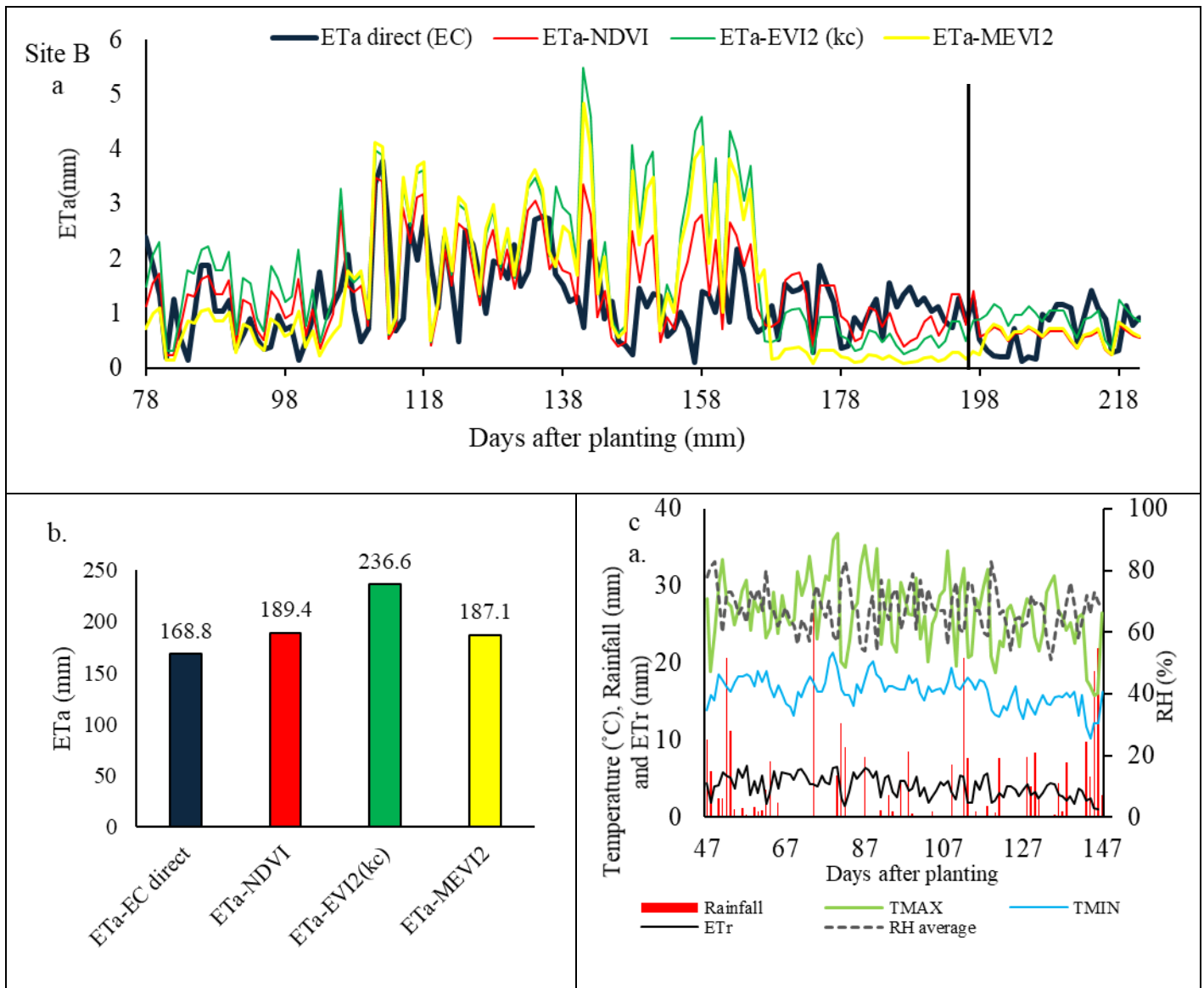


Figure 4.7 Graphs illustrating key climatic and evapotranspiration patterns at Site B: (a) temporal relationship between daily measured ETa from the Eddy Covariance flux tower and estimates from VI-based empirical models between days 78 and 221 after planting; (b) accumulated ETa derived from both observed EC flux tower data and VI-based model estimates; and (c) daily variations in rainfall, reference evapotranspiration (ETr), average relative humidity (RH), and maximum and minimum air temperatures (TMAX and TMIN) from 1 January 2022 to 11 April 2022

At Site A, three distinct growth phases were captured (S1, S2, and S3), while at Site B, two phases (II and III) were recorded (Tables 4.1 and 4.2). The empirical models were evaluated against EC-derived ETa values to assess their performance across the different stages (Table 4.9). At Site A, during the early growth stage (S1, 42–63 DAP), all empirical models underestimated ETa, with ETa-NDVI showing the largest underestimation (34.49%), followed by ETa-EVI2(Kc) (25.75%) and ETa-MEVI2 (25.10%). During the mid-growth stage (S2, 64–119 DAP), underestimations decreased, ranging from 24.03% for ETa-NDVI to 7.57% for ETa-EVI2(Kc) and 4.08% for ETa-MEVI2. In the late growth stage (S3, 120–160 DAP), ETa-NDVI continued to underestimate by 10.08%, while ETa-EVI2(Kc) and ETa-MEVI2 overestimated ETa by 20.1% and 24.45%, respectively. These results indicate that model accuracy varied with growth stage, with EVI2- and MEVI2-based models showing closer agreement with measured ETa during S2 but a tendency to overestimate during S3.

At Site B, the performance of the models showed contrasting behavior across phases II (78–196 DAP) and III (197–221 DAP). In Phase II, all models overestimated ETa, with deviations of 14.89% for ETa-NDVI, 41.22% for ETa-EVI2(kc), and 13.80% for ETa-MEVI2. In Phase III, however, ETa-NDVI and ETa-MEVI2 underestimated ETa by 10.71% and 14.37%, respectively, while ETa-EVI2(kc) continued to overestimate by 31%. Overall, these findings suggest that ETa-EVI2(kc) and ETa-MEVI2 were more suitable for capturing water use dynamics in cannabis (Site A), particularly during mid-growth stages, while ETa-NDVI demonstrated more consistent performance under taro conditions (Site B).

In addition to evaluating ETa trends, crop coefficients (Kc) were derived from the ratio of ETa to reference evapotranspiration (ETr) values for each phase (Table 4.10). At Site A, Kc values were 0.80, 0.75, and 0.64 for S1, S2, and S3, respectively. At Site B, Kc values were notably lower, with averages of 0.44 for Phase II and 0.29 for Phase III. These reduced values reflect the conditions of the rainfed taro field during the observation period and the method used for Kc derivation. The vegetation indices (NDVI, EVI2, and MEVI2) followed similar trends across sites, with generally higher values observed in Site A during peak growth compared to Site B.

Table 4.9 The variability in accumulated ETa for observed and simulated results in different growth phases for sites A and B

ROI	Growth Phase	DAP range	ETa-EC direct	ETa-NDVI	ETa-EVI2(kc)	ETa-MEVI2
Site A	S1	42-63	79.18	51.87	58.79	59.30
	S2	64-119	164.65	125.03	152.23	157.94
	S3	120-160	92.35	83.04	111.54	115.86
Site B	Phase II	78-196	151.24	173.73	213.68	172.12
	Phase III	197-221	17.53	15.65	22.96	15.01

Table 4.10 The correlation between Kc and the VI-based proxies during different growth phases

ROI	Growth Phase	DAP range	ETr (mm)	Kc	NDVI	EVI2(kc)	ETa-MEVI2
Site A	S1	42-63	4.50	0.80	0.52	0.59	0.60
	S2	64-119	3.94	0.75	0.57	0.69	0.72
	S3	120-160	3.52	0.64	0.57	0.77	0.80
Site B	Phase II	78-196	2.92	0.44	0.50	0.62	0.50
	Phase III	197-221	2.39	0.29	0.26	0.38	0.25

4.3.2 Adopting the best model to observe the water use of taro under different management practices

After validating the three models on cannabis and taro trials, ETa-NDVI was selected for application at Site C due to its consistent alignment with measured data and relatively low estimation error ($\pm 15\%$)

in the taro field). Site C consisted of three plots with different weed management practices (unweeded, weeded, and intermediate). The trial period began after the first round of weeding on 10 November 2023, corresponding to 50 days after sowing for the weeded and unweeded plots. The intermediate plot was at 68 days after sowing at the same time, as its planting had occurred 18 days earlier. To account for this difference, accumulated ETa was compared for intermediate (d_68) and intermediate (d_50). The percentage difference in accumulated ETa between these two timelines was 3.53%, which was considered negligible, allowing direct comparison between the plots (Figure 4.8b).

Daily ETa patterns revealed distinct differences among the management practices (Figure 4.8a). The weeded field consistently recorded the lowest water use across the observation period, with only a few instances where the intermediate field showed slightly lower values, particularly between 70 and 104 DAP. This temporary reduction in ETa corresponded with a marked shift in canopy condition (crop yellowing effect due to herbicide application) in the intermediate field. Over the full observation period, the unweeded field accumulated the highest ETa, reaching 407.3 mm, followed by the intermediate (d_68) plot at 328.6 mm and the intermediate (d_50) at 339.6 mm. The weeded field accumulated the lowest total ETa of 256.9 mm (Figure 4.8b). The unweeded plot therefore used 23.97% more water than the intermediate (d_68) field, while the weeded plot used 21.8% less than the same intermediate reference.

Climatic conditions during the observation period (Fig 4.8c) contributed to fluctuations in ETa. Rainfall occurred in intermittent pulses, with peak events coinciding with short-term increases in ETa across all plots. TMAX ranged between 25°C and 35°C, TMIN remained relatively stable between 10°C and 15°C. Relative humidity (RH) averaged above 60% throughout the trial, with occasional peaks above 80%. These environmental conditions provided sufficient variability to capture distinct crop water use responses across the management practices. Overall, the results indicate clear differences in ETa patterns between the three management strategies, with the unweeded field showing consistently greater water consumption compared to the weeded and intermediate plots.

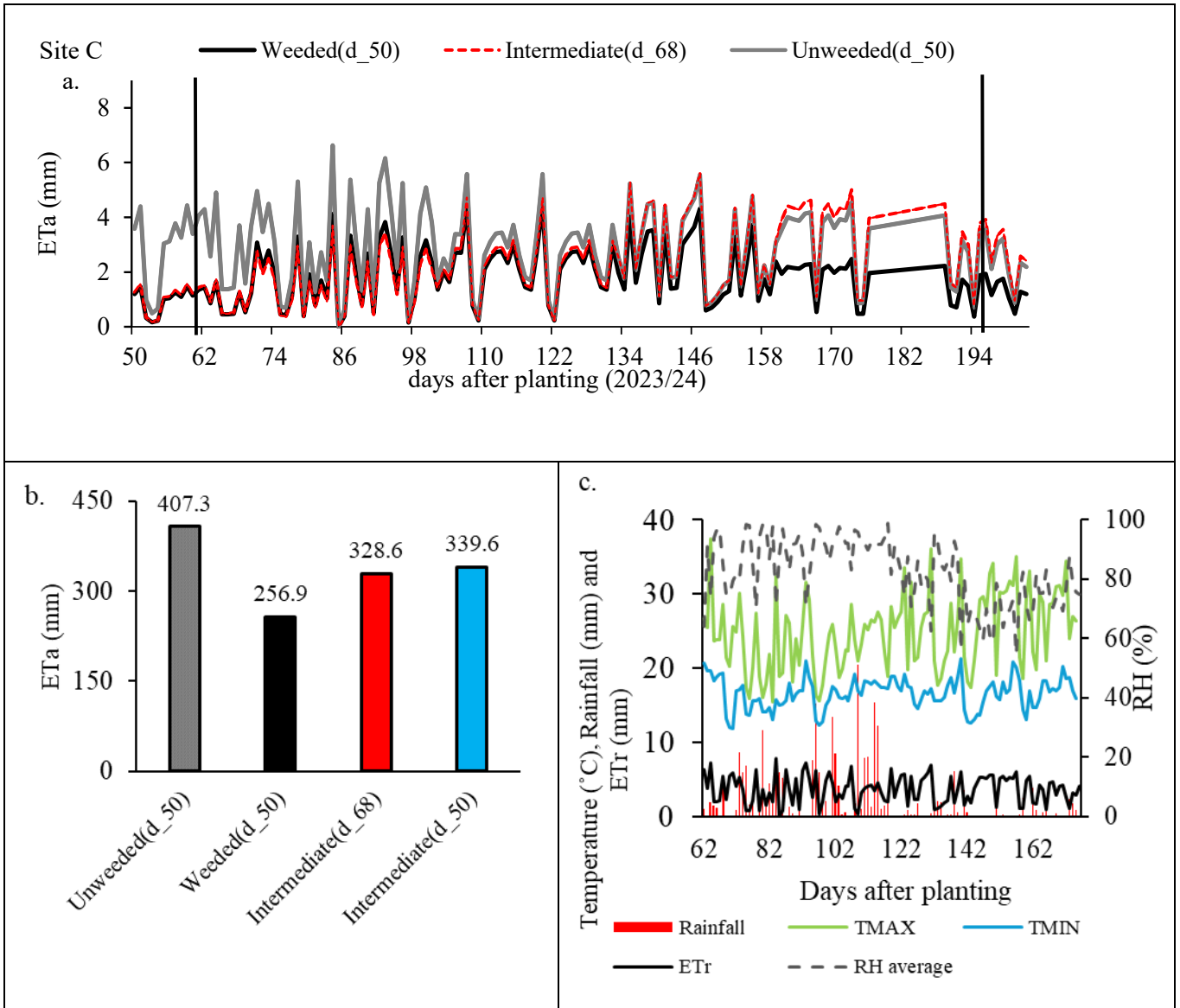


Figure 4.8 Graphs illustrating, (a) temporal relationship between daily measured ETa from the Eddy Covariance flux tower and estimates from the NDVI-based empirical model between day 50 and 203 after planting; (b) accumulated ETa derived from both observed EC flux tower data and the NDVI-based model; (c) daily variations in rainfall, reference evapotranspiration (ETr), average relative humidity (RH), and maximum and minimum air temperatures (TMAX and TMIN) from 22 November 2023 to 31 March 2024 at Site C

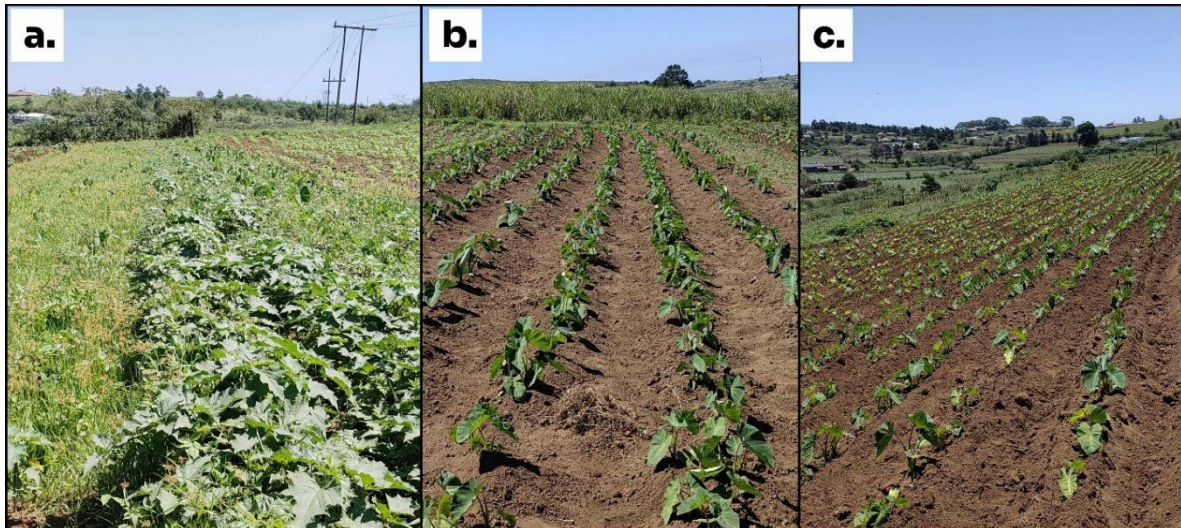


Figure 4.9 Differences in taro crop growth at the Swayimane study site (Site C) on 22 November 2023 under different weed management practices: (a) unweeded (62 DAP), (b) weeded (62 DAP), (c) intermediate (80 DAP)

The generation of ETa maps is an essential aspect of the effective dissemination of knowledge on observed findings in a way that is simple enough for a person without a scientific background to understand. The ETa trends for the three plots in site C are visualized in Figure 4.10. These maps were able to capture in detail the changes that took place throughout the observed period. Each image displayed the factors that contributed to the average value calculated using the VI-based empirical model. For example, according to the maps, the area with weeds that had broad leaves (as shown in Figure 4.9a) in the unweeded plot used the most water for a longer period compared to the other parts of that field. Another observation was the influence of erosion on ETa in the intermediate plot. The impact was more apparent in Figure 4.10e. The advantage of obtaining this data using multispectral UAV imagery with high spatial resolution lies in its ability to provide more insight with precision over time. These changes can be observed by generating land classification maps from the UAV imagery and overlaying them with the simulated ETa. That way, it would be easier to deduce the contribution from the different classes. The information presented in Table 4.11 gave context to Figure 4.10, with regard to the ETr and corresponding NDVI (Kc proxy) values on the date of image acquisition.

Table 4.11 ETa estimates for taro plots at the Swayimane study site (Site C) under different weed management practices, derived using the ETa–NDVI model on UAV image acquisition dates

Image	Day of Year	DAP	ETr (mm)	ETa-NDVI					
				UNWEEDED		WEEDED		INTERMEDIATE(d_68)	
				NDVI	ETa (mm)	NDVI	ETa (mm)	NDVI	ETa (mm)
a	22-Nov-23	62	6.90	0.68	4.71	0.23	1.57	0.24	1.66
b	08-Dec-23	78	6.98	0.83	5.79	0.43	3.01	0.39	2.70
c	19-Dec-23	89	1.59	0.86	1.37	0.62	0.98	0.55	0.88
d	10-Jan-24	111	3.74	0.85	3.17	0.71	2.65	0.70	2.60
e	25-Jan-24	126	2.08	0.81	1.68	0.62	1.28	0.70	1.46
f	06-Feb-24	138	6.57	0.84	5.51	0.72	4.76	0.84	5.52
g	21-Feb-24	153	5.63	0.76	4.28	0.52	2.93	0.78	4.39
h	15-Mar-24	175	5.50	0.75	4.12	0.41	2.25	0.83	4.55

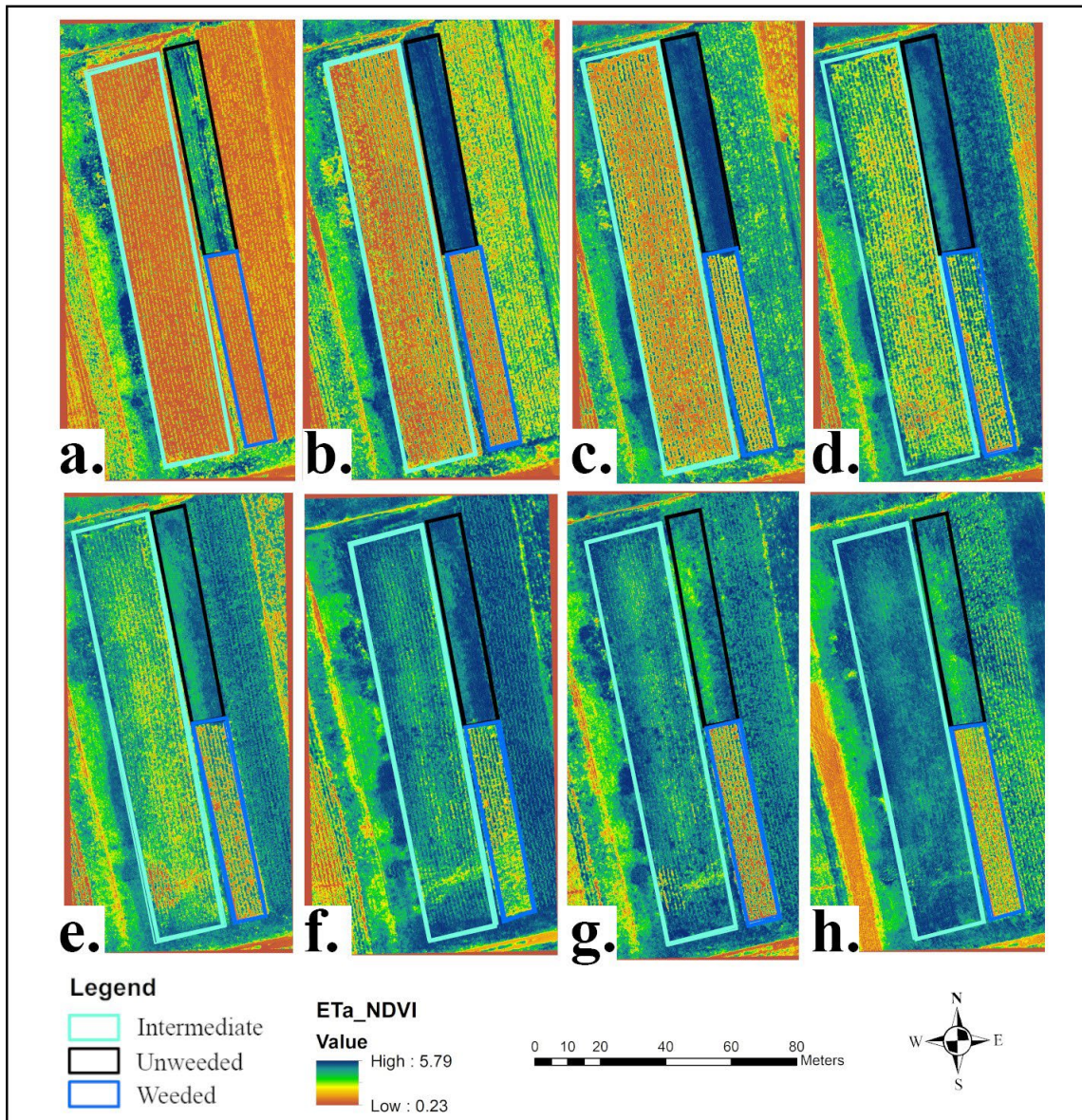


Figure 4.10 NDVI-based ETa model maps illustrating the spatio-temporal variation in taro crop water use across plots with different weed management practices at the Swayimane study site (Site C). The mapped estimates correspond to the ETa values reported in Table 4.11.

Based on the crop development stages outlined in Table 4.2, three growth phases (phases I, II, and III) were observed in this trial at site C, as shown in Table 4.12. Despite only six days being captured in phase I, and 7-days in phase III. This information was able to provide NDVI (Kc proxy) values presented in Table 4.13. These values were comparable with the validated data for phases II and III in site B (Table 4.10). According to the captured results for phase II, sites B and C (weeded field) had NDVI (Kc proxy) values of 0.50 and 0.51. This was a positive indication, considering that a large portion of both datasets was captured during this growth phase, and both plots were well-managed. The level of consistency suggests the potential robustness of the model, with its accuracy implying a higher likelihood of obtaining reliable results across different scenarios.

The NDVI (Kc proxy) had lower estimates in phase III than phase II for Site B (0.26) and C unweeded (0.75) and weeded fields (0.41), which is expected when vegetation has reached the maturation stage. However, it is important to note that the low Kc value of 0.29 during phase III in site B not only highlights the fact that the crop had reached its senescence stage, which generally slows down the crop growth rate. This value also indicates potentially low ETa estimates induced by seasonal variability. In this instance, the KC value was based on data measured in June, during the winter season in KwaZulu-Natal. Further studies should focus on ensuring that more data is captured in phases I and III, assessing the potential impact of other management practices in areas that have different field characteristics and climatic conditions.

Table 4.12 Distribution of simulated water use in taro plots at the Swayimane study site (Site C) under different weed management practices during different growth phases

Model	Growth Phase	DAP range	Unweeded _(d_50) (mm)	Weeded _(d_50) (mm)	Intermediate _(d_68) (mm)
ETa-NDVI	Phase I	50-56	16.26	5.44	5.75
	Phase II	57-196	375.41	242.86	301.17
	Phase III	197-203	15.64	8.55	17.26

Table 4.13 Changes in NDVI as a proxy for Kc across different growth phases in taro plots at the Swayimane study site (Site C) under contrasting weed management practices

kc proxy	Growth Phase	DAP range	ETr	Unweeded Field	Weeded Field	Intermediate (d_68-221)
NDVI	Phase I	50-56	3.42	0.68	0.23	0.24
	Phase II	57-196	3.72	0.79	0.51	0.63
	Phase III	197-203	2.98	0.75	0.41	0.83

4.3.3 Assessing the cost and benefit of adopting these recommended weed management practices

This section aimed to evaluate the practicality of implementing these strategies. It is well established that land management significantly influences crop development. When taro received adequate water, sunlight, and nutrients, its health was physically manifested by maximum root depth, as well as an increased number and size of leaves and corms, as shown in Figure 4.11. After determining the management expenses and revenue generated, the unweeded, weeded, and intermediate fields had a net profit of R3 083 (\$171), R16 339 (\$908), and R13 639 (\$758) (Table 4.15). Weeding produced R2 700 more than the profit generated by the intermediate field, which translates to 19.82%.

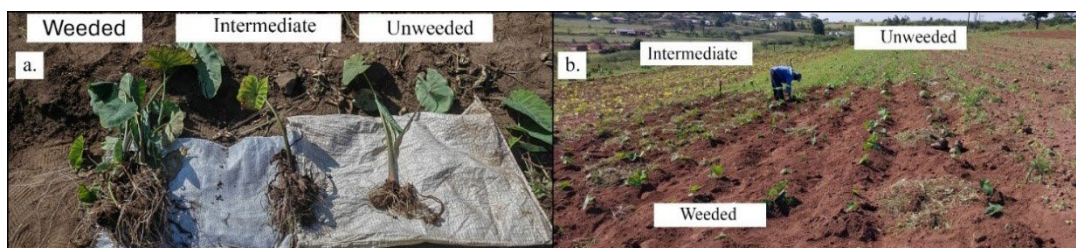


Figure 4.11 Images illustrating (a) the development of taro under different management practices and (b) the specific taro plots included in the investigation

Table 4.14 Management expenses associated with different weed management practices during the growth of taro at the Swayimane study site (Site C)

Weed management practice	Input	Cost (ZAR)	Cost (USD)
Unweeded	Cultivator	R 300	\$16.67
	no extra input	R 0	\$0
	Total	R 300	\$16.67
Weeded	Cultivator	R 300	\$16.67
	weeding (9 times)	R 5 400	\$300
	Total	R 5 700	\$316.67
Intermediate	Cultivator	R 300	\$16.67
	Herbicide and application (R1782 + R 300)	R 2 082	\$115.67
	Cattle cultivation	R 480	\$26.67
	Manual labour	R 600	\$33.33
	Total	R 3 462	\$192.33

Table 4.15 Potential yield and net profit margins associated with different weed management practices in taro at the Swayimane study site (Site C)

Management Practice	Corm mass per plant (g)	Number of plants in a field	Mass of corms per field (kg)	Revenue per field	Management expenses	Net Profit (ZAR)	Net Profit (USD)
Unweeded	156.2	3332	520.46	R 3 383	R 300	R 3 083	\$171
Weeded	1017.6	3332	3390.64	R 22 039	R 5 700	R 16 339	\$908
Intermediate	789.6	3332	2630.95	R 17 101	R 3 462	R 13 639	\$758

4.4 Discussion

4.4.1 UAV potential in smallholder farms

The use of multispectral UAVs has demonstrated the capability of providing high-resolution spatiotemporal ETA, which can enhance crop management practices at local spatial scales (Ramírez-Cuesta et al., 2020). Although the range covered by UAVs is limited to smaller areas compared to open-source satellites, their ability to acquire accurate data with minimal influence from atmospheric

factors also creates the opportunity to enhance our understanding of land cover effects on crop water use in resource-limited regions. In an era where climate change is among the key drivers of sustainable innovations, these platforms can be a great resource for extracting valuable information on NUCs that are under-researched (Abrahams et al., 2023). Although both EC and UAV-based approaches provide valuable insights into crop water use, several factors can contribute to inaccuracies in ETa estimates. For EC systems, environmental conditions such as high relative humidity (>70%), low wind speeds, and stable atmospheric conditions suppress turbulence, reducing flux detection and leading to underestimation of ETa (Zhang et al., 2023). Sensor interference caused by dew, rainfall, or dust deposition on the analyzer can further distort readings (Zitouna-Chebbi et al., 2018).

For UAV-based multispectral imagery, inaccuracies may arise from both technical and environmental sources. Image quality is highly sensitive to illumination, shadowing, and atmospheric conditions at the time of flight. Variability in solar angle, sensor calibration, or reflectance distortions due to soil background and canopy structure can alter VI values (El Imanni et al., 2023). Flight timing also plays a role, as UAV surveys conducted under variable cloud cover or following rainfall may not capture true canopy conditions (Gokool et al., 2023). These factors highlight the importance of calibration, frequent acquisition of imagery (to accurately depict the fluctuations in meteorological conditions) and validation. The lack of more images during the growing season partly explains some of the discrepancies between observed and simulated data in this study.

4.4.2 Evaluation of VI-based ETa models

The validated data from this study confirmed that ETa-NDVI, ETa-EVI2(kc), and ETa-MEVI2 could provide reliable ETa results. While the NDVI has traditionally been widely used, its limitations became evident under dense canopy or irrigated conditions. Despite ETa-NDVI being a suitable model for observing taro water use, no studies support it as the best-performing model except for Abbasi et al. (2023a), where the model accurately estimated the long-term annual average ETa of wheat. According to D'Urso (2010), ETa-NDVI will always have lower estimates, under well-watered and unstressed conditions, because Kc maximizes at 1.2 while the empirical model does the same at 1 (the model does not account for this parameterization). This pattern, where ETa-NDVI had the lowest performance, was observed in site A, which grew irrigated cannabis. Jarchow et al. (2022) highlighted that the NDVI is sensitive to imagery that does not have maximum vegetation cover. This could be the reason that best explains why the ETa-NDVI model was more consistent with measured data in the rainfed taro field (site B). One of the main limitations of this model is its suitability in unstable conditions and unreliability in extreme events such as disease outbreaks and floods (Khand et al., 2017).

ETa-EVI2(kc) was the superior model in a sugarcane water use study conducted by Woldemariam et al. (2024). Similar findings were observed in site A, which suggests that the EVI2-based models are more sensitive to irrigated crops or those with greater canopy density. In site B, EVI2-based models recorded higher values during the peak growing season. Findings from other studies that adopted the non-modified version of ETa-MEVI2 also noted similar performances when compared to the NDVI-based models (Nouri et al., 2020; Abbasi et al., 2023a). The ETa-MEVI2 underestimated towards the end of the season, and this could be attributed to the decrease in plant available water due to changes in seasons (winter), which often causes a decrease in LAI (Leaf Area Index- is directly proportional to EVI2 when using Beer-Lambert's equation), to match environmental conditions that enable photosynthesis (Nagler et al., 2013). The opposite was observed in site A, where ETa-MEVI2 overestimated towards the end of the growth cycle of cannabis. Nouri et al. (2020) confirmed that EVI2 has a greater sensitivity to crop structure and greenness compared to NDVI.

In summary, the NDVI was more reliable under sparse or rainfed conditions, while EVI2 and MEVI2 outperformed it under dense canopy or irrigated systems due to their structural resilience to saturation and soil background effects. These insights emphasize the importance of index selection based on vegetation dynamics and environmental conditions, especially for developing context-specific ETa models in smallholder systems.

4.4.3 Insights into Crop Water Use, Weed Competition, and Management Implications from UAV-Based ETa Monitoring

This study demonstrated the potential of empirical ETa models derived from multispectral UAV imagery for monitoring crop water use in smallholder farms. The findings provided insight into the sensitivity of different VIs to crop-environment interactions, especially under varying water management conditions. The proxies successfully captured Kc values across different growth phases and management practices, demonstrating their potential as an effective tool for refining parameters used to identify suitable areas.

Mengistu et al. (2014) investigated the water use of taro in the Mbongolwane wetland (approximately 40 km west of Eshowe, KwaZulu-Natal, South Africa) and reported an average Kc value of 0.6. Fares (2008) found Kc values of 1.05, 1.15, and 1.1 for the early, mid, and late stages of taro under flood irrigation in Hawaii. These comparative values demonstrate the variability in water requirements across environments and irrigation regimes. Although NUCs are severely under-researched, there is evidence supporting the contribution of environmental effects on their development. Mabhaudhi et al. (2013) conducted a study that observed taro's response to varying water regimes (30%, 60%, 100%) in Pretoria, South Africa. Findings from the study demonstrated a direct correlation between the unstressed and well-watered taro (100%) and higher yield, canopy size, and plant height. These findings were consistent with observations in this study. The taro in the unweeded field had less access to water, resulting in lower yield, canopy size, and plant height, which is evident in Figure 4.12. Overall, higher water availability (100%) led to increased yield, larger canopy size, and greater plant height trends that were consistent with the well-managed taro plots observed in this study.

Importantly, this study also highlights the influence of weed biomass on taro ETa. The presence of unmanaged weeds in the unweeded field altered canopy dynamics by increasing total vegetative cover, which elevated ET rates due to added transpiring surfaces and interspecies competition for water. This is reflected in lower crop vigor, smaller canopy size, and reduced yield. Weeds can reduce stomatal conductance in taro by intensifying water stress, thereby diminishing both transpiration and photosynthetic activity. These findings underscore the critical need for effective weed management, not only to improve crop productivity but also to optimize water use efficiency in water-scarce environments. The improved water use efficiency in the weeded and intermediate plots translated to improved economic benefits (cost benefit analysis). This finding agreed with results from Fadlallah et al. (2019) on work done with herbicides in Egypt.

Although the weeded field generated a substantial amount of money through higher yields, some factors need to be considered before adopting the practice. This approach has the potential to keep people employed during the growing season, but in many African countries, some cannot afford to pay for the work. The practice also contradicts the guidelines set by conservation agriculture (CA), which are against tilling. Constant tilling has been found to degrade soil quality and increase the potential of becoming more prone to erosion (Reimer et al., 2019). Over time, the loss of organic matter through this process can cause a reduction in soil fertility, resulting in potential low yield turnover. CA researchers have encouraged farmers to adopt PWM to preserve the soil (Magar et al., 2022). To some degree, methods applied in the intermediate field align with CA guidelines (Pagar et al., 2019). The farmer demonstrated an understanding of maintaining the soil quality by integrating

weed management strategies and ensuring they obtain reasonable yields with low input while minimizing tilling.

4.5 Conclusion

The ETa-NDVI model using UAV imagery was identified as the most suitable approach for estimating taro water use. When applied across fields managed with different weed control practices, results showed the weeded field used the least water (21.84%), while the unweeded field used the most (23.97%), with the farmer-managed (intermediate) plot falling in between. These findings highlight the model's capability to detect ETa variations driven by weed density, making it a valuable tool for arid and semi-arid regions. The high spatial resolution provided by multispectral UAV imagery enabled detailed ETa mapping, revealing intra-field variability and illustrating the impact of herbicide use and management practices. This sensitivity to management interventions underscores the model's utility for site-specific decision-making in land and water resource management.

Importantly, these findings have broader implications for smallholder agriculture. The ability to generate reliable, high-resolution ETa maps using UAVs and empirical models offers extension officers and decision-makers a practical tool to tailor water use recommendations, improve irrigation scheduling, and guide targeted weed control interventions. In resource-limited settings where ground data is scarce, this model could underpin evidence-based policies for water allocation and crop support programs. However, it is still important to acknowledge the digital divide that exists between researchers and smallholder farmers, especially in the context of SSA. Therefore, strategic collaboration between research institutions and government agencies is vital for establishing capacity-building infrastructure that bridges existing gaps and addresses practical challenges, such as the high cost of UAV technology and the specialized skills required to operate them effectively (Choruma et al., 2024).

The technical results regarding weed distribution and water consumption presented here provide a critical empirical basis for the broader synthesis and discussion in Chapter 5. Chapter 5 integrates these findings with the spatial weed mapping results from Chapter 3 to evaluate the overall impacts of weed management on taro productivity, water-use efficiency, and economic outcomes. By linking spatial weed dynamics with crop water use, the subsequent chapter draws on this evidence to develop more holistic recommendations for sustainable weed management and irrigation strategies in smallholder systems.

Furthermore, these tools can contribute to climate adaptation strategies by helping farmers optimize water use under changing rainfall and temperature patterns. Future research should explore integrating RS-based ETa models with gridded and in-situ meteorological data to enhance robustness in areas lacking weather stations. Refining the empirical relationships between vegetation indices and crop coefficient (Kc) across growth stages and diverse agroecological zones will improve scalability and seasonal adaptability.

5. GENERAL DISCUSSION

5.1 Introduction

Following the detailed technical assessments of weed mapping (Chapter 3) and water use (Chapter 4), this general discussion aims to synthesize the research findings detailed in the preceding chapters to reflect on the project's overarching objectives and its contribution to smallholder farming resilience. This project sought to demonstrate how UAV technologies and big-data geospatial cloud computing infrastructure (like GEE) can be effectively applied for PA applications, specifically PWM, by accurately quantifying crop-weed dynamics.

The technical core of this study involved three primary areas of investigation:

1. Literature review identifying the impacts of crop–weed competition and the potential of PWM.
2. Developing cloud-based mapping algorithms using multispectral UAV imagery to generate reliable weed distribution maps.
3. Evaluating VI-based empirical models derived from UAV imagery to estimate actual evapotranspiration (ET_a), thereby quantifying the impacts of weed water use on crop productivity and available water resources.

This work aimed to address the critical constraint of poor weed management, which often results in low yields and inferior product quality in smallholder fields, by offering cost-effective and site-specific solutions tailored for spatially heterogeneous smallholder farm settings.

5.2 Revisiting the Objectives of the Study and Summary of Key Findings

The main aim of the project was to accurately identify and map the spatial distribution of weeds and to understand and quantify the impacts of weed water use on crop health, quality, yield, and available water resources, ultimately guiding more effective weed management in the future.

The following four specific objectives formed the basis of the project:

Objective 1: To provide a literature review on the impacts of crop-weed competition on crop yields and quality, as well as the potential of PWM to mitigate these impacts.

Summary of Key Findings:

- The literature review confirmed that poor weed management is often the primary factor contributing to low yields and inferior product quality, especially for slow-growing crops like taro during early developmental stages.
- PWM (also called Intergrated Weed Management or Site-Specific Weed Management) is advocated as an efficient and sustainable alternative to conventional, uniform control methods.
- UAVs emerged as the most frequently utilized RS platform for PWM applications, primarily due to their ability to provide cost-effective, very-high-spatial-resolution data at user-defined intervals, making them suitable for smallholder farms.

Objective 2: Develop and set up a trial that will enable the impacts of crop-weed interactions to be quantified through traditional and UAV-based approaches.

Summary of Key Findings:

- A field trial focusing on crop-weed competition in taro was successfully developed and established in the Swayimane community in KwaZulu-Natal, South Africa.
- The trial included three distinct weed management plots: weeded (weeded biweekly), unweeded, and intermediate (where the farmer applied multiple conventional practices).
- The project successfully integrated both traditional measurements and UAV-based data collection to quantify the resulting crop-weed dynamics.

Objective 3: Map and identify weeds during the various NUC growth stages.

Summary of Key Findings:

- A pragmatic cloud-based supervised classification algorithm was developed using UAV multispectral imagery within the GEE platform.
- The OBIC utilizing textural features derived from the GLCM, combined with the GTB classifier, was the best-performing algorithm.
- This technique achieved a high OA of 98.82% (Kappa coefficient 0.98) during the EV growth phase when using 300 training data points.
- The incorporation of textural features (GLCM) proved essential for distinguishing spectrally similar land cover types, which is often difficult using spectral information alone.
- The effectiveness of the weed distribution maps decreased substantially over time, emphasizing the importance of early detection of weeds for implementing sustainable control methods. Reliable maps could be produced if PWM were applied from the beginning.

Objective 4: Quantify the water use of NUCs and weeds using UAV imagery.

Summary of Key Findings:

- The study validated the viability of VI-based empirical models using UAV imagery to estimate ET_a.
- The ET_a-NDVI model was identified as the most suitable approach for estimating taro water use in the rainfed smallholder farm context (Site C), demonstrating consistency with measured data and acceptable estimation error (less than 15%).
- Water use quantification revealed the heavy burden of weed competition: the unweeded plot accumulated the highest ET_a (407.30 mm), consuming 23.97% more water than the intermediate plot.
- Conversely, the weeded plot used the least water (256.90 mm), representing 21.80% less than the intermediate plot, demonstrating enhanced water use efficiency through management.

- The superior water use efficiency in the managed plots translated into substantial economic benefits. The weeded field generated the highest net profit (R16,339, or \$908). Weeded fields produced 28.9% more yield and achieved a 19.8% higher profit margin compared to intermediate plots, while unweeded yields and profits were drastically lower.

5.3 Challenges Experienced During the Study's Duration

The implementation of advanced technological workflows (UAV and cloud computing) in smallholder agricultural settings encountered several practical and technical limitations:

Technical and Data Limitations:

- **Data Acquisition Accuracy:** The project lacked a GPS device with sub-centimeter differential correction accuracy, which meant that training datasets for classification algorithms had to be generated via visual inspection.
- **Sensor Limitations:** The multispectral sensors used lacked specific spectral bands (e.g., shortwave infrared or those required for albedo derivation), which restricted the ability to use more physically based approaches like traditional surface energy balance methods (SEBAL, METRIC, SEBS) for ETa estimation.
- **Image Consistency and Frequency:** Image quality is highly sensitive to external factors, including illumination, shadowing, sensor calibration, and atmospheric conditions. Furthermore, the lack of more frequent imagery captured during the growing season contributed to discrepancies between observed and simulated ETa data.
- **Equipment Consistency:** The primary UAV platform (DJI-M-300) was occasionally unavailable during Site C operations, necessitating the use of the alternative DJI Mavic 3 multispectral platform, which introduced complexity due to differing band specifications and ground sampling distances.
- **Growth Stage Dependency:** The accuracy of weed mapping dropped significantly over time (e.g., Trial 1 results), suggesting that maps become unreliable if the training data does not account for changes in the spectral reflectance and geometric properties of taro and weeds as they develop. In severe cases, where weeds dominated the canopy cover, the underlying crop was obscured, making the classified map unreliable for studies focused on crop development details.

Computational and Algorithmic Constraints:

- **GEE Platform Restrictions:** While cloud-based platforms like GEE remove many hardware barriers, users are reliant on good internet connectivity. The platform also limits the users' ability to test more advanced classification models, as it provides access to only four classification algorithms and lacks direct integration of CHM and DL frameworks.
- **Training Data Digitization:** The GEE platform's visualization limit (up to 2 m zoom level) made it challenging to digitize accurate training datasets from high-resolution UAV imagery, requiring manual delineation via separate software like ArcMap, which introduced workflow continuity issues.
- **Advanced Algorithm Barriers:** DL algorithms, although highly accurate, are complex, computationally demanding, require specialized skills, and need large volumes of data for training, typically limiting their feasibility for widespread adoption by smallholder farmers.

Operational and Adoption Barriers:

- **Investment and Feasibility:** The adoption of geospatial information technologies is lagging in the developing world due to the perception of high initial investment costs and feasibility considerations. The cost of UAV technology and the specialized skills required for operation further hinder widespread adoption by smallholder farmers.

- **Digital Divide:** A major barrier is the digital divide between researchers and smallholder farmers, marked by a lack of awareness and digital skills among the farming community, highlighting the need for co-learning and participatory approaches.

- **Management Timing Issues:** Timing discrepancies were observed, such as delays in applying weed management in Site C due to farmer concerns over herbicide effects on adjacent fields, which affected the consistency of treatment conditions and complicated the interpretation of the seasonal crop response and water use efficiency.

This synthesis leads to the final conclusions and strategic recommendations for future research and community adoption presented in Chapter 6.

6. GENERAL CONCLUSION

This project successfully demonstrated that UAV technology, combined with cloud computing platforms like GEE and appropriate analytical techniques, provides a practical and valuable resource for developing reliable, high-resolution maps essential for early weed detection and water use monitoring in NUCs.

Effective weed management is shown to be crucial, as poor weed management significantly limits NUC yields and increases water consumption. The optimized productivity demonstrated in managed plots translates directly into improved economic benefits for smallholder farmers.

6.1 Recommendations

Recommendations focus on overcoming the barriers to the adoption of PA technologies, particularly the digital divide and high investment costs, while enhancing institutional and knowledge transfer capacity:

6.1.1 Capacity building and collaboration

- Strategic Collaboration for Capacity Building: Research institutions and government agencies must strategically collaborate to establish infrastructure that addresses the digital divide and operational challenges.
- Bridging the Digital Divide: Intentional collaboration between research organizations and the government is essential for developing capacity-building infrastructure that helps bridge the existing gap between researchers and smallholder farmers.
- Integrating UAV Monitoring into Extension Programs: Agricultural extension programs should be encouraged to integrate UAV-based weed monitoring into smallholder training initiatives.
- Developing User-Centered Tools: Promote the co-creation of digital tools with end users, such as mobile alerts linked to weed infestation maps, to improve usability and adoption at the farm level.

6.1.2 Operational and economic adoption

- Advocating for Accessibility Solutions: Advocate for subsidies or shared-service models to make UAV-based monitoring technologies more accessible and affordable for smallholder farmers in rural communities. Specialists can leverage innovative UAV-based business enterprises to offer a more affordable option where the investment cost is shared across multiple farms by a UAV service provider.
- Policy Support: Supportive policy frameworks and subsidies are crucial for purchasing UAV models, similar to examples seen in other countries.
- Implementing Early Detection and Control: Implement PWM from the beginning of the growth cycle for maximum effectiveness, as the reliability of weed distribution maps decreases substantially later in the season when the crop canopy obscures weeds.

6.1.3 Technical refinement

- Increasing Image Acquisition Frequency: Future studies should prioritize increasing the frequency of image acquisition across all crop growth stages to improve model performance and validation accuracy, particularly since the early growth phases often had limited imagery for validation in this study.

- Refining Classification Inputs: Incorporate high-resolution CHMs and explore the integration of LiDAR data with multispectral imagery to further refine classification results.
- Enhancing VI-based ETa Validation: Validating VI-based ETa models with more comprehensive in-situ measurements is essential to ensure robust and reliable water use estimates.

6.2 Future Research Opportunities

Future research should focus on enhancing model scalability, testing advanced computational techniques, and applying the derived models across diverse agricultural contexts:

6.2.1 Computational and algorithmic advancement

- Exploring DL Algorithms: There is a need to explore the potential of DL algorithms and crop CHMs regarding UAV image classification techniques. This includes investigating the application of DL classifiers such as CNNs and YOLO using alternative processing environments, given the limitations of platforms like GEE.
- Improving Model Generalizability: Future work should focus on expanding the number of training datasets and sampling locations to help improve the generalizability of the models and reduce potential bias.
- Addressing GEE Limitations: The current GEE environment provides access to only four classification algorithms and lacks direct integration of CHM and DL frameworks; future research could focus on overcoming these limitations.

6.2.2 Model scalability and adaptability

- Refining VI-kc Relationships: Future research should focus on refining the empirical relationships between VIs and Kc across different growth stages and agroecological zones to enhance model scalability and adaptability.
- Testing VI-based Models in Diverse Zones: The VI-based models need to be tested in different agroecological zones to ensure their robustness and accuracy across varying climatic and environmental conditions.
- Integrating Meteorological Data: Research should explore integrating RS-based ETa models with gridded and in-situ meteorological data to enhance robustness in areas lacking weather stations.

6.2.3 Investigating management impacts

- Assessing Diverse Weed Management Practices: Future studies should investigate other weed management practices and their effect on actual evapotranspiration, considering site variables such as soil properties, topography, aspect, type of weed species, and seasonality.
- Focus on NUCs and PWM: Continued research on PWM using UAVs for NUC and weed combinations is required, leveraging findings from studies conducted on major crops as guides.

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APPENDIX

A1. Capacity Building

Capacity building is a core mandate of the Water Research Commission (WRC), aimed at strengthening knowledge, skills, and institutional capabilities within the water and science sectors. In alignment with this mandate, Project No. C2023/2024-01248 — *Mapping and assessing the impacts of crop–weed competition in neglected and underutilized crops* — integrates capacity development as a central component throughout its implementation and to ensure post-project sustainability. Since project inception, focused efforts have been directed toward: (i) developing the competencies of postgraduate students and early-career researchers, and (ii) enhancing institutional capacity to improve agricultural productivity and promote the sustainable use of natural resources. These activities are of significant value to the WRC and are detailed in the subsections that follow.

The project budget provides support for two full-time MSc students. In addition, Ms. Ameera Yacoob was registered for an MSc degree and, although not directly funded by the project, she received ongoing technical and mentorship support due to an alignment of her research with the project objectives. Furthermore, in April 2024, Ms. Sanelisiwe Mchunu joined the project as an Honours student, focusing on evaluating appropriate PA techniques for smallholder farming systems, and received partial financial support from the project. Table 4.1 below summarizes the postgraduate students.

Table A.1 Postgraduate students supported and engaged in capacity building through the project

Name	Gender	Race	Degree	Discipline	Notes
Mr Knowledge Tinotenda Muchaonyerwa	Male	Black	MSc	Hydrology	Registered 29 March 2023 MSc degree completed: to graduate in 2026
Ms Evania Chetty	Female	Indian	MScAgric	Food Security	Registered 04 April 2023 MSc degree completed: graduated in 2025
Ms Ameera Yacoob	Female	Indian	MSc	Hydrology	Registered March 2023 MSc degree completed: graduated in 2025
Ms Sanelisiwe Mchunu	Female	Black	BSc Hons	Hydrology	Registered March 2024 BSc Hons degree completed: graduated in 2025

A1.1 Postgraduates

A1.1.1 Postgraduate candidates

A1.1.1.1 Student 1: Mr Knowledge Muchaonyerwa

Student 1: MSc Title

Mapping and assessing the impact of weeds on neglected and underutilized crops in smallholder farms using cloud computing and multispectral UAV imagery

Mr Muchaonyerwa was registered for an MSc in Hydrology and was fully funded by this project. He was supervised by Dr M Mahomed, Dr S Gokool, and Prof. A. Clulow. His research aimed to explore and assess the potential of PWM and UAV technologies to quantify the impact of weeds on NUCs, enabling more informed decision-making for effective weed management. This research plays a crucial role in enhancing crop yields, particularly for smallholder farmers, which can contribute to addressing issues such as poverty, job creation, food security, and malnutrition. As part of his methodology, Mr Muchaonyerwa had also been evaluating the effectiveness of various image classification techniques for mapping the distribution of weeds on NUCs at different crop growth stages. Throughout his MSc studies, significant capacity and competency development were achieved, including:

Technical and research skills

- Installation and operation of an EC flux tower and automatic weather station (linked to WRC Project C2021-2022-00800)
- Development and management of the experimental field site using a split-plot trial design (weeded [served as the control] vs un-weeded treatments)
- Pre-processing, processing and analysis of UAV multispectral imagery
- In-situ data collection and weed removal to support ground-truthing
- Data analysis and interpretation of initial datasets
- Programming and data analytics using GEE and R statistical software
- Demonstrating UAV applications for quantifying water use in NUC and weed systems

Scientific communication and dissemination

- Presentation and exhibition of research at:
 - Sustainability Research and Innovation Congress (SRI 2024), Africa Satellite Event (21-24 May 2024, Durban, South Africa),
 - University of KwaZulu-Natal (UKZN) Postgraduate Research & Innovation Symposium (October 2024, Durban, South Africa), and the
 - South African Hydrological Society Conference (October 2024, Cape Town, South Africa).

Professional development

- Successfully completed his MSc degree and will graduate in 2026
- Obtained a UAV pilot's licence, supported by experience gained through this project

A1.1.1.2 Student 2: Ms Evania Chetty

Student 2: MSc Title

Exploring the use of Unmanned Aerial Vehicle (UAVs) RGB data for crop monitoring and mapping within a smallholder farm setting: a case study in Swayimane.

Ms. Chetty was funded directly through this project and received technical and supervisory support from Dr. S Gokool and Dr. M Mahomed. She was registered for an MSc in Agriculture. While the specific focus of her MSc is not fully aligned with the central objectives of the project, her work contributes valuable knowledge on the application of remote sensing to improve agricultural productivity and resource-use efficiency in smallholder systems. These insights support the broader motivation and technical foundation upon which this project is built.

Her research focused on assessing the potential of UAV RGB imagery to enhance precision agriculture (PA) practices for smallholder farmers. Given the financial constraints often faced by these farmers, investigating cost-effective RGB-based monitoring solutions offers a practical alternative to more expensive multispectral or hyperspectral sensors, and aligns strongly with the project's overarching emphasis on accessibility and sustainability. Since joining the project, Ms. Chetty has developed a range of scientific and technical competencies, including:

Technical and research skills

- Installation and operation of an EC flux tower and automatic weather station (linked to WRC Project C2021-2022-00800)
- Collecting extensive in-situ crop monitoring data (LAI, chlorophyll content, canopy temperature, canopy height) and training data for land-use/land-cover (LULC) mapping (June 2023 – May 2024)
- Pre-processing and processing UAV-acquired imagery
- Programming using GEE and R statistical software
- Field site visits, dataset management, and analysis of results

Scientific communication and dissemination

- Presented her research findings at:
 - Fountainhill Estate Research Symposium (October 2023, Wartburg, South Africa).
 - Sustainability Research and Innovation Congress (SRI 2024), Africa Satellite Event (21-24 May 2024, Durban, South Africa),
 - University of KwaZulu-Natal (UKZN) Postgraduate Research & Innovation Symposium (October 2024, Durban, South Africa), where she received an award for her presentation,
 - South African Hydrological Society Conference (October 2024, Cape Town, South Africa).

Professional development

- Successfully completed her MSc degree and graduated in 2025.

Further details on Ms. Chetty's research study are provided in **Appendix D**.

A1.1.1.3 Student 3: Ms Ameera Yacoob

Student 2: MSc Title

Advancing Precision Water Management in Smallholder Sugarcane Farming: Leveraging Unmanned Aerial Vehicle-Based Remote Sensing and Machine Learning for ET and Water Stress Assessment

Ms. Ameera Yacoob registered for an MSc in Hydrology in 2023, funded through WRC Project C2021-2022-00800. While she was not directly funded by this project (C2023/2024-01248), she received ongoing support, research collaboration opportunities (co-authorship) and mentorship due to the alignment between her MSc research and the project's broader objectives. Throughout her MSc, Ms. Yacoob demonstrated significant capacity and competency development across multiple domains, including:

Technical and research skills

- Installation, operation, maintenance, and bi-weekly monitoring of an EC flux tower and automatic weather station (June 2023 – May 2024)
- Collection and analysis of in-situ crop monitoring data (LAI, chlorophyll content, canopy temperature, canopy height) over the same period
- Pre-processing and processing workflows for UAV-acquired imagery
- Programming using Google Earth Engine and R statistical software

Scientific communication and dissemination

- Presentation and exhibition of her research at:
 - Fountainhill Estate Research Symposium (October 2023, Wartburg, South Africa)
 - Sustainability Research and Innovation Congress (SRI 2024), Africa Satellite Event (21-24 May 2024, Durban, South Africa),
 - University of KwaZulu-Natal (UKZN) Postgraduate Research & Innovation Symposium (November 2023 & October 2024, Durban, South Africa), where she received awards for her research presentations,
 - South African Hydrological Society Conference (October 2024, Cape Town, South Africa), and the
 - South African National Committee on Irrigation and Drainage (SANCID) Symposium (06-08 May) 2025.

Professional development

- Successfully completed her MSc degree, graduating cum laude in 2025
- Gained mentorship and supervisory experience by supporting Dr Mahomed and Dr Gokool in the supervision of Ms. Sanelisiwe Mchunu (Honours student-discussed below)
- Awarded a UAV pilot's licence, supported by experience gained through WRC-funded research activities (C2021-2022-00800, C2023/2024-01248)
- Progressed to a PhD in 2025, continuing research on UAV applications for environmental and agricultural challenges
- Selected to participate in the 2025 DTU Next Generation Digital Action Tech Summit in Copenhagen, Denmark, based on the strength of her MSc achievements and proposed PhD work

A1.1.1.4 Student 4: Ms Sanelisiwe Mchunu

Student 3: MSc Title

Leveraging satellite earth observation data for estimating crop water use in smallholder farms

Miss Sanelisiwe registered for a BSc Honours in Hydrology in March 2024. She was supervised by Dr Gokool and Dr Mahomed. Although her research was not fully aligned with the main objectives of this project, she received partial funding, technical support, and co-supervision through the project due to the complementary nature of her research topic. Her work provides important insights into the challenges faced by smallholder farmers, reinforcing the project's emphasis on promoting sustainable and efficient agricultural water use. Her research focused on evaluating the use of satellite Earth observation data to estimate crop water use in smallholder farming systems. These findings offer valuable contributions to understanding water use efficiency and improving crop productivity in resource-constrained environments. Throughout her Honours study, Ms Mchunu developed capacity and competency in the following areas:

Technical and research skills

- Pre-processing and processing of UAV-derived imagery
- Programming using Google Earth Engine
- Data management, interpretation, and scientific analysis

Professional development

- Successfully completed her BSc Honours and graduated in 2025

Further details on Ms. Mchunu's research study are provided in **Appendix E**.

In addition to the above-mentioned, agriculture, food security, and crop science are well-established areas of research; however, this work focuses specifically on the appropriateness of a solution tackling a major constraint to crop production, which is relevant to these areas of research, and therefore carefully examines its effectiveness in such a setting as smallholder farms. Hence, the real payoff is in witnessing the postgraduate students collecting the data, using it to inform the community, and learning how to better manage weed practices to ensure optimal and quality productivity. Subsequently, this project also exposes the postgraduate students to participating and being a part of the overlap of science, multi-disciplinary work, as well as elements of good systems engineering. Also, in gaining understanding and knowledge on the blending of technical and societal components.

While there has also been much published work highlighting the challenges in agriculture, the work in this project is brought to life by the actual setting up of a trial, monitoring the weed and crop growth throughout the growth cycle of the NUC and using the UAV in the process. This, itself, is also a valuable learning process for the postgraduate students.

The postgraduate students have been actively disseminating their research through publications and presentations, fostering dialogue between science and society, enhancing student visibility, and raising awareness among stakeholders and the broader public about the significance of the research for South Africa's future.

A1.1.2 Early career/establishing researchers

Staff skills development and early career/establishing researchers:

This project also highlights the importance of human capacity building through the development of early-career researchers. For instance, the progression of the project leader, Dr Maqsooda Mahomed, and the principal researcher, Dr Shaeden Gokool, is a prime example. Both began their careers as postgraduate students on earlier WRC projects (K5/2512, K5/2790//4, C2021-2022-00800) and have now advanced to lead water commission-funded research projects as first-time project leaders. Additionally, the project includes senior researchers and expert team members—Professors Alistair Clulow and Tafadzwanashe Mabhaudhi, Dr Mbulisi Sibanda, and Mr Richard Kunz—who contribute their expertise. This collaboration also ensures that the early-career researchers receive the necessary support, guidance, and mentorship to complete the project.

Furthermore, the opportunities provided by the WRC for early career researchers help foster skill development and exposure to a range of academic and scientific endeavours. For instance, Dr Mahomed and Dr Gokool applied for and were successful in being awarded an AfOX (Africa Oxford Initiative) catalyst grant. As part of the grant, Dr Mahomed visited the University of Oxford in June/July 2024 for a study period under the AfOX Scholarship, alongside the REACH program at Oxford (www.reachwater.org.uk). The REACH program (2015-2025), led by the University of Oxford in collaboration with other prestigious research institutions, is funded by the UK Foreign, Commonwealth & Development Office (FCDO). During her visit, Dr Mahomed contributed to the development of collaborative research between the University of KwaZulu-Natal and the University of Oxford, with a focus on scaling up UAV research. This included discussions on creating an open-access decision support tool to assist smallholder farmers in using UAV data to enhance agricultural operations. The visit also provided an opportunity to explore potential funding sources to further this work and discuss the WRC's role in advancing UAV research for precision agricultural management.

Additionally, project members Dr Mahomed and Dr Gokool enrolled in a UAV pilot training course to strengthen their technical skills and operational knowledge in drone-based research. They have successfully completed all theoretical requirements and are now pending the final practical assessment to obtain their UAV pilot licenses.

A1.2 Institutions

Institutional capacity enhancement during the 2024/2025 period occurred through strengthened access to research infrastructure, technical resources, and skills development opportunities.

Postgraduate students working on this project have benefited from equipment procured through previous and ongoing research initiatives, including:

- Unmanned Aerial Systems: DJI-M-300, Mavic 3 Multispectral (Universal Edition), Mavic 3 Thermal (Universal Edition), and a MicaSense Altum multispectral sensor
- In-situ monitoring instrumentation: Surface renewal system or EC flux tower, Automatic Weather Station, hand-held GPS, LAI-2250, and SPAD meters
- Computing and institutional support: High-performance workstations, licensed and open-source GIS/RS software, high-speed internet, access to university vehicles, and administrative support

Additionally, human resources (including academic and technical staff, undergraduate assistants, postgraduate researchers, and postdoctoral fellows) have been mobilized to support the project's implementation.

Capacity development has also been supported through professional skills training available at the University of KwaZulu-Natal. For example, the *Data Science Initiative for Africa (DSI-A) – WASHA Takwimu Training Programme* offered a series of short courses (18 March – 28 June 2024) covering:

- Programming fundamentals in R and Python
- Core data science concepts and workflows
- Introductory ML and DL techniques

Lastly, Earth observation for hydrological analysis & IWRM Training workshop (24-28 November 2025): Overview of Earth Observation tools for hydrological application, identification of knowledge gaps, Co-developed research and training roadmaps. Theory and Practical Training on EO Technologies, QGIS, Google Earth Engine and UAV/Drone Data.

APPENDIX B

B1. Knowledge Dissemination

The dissemination of knowledge generated from this project has been facilitated through the following activities:

B1.1 Publications

- i. Gokool S, Mahomed M, Clulow A, Sibanda M, Kunz R, Naiken V, Mabhaudhi T. 2024. Exploring the Potential of Remote Sensing to Facilitate Integrated Weed Management in Smallholder Farms: A Scoping Review. *Drones*. 8 (3):81. <https://doi.org/10.3390/drones8030081>
- ii. Chetty E, Shaeden Gokool S, and Mahomed M. A comparative analysis of multi-spectral and RGB acquired UAV data for cropland mapping in smallholder farms. *In Submission: Frontiers in Plant Science*
- iii. Muchaonyerwa K, Mahomed M, Gokool S and Clulow A. Assessing weed mapping techniques for precision management in a smallholder farming context using multispectral UAV imagery and geospatial cloud computing infrastructure. *In Submission: Springer Nature-Environmental Monitoring and Assessment*

B1.2 Presentations and symposiums

- Dr Shaeden Gokool delivered an oral presentation on “The use of UAV-derived data to guide and inform precision agriculture practices in smallholder farms,” at the 7th Fountainhill Estate Research Symposium (October 2023)
- Miss Evania Chetty delivered an oral presentation on “Exploring the use of RGB Unmanned Aerial Vehicles for Crop Monitoring and Mapping Within a Smallholder Farm Setting: A Case Study in Swayimane,” at the Fountainhill Estate Research Symposium (October 2023).
- Ms Evania Chetty played a pivotal role in hosting an initiative on the Pietermaritzburg campus on 20th March 2024 to promote the themes and messages of World Water Day. World Water Day has been celebrated annually since 1993, instituted by the United Nations, with the theme for 2024 focusing on ‘Leveraging Water for Peace’ and highlighting the crucial role water plays in creating the stability and prosperity of the world. As part of the activities that were carried out to underline the importance of water and promote its efficient use, Ms Evania Chetty conducted a practical demonstration of the UAVs that she is using in her research study, along with exposing undergraduate and postgraduate students at the University of KwaZulu-Natal in Pietermaritzburg to the skills she has learnt during the course of her research, as well as, provided discussions on her research study as a motivation towards how UAVs can be used for sustainable water management practices. This event has been posted on the University of KwaZulu-Natal’s website and can be accessed from: <https://saees.ukzn.ac.za/news/hydrators-student-club-commemorates-world-water-day-with-campus-event/>
<https://ww2.caes.ukzn.ac.za/news/hydrators-student-club-commemorates-world-water-day-with-campus-event/>
- Mr Knowledge Muchaonyerwa and Ms Evania Chetty attended the Sustainability Research and Innovation Congress (SRI 2024), Africa Satellite Event (21-24 May 2024) together with project members (Dr Maqsooda Mahomed and Dr Shaeden Gokool) that took place at the Southern Sun Elangeni Hotel in Durban, South Africa. As part of the event, the project team was given the opportunity to host an exhibition through the University of KwaZulu-Natal. During the exhibition, project members and students were involved in showcasing their WRC

research activities through the display of posters, practical demonstrations of the UAVs, as well as through engaging talks and discussions with various researchers and academics who were present at the event.

- Ms Evania Chetty delivered an oral presentation on “Exploring the Use of Unmanned Aerial Vehicle RGB Data for Crop Monitoring and Mapping within Smallholder Settings” at the South African Hydrological Society Symposium (SAHS), which was held from 2-4 October 2024 at the Protea Breakwater Lodge in Cape Town.
- Mr Knowledge Muchaonyerwa delivered an oral presentation on “Mapping to Assess Precision Weed Mapping in a Smallholder Farm Using Multispectral UAV Imagery and Geospatial Cloud Computing Infrastructure” at the South African Hydrological Society Symposium (SAHS), which was held from 2-4 October 2024 at the Protea Breakwater Lodge in Cape Town.
- Ms Evania Chetty delivered an oral presentation on “A comparative analysis of Multi-spectral and RGB-acquired UAV data for Land Cover Mapping of Smallholder Farms” at the University of KwaZulu-Natal Postgraduate Research & Innovation Symposium (PRIS) that took place between 29-30 October 2024 at the Coastlands Hotel in Durban, South Africa. She also received an award for her oral presentation in the category of best oral presentation.
- Mr Knowledge Muchaonyerwa also delivered an oral presentation on “Assessing mapping techniques for precision weed management in a smallholder farm using multispectral UAV imagery and geospatial cloud computing infrastructure” at the University of KwaZulu-Natal Postgraduate Research & Innovation Symposium (29-30 October 2024).

B1.3 Popular articles and social media

The research being undertaken in this project as well as the various activities that the project members and students have been involved in, have featured in several of the Centre for Water Resources Research (CWRR) monthly newsletters, which are widely distributed to various individuals, institutions and organizations involved in the water resources and environmental sector. These newsletters can be accessed from: <https://cwrr.ukzn.ac.za/newsletters/>.

In addition, these articles are further disseminated on CWRR social media pages, i.e., Facebook (TheCWRR), Instagram (@cwrr_ukzn) and X (TheCWRR), to reach a wider audience.

B1.4 Community engagement

This project positioned itself at the centre of operationalising research for the benefit of the people on the ground. As such, the project focused on smallholder farms due to their influence in the food production system to address and eradicate current and future food insecurity, malnutrition and poverty concerns. Subsequently, the research study site where the trial was developed and set up was located within the Swayimane Community. Regular community engagement has been a strong feature of this project as the project team members and the local community of Swayimane, particularly the farmers, have been working closely together to share knowledge and ensure that the objectives of the project cater to their needs. The farmers were also actively involved in the setup of the trial, whereby half of the cultivated area was being weeded and the other half remained unweeded. Furthermore, farmers were compensated for any crop losses that occurred in the un-weeded area. This was done to gain the confidence of the farmers to participate in the research activity without concerns of any potential loss of profits/livelihoods.

By involving the smallholder farmers throughout the research trial, they were exposed to information that may serve to guide more effective weed management practices in the future, as well as provide them with spatially explicit information in near real-time allowing for more sustainable agricultural

management decisions and interventions to be effected at the right place and time, thereby serving to ensure that agricultural productivity is enhanced whilst critical resources are optimally used. This can, in turn, aid in strengthening the ability of the agricultural sector to contribute to addressing food security (improved quality of life, producing more and/or quality foods with the same or less water) and socioeconomic (such as job creation and economic development) challenges, whilst also building resilience within the sector to potential stressors.

Coincidentally, the project's study site belonged to a grandmother (now deceased), who had handed over most of her farming activities to her grandson, Luyanda, who is a BSc graduate student from the UKZN. As we are aware, South Africa is a very diverse country, with people having different traditions, myths and beliefs when it comes to research and technological advancements, which can often hinder the dialogue between scientists and communities. However, the likelihood of lending an ear to our own dear ones stands a greater chance of raising the level of knowledge among the young and old when it comes to concepts like PA and IWRM, in aiding the delivery of innovative knowledge-based products, activities and services tailored to meet the capacity-building needs of the broad development community. Subsequently, as an innovative approach to knowledge exchange and dissemination growth and evolution, the project played a pivotal role in also educating the young generation, like Luyanda, who are to be the future leaders of our country and also to help in bridging gaps and building an interaction with the older and hesitant generations in the pursuit of disseminating the knowledge.

A particularly encouraging outcome emerged following the harvesting of the study trial on 15 April 2024. In the subsequent planting season, farmers adopted key recommendations that were shared with them based on the project's findings, specifically shifting from sporadic to more frequent weed management. They implemented weekly weeding practices, which differed significantly from their previous approach. The farmer reported noticeable improvements in crop growth and shared images with the project team as evidence of the enhanced performance. This reflects early uptake of research-driven best practices and demonstrates the practical benefits of the project's engagement with smallholder farmers.

Additional engagements had also taken place as follows:

20-24 March 2023:

- Research team members, Dr S Gokool and Dr M Mahomed, hosted an informal workshop on introducing and educating the postgraduate students working on this project to the GEE platform, as well as how to conduct a systematic and scoping literature review. This was undertaken to assist the students in their research avenues.

13 September 2023:

- On 13 September 2023, a stakeholder engagement session organised by the Institute of Natural Resources (INR) was held at the Mbava Community Hall in the Swayimane area. The invitation was extended by Ms Brigid Letty, who serves on the project's Reference Group. The event provided a platform for knowledge exchange, discussion of agricultural challenges, and exploration of innovative farming approaches with local smallholder farmers.

Postgraduate students, Ms Chetty and Mr Muchaonyerwa, attended the session alongside INR staff conducting related research in the area. They engaged with community members to understand existing agricultural practices while sharing insights from modern research initiatives. The students collaborated to deliver a joint presentation outlining the objectives and intended methodologies of their respective WRC-supported projects.

Community participants expressed strong interest in the potential application of UAV-based precision agriculture, particularly regarding improved productivity and food security. The engagement was viewed as highly valuable by the students, offering both learning and outreach opportunities. Building on this momentum, the project intends to collaborate with other WRC initiatives operating in the region to organise a dedicated workshop aimed at enhancing farmers' understanding of UAV operations and their practical benefits.

16 November 2023:

- Project Leader, Dr Maqsooda Mahomed, and Principal Investigator, Dr Shaeden Gokool, participated in the inaugural Institute of Natural Resources (INR) Multi-Stakeholder Platform meeting held at the Gcumisa Traditional Court in Swayimane. The meeting was convened under the Promoting Local Innovation (Prolinnova)–South Africa and ELIFaNS initiatives, with a focus on strengthening collaboration, knowledge sharing, and coordination among organisations conducting research in the Gcumisa area.

During the session, Dr Mahomed delivered a presentation outlining the objectives and activities of the WRC-funded projects currently being implemented in the region, including this study. The engagement facilitated productive dialogue on opportunities for future multi-sector collaboration and deeper engagement with farmers to support agricultural innovation and resilience.

12 and 15th September 2023, 20th October 2023:

- Dr Maqsooda Mahomed and Dr Shaeden Gokool delivered talks at three different career day events to enlighten scholars about the potential career opportunities that can be pursued in this research space.

A career day is a valuable opportunity to cultivate a learner's mindset and provide them with a chance to learn about careers that align with their interests and skills, so they can start at an early age to narrow down what careers to pursue in the future. During September and October 2023, members of this project team participated in Springhaven, Ridgeview, and Allandale Primary School's career day. Learners were given an overview of a variety of careers that UKZN offers and were given further insight into the cutting-edge research that the members of the project team are currently involved in, particularly on UAVs and their role within the PA area.

10th-11th March 2024:

- Postgraduate students, Ms Chetty and Mr Muchaonyerwa, attended and participated in a capacity-building workshop that was hosted by the Institute of Natural Resources (INR) at African Enterprise from 10-11 March 2024. This workshop convened stakeholders from the "Expanding the Promotion of Local Innovation for Food Security and Healthy Nutrition to Strengthen Resilience with a Focus on Women" (ELI-FaNS) project, which focuses on participatory innovation development. Key discussions addressed the differentiation between local innovations and interventions. The importance of documenting findings was emphasized using real-life challenges and solutions that were observed by the participants. The workshop underscored the necessity for researchers to develop project designs that actively engage with farmers, fostering symbiotic relationships. This collaborative approach aims to ensure that innovations are effective and contextually relevant, thereby promoting sustainable development within farming communities. The workshop provided participants with valuable opportunities to enhance their skills and knowledge, contributing to the success of projects that focus on local innovations.

13th-14th March 2024:

- Dr Maqsooda Mahomed attended a Drones Technology Conference that was held at the Protea Balalaika Hotel in Sandton. As part of the conference, she shared experiences and knowledge relating to the use of UAVs in science and research. In addition, as part of the 2-day event, she was exposed to various discussions which included the following:
 - The development of drone ecosystem in Africa
 - Drones as a means to improve service delivery
 - Laws and regulations regulating the flying of drones
 - Registration requirements for drone flying in South Africa
 - Preventing the use of drones from threatening civilian safety and destroying economic institutions
 - Drones as Rescue Devices in Urgent Situations
 - Increase work efficiency and productivity
 - Decrease workload and production costs
 - Improve accuracy and precision
 - Refine service and customer relations

05th-10th October 2024:

- Dr Maqsooda Mahomed attended the XIIth Scientific Assembly of the International Association of Hydrological Sciences at IIT Roorkee in India, where she delivered both an oral and a poster presentation on the research and key findings of this study.

11th-21th October 2024:

- Dr Maqsooda Mahomed visited the Hydro-Remote Sensing Applications (H-RSA) Group in the Department of Civil Engineering at IIT Bombay. She engaged in a series of discussions and academic activities with Prof. Raaj Ramsankaran and his team, including presenting this research and exploring the way forward on developing and coding a decision support system (DSS) to communicate UAV-derived findings to end users.

APPENDIX D

D1. Exploring the use of unmanned aerial vehicle RGB data for crop monitoring and mapping within a smallholder setting: a case study in Swayimane

This MSc study was undertaken by postgraduate student Ms Chetty, who successfully completed her degree and graduated in 2025. A brief overview of her research contribution is presented below:

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

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

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

APPENDIX E

E1. Leveraging satellite earth observation data for estimating crop water use in smallholder farms

This research was conducted as part of an Honours degree by postgraduate student Ms Mchunu, who successfully completed her studies and graduated in 2025. A brief overview of her research contribution is provided below:

The primary aim of this study is to assess the use of satellite imagery for estimating evapotranspiration (ET) in smallholder farms. The research addresses the growing concern of water scarcity and improving irrigation management for smallholder farmers, who face challenges such as limited access to financial resources, which restricts them from investing in advanced irrigation technologies needed for sustainable agricultural practices. By utilising satellite-derived data and vegetation indices (VIs), this study seeks to identify an efficient and scalable approach for determining crop water use to enhance smallholder farm productivity and sustainability. The research utilised Sentinel-2 satellite imagery alongside various VIs, including the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), and their scaled versions, to effectively estimate ET in smallholder farms. The study's objective was to determine the most suitable index for accurately estimating ET at a smallholder farm scale. Observed ET values from ground-based methods were compared with the satellite-simulated ET values to evaluate the performance of each VI model. The results from this research revealed that NDVI and its scaled versions, particularly the NDVIKc model, provided the most accurate results for estimating ET, with an R^2 value of 0.93 and an RMSE of 0.55, indicating a strong match between observed and simulated ET values. In comparison, EVI models were less accurate, with lower R^2 values and higher RMSE. Sentinel-2 satellite imagery combined with NDVI and NDVIKc models offers a precise, cost-effective, and scalable method for estimating ET in smallholder farms. This approach can improve irrigation management and crop productivity, helping smallholder farmers address water scarcity and enhance food security through precision agriculture. The findings highlight the potential of remote sensing technologies to support sustainable agricultural practices in resource-limited environments.