ENHANCING THE ESTIMATION OF EQUIVALENT WATER THICKNESS IN NEGLECTED AND UNDERUTILIZED TARO CROPS USING UAV ACQUIRED MULTISPECTRAL THERMAL IMAGE DATA AND INDEX-BASED IMAGE SEGMENTATION

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ABSTRACT

Due to the impact of climate variability and change, smallholder farmers are increasingly faced with the challenge of sustaining crop production. Taro, recognized as a future smart neglected and underutilized crop due to its resilience to abiotic stresses, has emerged as valuable for diversifying crop farming systems and sustaining local livelihoods. Nonetheless, a significant research gap exists in spatially explicit information on the water status of taro, contributing to the paradox of its ability to adapt to diverse agro-ecological conditions. Precision agriculture, including the use of unmanned aerial vehicles (UAVs) equipped with high-resolution multispectral and thermal imagery, has proven effective in farm-scale monitoring and provides near-real-time information on crop water status. Hence, this study sought to evaluate the utility of multispectral and thermal infrared UAV imagery in understanding taro's water status. Leveraging deep learning techniques to evaluate the use of thermal remote sensing and three index-based segmentation techniques in predicting the canopy equivalent water thickness (EWT) of taro crops, this study sought to determine EWT as a proxy to its water status in smallholder farmlands. The study findings illustrate a significant difference in the prediction accuracies of taro EWT with and without the thermal band ($P < 0.05$). Additionally, results ($R^2 = 0.92$, RMSE = 8.04 g/m^2, and rRMSE = 15.31% including the thermal band and 0.91, 8.73 g/m^2, and 16.64% excluding the thermal band) reveal the value of the Excess Green minus Excess Red (ExGR) technique in accurately predicting EWT_{canopy}. Furthermore, the near-infrared, red edge, and thermal sections of the electromagnetic spectrum, together with their derived indices, were critical in estimating taro EWT. This study serves as a foundation for a robust, efficient, and spatially explicit monitoring framework of neglected and underutilized crops such as taro. Furthermore, this study offers valuable insights into neglected and underutilized crop water use within smallholder farming systems, critical for optimizing crop productivity and mitigating the effects of climatic variability and change.

INTRODUCTION

The world is challenged by the pressing need to sustain food supply and ensure food security due to climate change and the increasing global population (Din et al., 2022; Hillary Mugiyo et al., 2021). Recently, driven by water scarcity, there has been increasing interest in the potential use of neglected and underutilised crop species (NUS) in addressing food and nutrition challenges (Chivenge et al., 2015; Mabhaudhi et al., 2017; Hillary Mugiyo et al., 2021). NUS, characterised by historical domestication with limited scientific research and predominantly confined to smallholder farming systems, have emerged as key drought-tolerant crops for diversifying communal cropping systems (Chivenge et al., 2015; Mabhaudhi et al., 2017). Taro (*Colocasia esculenta (L)*) is one of the oldest and most widely cultivated NUS crops in the world's tropical and subtropical regions (Mabhaudhi et al., 2011; Mawoyo et al., 2017; Van Wyk, 2021). In South Africa, taro, locally known as *amadumbe*, is known to be heat tolerant and primarily cultivated for subsistence, especially within small and marginalised communities (Joshi et al., 2020; Mabhaudhi et al., 2014; Oyeyinka & Amonsou, 2020; Van Wyk, 2021). Taro is identified as a future smart food under the NUS category because of its edible tubers, which are rich in carbohydrates, protein, and vitamins (Kapoor et al., 2022; Li & Siddique, 2018). Despite taro and indeed other NUS's value, literature shows that they have largely been ignored.

Thermal infrared remote sensing has emerged as a valuable tool for crop water assessment and monitoring, offering a direct correlation with crop water biophysical and biochemical elements (Khanal et al., 2017; Messina & Modica, 2020). The recent advancements in image acquisition, like unmanned aerial vehicles (UAVs) mounted with light-weight multispectral sensors provide, spatially explicit near-real-time information on crop water status (Hussain et al., 2020). In addition to ultra-high spatial resolutions of UAV multispectral thermal imagery, image enhancement techniques and robust algorithms have been demonstrated to improve model accuracies. For instance, Index-Based Image Segmentation has been demonstrated to be effective in robustly segmenting plants in colour images, enabling the extraction of vegetation cover and removing soil background for enhanced crops spectral signatures (Hamuda et al., 2016). (Lu et al., 2022). The Excess Green (ExG) and Excess Red (ExR) indices were proposed by Woebbecke et al. (1995) and Meyer et al. (1999), respectively, to enhance plant segmentation accuracy by emphasizing plant greenness by accounting for the relative proportions of red and physiological green. Additionally, Meyer and Neto (2008) leveraged the strength of both ExG and ExR to develop the Excess Green minus Excess Red (ExGR) index to improve crop water assessment and monitoring using thermal remote sensing systems.

In this regard, leveraging the capabilities of deep learning, this study sought to assess the performance of thermal remote sensing and index-based segmentation techniques in improving canopy EWT estimation of smallholder taro crops using UAV multispectral thermal imagery. Specifically, the study sought to: (1) assess the potential of the UAV thermal band in estimating EWT of smallholder taro, (2) compare the performance of crop canopy images extracted using the ExG, ExR, and ExGR color indices in improving EWT estimations of taro crop, and (3) evaluate the potential of UAV multispectral thermal imagery in EWT estimations of taro crop in smallholder farming systems.

MATERIALS AND METHODS

Study area description and the experimental field

This research was conducted in the rural community of Swayimana, situated within the uMshwathi Municipality, northeast of Pietermaritzburg city, KwaZulu-Natal, South Africa (29°31′ 24'' S; 30°41′ 37'' E) (Figure 1).

The taro experimental plot was cultivated during the early rainy season, aligning with its optimal growing conditions. The selected plot covered 2864.56 m^2 and was rainfed. The taro crop was sown in mid-October 2022 and was approximately 171 days old at the time of the experiment. Specifically, the crop was intermediate between the late vegetative and early maturity growth stages. The selection of this growth stage is crucial for capturing the developmental dynamics of the crop during a period of heightened canopy growth, providing valuable insights for the research objectives.

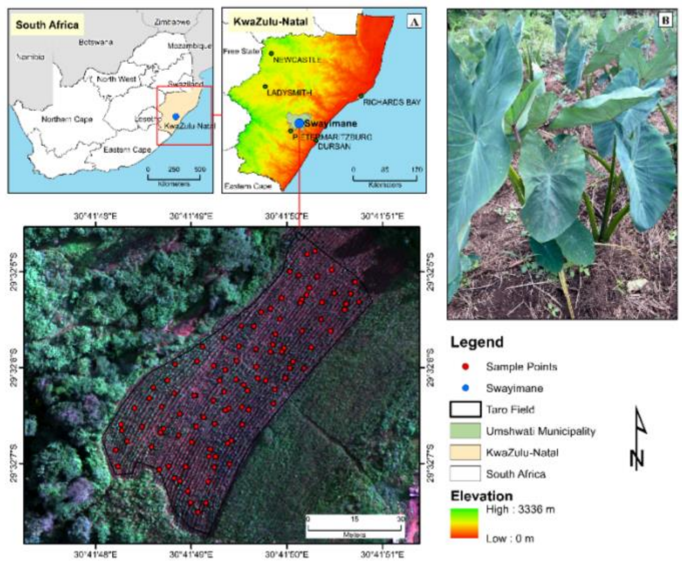

Figure 1. a) Location of experimental field in Swayimane and b) taro crops.

Field Sampling and in-situ measurements

A polygon delineating the taro field was created using Google Earth Pro and imported into ArcMap 10.6 to facilitate the generation of 100 stratified random sampling points. This approach was adopted to ensure variability and accurate representation of all taro crops within the field. These sampling points were subsequently uploaded into a Trimble handheld Global Positioning System (GPS) with a sub-centimetre accuracy, enabling precise location of each sampling point within the taro field. In-situ measurements were obtained at each sampling point to compute respective EWT values.

A portable LiCOR-2200C Plant Canopy Analyzer was used to obtain the leaf area index (LAI) of the crops. The LAI measurements were obtained using the 38° zenith angle with a 270° view cap and the ABBBB sequence, where A corresponds to a reference reading 'above' the canopy and B corresponds to a reading 'below' the canopy. Thereafter, the above ground biomass of each sampled crop was obtained, and the fresh weight (FW) obtained using a calibrated scale with a 0.5 g measurement error. The sampled biomass was then placed in a labelled brown paper bag and dried in an oven at 60 °C, until a constant dry weight (DW) was reached (approximately 72 hrs).

UAV platform and multispectral-thermal camera

The DJI Matrice 300 (M300) platform, mounted with a MicaSense Altum camera and Downwelling Light Sensor 2 (DLS 2) was used to collect multispectral-thermal imagery. A total of 1626 raw images of the experimental field were obtained and pre-processed in Pix4D photogrammetry software. Ground reference points surveyed prior to fieldwork were then used to improve the geometric accuracy of the acquired images in ArcGIS 10.6. Lastly, EWT_{canopy} in-situ measurements and the locational of each sampled taro point were overlaid with UAV multispectral-thermal image. The multispectral and thermal reflectance data of taro was extracted from the UAV imagery and used to derive vegetation indices (VIs) for the development of the EWT_{canopy} prediction model. These VIs were selected based on their optimal performance in literature and relationship with crop water status (Baluja et al., 2012; Ozelkan, 2020; Zhang & Zhou, 2019).

Index-based image segmentation of taro crops' spectral signatures

To delineate the crop canopy and eliminate soil background from the multispectral thermal image, an index-based segmentation technique was employed. Specifically, The Excess Green (ExG), Excess Red (ExR), and Excess Green minus Excess Red (ExGR) color indices were computed using the green, red, and blue bands of the UAV multispectral thermal imagery (Hamuda et al., 2016; Meyer et al., 1999; Meyer & Neto, 2008; Woebbecke et al., 1995). Finally, the threshold method was used to generate a binary image from the gray-level histograms obtained during the index-based segmentation process (Shu et al., 2021).

Model development and statistical analysis

In this study, we employed a deep machine learning approach to estimate EWT_{canopy} using UAV derived multispectral optical and thermal datasets. The study utilised a three-layer neural network model consisting of an input layer, a hidden layer, and an output layer. A rectified linear unit (ReLU) was applied to stimulate the EWT_{canopy} prediction model with the maximum epochs set to 200 interactions, indicating that the weights in the hidden layers were iteratively adjusted 200 times to reduce error and enhance EWT_{canopy} prediction accuracy. Thereafter, the SoftMax activation function was used to transform the raw outputs of the neural network into a vector of probabilities, and the Adaptive moment estimation (Adam) optimizer was used to optimise the results of the output model. Furthermore, the dropout regularization technique was applied to avoid overfitting and improve the generalization of the model (Deepan & Sudha, 2020). The hyperparameters of the DNN model were tuned to a learning rate of 0.001, batch size of 32 and an input and hidden layer dropout of 0.4 and 0.2, respectively.

RESULTS AND DISCUSSION

Performance of the thermal band in predicting EWT_{canopy} of taro crops

The performance of the thermal band in predicting EWT_{canopy} of taro crops revealed a consistent trend across the various index-based segmentation techniques. It was observed that the exclusion of the thermal band in EWT_{canopy} analysis resulted in lower estimation accuracies ($P < 0.05$), emphasising the importance of the thermal band in characterising taro crop water status. Surprisingly, our study found no significant difference in prediction accuracies when thermal data was considered in comparison to its exclusion in the ExGR-based model. These results underscore the effectiveness of the ExGR-based technique, particularly its robust performance irrespective of the inclusion and exclusion of the thermal channel.

Additionally, it was observed that the thermal band was among the topmost predictor variable across all EWT_{canopy} models. Literature confirms the invaluable role of thermal infrared remote sensing in assessing and monitoring crop water status, establishing a direct correlation with crop water biophysical and biochemical elements (Khanal et al. 2017, Messina and Modica 2020, Krishna et al. 2021). The use of thermal remote sensing is based on the premise that thermal characteristics of crop leaves are effected by leaf transpiration, which decreases in a state of water deficit, resultantly reducing leaf and canopy temperatures (Maes and Steppe 2012, Gerhards et al. 2019). The findings of this study align with a recent study by Guan and Grote (2023), which achieved an R^2 of 0.74 when incorporating the thermal channel, compared to an R^2 of 0.63 with the thermal band excluded, highlighting the integration of multispectral and thermal data and its combined value in understanding crop water status. The findings of this study are further corroborated by those of García-Tejero et al. (2018) who concluded that the thermal band is feasible for monitoring almond water stress for irrigation scheduling, and Cheng et al. (2023) who highlighted the applicability of thermal imaging in assessing the crop water conditions of summer maize crop.

Performance of index-based segmentation techniques for the estimation of taro EWT_{canopy}

This study shows that the inclusion of soil background reduces the accuracy of EWT_{canopy} predictions within taro crop (R^2 of 0.61, RMSE of 25.35 g/m^2, and rRMSE of 43.87%). It was noted that the prediction accuracy of taro EWT_{canopy} improved significantly after the removal of soil background through the ExGR-based image segmentation technique, yielding an optimal R^2 of 0.92, RMSE of 8.04 g/m^2 and rRMSE of 15.31. These results align with the broader consensus in the literature. Xu et al. (2021) and Li et al. (2022) for instance emphasized the challenge posed by soil background in influencing crop canopy spectra, particularly in UAV-derived imagery. Notably, while the ExG and ExR techniques demonstrated acceptable accuracy in quantifying taro EWT_{canopy} (R^2 of 0.90, and R^2 of 0.76, respectively), the ExGR method outperformed both these techniques. This notable enhancement can be attributed to the inherent capabilities of the ExGR technique in effectively mitigating soil background interference (Zhai et al. 2023). The comprehensive nature of the ExGR method combines the advantages of both the ExG and ExR by simultaneously leveraging ExG for extracting the crop canopy and ExR for eliminating background noise (Meyer et al. 2004, Hamuda et al. 2016, Riehle et al. 2020, Upendar et al. 2021).

Overall, the removal of soil background has proven imperative for enhancing the accuracy of taro EWT_{canopy} predictions. These findings are further supported by Shu et al. (2021) that reported a significant increase in prediction accuracy from R^2 of 0.45 and RMSE of 7.13 before to an R^2 of 0.74 and RMSE of 3.68 after performing soil background removal in estimating the SPAD chlorophyll content of a maize crop. These parallel findings underscore the significance of addressing soil background interference for accurate and reliable estimations in crop water-related assessments.

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