Research Paper

Use of Vegetation Indices Derived from Unmanned Aerial Vehicles (UAVs) Imagery for Monitoring Growth and Yield of Paddy and Identifying Weeds in Paddy Fields: A Case Study in Sri Lanka

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ARTICLE INFO

Article history:
Received : 17 May 2024
Revised version received : 27 June 2024
Accepted : 09 September 2024

Citation:
Herath, H.M.S., Bandara, R.M.U.S., Senadheera, P., Hafeel, R.F., Krishanthi, P.A.M., Jayasinghe, A.A.U.M., Maheshika, N.M.S., Dissanayake, D.A.J., Senanayake, D.M.J.B., Rathnayake, K.M.K.I., Nuwan, S.H., De Silva, P., Ariyaratne, M., Marambe, B. (2024). Use of vegetation indices derived from unmanned aerial vehicles (UAVs) imagery for monitoring growth and yield of paddy and identifying weeds in paddy fields: A case study in Sri Lanka. *Tropical Agriculturist, 172*(3), 01-15.

Abstract

The use of drone-based imagery enables data-driven decision making, by optimizing farming practices to enhance crop yields. This study was conducted to evaluate various vegetation indices for monitoring the growth of rice plants and detecting weeds in paddy fields. Field experiments were conducted at the Rice Research and Development Institute (RRDI) at Batalagoda [Agroecological region (AER): IL1] in Sri Lanka during the 2021 *Yala* cultivating season (March to September). Five rice varieties, namely, Bg 250, Bg 300, Bg 359, At 362, and Bg 450, along with three weed species (*Echinochloa crus-galli, Ischaemum rugosum, Cyperus iria*) were included in the study. Data was collected using a DJI Phantom 4 Multispectral drone, with flights conducted at seven-day intervals. Image analysis was performed using PIX4Dfields software. A positive correlation was observed between the Normalized Difference Vegetation Index (NDVI) values and the paddy yield, highlighting the potential of NDVI as a reliable indicator for monitoring rice plant growth. Further, the modified Excess Green (ExG) Index in Red-Green mode successfully identified the presence of weeds at 14 days after sowing (DAS). The Weed Detection Index (WADI) in both spectral and Red-Green modes proved most effective for identifying weeds at 55 DAS. The findings underscored the utility of precision agriculture (PA) technologies in paddy farming, particularly for weed detection. The application of these indices can contribute significantly to the development of site specific weed management strategies, enhancing the sustainability and efficiency of paddy production in Sri Lanka.

Keywords: **Drone Imagery, Precision agriculture, Site specific weed management, Unmanned Aerial Vehicle, Vegetation indices**

Introduction

Rice (*Oryza sativa* L.), which is the de husked paddy, is one of the most important staple foods in the world, serving as a primary source of calories and nutrition for more than half of the global population. It plays a crucial role in the diets of billions, particularly in Asia, where countries such as China, India, Indonesia, and Bangladesh are major consumers. Although smaller at global scale, rice is the most important crop for food security and human well-being in Sri Lanka. The extent of paddy cultivation in the *Maha* (October to February) and *Yala* (March to September) seasons in Sri Lanka are estimated to be 748,000 ha and 368,906 ha, respectively. More than 1.8 million farm families are dependent on the paddy crop, which provides 42% of the daily protein requirement and 34% of the daily calorie requirement of a person (Rice Research and Development Institute, 2022; Department of Census and Statistics, 2022). Biotic and abiotic factors are the major challenges which cause yield reductions. Weeds are recognized as a major biotic factor which contributes to significant losses in paddy yields annually, which is estimated to be in the range of 20 to 40% (Herath *et al.*, 2018).

Weed density and composition in paddy farming systems are highly dynamic, making weed management a significant challenge in paddy cultivation. Currently, the most common method for controlling weeds is the application of herbicides, which is favoured for their effectiveness and ease of use. However, the widespread and intensive use of herbicides has led to several negative consequences, including the emergence of herbicide resistant weed species (Marambe and Amarasinghe, 2002), shifts in weed populations (Marambe, 2002), chronic health issues and environmental pollution. These issues highlight the urgent need for a more sustainable weed management approach in rice farming. There is a growing interest in integrating advanced technologies such as Unmanned Aerial Vehicles (UAVs) into agricultural practices (Sankaran *et al.*, 2015) with a view to overcome those issues in paddy cultivation.

The UAVs, commonly known as drones, have revolutionized precision agriculture (PA) by providing high-resolution, real-time data that can be used to monitor crop health, assess soil conditions, and detect weed infestations (Matese *et al.*, 2015). In rice farming, one of the most promising applications of UAVs is the use of imaging technology to develop vegetation indices that can accurately differentiate between crop plants and weeds. These vegetation indices, derived from UAV captured images, analyze the spectral reflectance properties of plants to identify specific vegetation characteristics, including the presence and density of weeds (Huang *et al.*, 2018).

The Normalized Difference Vegetation Index (NDVI) is one of the most widely used vegetation indices in precision agriculture, leveraging the difference between near-infrared that the vegetation strongly reflects, and red light that the vegetation absorbs, to assess plant health. This index is particularly useful in distinguishing healthy crops from weeds, as weeds often exhibit different spectral characteristics due to variations in leaf structure, chlorophyll content, and water status (Jones & Vaughan, 2010). The UAVs equipped with sensors capable of capturing NDVI data can quickly and accurately map the distribution of weeds across large rice fields, enabling early detection and targeted management practices (Huang *et al.*, 2018). The analysis of NDVI maps would help in identifying areas where weeds are likely to be affecting crop growth allowing for more precise interventions.

The Near-Infrared (NIR) imaging is a powerful tool used in weed management. The NIR wavelengths are particularly sensitive to the physiological state of plants, including moisture content and cellular structure. Weeds often differ from rice plants in these aspects, making NIR imaging an effective method for differentiating between the two Sankaran *et al.*, 2015). The NIR imaging is especially valuable when visual identification of weeds is challenging due to factors such as similar colour between weeds and crops or dense vegetation cover.

The integration of NDVI and NIR imaging provides a comprehensive approach to weed management in paddy fields. By combining the strengths of both indices, UAVs can offer detailed insights into the presence of weeds, their distribution, and impact on crop yields (Rosle *et al.*, 2019). The NDVI provides a broad overview of vegetation health and stress, while NIR imaging offers more detailed information on the physiological differences between weeds and paddy plants. This dual approach enables more precise targeting of weed control measures, optimizing the use of herbicides and other resources (Chlingaryan *et al.*, 2018). The use of UAV derived vegetation indices for weed management in paddy fields offers several advantages. These indices enable farmers to detect weeds early, with precision, allowing for targeted interventions that reduce the reliance on herbicides and mitigate the environmental impact of paddy cultivation (Jones & Vaughan, 2010).

This study explores the development and application of UAV-derived NDVI and NIR imaging in managing weed populations in paddy fields in Sri Lanka, emphasizing their role in advancing sustainable and precision agriculture practices for paddy cultivation.

Materials and Methods

The field experiments were carried out at the Rice Research and Development Institute (RRDI) at Batalagoda (North Western province; agro-ecological region: IL1) in Sri Lanka during the 2021 *Yala* season (March to September). A DJI Phantom 4 Multispectral drone (Figure 1) was used to acquire the UAV data. The study deployed five rice varieties in different age-classes (days from seed sowing to harvest), namely, Bg 250 (2 ½ months), Bg 300 (3 months) (Bg 300), At 362 (3 ½ months) and Bg 450 (4 ½ months). The monocotyledonous weeds used as indicators were *Echinochloa crus-galli* (annual grass), *Ischaemum rugosum* (annual grass) and *Cyperus iria* (annual sedge).

Figure 1. DJI Phantom 4 Multispectral drone

The three treatments included, T_1: Rice varieties established through direct sowing (DS) in separate field plots that were maintained without any weeds (weed-free plots), T_2: Experimental plots were established using the above ten rice varieties and the three selected weed species, and T_3: The three weed species grown separately without rice varieties.

The experiment was conducted in a randomized complete block design with three replicates, with each plot at the size of 6 m x 3 m. Pre-germinated seed paddy of all rice varieties were broadcasted on the plots at a rate of 100 kg ha^{-1} (180 g/plot) while a combined lot of viable seeds of the three weeds at equal weight was broadcasted at a rate of 1 kg ha^{-1} (1.8 g/plot). Land preparation, fertilizer application and other management practices, excluding weed control, were carried out according to the recommendations of the Department of Agriculture (DOA). All weeds in T_1 were manually removed at weekly intervals, and all weeds other than the planted weed species were removed from T_2 and T_3 at weekly intervals. In addition to that, SPAD meter readings of randomly selected five plants were collected at the panicle initiation stage of all varieties, i.e. 25 DAS for Bg 250, 30 DAS for Bg 300, 45 DAS for Bg 359 and At 362, and 75 DAS for Bg 450, and yield data of the whole plot was recorded at harvest.

Image acquiring process

The DJI Phantom 4 Multispectral drone was used for imaging. It was equipped with the gimbal-based imaging system with a RGB camera and multispectral camera. The multispectral camera captures five wavelengths including, blue (0.44-051 μm), green (0.52-0.59 μm), red (0.63-0.68 μm), red-edge (0.69-0.73 μm) and infrared (0.76-0.85 μm). Resolution of the multispectral cameras is 1600 x 1300 pixels. Flight planning of 12 m altitude with 80 % forward and 70 % slide – overlaps were designed using DJI Ground Station Pro® software. Data were collected over the experimental fields from 10 a.m. to 11 a.m., once in every seven days from the establishment of crop to harvesting.

Calculation of Vegetation indices

Different vegetative indices and orthomosaic map (visible images) were generated by using Pix4Dfields 1.10.1 software. In this study, NDVI was used as a tool to monitor the growth of rice crops, and was calculated using the formula presented in Table 1 (Groten, 1993). Further, four RGB vegetation indices including vegetation index for weed (WDVI) (Yu *et al.*, 2022), Green normalized difference vegetation index (GNDVI) and Normalized difference red edge (NDRE) (Boiarskii and Hasegawa, 2019) were also estimated using formula presented in Table 1. Moreover, Excess Green (ExG) (Woebbecke *et al.*, 1995) to differentiate green vegetation (crops and weeds) for spot-based herbicide spraying was used as is given in Table 1. In the present study, modifications were made to ExG index by replacing R, G and B normalized RGB coordinates of ExG index with digital number (reflectance measurements) of red, green and blue channels and created new index (2G-R-B). These modifications were done using the custom index option of the software under the vegetative indexes. Thus, in the ExG index (2g-r-b; Table 1), the g, r, and b parameters were replaced with digital number of red, green and blue channels (G, R, and B; Woebbecke *et al.* 1995) to generate the maps from Red-Green-Blue (RGB) reflectance images. Since "2G-R-B" was originally derived in this study, the maps developed can be named as "2G-R-B index maps".

Image and data analysis

The interval capture technique was employed to generate six distinct image sets during a single autonomous UAV flight. These images comprised five multispectral image sets corresponding to the blue, green, red, red-edge, and near-infrared (NIR) bands, along with one RGB image set captured by the UAV's onboard camera and the P4M sensor. The captured multispectral images were processed to produce multispectral reflectance maps for the five spectral bands, while the RGB images were used to generate the NDVI image and the RGB orthomosaic.

With the superior quality of the onboard camera is UAV, the RGB image set was selected for further processing and analysis. This choice was based on the high resolution capabilities of the onboard camera, which provided detailed imagery suitable for creating accurate RGB orthomosaic images, essential for detailed mapping and analysis. The combination of multispectral and RGB data enabled comprehensive monitoring and assessment of the vegetation health and other relevant parameters across the studied area. The PIX4Dfields.1.10.1 data analysis software was used to process the images with the different indices mentioned above.

Table 1. Vegetation indices used in the study

Vegetation index Full form	Index	Formula*
Normalized difference vegetation index	NDVI	NDVI = (NIR - R) / (NIR + R)
Vegetation index for weed	WDVI	$WDVI_{NIR}$ = log G/NIR RE/NIR
Excess green index	ExG	ExG = 2g-r-b = 2G–(R+B/(B+G+R)
Modified green index	Modified ExG	Modified ExG = 2G – R – B
Green normalized difference vegetation index	GNDVI	GNDVI = (NIR – G) / (NIR + G)
Normalized difference rededge	NDRE	NDRE = (NIR-RE) / (NIR + RE)

** The NIR represents the reflectance value of the near-infrared band; g = Normalized value of the green (G) band where g = G/(R + G + B); r = Normalized value of the red (R) band where r = R/(R + G + B); b = Normalized value of the blue (B) band where b = B/(R + G + B). R, G and B represent the digital number (reflectance measurements) of red, green and blue channels, respectively; RE = red edge.*

The SPAD reading and yield data were subjected to analysis using statistical package, STAR for Windows version 2.1 (International Rice Research Institute, 2014).

Results and Discussion

Normalized Difference Vegetation Index (NDVI): An indicator of growth stages of paddy

The NDVI is one of the most widely used vegetation indices, serving as a crucial tool for differentiating various growth phases in rice. In this study, distinct NDVI values were observed at different growth stages of rice varieties that provide harvest in 2 ½ months, 3 months, 3 ½ months and 4 ½ months. The mean variation in NDVI throughout the growth cycle is illustrated in Figure 2. Paddy plant undergoes three sequential stages of growth, namely, the vegetative stage, reproductive stage, and the ripening stage, where the duration of two latter stages in the tropics are generally fixed at 35 and 30 days, respectively, while the vegetative phase determining the overall growth duration of the crop up to harvest (IRRI, 2007).

The NDVI curve closely mirrors the typical growth cycle of rice. During the vegetative period, NDVI values for the varieties in the 2 ½-months age class varied from 0.24 to 0.4, the 3-months age class from 0.25 to 0.56, the 3 ½-months age class from 0.23 to 0.87 and the 4 ½-months age class 0.22 to 0.91, respectively. The results clearly showed that the maximum NDVI recorded during the vegetative stage of different rice varieties increased with age class. As the plants transitions into the reproductive stage, the NDVI values of rice varieties from different age classes varied from 0.4 to 0.85 (2 ½ months), 0.25 to 0.85 (3 months), 0.57 to 0.9 (3 ½ months), and 0.64 to 0.91 (4 ½ months).

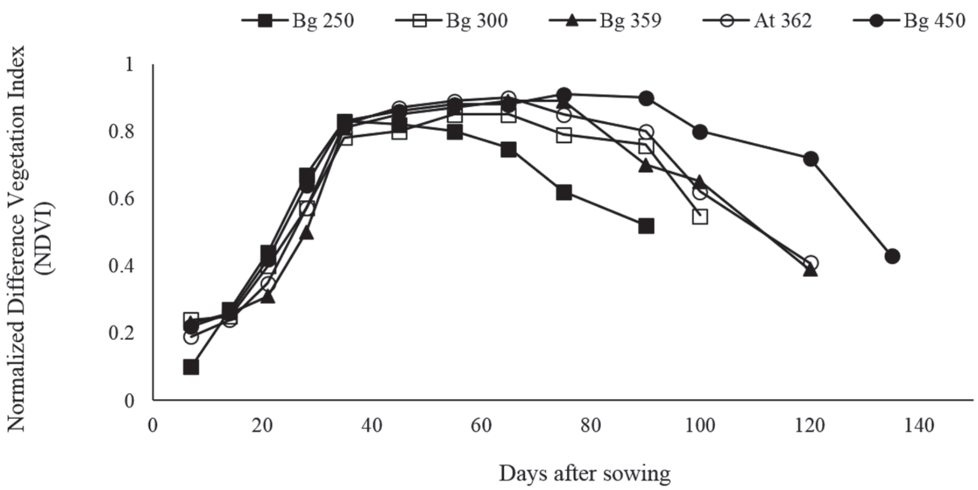

Figure 2. Variation of the average NDVIs during the life cycle rice varieties in the age classes of 2 ½, 3, 3 ½ and 4 ½ months.

The NDVI exhibited an increasing trend during the vegetative period, recording the highest in the reproductive stage (Figure 2). However, a decline in NDVI was recorded during the ripening stage for all the varieties assessed across the age classes.

This variation in NDVI across different stages of crop growth is invaluable for determining the precise growth stage of the rice crop, as it closely follows the typical growth curve. The UAV technology, combined with NDVI data, offers a powerful tool for monitoring and assessing paddy crop development. Rokhmatuloh *et al.* (2019) also reported that NDVI values for paddy crop vary from 0.21 to 0.84 throughout its growth cycle. As reported in the present study, Raza *et al.* (2019) observed NDVI variations from 0.2 to 0.78 across the three main growth stages in paddy, and that the NDVI variation throughout the crop life cycle follows a sigmoidal curve.

Correlation between SPAD Meter Values, NDVI, and Rice Yield:

The SPAD meter values, which reflect the chlorophyll content in leaves, are indicative of the crop health (Ling *et al.*, 2011). Variations in light reflectance are also influenced by chlorophyll concentration. A strong positive correlations (P<0.001) were observed between SPAD values and NDVI values at the panicle initiation stage (PI) in Bg 250 (r = 0.76), Bg 300 (0.89), Bg 359 (0.84), At 362 (0.77) and Bg 450 (0.9) during vegetative growth period (Figure 3). This finding aligns with the observations of Roslin *et al.* (2021) who also reported a positive correlation between SPAD and NDVI in rice varieties at the PI stage. Ali *et al.* (2014) reported that the SPAD meter and NDVI measurements at PI to booting stage of dry direct-seeded rice can satisfactorily be used to predict paddy yields at maturity.

Furthermore, the rice yield exhibited a significant positive correlation (r = 0.94; P<0.05) with NDVI at 35 DAS (Figure 4). The positive correction of NDVI at PI of paddy plant (Rehman *et al.*, 2019; Zheng *et al.*, 2022) highlights the utility of NDVI and the potential use of UAVs equipped with multispectral cameras in assessing and predicting paddy yield levels.

Figure 5 illustrates spectral colour mode maps derived from that each vegetation index (*i.e.* NDVI, WDVI, NDRE, GNDVI and Modified ExG) estimated at 21 DAS showed. The ExG index combined with the Red-Green colour mode successfully distinguished weeds from rice as early as 14 DAS (Figure 6) and continued to show its effectiveness at 21 DAS (Figure 7) making it the most reliable index in weed identification.

Specifically, the modified ExG map (2G-R-B index map) highlighted the soil in red, rice in yellow, and weeds in light green. Weed differentiation was more pronounced at 21 DAS compared to 14 DAS using the ExG index in the Red-Green colour mode.

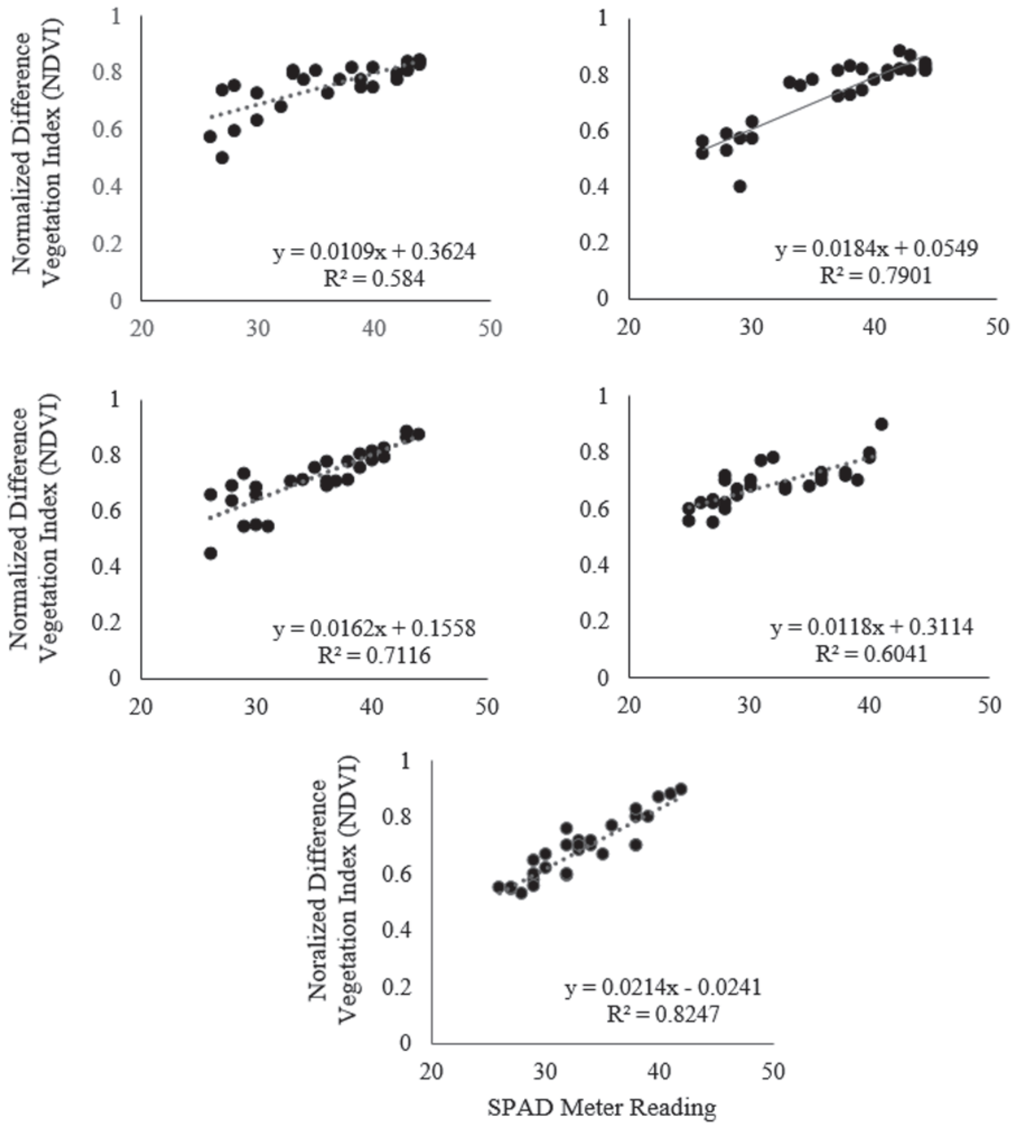

Figure 3. Correlation between average NDVI and SPAD meter readings at panicle initiation of rice varieties in different age classes

Use of Vegetation Indices for Weed Differentiation in Rice Fields

This differentiation is crucial for targeted, spot-based weed management, as opposed to blanket applications, especially when utilizing herbicides. The ExG index map can thus be effectively integrated with precision spraying systems to enable targeted weed management in rice cultivation.

Temporal Differentiation of Weeds using Vegetation Indices:

Weed differentiation was performed on a temporal basis, with the modified ExG and weed detection (WADI) indices in spectral colour mode providing the most accurate results at 55 DAS (Figure 8).

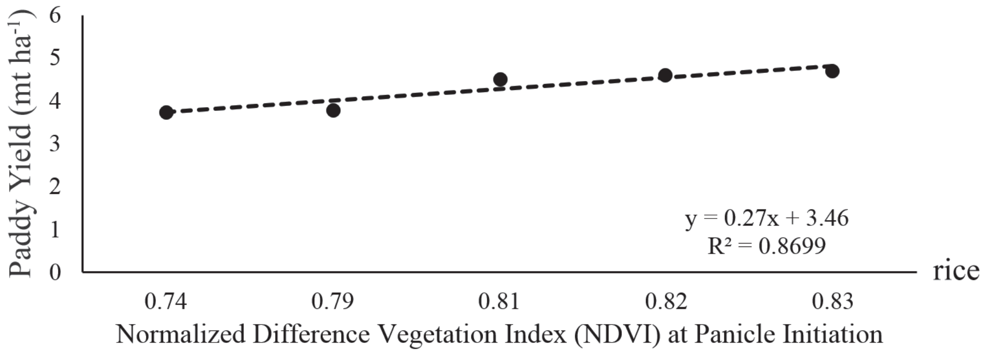

Figure .4: Correlation between average NDVI and Yield of rice varieties in different age classes

Specifically, the WADI spectral mode map displayed rice in green and weeds in yellow-red, indicating WADI's utility for weed differentiation at this growth stage. This result aligns with Yu *et al.* (2022) who reported that WDVI is effective in distinguishing weeds from rice.

Similarly, the modified ExG index in spectral mode was successful in differentiating rice (green) from weeds (red) at 55 DAS. The ExG index has been extensively used for weed and crop detection (Woebbecke *et al.*, 1995; Moorthy *et al.*, 2015). Štroner *et al.* (2023) also identified ExG as one of the most effective indices for filtering green vegetation. In this study, both WADI and modified ExG indices in spectral mode yielded the best results in differentiating weeds from the paddy crop at 55 DAS.

Furthermore, the Red-Green mode also produced promising results as illustrated in Figure 9 where patches were easily distinguishable (green) and paddy plants appearing as dark yellow. Both WADI and modified ExG are beneficial for developing weed maps in paddy fields and could potentially be used to identify weed species in rice cultivation. This approach of weed-crop differentiation and map development would pave the way for site-specific and sustainable weed management. Moreover, as the modified Excess Green Index maps (2G-R-B index maps) were able to differentiate paddy varieties from weeds, a new method can be proposed to develop images from Red-Green-Blue (RGB) reflectance images to detect paddy crop from weeds in the broadcasted paddy fields.

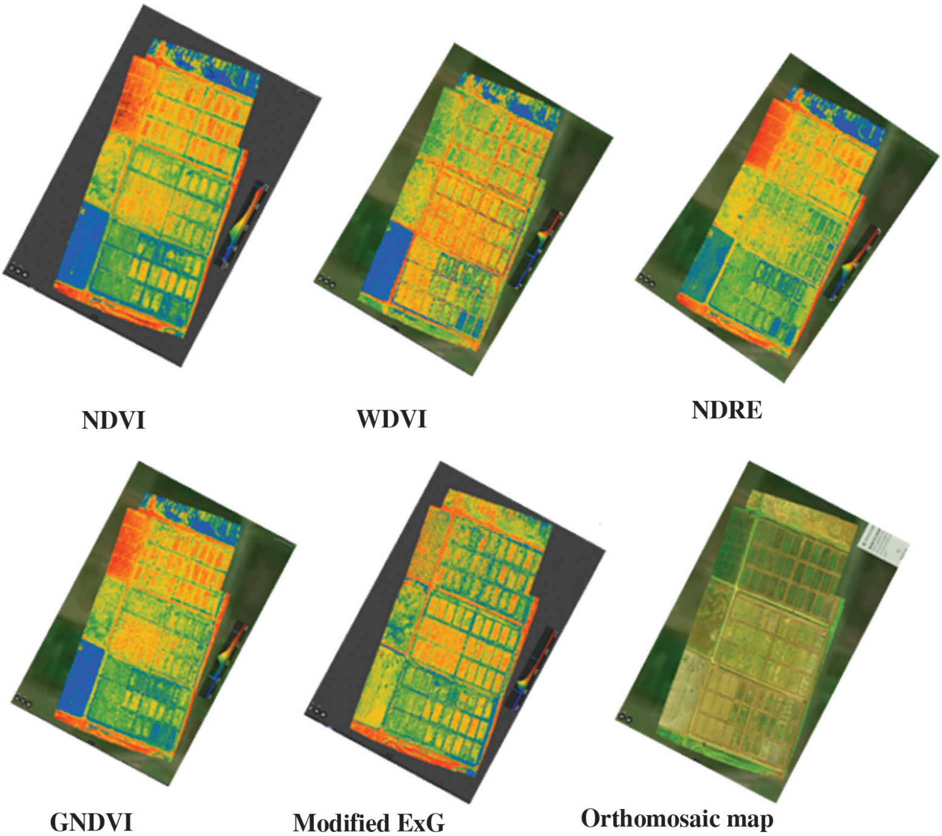

Figure 5. Common weed identification with different vegetation indices at 21 DAS (NDVI = Normalized Difference Vegetation Index; WDVI = Vegetation Index for Weeds; NDRE = Normalized Difference Red Edge; GNDVI = Green Normalized Difference Vegetation Index; Modified ExG = Modified Excess Green Index)

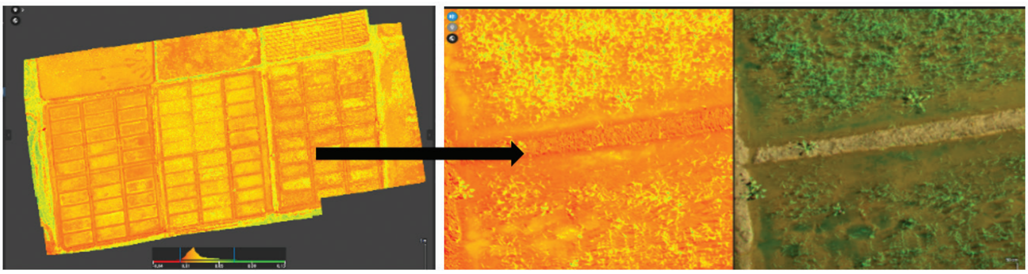

Figure 6. Modified Excess Green Index (ExG) with Red-Green colour mode in plot with paddy and weed mix at 14 days after sowing (DAS).

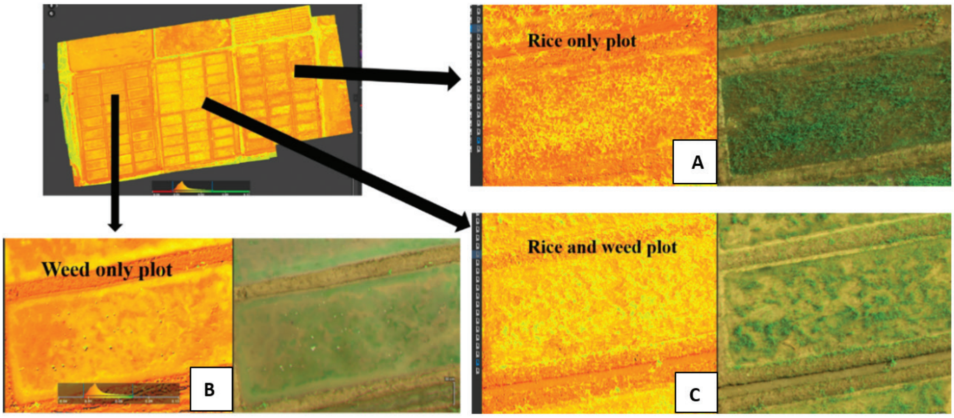

Figure 7. Modified ExG index with Red-Green colour mode at 21 days after sowing. (A) Plot with only a rice variety, (b) plot only with weeds; and (C) plot with a mix of rice variety and weeds

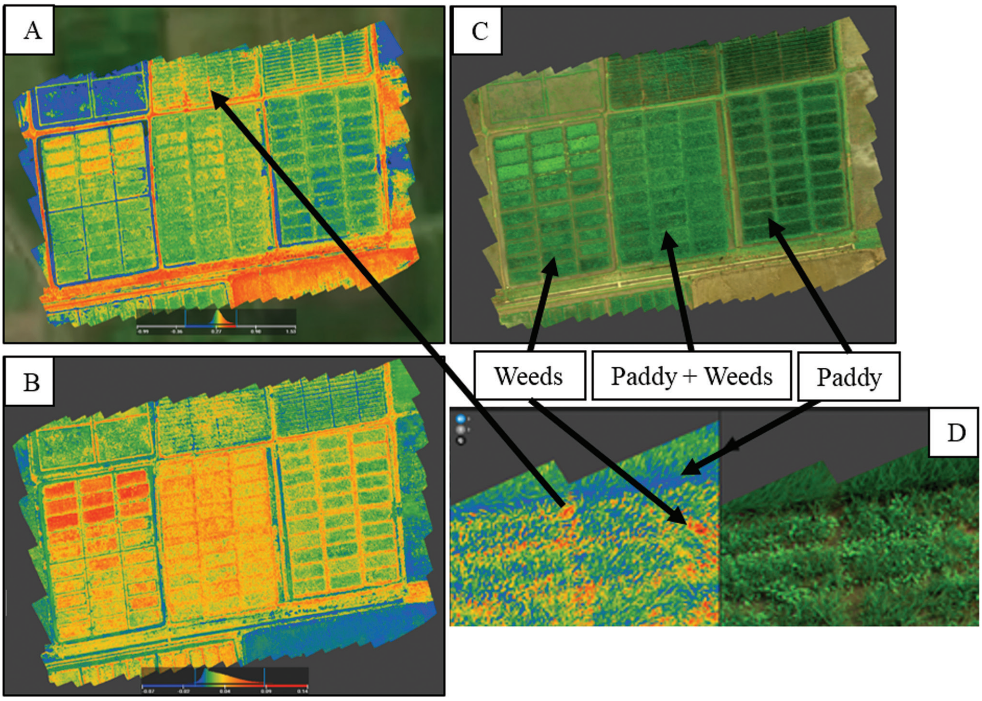

Figure 8. Spectral mode maps of (A) Weed Detection Index - WADI and (B) Modified Excess Green index – Modified ExG, (C) Orthomosaic Map and (D) a close up Map of 'A', at 50 cm above ground, 55 DAS.

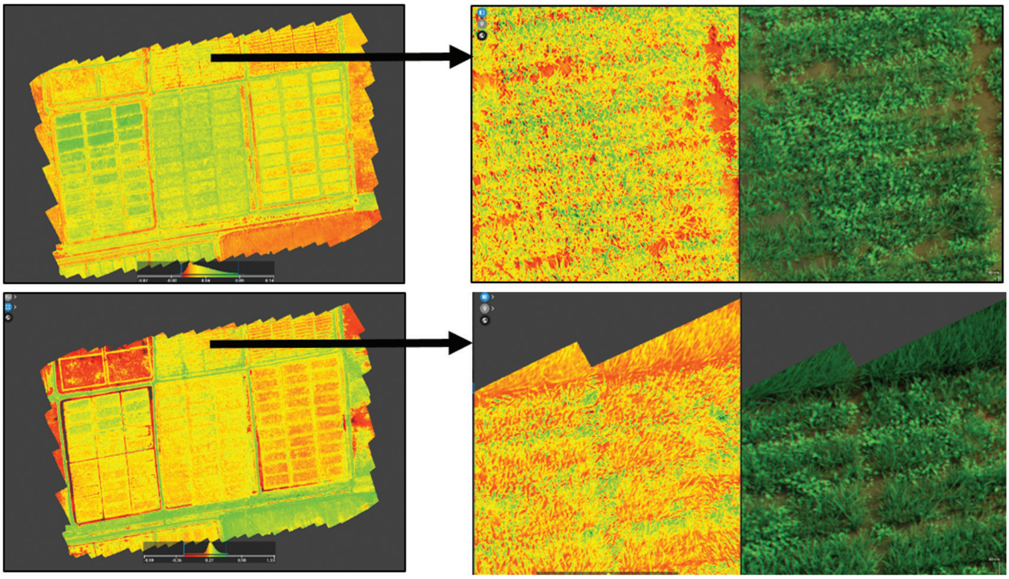

Figure 9. Red-Green mode maps of (A) Weed Detection Index - WADI and (B) Excess Green Index - ExG, and their respective close-ups (C) and (D) at 50 cm above-ground, at 55 days after sowing.

Conclusions

The application of UAV technology in rice cultivation has proven to be a valuable tool for precision agriculture, enabling effective monitoring of crop growth, yield prediction, and weed management. Our findings demonstrate that NDVI is a reliable indicator for distinguishing different growth stages in paddy plants, while UAV-based multispectral imaging can accurately predict paddy yield levels. Notably, the ExG index in Red-Green mode was effective for early weed differentiation at 14 DAS, and both ExG and WADI indices in spectral colour mode yielded the best results at 55 DAS, effectively distinguishing weeds from paddy plants. These indices, when used in combination with Red-Green mode, offer a powerful approach for identifying weed patches in rice fields.

Integration of these indices, particularly the modified ExG and WADI with UAV technology, presents a promising method for spot-based weed management. This approach can be coupled with spray drones to implement precise herbicide applications, thereby enhancing the sustainability of weed management practices in rice cultivation.

Acknowledgement

The authors wish to acknowledge the National Research Council (NRC Project grant: EWC-18-04) for providing financial assistance for the study.

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