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Assessment of the Optimal Flight Time of RGB Image Based Unmanned Aerial Vehicles for Crop Monitoring

[*1]Ruwanpathirana PP, [1]Madushanka PLA, [1]Jayasinghe GY, [2]Wijekoon WMCJ, [3]Priyankara ACP & [4]Kazuhitho S

[1]Department of Agricultural Engineering, Faculty of Agriculture, University of Ruhuna, Kamburupitiya,81100, Sri Lanka

[2]Department of Soil Science, Faculty of Agriculture, University of Ruhuna, Kamburupitiya,81100, Sri Lanka

[3]Computer Unit, Faculty of Agriculture, University of Ruhuna, Kamburupitiya, 81100, Sri Lanka

[4]Regional Agricultural Engineering, Faculty of Agriculture, University of the Ryukyus, 1 Senbaru, Nishihara-cho, Okinawa, Japan

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[*]Corresponding Author
Email:pranith.piyumal@ageng.ruh.ac.lk

ABSTRACT

Unmanned Aerial Vehicles (UAVs) have been developed as a feasible tool for agricultural surveillance. Despite the fact that many researchers have focused on UAVs' ability to offer information on crop growth and development, study on the efficacy of day time period for images is extremely uncommon. As a result, the purpose of this research was to assess the best flying duration for RGB-based UAV technology for field crop monitoring and to develop a procedure for monitoring sugarcane using UAVs in Sri Lanka. The study was conducted on a five-month-old sugarcane field (1 hectare) in Ampara, Sri Lanka. All flights were missioned using a DJI Mavic pro drone (RGB) at flying heights, speeds, frontal overlap, and lateral overlap of 50 m, 4 m/s, 75%, and 70%, respectively. During the experiment day, images were captured during three flying time periods: T1 (07:00 – 09:00 h), T2 (10:00 – 12:00 h), and T3 (13:00 – 15:00 h), with three replicates per flight, and plant density (PD) data were manually recorded for 19 plots (5m×5m). The orthomosaic images were processed using Agisoft PhotoScan software, and the classification and accuracy assessments were carried out using Arc GIS to generate vegetation fraction (VF) and Green-red vegetation index (GRVI) values. To determine the optimal flying time, a relationship between UAV-based VF and plant density (PD) was generated. T2 performed better in vegetation mapping, with an overall accuracy of 88.37% and a Kappa coefficient of 0.75, because more shadowing regions were identified on the other two flights. At T2, the most significant correlation between VF and manual plant density was detected (R^2 = 82.9%, SE = 2.20, $P<0.05$). T2 demonstrated a very strong relation between GRVI and PD (R^2 = 82.1%, SE = 2.25, $P<0.05$). Overall, the ideal flight time can give more accurate and accurate crop monitoring results. The study concludes that the time range 10:00 – 12:00h might be used to acquire UAV images for crop monitoring.

1. Introduction

Agricultural monitoring on a regular basis is essential for addressing field constraints such as field gap detection, pest and disease concerns, weed management, and water stress issues in crop cultivations, resulting in enhanced production [1]. Traditional visual inspection is less productive since it involves more effort, money, and time. Precision farming technology has lately emerged as one of the most potential substitutes for manual crop monitoring [2].Satellite remote sensing imagery outperforms conventional crop monitoring methods [1,3]. However, it has certain disadvantages, such as lower spatial resolution, cloud cover, air attenuation, and difficult and/or costly collection [4]. Unmanned aerial vehicles (UAVs), which are GPS-equipped autonomous powered aerial vehicles that can fly autonomously or be piloted remotely, have recently been promoted as a means of overcoming the limitations of satellite data because UAVs can be deployed quickly and repeatedly, resulting in lower costs, greater flexibility in terms of flying heights and mission timing, and higher spatial resolutions [1,4]. Recently, scientists have focused on studying the potential of Unmanned Aerial Vehicles (UAVs) to provide information for a range of applications, such as crop status and vigor monitoring, as well as stress and disease conditions [5,6]. According to the literature, UAVs may be used to create crop development monitoring by vegetation analysis for *Glycine max* [7], *Zea mays* [8], *Triticum aestivum* [9], *Saccharum officinarum* [1,10], and *Oryza sativa* [11] and plant height evaluation for diverse crops [12–15]. Due to their inexpensive cost, visible range (Red (R), Green (G), and Blue (B)) cameras have been promoted over near infrared-based cameras.

Because of the illumination, the efficacy of the UAV images would be impacted throughout flight time. Due to the direction of the Sunlight, shadows may emerge mostly as a result of the objects present in the study area. Furthermore, certain materials are strongly reflected, resulting in highly saturated images with limited efficacy [16]. As a result, the ideal time should be required to minimize lighting impacts while capturing images with UAVs, and this would ultimately affect the image quality. However, studies and applications on the influence of flying time of day on crop monitoring in the Sri Lankan context are limited, and a complete investigation comparing actual field conditions is required. As a result, the goal of this study was to determine the best time of day for UAVs to acquire RGB images and to create a work flow with flying parameters for crop monitoring in Sugarcane in Sri Lanka.

2. Material and Methods

2.1. Study area

The study was conducted on cultivated land in Galoya plantations in Hingurana (7°16'N, 81°41'E) on the sugarcane field nearly 14 kilometers from Ampara, Sri Lanka (Figure 1). The long-term average temperature in this area is 28°C, with annual precipitation ranging from 300 to 350 mm. Sugarcane, paddy, maize and groundnut are the major agricultural crops in this area [17].

2.2 Data collection

Nine flights were conducted over a 1 ha irrigated, five-month-old sugarcane field during the whole trial on 04th October 2019. During the investigation, the DJI Mavic pro drone (DJI, Shenzhen, China) was utilized to collect RGB images. It has a payload limit of around 1.5kg and a flying endurance of around 30 minutes with full payload. The images were taken on the 1 ha field at three distinct flight periods; T1 (07:00 – 09:00 h), T2 (10:00 – 12:00 h), and T3 (13:00 – 15:00 h) on the experiment day, with three replicates per mission. Flight plans were created using Drone Deploy software [18], which was configured with 4m/s flying speed, 75% frontal and 70% lateral overlap, and a 50 m flying height [19].The images have a resolution of 1.5 cm/pixel. Prior to flight, the UAV made artificial markings were placed on the nine locations of field that had to be visible in the images in order to be utilized as ground control points (GCPs). To validate the results, field plant density values were manually recorded from a total of nineteen 5 m X 5 m plots using GPS, and field anomalies were also recorded at the same time.

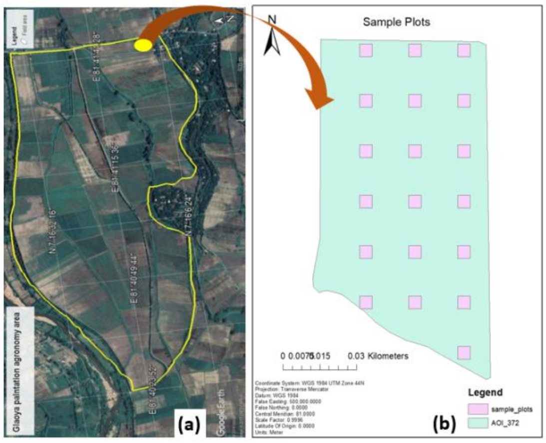

Figure 1. Map of the Study area a) location of the study, b) Area of interest with sample plots

2.3 Data Processing and Analysis

Following image capture, the ortho-mosaicked images with true RGB color were analyzed using Agisoft photoScan pro software [20], as shown in Figure 2. The mosaicked images were georeferenced using manually generated nine GCP points.

The green-red vegetation index (GRVI) is considered as the one of the best RGB-based vegetation indices since it can effectively classify images of vegetation and other non-vegetation ground covers [21].Therefore, in this study, GRVI values were computed from each mosaicked images using the equation 01 utilizing the raster calculator in ArcGIS software based on these othophoto of RGB spectral bands.

$$GRVI = \frac{Rg-Rr}{Rg+Rr} \text{.................................Eq.01}$$

Where Rg denotes the reflectance of the green band and Rr denotes the reflectance of the red band. The “GRVI = 0” threshold was utilized to distinguish between green vegetation and non-vegetation coverage [22]. Using zonal statistics [23], the mean values of VIs for each plot were determined. Using the retrieved GRVI maps, the fractional vegetation cover (FVC) was calculated as the ratio of the number of pixels classified as vegetation to the total number of pixels. The mosaic images for each flight were classified as vegetation or non-vegetation using maximum likelihood classification method. The accuracy was evaluated using kappa accuracy assessment method in order to select the best vegetation index, and ultimately, FVC values were recorded.There were 100 stratified points were evaluated with comparing the RGB image to assess the overall accuracy and kappa coefficient values for each classified maps.

Simple linear regression was used to examine the relationship between extracted FVC values from supervised classification maps and GRVI maps. Furthermore, a connection between UAV-based VF and plant density was created. These models were used to determine the best flying duration based on coefficient of determination (R^2) and standard error (SE)values.

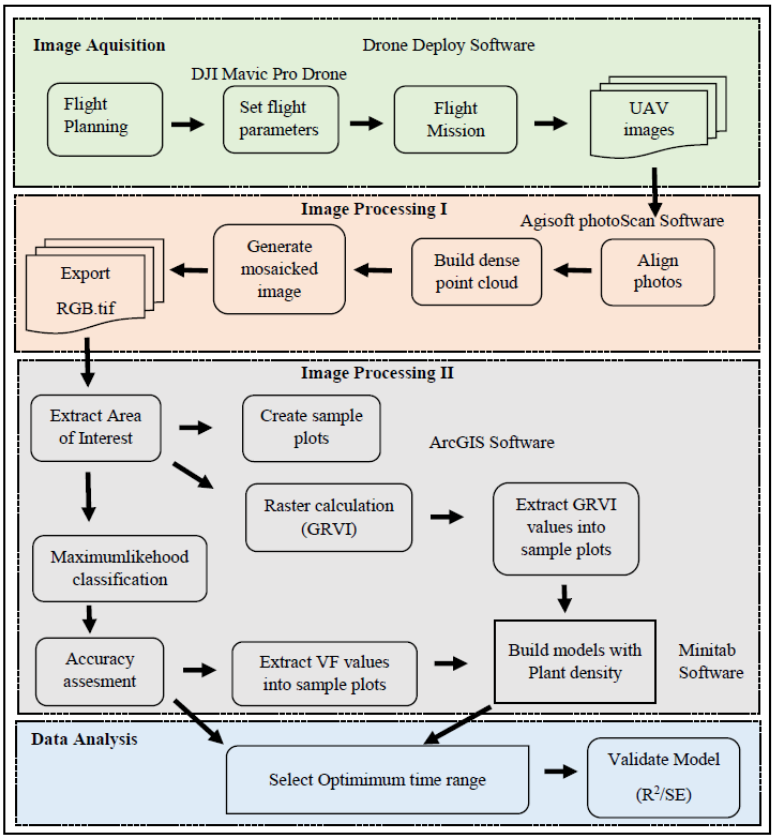

Figure 2. The work flow of image processing and data analysis (UAV = unmanned aerial vehicle, RGB =Red, Green, Blue spectral images, VF= vegetation fraction, GRVI = green-red vegetation index, R^2 = coefficient of determination, SE = standard error)

3. Results and Discussion

3.1 Classification of vegetation and non-vegetation areas

Based on the three spectral bands, each flight was categorized into two binary classes: vegetation and non-vegetation areas, and Figure 3A and 3B displays the RGB mosaicked images and classification output of vegetation/non-vegetation maps for each flight times. Table 1 displays the results of the accuracy evaluations. Despite the fact that all of the flights had improved accuracy results in the classification, the overall accuracy and kappa coefficient values were the highest in the T2 time period, at 88.37% and 0.75, respectively.

Table 1. Accuracy assessment outputs of vegetation and non-vegetation classification

Class/Accuracy	T1	T2	T3
Overall Accuracy %	79.07	88.37	79.07
User's Accuracy			
• Vegetation %	73.68	76.92	66.67
• Non-Vegetation %	83.33	93.33	85.71
Producer's Accuracy			
• Vegetation %	77.78	83.33	71.43
• Non-Vegetation %	80	90.32	82.76
Kappa Coefficient	0.549	0.75	0.53

(T1 = 07:00-09:00h, T2 = 10:00-12:00h, T3 = 13:00-15:00h)

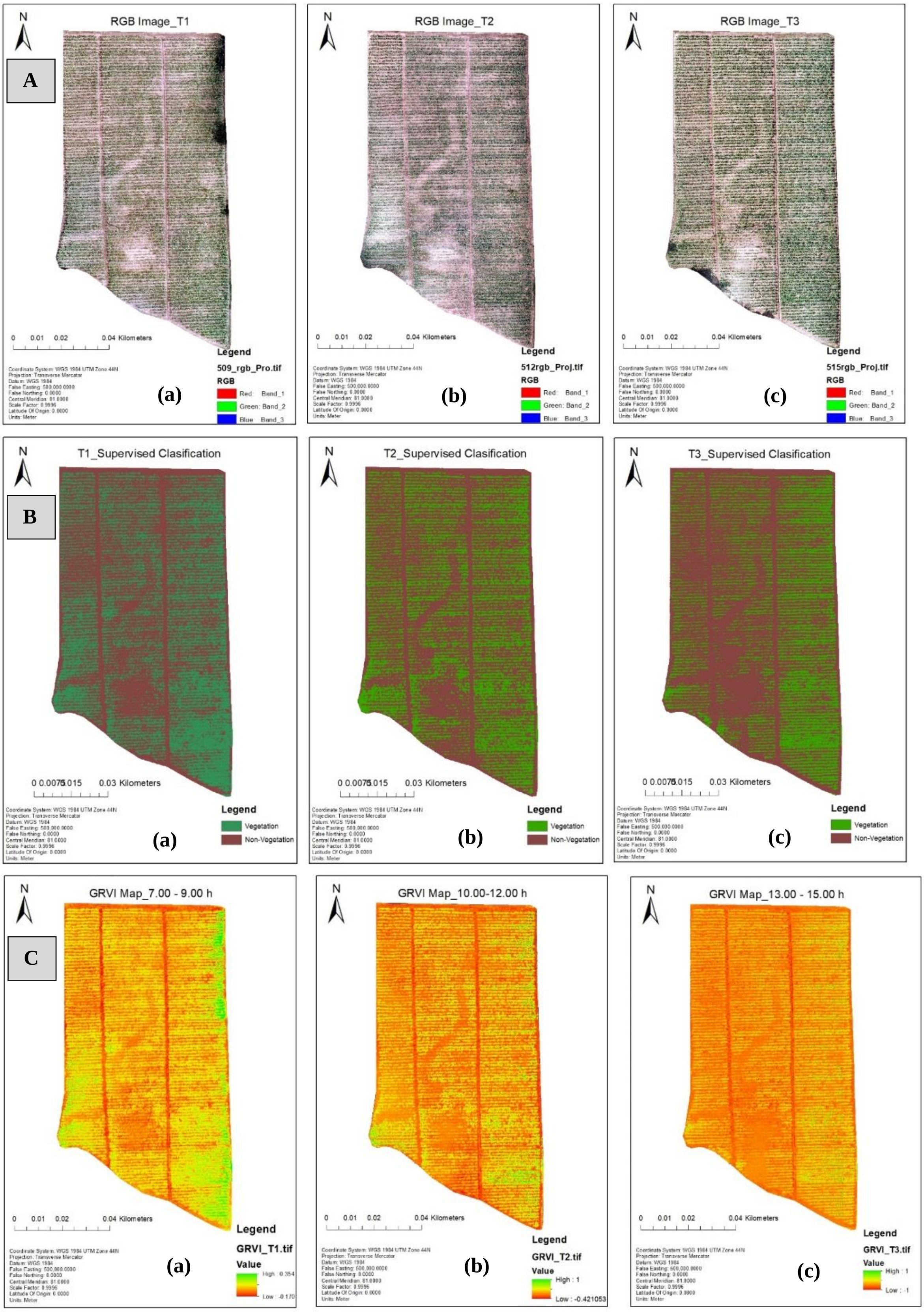

Figure 3. (A)RGB mosaicked images, (B) Classified images and (C) GRVI maps[a) T1 = 07:00-09:00h, b) T2 = 10:00-12:00h, c) T3 = 13:00-15:00h]

The kappa coefficient value ranges from -1 to +1, with +1 indicating better classification ability [24]. The user's accuracy for vegetation regions was 76.92%, while the producer's accuracy for T2 flight time was 83.33%.

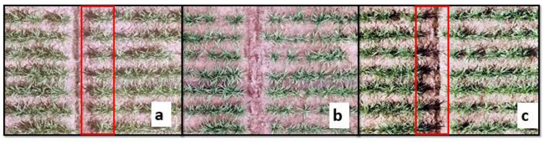

Figure 4. Shadowing areas showed in RGB mosaic images at different flight times [a) T1 = 07:00-09:00h, b) T2 = 10:00-12:00h, c) T3 = 13:00-15:00h]

Due to the direction of sunlight in the T1 and T2 flights, it is noticed that numerous shadowing regions were generated by elements such as bigger trees, concrete posts, and sugarcane trees (Figure 4).This causes the accuracy of assessment results to be reduced. As a result, in Sri Lanka, mid-day time would be preferable than early morning or early evening time to decrease the shadowing impact for image acquisition. However, the accuracy results indicated a significant level of success for the extraction of vegetation fractions from classified maps.

3.2 Determination of Phenology variations and vegetation cover analysis

Figure 3C depicts the GRVI maps, which demonstrate the variance in phenology distribution across the field. The value 0 implies that there are no phenology characteristics, whereas 1 suggests that there are many phenology characters [23]. The results indicate that all of the flights had low GRVI values due to the presence of less vegetation than soil regions. T2 and T3, on the other hand, had the highest GRVI values (0.04 and 0.11, respectively), indicating greater vegetation at the sample plots than T2. The spectral reflectance of shadowed regions would be affected, causing the GRVI estimates to be reduced.

3.3 Determination of relationship between vegetation cover and plant density

Linear regression models were developed for each time period based on UAV-based VF and observed plant density (Figure 5). The highest correlation was observed between 10:00 h and 12:00 h, with R^2 = 82.9% and SE = 2.20, while the worst performance was recorded between 13.00 h and 15:00 h, with R^2 = 58.1% and SE = 3.44. According to the data, the mid-day period had a significant correlation.

The relationship between UAV-based GRVI measurements and ground-truth plant density is depicted in Figure 6. The highest correlation was found between 10:00 h and 12:00 h (T2). The T2 model developed successfully explains 82.1% in plant density, which was significant at a 0.05 significance level with a standard error of 2.25 plants. A recent study showed virtually comparable results when assessing sugarcane stalk density using RGB-based vegetation indices. The study generated a model with R^2 of 0.754 and RMSE of 7.16 stalks between stalk density and Excess green index (ExG) [25]. As a result, the time period 10:00-12:00 h (T2) could be employed to capture images using UAVs.Therefore, the proposed methodology can be used to monitor the sugarcane fields in any areas of Sri Lanka.

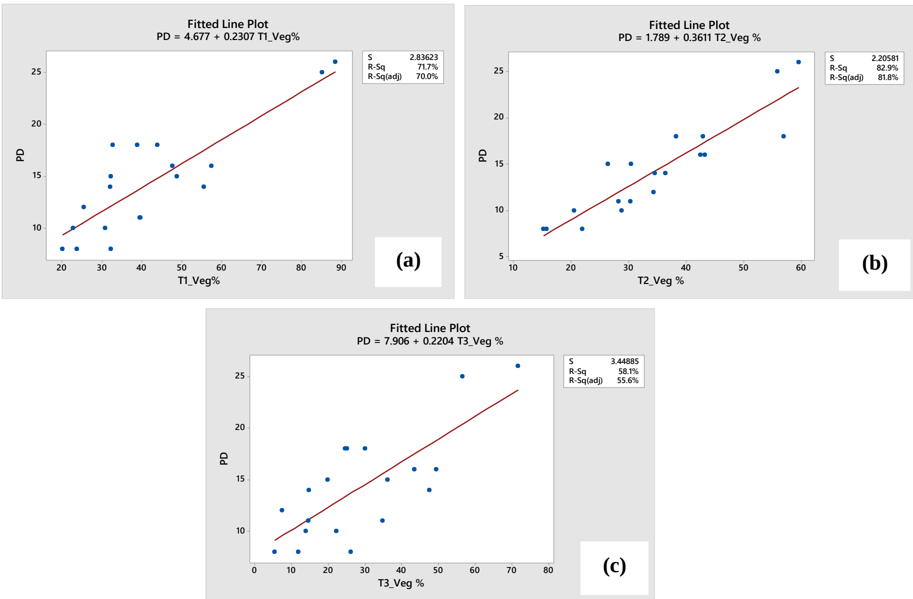

Figure 5. Relationship between the vegetation % and Plant density [a) T1=07:00-09:00h, b) T2=10:00-12:00h, c) T3=13:00-15:00h]

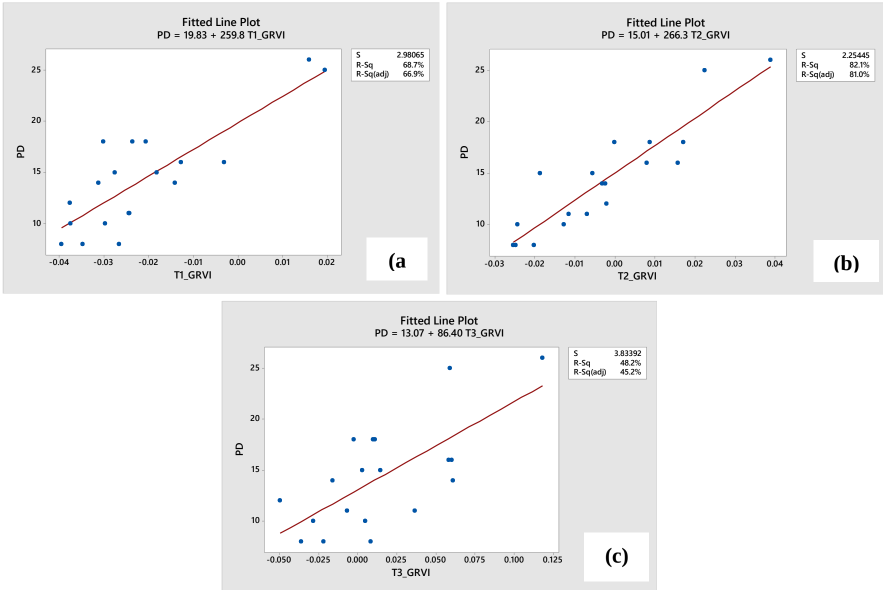

Figure 6. Relationship between the GRVI and Plant density [a) T1=07:00-09:00h, b) T2=10:00-12:00h, c) T3=13:00-15:00h]

4. Conclusion

This study illustrates the effectiveness of using RGB image-based UAVs to assess the vegetation cover of a sugarcane field for better planning and decision making. The results indicated that a mid-day flight time period (T2) would be best for producing better image classification results, because early morning and evening sessions generate shadowing areas in the images due to the sun's direction. The most significant association between VF and manual plant density was found in T2 (10:00 -12:00 h) (R^2 = 82.9%, SE = 2.20, P 0.05). The T2 indicated a very strong relationship between GRVI and PD (R^2 = 82.1 percent, SE = 2.25, P 0.05).As a result, a time period of 10:00 -12:00 h would be optimum under UAV flight parameters of 50 m flying altitudes, 4 m/s flying speed, 75% frontal and 70% lateral overlap to collect effective RGB images in Sri Lanka. As an outcome, the suggested technique has a high potential for selecting the best flying time for a day in Sri Lanka and it can be useful to identify the field level problems in sugarcane cultivations. The future studies are needed to develop methodologies to detect different physiological characteristics of sugarcane plants at different environmental conditions.

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References

1. de Souza CH, Lamparelli RA, Rocha JV, Magalhães PS. Mapping skips in sugarcane fields using object-based analysis of unmanned aerial vehicle (UAV) images. Computers and Electronics in Agriculture. 2017;143:49-56.
2. Csillik O, Cherbini J, Johnson R, Lyons A, Kelly M. Identification of citrus trees from unmanned aerial vehicle imagery using convolutional neural networks. Drones. 2018;2(4):1-16.
3. Zhang J, Huang Y, Pu R, Gonzalez-Moreno P, Yuan L, Wu K, Huang W. Monitoring plant diseases and pests through remote sensing technology: A review. Computers and Electronics in Agriculture. 2019;165:1-14.
4. Maimaitijiang M, Sagan V, Sidike P, Hartling S, Esposito F, Fritschi FB. Soybean yield prediction from UAV using multimodal data fusion and deep learning. Remote Sensing of Environment. 2020;237:1-20.
5. Maresma Á, Ariza M, Martínez E, Lloveras J, Martínez-Casasnovas JA. Analysis of vegetation indices to determine nitrogen application and yield prediction in maize (Zea mays L.) from a standard UAV service. Remote Sensing. 2016 Dec;8(12):973-988.
6. Ni J, Yao L, Zhang J, Cao W, Zhu Y, Tai X. Development of an unmanned aerial vehicle-borne crop-growth monitoring system. Sensors. 2017;17(3):502-527.
7. Arantes BHT, Moraes VH, Geraldine AM, Alves TM, Albert AM, da Silva GJ, et al. Spectral detection of nematodes in soybean at flowering growth stage using unmanned aerial vehicles. Cienc Rural. 2021;51(5):1-9.

8. García-Martínez H, Flores-Magdaleno H, Khalil-Gardezi A, Ascencio-Hernández R, Tijerina-Chávez L, Vázquez-Peña MA, et al. Digital count of corn plants using images taken by unmanned aerial vehicles and cross correlation of templates. Agronomy. 2020;10(4):1-20.

9. Fu Z, Jiang J, Gao Y, Krienke B, Wang M, Zhong K, et al. Wheat growth monitoring and yield estimation based on multi-rotor unmanned aerial vehicle. Remote Sensing. 2020;12(3):508-527.

10. Sanches GM, Duft DG, Kölln OT, Luciano AC, De Castro SG, Okuno FM, Franco HC. The potential for RGB images obtained using unmanned aerial vehicle to assess and predict yield in sugarcane fields. International journal of remote sensing. 2018;39(15-16):5402-5414.

11. Zhao H, Lee J. The Feasibility of Consumer RGB Camera Drones in Evaluating Multitemporal Vegetation Status of a Selected Area: A Technical Note. Papers in Applied Geography. 2020;6(4):480-488.

12. Kawamura K, Asai H, Yasuda T, Khanthavong P, Soisouvanh P, Phongchanmixay S. Field phenotyping of plant height in an upland rice field in Laos using low-cost small unmanned aerial vehicles (UAVs). Plant Production Science. 2020;23(4):452-465.

13. Watanabe K, Guo W, Arai K, Takanashi H, Kajiya-Kanegae H, Kobayashi M, Yano K, Tokunaga T, Fujiwara T, Tsutsumi N, Iwata H. High-throughput phenotyping of sorghum plant height using an unmanned aerial vehicle and its application to genomic prediction modeling. Frontiers in Plant Science. 2017;8:1-11.

14. de Souza CH, Lamparelli RA, Rocha JV, Magalhães PS. Height estimation of sugarcane using an unmanned aerial system (UAS) based on structure from motion (SfM) point clouds. International journal of remote sensing. 2017;38(8-10):2218-2230.

15. Zhang H, Sun Y, Chang L, Qin Y, Chen J, Qin Y, Du J, Yi S, Wang Y. Estimation of grassland canopy height and aboveground biomass at the quadrat scale using unmanned aerial vehicle. Remote sensing. 2018;10(6):851-870.

16. Mesas-Carrascosa FJ, Notario García MD, Meroño de Larriva JE, García-Ferrer A. An analysis of the influence of flight parameters in the generation of unmanned aerial vehicle (UAV) orthomosaicks to survey archaeological areas. Sensors. 2016;16(11):1838.

17.Wijesinghe P, Jayasooriya C, Wijesinghe R, Kumara SK. Sustainability of Crop Production System in South East Dry Zone of Sri Lanka: With Special Reference to Groundnut, Green Gram and Sugarcane. Hector Kobbekaduwa Agrarian Research and Training Institute; 2019.

18. Putch A. Linear measurement accuracy of DJI drone platforms and photogrammetry. 2017;1–17.

19. Sangha HS, Sharda A, Koch L, Wang G, Prabhakar P. Impact of camera lens angle and sUAS flying altitude on spatial crop canopy temperature evaluation. InAutonomous Air and Ground Sensing Systems for Agricultural Optimization and Phenotyping IV 2019 May 14 (Vol. 11008, p. 1100805). International Society for Optics and Photonics.

20. Agisoft. Agisoft PhotoScan User Manual: Professional Edition. Agisoft LLC [Internet]. 2018;127. Available from: http://www.agisoft.com/pdf/photoscan-pro_1_4_en.pdf (Accessed on: 01/09/2021).

21. DadrasJavan F, Samadzadegan F, Pourazar SH, Fazeli H. UAV-based multispectral imagery for fast Citrus Greening detection. Journal of Plant Diseases and Protection. 2019;126(4):307-318.

22. Motohka T, Nasahara KN, Oguma H, Tsuchida S. Applicability of Green-Red Vegetation Index for remote sensing of vegetation phenology. Remote Sensing. 2010;2(10):2369–2387.

23. Bendig J, Yu K, Aasen H, Bolten A, Bennertz S, Broscheit J, Gnyp ML, Bareth G. Combining UAV-based plant height from crop surface models, visible, and near infrared vegetation indices for biomass monitoring in barley. International Journal of Applied Earth Observation and Geoinformation. 2015;39:79-87.

24. Allouche O, Tsoar A, Kadmon R. Assessing the accuracy of species distribution models: prevalence, kappa and the true skill statistic (TSS). Journal of applied ecology. 2006 Dec;43(6):1223-1232.

25. Sumesh KC, Ninsawat S, Som-ard J. Integration of RGB-based vegetation index, crop surface model and object-based image analysis approach for sugarcane yield estimation using unmanned aerial vehicle. Computers and Electronics in Agriculture. 2021;180:1-12.