Evaluation Trial of Drought Damage of Rice Based on RGB Aerial Image by UAV

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ABSTRACT

Unmanned Aerial Vehicle (UAV) remote sensing is recommended to evaluate damage quickly and quantitatively. Therefore, this study aimed to explore the use of RGB aerial images by UAV for evaluating drought damage of rice through canopy color and coverage. The procedures were conducted in the dry season of 2018 (August – September 2018) at the Balitkabi Experimental field, Muneng, Probolinggo, Indonesia. A split-plot experimental field design was used with 2 factors, namely drought treatments at growth stage (Vegetative/P1, Reproductive/P2, Generative/P3, and Control/P0), and varieties (Jatiluhur/V1, IPB9G/V2, IPB 3S/V3, Hipa 19/V4, Inpari-17/V5, Mekongga/V6, Mentik Wangi/V7, Ciherang/V8). Canopy temperature data were then obtained using FLUKE 574 Infrared Thermometer, while images were taken with an RGB camera (Zenmuse X5) attached to Drone DJI Inspire I. The images were taken twice during the treatment (4 DAT and 15 DAT), followed by analysis using QGIS 2.18 and ImageJ. The results showed that RGB aerial images by UAV could be used in agricultural insurance in Indonesia, and similar countries around the world. Although the effect on yield needed to be evaluated, quick assessment by UAV was still an effective tool. In addition, drought damage evaluation through canopy color was better than canopy coverage in terms of analysis. The conversion from RGB to *Lab* color space increased the determination coefficient in multiple regression of color values against temperature difference (T_c-$T_{a)}$.

Keywords: Agricultural insurance; drought damage; RGB aerial image; UAV

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INTRODUCTION

Drought is one of the threats for rice farmers that can reduce yields and cause huge losses. To address these effects, agriculture insurance was first implemented in 2013 in Indonesia to protect farmers from crop losses due to drought, flood, pest, and disease attacks (Giamerti et al., 2021), However, direct measurements of soil water content and crop characteristics in the field cannot represent the spatial variability of crop water status. The use of these methods is also inefficient in terms of time, energy, and costs (Li et al., 2010), indicating the need for an evaluation system.

In line with these findings, unmanned aerial vehicle (UAV) is an advanced field phenotyping platform for providing high spatiotemporal resolution data. Recently, the vehicle has been used in several studies (Park et al., 2017; Poblete et al., 2018; Quebrajo et al., 2018; Yang et al., 2018; Zhang et al., 2019) to monitor agricultural status with near-earth aerial photos. The use of UAVs to quickly and quantitatively assess damage is also recommended. Moreover, agricultural studies have used the interpretation of remote sensing images for crop monitoring (Zhang & Kovacs, 2012), which includes crop classification, crop health, yield assessment, biomass, and planting density estimation (Qin et al., 2022). The main advantages of this approach are its ability to provide images below cloud cover and simple mission planning during operation, which doesn't require a lot of human resources (Floreano & Wood, 2015). Drone is widely recognized as a remote sensing imaging that is applicable for smaller areas and plots, including rice fields in Indonesia.

In recent years, UAV has been used for the detection and quantification of plants stressed by drought, such as turfgrass (J. Zhang et al., 2019; Hong et al., 2019). The evaluation by remote sensing is mostly based on multispectral reflectance (Araus & Cairns, 2014) because multispectral images use wavebands of red and near infra-red frequently to predict key traits on the plant. However, the camera used in this process is still relatively expensive. To address this challenge, several studies have recommended the use of RGB aerial images. Digital images are composed of pixels, which are a combination of the color channels red-green-blue (RGB). Building on this idea, Pagola et al., 2009 reported a negative correlation between the N-content of barley leaves and yield, where N-content was estimated using digital image analysis. Previous studies also found similar or better correlations with N status compared to spectral approaches when color analysis was reduced to segmented RGB images. The red and green channels are often considered the most informative compared to the blue channels (Baresel et al., 2017). Therefore, this study aimed to explore the use of RGB aerial images by UAV to evaluate drought damage of rice through canopy color and coverage.

METHODS

This study was conducted during the dry season of 2018 (August – September 2018) at Balitkabi Experimental Field, Muneng, Probolinggo, Indonesia. A split-plot experimental field design was used, which comprised 2 factors, namely drought treatments at the growth stage (Vegetative/P1, Reproductive/P2, Generative/P3, and Control/P0), and varieties (Jatiluhur/V1, IPB9G/V2, IPB 3S/V3, Hipa 19/V4, Inpari-17/V5, Mekongga/V6, Mentik Wangi/V7, Ciherang/V8) as indicated in Figure 1. Rice was planted at different seasons in each drought treatment following the growth stage, P1 (July 24th), P2 (July 10th), P3 (June 12th), and P0 (June 12th) as shown in Table 1. Furthermore, on September 2nd irrigation was stopped at the same time in all drought treatments. RGB image was captured by a drone at 4 Days After Treatment (DAT) and 15 DAT.

Ground data, such as canopy temperature data was obtained using FLUKE 574 Infrared Thermometer, at 1 m from the edge of the plot using 45^0 points of

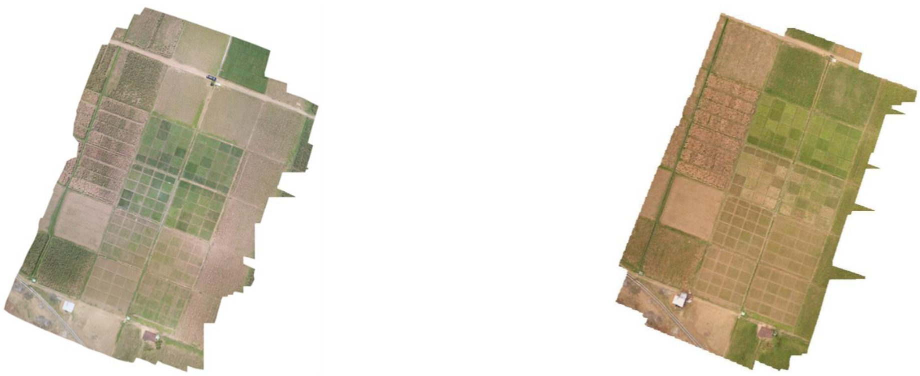
Table 1. Date of transplanting and drought treatment on each growth stage

Treatment (growth stage)	Transplanting	Drought treatment	4 Days after treatment	15 Days after treatment
P0	June 12^{nd} 2018	Sept 2^{nd}, 2018	86 Days after transplanting	97 Days after transplanting
P3	June 12^{nd} 2018	Sept 2^{nd}, 2018	86 Days after transplanting	97 Days after transplanting
P2	July $10^{th,}$ 2018	Sept 2^{nd}, 2018	58 Days after transplanting	69 Days after transplanting
P1	July $24^{th,}$ 2018	Sept 2^{nd}, 2018	44 Days after transplanting	55 Days after transplanting

	IP0V1	IP0V3	IP0V2	IP0V6	IIIP0V3	IIIP0V8	IIIP0V1	IIIP0V5
P0	IP0V7	IP0V5	IP0V8	IP0V4	IIIP0V6	IIIP0V4	IIIP0V2	IIIP0V7
	IVP0V2	IVP0V5	IVP0V7	IVP0V3	IIP0V5	IIP0V2	IIP0V6	IIP0V1
	IVP0V8	IVP0V6	IVP0V4	IVP0V1	IIP0V4	IIP0V7	IIP0V8	IIP0V3
	IP3V4	IP3V1	IP3V6	IP3V7	IIIP3V7	IIIP3V5	IIIP3V2	IIIP3V8
P3	IP3V6	IP3V5	IP3V8	IP3V2	IIIP3V3	IIIP2V4	IIIP3V1	IIIP3V6
	IVP3V8	IVP3V4	IVP3V4	IVP3V6	IIP3V8	IIP3V4	IIP3V3	IIP3V2
	IVP3V2	IVP3V5	IVP3V7	IVP3V3	IIP3V1	IIP3V6	IIP3V7	IIP3V5
	IP2V1	IP2V3	IP2V5	IP2V8	IIIP2V3	IIIP2V6	IIIP2V7	IIIP2V2
P2	IP2V6	IP2V4	IP2V2	IP2V7	IIIP2V8	IIIP2V1	IIIP2V4	IIIP2V5
	IVP2V7	IVP2V2	IVP2V8	IVP2V3	IIP2V2	IIP2V7	IIP2V3	IIP2V8
	IVP2V5	IVP2V6	IVP2V1	IVP2V4	IIP2V1	IIP2V5	IIP2V4	IIP2V6
	IP1V8	IP1V4	IP1V1	IP1V3	IIIP1V4	IIIP1V1	IIIP1V2	IIIP1V7
P1	IP1V2	IP1V5	IP1V7	IP1V6	IIIP1V3	IIIP1V6	IIIP1V8	IIIP1V5
	IVP1V4	IVP1V1	IVP1V7	IVP1V5	IIP1V1	IIP1V3	IIP1V7	IIP1V8
	IVP1V3	IVP1V6	IVP1V2	IVP1V8	IIP1V5	IIP1V4	IIP1V2	IIP1V6

N

Figure 1. Experimental plot



(a) 4 DAT (b) 15 DAT

Figure 2. Drone image at (a) 4 DAT and (b) 15 DAT

view between the canopy and the thermometer, as the measurement was made every day during the drought treatment (07:00). The image was taken twice by Drone DJI Inspire I using the RGB camera (Zenmuse X5) attached to the drone during the treatment (September 6th /4 DAT and September 17th /15 DAT) as shown at Figure 2. Subsequently, all image data were analyzed using QGIS 2.18 and ImageJ in this study.

Ground images (RGB image) were taken by camera NIKON COOLPIX every 3 days during the treatment, 1 meter from above rice canopies and soil surface to obtain images of its lowermost. Sample of images shown at Figure 3.

Image Analysis

Analysis of R, G, and B used QGIS in splitting each band and calculating their value using ImageJ. The RGB image was converted to *L*, *a,* and *b* image space color which obtained *Lab* value on each channel. Subsequently, canopy coverage was analyzed using

(a) 4 DAT (b) 15 DAT

Figure 3. Ground image at (a) 4 DAT and (b) 15 DAT

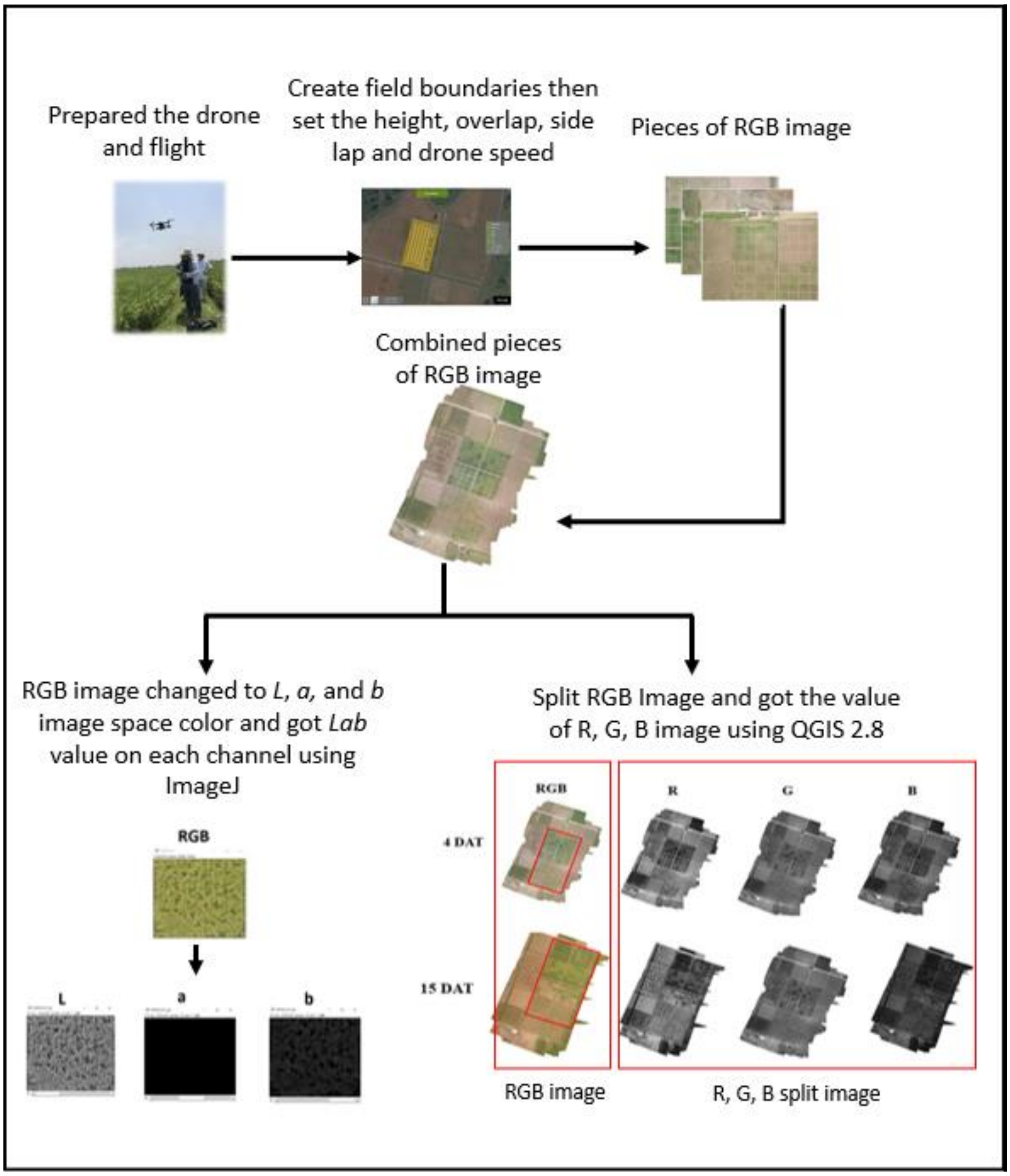


Figure 4. The method to get the RGB image by UAV and analyze the image by splitting to R, G, B, and L, a, b to get the value of each band and space color

ImageJ. Drought damage evaluation used $T_c - T_a$, where T_c was Canopy temperature, while T_a was Air temperature. Figure 4 ilustrate the method to get the RGB image by UAV and analyze the image by splitting to R, G, B, and L, a, b to get the value of each band and space color

Several regression analyses used temperature difference (T_c-T_a) as a dependent variable and independent variable (UAV images) of a value of RGB, and *Lab* space color. Furthermore, the calculation of the estimate of temperature difference was conducted (prediction of temperature difference using UAV images)

RESULTS AND DISCUSSION

Canopy Temperature and Canopy Coverage

Canopy temperature during the treatment was presented in Figure 5, indicating that during the treatment, canopy temperature was almost stable on control. However, stressed plants had an increasing trend. A significant difference in canopy temperature between control and stress plants was shown specifically after 8 DAT. It was higher at the stressed plant compared to control ones at significant levels of α:0.05 and 0.01.

In this study, monitoring the water stress was important in optimizing the yields. Infrared thermometers could be used to detect canopy temperatures rapidly and non-destructively. Furthermore, the drought damage was quantified by determining the difference between canopy and air temperature. Water-stressed plants exhibited a higher temperature compared to non-stressed plants, therefore plants could reduce transpiration as presented in Figure 5 (DeJonge et al., 2015) . The effect of drought damage on yield was further described in another study (Didi et al., unpublished).

The canopy temperature of the stressed plant (15 days after treatment) was higher compared to the control, however its canopy coverage was lower than the control. Canopy temperature and coverage in response to the drought treatment in each variety, both control and stressed plant, could be seen in Figure 6 (a) and 6 (b). In addition, Inpari-17 exhibited the lowest canopy temperature among varieties both in control and under stress, while it had the highest canopy coverage among varieties under stress. IPB 9G had the largest different canopy temperature between the control and stressed plant, while it displayed the highest canopy temperature and lowest canopy coverage of the stressed plant. It could be concluded that IPB 9G suffered the most from drought compared to other varieties.

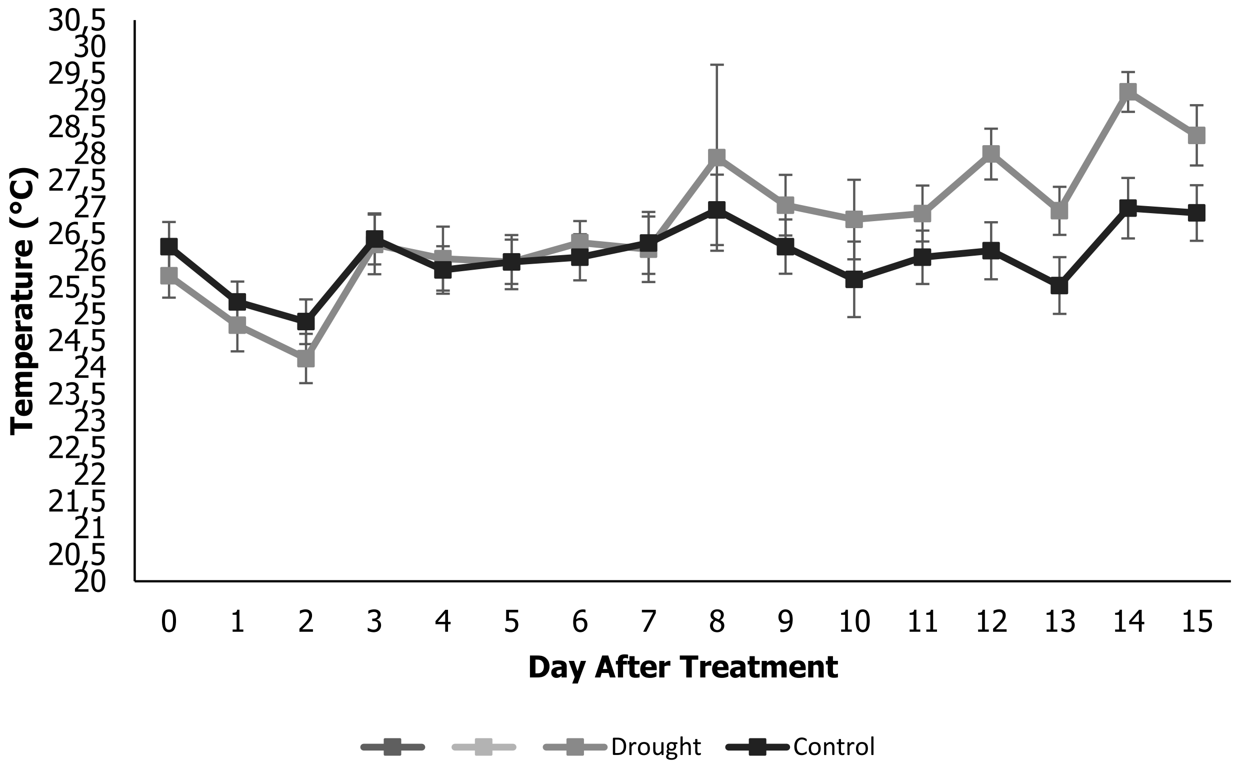
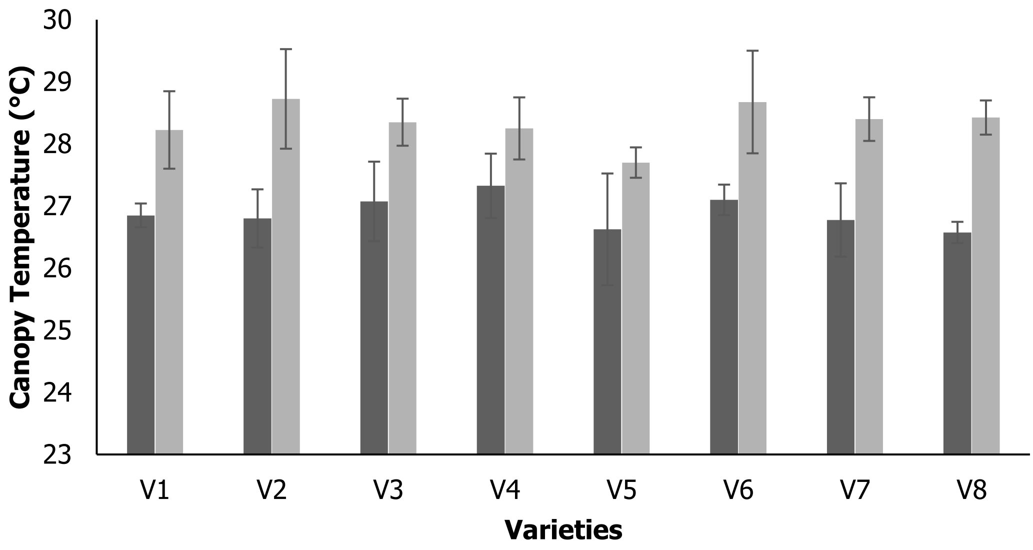
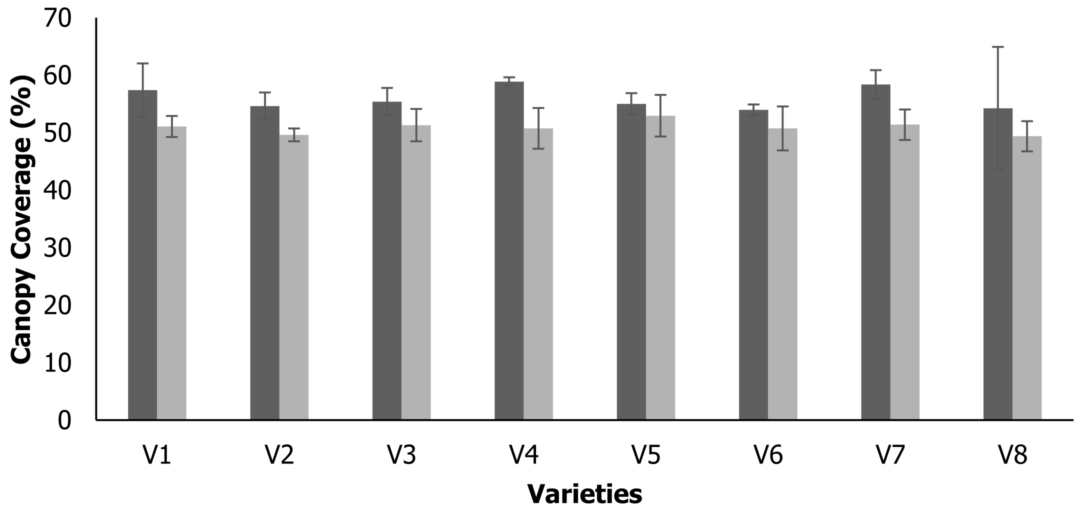


Figure 5. Change of canopy temperature during a treatment



(a)



(b)

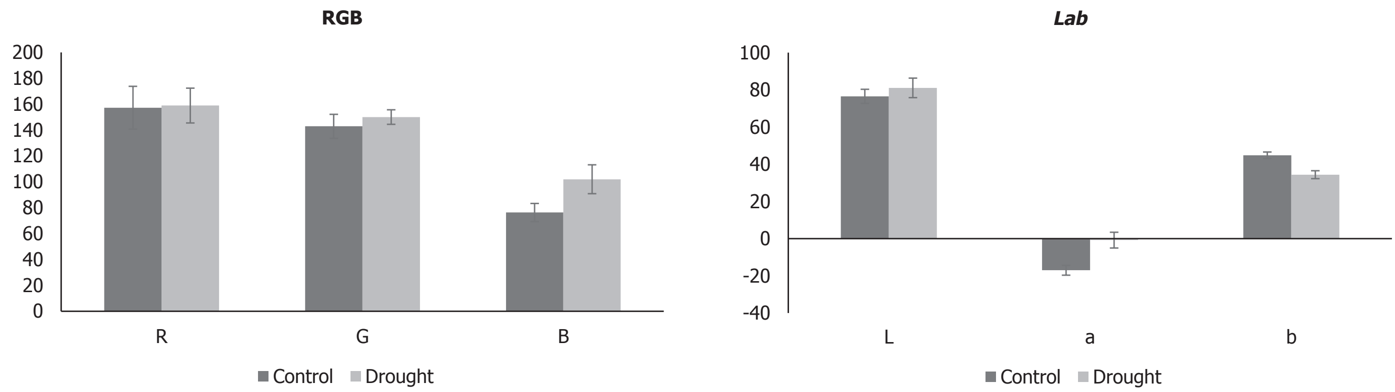
Notes: V1: Jatiluhur; V2: IPB 9G; V3: IPB3S; V4: Hipa 19; V5: Inpari-17; V6: Mekongga; V7: Mentik Wangi; V8: Ciherang

Figure 6. Canopy temperature (a) and canopy coverage (b) on the different varieties and treatment RGB value was away

The canopy temperature increased during drought treatment as an effect of the stomatal closure as the primary response to the drought. It was known for protecting plants from losing water which could lead to death, as presented in previous studies regarding rice canopy temperature, showing a correlation between rice canopy temperature, water stress, leaf rolling, and growth. According to a study by Zhang et al. (2007), drought also caused an increase in leaf rolling and reduced the dry weight of rice.

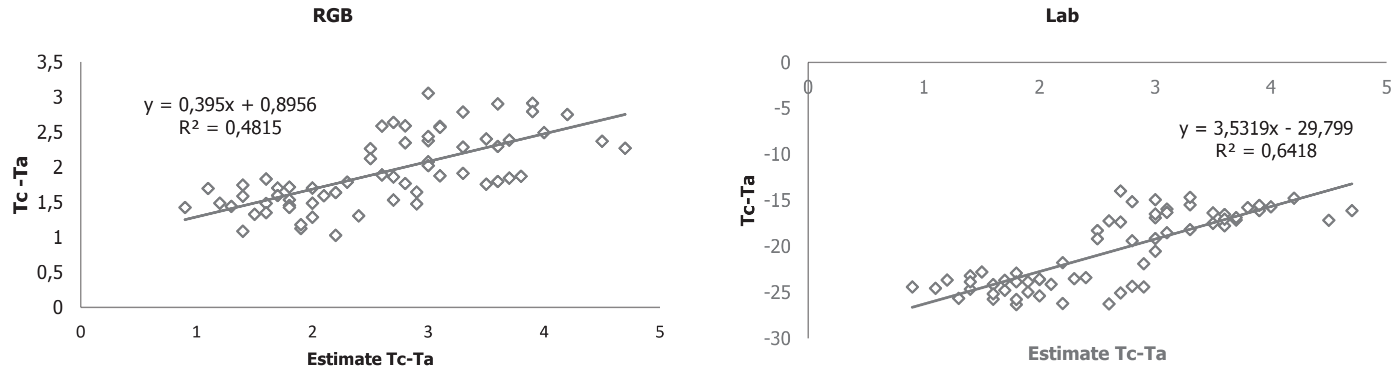
Recognizing UAV Images

Evaluation of drought damage using UAV images through canopy color was analyzed in this study.



(a) (b)

Figure 7. RGB (a) and *Lab* (b) value on the treatment



(a) (b)

Figure 8. Relationship between canopy temperature with UAV image R, G, B (a) and *L, a, b* space color (b)

Canopy color determined R, G, and B values and *L, a, b* space color values, showing that R, G, and B values increased because of the drought as shown in Figure 7 (a), *L* on the *lab* space color increased as well, while *a* and *b* values decreased as indicated by Figure 7 (b).

Drought damage reduced canopy coverage and changed canopy color, which was more quantitatively evaluated by Lab than RGB. In the Lab color space, the *a* axis (position between red and green, while green indicated negative values) had the highest determination coefficient of canopy temperature. Color acceptability decision-making was greatly simplified by the transformation of RGB values to a uniform color space in which the distance between points was directly proportional to the perceived color difference.

The drought treatment in this experiment changed the canopy color from RGB to *Lab* color space, increasing the determination coefficient in several regressions of color values against temperature difference (T_c-T_a). However, analyzing the relationship between temperature difference and estimating temperature difference by the value of RGB (Figure 8 (a) and *Lab* (Figure 8 (b)) found the possibility of using the independent variable (UAV images) to analyze drought damage, specifically on *Lab* space color since it had higher determination coefficient (R:0.6418) than RGB (R:0.4815). A similar study by Zhan et al., (2019), indicated that the combination of UAV RGB images and thermal images could be used for monitoring water stress in maize crops since the 4 Tc-based crop water stress indicators all showed high correlations with stomatal conductance (R2 > 0.54).

CONCLUSION

In conclusion, drought damage evaluation through canopy color was of higher quality compared to canopy coverage in terms of analysis of RGB aerial images. The conversion from RGB to *Lab* color space increased the determination coefficient in several regressions of color values against T_c-T_a. The results in this study suggested that RGB aerial images by UAV must be used in the agricultural insurance in Indonesia, and similar countries around the world. Although the impact on yield needed to be evaluated, the quick assessment by UAV could be an effective tool.

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CONFLICT OF INTEREST

The authors declare no conflict of interest.

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