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Estimation of blight and spot diseases severity in Ciherang and Ciliwung rice varieties based on vegetation index algorithms

LA ODE SANTIAJI BANDE♥, ASMAR HASAN♥♥
Department of Plant Protection, Faculty of Agriculture, Universitas Halu Oleo. Jl. H.E.A Mokodompit, Kendari 93231, Southeast Sulawesi, Indonesia.
Tel.: +62-812-4146745, ♥email: ldsantiajibande_faperta@uho.ac.id, ♥♥asmarhasan_faperta@uho.ac.id

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Abstract. *Bande LOS, Hasan A. 2024. Estimation of blight and spot diseases severity in Ciherang and Ciliwung rice varieties based on vegetation index algorithms. Biodiversitas 25: 1015-1021.* Blight and spot diseases are often associated with rice plant, causing high disease severity and potentially reducing crop production. One effective disease management strategy is using resistant varieties and intensive disease monitoring through camera sensor technology and vegetation index-based image processing. Therefore, this study aimed to assess the severity of blight and spot diseases on two rice plant varieties based on vegetation indexes. Image recording was carried out on rice field and leaf samples of Ciherang and Ciliwung varieties. This was followed by image processing based on normalized difference vegetation index (NDVI) to determine the proportion of sick/healthy plants in the field and dark green color index (DGCI) to quantify disease severity. The results showed that the proportion of healthy plant in Ciliwung rice field was greater than in Ciherang as shown by NDVI. Based on DGCI, Ciliwung also had a relatively lower level of disease severity compared to Ciherang, although the difference was not statistically significant. Blight disease caused more severe damage to rice leaf than spot disease based on image processing results. Furthermore, a positive correlation was observed between the increase in DGCI and NDVI.

Keywords: Blight disease, digital image processing, dark green color index, normalized difference vegetation index, rice, spot disease

INTRODUCTION

Rice production is threatened by various diseases, including leaf blight and spot, significantly reducing crop yields and affecting the quality. Bacterial leaf blight is generally caused by the pathogen *Xanthomonas oryzae* pv. *oryzae* (Xoo). Yield losses due to this disease are estimated at approximately 50% worldwide and 81.3% in India (Shekhar et al. 2020). When infection occurs at the maximum tillering stage, the potential for reducing crop yields may reach 20-40%. However, when infection occurs at the early stages of growth, it potentially causes severe crop yield losses reaching 50% (Chukwu et al. 2019).

Leaf spot disease is generally caused by the pathogenic fungi of different species, such as, brown spot disease is caused by *Drechslera oryzae* (Breda de Haan) Subram. & Jain [syn. *Bipolaris oryzae*; *Helminsthosporium oryzae*, teleomorph: *Cochliobolus miyabeanus* (Ito & Kurib)] (Mew and Gonzales 2002; Mau et al. 2020). Meanwhile, blast spot disease is attributed to *Pyricularia oryzae* Cav. [syn. teleomorph: *Magnaporthe oryzae*] (Asibi et al. 2019; Sahu et al. 2022), causing yield losses ranging from 52% (Barnwal et al. 2013) to 100% (Mau et al. 2020). A high intensity of blast disease in the field could decrease rice yield (Sudiarta et al. 2021). Due to the large impact of blight and spot diseases on crop yield, diagnosis and control efforts are crucial to minimize the impacts.

Common control methods entail planting disease-resistant varieties, but the varying levels of resistance among rice varieties, including Ciherang and Ciliwung, present challenges in selecting truly disease-resistant varieties. Another method is to carry out regular and routine monitoring to measure disease severity. Measurement of disease severity is crucial in diagnosing plant diseases because it is closely related to the level of resistance, appropriate control time, and future crop yield losses. However, conventional monitoring methods based on visual observation can be time-consuming and inaccurate, specifically when carried out over large planting areas. This reflects the need for more efficient and accurate monitoring methods. These methods include using camera sensors and digital image processing based on vegetation index algorithms such as normalized difference vegetation index (NDVI) and dark green color index (DGCI).

Camera sensor technology and digital image processing based on NDVI have been widely used for measuring rice plant diseases in the field (Phadikar and Goswami 2016; Zhang et al. 2018; Zheng et al. 2023). However, there have been no reports regarding the use of DGCI for the same purposes. Previous studies only used DGCI to determine the chlorophyll and nitrogen levels in plant leaf (Karcher and Richardson 2003; Rorie et al. 2011; Saberioon et al. 2013; Rhezali and Rabii 2020; Gée et al. 2023). There is also no information describing severity levels of blight and spot diseases in Ciherang and Ciliwung rice varieties.

This study aimed to assess the severity of blight and spot diseases in Ciherang and Ciliwung varieties based on NDVI and DGCI vegetation indexes. The results provide insight into the resistance of these two rice varieties, which will aid in successful management of disease control.

MATERIALS AND METHODS

Study area

Image recording and sampling of rice leaf from Ciherang and Ciliwung varieties were conducted in rice field at Lebo Jaya Village, Konda Sub-district, South Konawe District, Southeast Sulawesi Province, Indonesia (4°05'45.7"S 122°28'41.8" E), and all stages of the study were conducted between May and July 2023.

Vegetation index-based image recording and processing

This study focused on measuring blight and spot diseases severity using a digital image processing method based on NDVI and DGCI vegetation index algorithms. The stages of this study can be described as follows:

NDVI vegetation index

NDVI vegetation index was used to assess the proportion of diseased plants in rice field in a plot, using the single image-NDVI (SI-NDVI) method. This entailed processing a single image containing information from the Near-Infrared (NIR) and visible light (blue) spectra. The method comprised five rice plots with recorded images, including three plots for Ciherang variety, each measuring approximately 90×32 m (length × width), and two plots for Ciliwung variety, each measuring 60×24 m (length × width).

Rice field images were recorded based on the methodology by Hasan et al. (2021) with slight modifications. Recordings were taken from 09:00 am UTC+8 under clear sky conditions, using Canon EOS 750D camera with a lens featuring an On-Lens IR-Ultra Blue filter (www.spencercamera.com). This filter captured the visual light spectrum in the blue range (300-450 nm) and NIR range (700-1100 nm). The camera, mounted on a tripod for stability, was positioned at an angle of approximately ±30°C at the farthest point of rice field. The settings were configured in aperture priority mode with an aperture of 29, shutter speed and ISO set to auto, flash disabled, white balance adjusted, and a lens focal length of 29.0 mm. The captured RAW format images were converted to JPEG format with a resolution of 300 dots per inch (dpi) using the Digital Photo Professional version 4 application.

SI-NDVI images were processed using the Fiji-ImageJ application with the Photo Monitoring plugin installed (Horning 2012; Schindelin et al. 2012). NDVI values were obtained by extracting image data using the Histogram tool (Fiji-ImageJ), where the range was between -1.00 - 1.00. The proportion of values was calculated based on the plant disease incidence (modified) formula as follows (Rodrigues et al. 2019):

$$NDVI\ values\ proportion = \frac{\sum Frequency\ of\ NDVI\ values\ in\ specific\ range}{\sum Frequency\ of\ all\ NDVI\ value\ ranges} \times 100 \quad (1)$$

The range of NDVI values can be categorized as follows: -1.00 to 0.00: an area without living vegetation, 0.01 to 0.10: a diseased plant area, and 0.11 to 1.00: a healthy plant area with varying degrees of health.

DGCI vegetation index

DGCI vegetation index was used to discern disease severity based on the disease observed. Leaf samples were collected the day following NDVI image recording and each rice field plot was subdivided into six subplots, measuring approximately ±1.5 m². In each subplot, 15 rice plant leaves were randomly collected, each originating from a different clump, resulting in a total of 90 leaves sampled in each plot. Leaf samples for each subplot were scanned using a Canon Lide 120 scanner at a resolution of 300 dpi.

RGB image of each leaf was converted to hue, saturation, and brightness (HSB) color space using the Fiji-ImageJ application. Subsequently, values for each hue, saturation, and brightness parameter were extracted for each converted image. DGCI value for each leaf image was calculated using the formula as follows (Karcher and Richardson 2003):

$$DGCI\ value = [((H - 60)/60) + (1 - S) + (1 - B)]/3 \quad (2)$$

Similar to NDVI, DGCI was a unitless parameter ranging from 0.00 (very yellow) to 1.00 (dark green) (Rhezali and Rabii 2020). DGCI values obtained from the image processing were then categorized into several disease severity classes (Table 1). Categorizing disease severity percentages based on DGCI facilitates a more straightforward field assessment. First, 10 disease severity classes were determined, namely 10-100%, then the highest (max) DGCI values i.e. 0.44 ≈ 44% were determined from image processing of all symptomatic leaves, while lowest (min) DGCI values were determined to be 0.00 ≈ 0%. The value of 0.00 was determined as the minimum value for measuring the DGCI index in this study with the aim of facilitating the categorization of disease severity based on DGCI values close to 0.00 in future studies. DGCI value interval of symptomatic leaves in each disease severity class was calculated using the category class width determination formula as follows (Tsokos and Wooten 2016):

$$Interval\ values = \frac{Max_{DGCI\ value} - Min_{DGCI\ value}}{Number\ of\ class\ categories_{Disease\ severity}} \quad (3)$$

Table 1. Disease severity categories (%) based on DGCI

DGCI index*	Disease severity (%)
> 0.44	0 or Healthy (no symptoms)
0.41-0.44	10
0.37-0.40	20
0.33-0.36	30
0.29-0.32	40
0.25-0.28	50
0.21-0.24	60
0.17-0.20	70
0.13-0.16	80
0.09-0.12	90
< 0.09	100

Note: * the calculation result of formula 3

Additionally, several images of leaf samples showing disease and those without had RGB profile visualized using the Fiji-ImageJ application. This visualization aimed to observe the impact of damage due to disease on the ability of leaf to absorb the red, green, and blue light spectrum. Healthy plant leaf, containing chlorophyll for photosynthesis, actively absorbs more red and blue light than green light. This resulted in more green light being reflected by leaf and recorded by the camera sensor compared to red and blue (Kitchen and Goulding 2001).

Statistical analysis

Descriptive analysis of NDVI data entailed determining the proportion of each index value category in each image. The Friedman test assessed differences in disease severity levels based on DGCI between plots and varieties. A simple linear regression analysis was conducted to evaluate the relationship between DGCI and NDVI, while all statistical analysis were performed using Microsoft Excel (Microsoft Office Home and Student 2021 version).

RESULTS AND DISCUSSION

Proportion of diseased plants in a crop field

The results of image processing using NDVI showed that Ciherang in plots 1, 2, and 3 had NDVI values between 0.11 and 1.00 (total of green area) at proportions of 37.28, 23.93, and 42.50%, respectively. Meanwhile, Ciliwung showed higher percentages, specifically 46.52 and 64.01% in plots 1 and 2. Figure 1 also shows that Ciherang had the highest average percentage of NDVI values between 0.01 to 0.10, and ≤0.00 in plots 1, 2, and 3. These percentages were 33.10% (obtained from the average values of 29.67, 32.87, and 36.76, or the average of the red area) and 32.33% (obtained from the average values of 33.05, 43.20, and 20.74, or the average of brown area), respectively, showing that the proportion of Ciherang variety falling into the diseased category (index value 0.01-0.10) was greater than Ciliwung.

Ground-check of plant samples for estimating disease severity

This study used NDVI to estimate the proportion of diseased rice field followed by DGCI to gauge the severity of disease in individual plants. Based on the ground-check results, leaf blight, and spot diseases were the dominant disease in Ciherang and Ciliwung. Differentiating between the two diseases was challenging as spot symptoms potentially caused by multiple fungal pathogens, were almost always found on leaf of the same plant. These pathogens cause varying degrees of damage based on the most dominant disease present on leaf, hence, DGCI value for each diseased leaf differed. Some samples of healthy and symptomatic leaves of each cultivar (for comparison) along with the hue (H), saturation (S), brightness (B), and DGCI are shown in Figures 2 and 3.

When blight disease dominated almost the entire leaf, DGCI was approximately 0.181 (Figure 4.A), but when the disease was not yet dominant, DGCI was around 0.279 (Figure 4.B). Similarly, when spot disease dominated almost the entire leaf without blight disease, DGCI was 0.434 (Figure 5.A), but in cases where blight and spot diseases were both present on leaf, DGCI was 0.404 (Figure 5.B). When leaf showed no blight or spot diseases, DGCI ranged from 0.446 to 0.450 (Figures 6.A and 6.B). This means that blight had caused more serious damage than spot disease. A low DGCI value shows damage to leaf, specifically the chlorophyll part, which became more severe with leaf color changing from yellow to brown. The degradation of chlorophyll due to infection by pathogens causing blight or spot diseases leads to diseased leaf areas losing the ability to absorb red light. This was reflected in the red-light graph, compared with non-diseased leaf. When the variation in DGCI value was translated into a percentage of disease severity, leaf having blight disease with DGCI of 0.181 and 0.279 corresponded to disease severity of 70 and 50%, respectively. Meanwhile, those manifesting spot disease with DGCI of 0.404 and 0.434 corresponded to disease severity of 20 and 10%, respectively (Table 1).

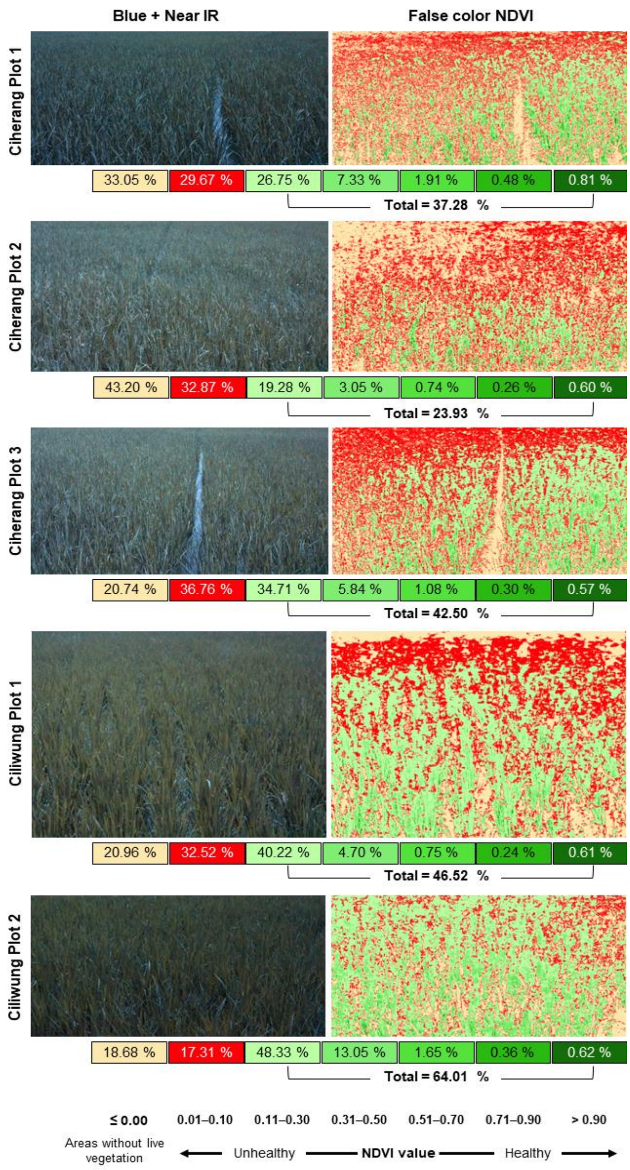


Figure 1. Comparison of diseased (red label) and healthy (green label) rice fields in Ciherang and Ciliwung based on NDVI vegetation index

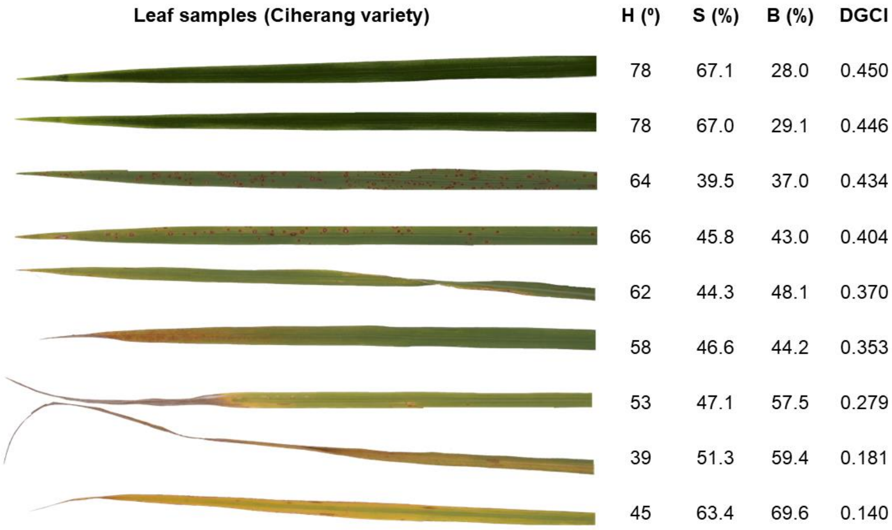


Figure 2. Rice leaf samples (Ciherang variety) with hue (H), saturation (S), brightness (B), and DGCI values

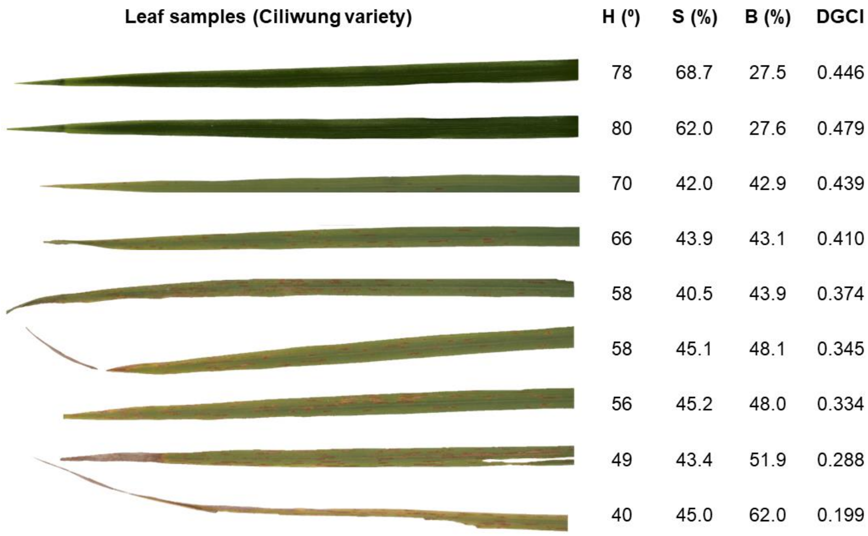


Figure 3. Rice leaf samples (Ciliwung variety) with hue (H), saturation (S), brightness (B), and DGCI values

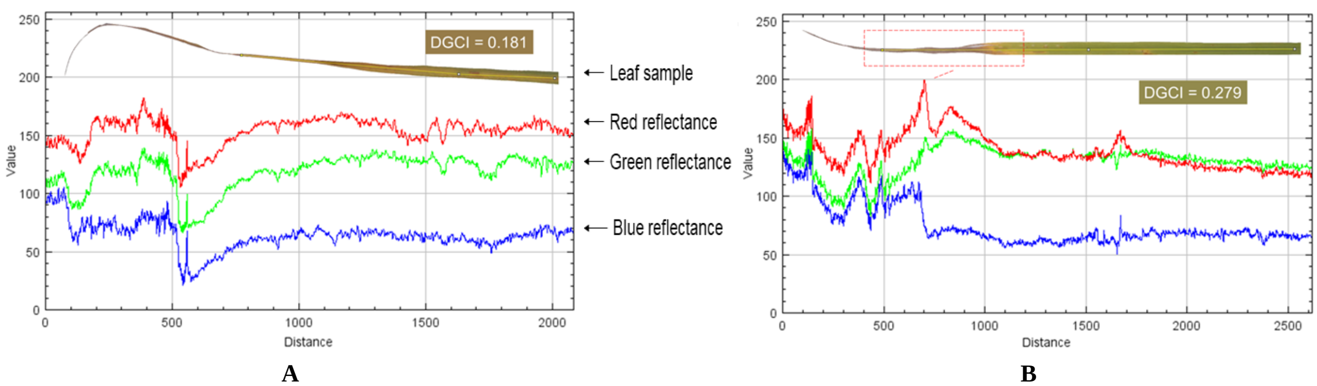
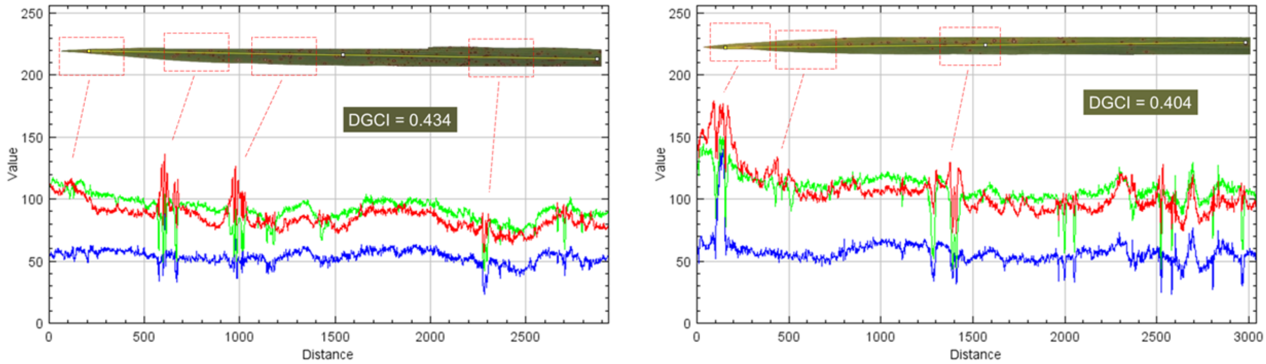
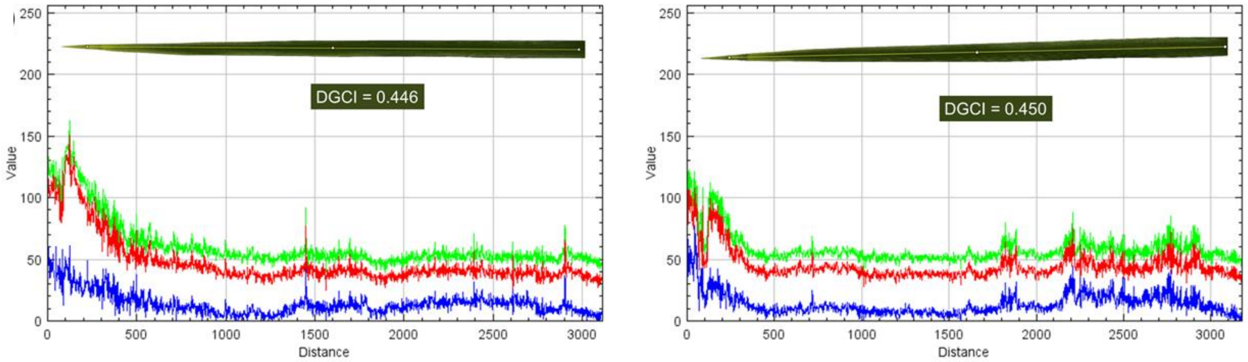


Figure 4. Comparison of DGCI and RGB profile graphs of rice leaf image samples with blight disease predominantly across the entire leaf (A) and blight disease confined to the tip of the leaf (B). Red line = red reflectance, Green line = green reflectance, and Blue line = blue reflectance



A B

Figure 5. Comparison of DGCI and RGB graphs of rice leaf image samples with only spot disease (A) and spot disease + slight blight on the tip of leaf (B). Red line = red reflectance, Green line = green reflectance, and Blue line = blue reflectance



A B

Figure 6. DGCI and RGB profile graphs of image samples of rice leaf without disease (A and B). Red line = red reflectance, Green line = green reflectance, and Blue line = blue reflectance

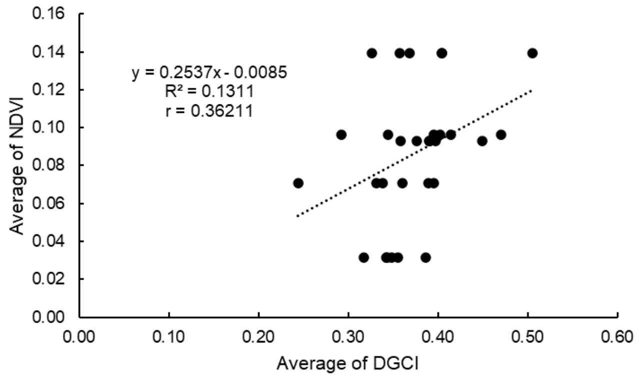


Figure 7. Relationship between DGCI and NDVI

Table 2 shows that the lowest average disease severity was observed in Ciliwung in plots 1 and 2, each at 20.00%, and in Ciherang (plot 3) at 18.33%. Meanwhile, the highest average disease severity was found in Ciherang plots 1 and 2 at 31.67 and 30.00%, respectively. The Friedman test results showed no significant difference in average disease severity between plots of the same or different varieties (Table 2). This suggested that both rice varieties were infected by blight and spot disease with relatively the same level of disease severity. Based on the standard deviation values, disease infection in Ciherang (plots 2 and 3) appeared to be relatively more evenly distributed compared to Ciliwung, as evidenced by a lower standard deviation value. This observation may also imply that plant resistance of Ciherang was more consistently uniform than Ciliwung.

Relationship between DGCI and NDVI

The simple linear regression analysis (Figure 7) showed a positive relationship between the DGCI and NDVI values. This suggests a connection between the proportion of diseased rice field estimated based on NDVI and the level of disease severity quantified with DGCI. However, the relationship between the two vegetation indexes had a relatively low correlation value of 0.362.

Discussion

NDVI serves as a valuable tool for estimating the size of plant area experiencing health problems. This method has proven useful for early disease detection and assessment of plant disease severity (Hasan et al. 2021; Taufik et al. 2023a,b). However, in this study, it is crucial to acknowledge the limitations of NDVI in precisely identifying factors disrupting plant health. This suggests the need for ground-check activities to validate the causes of plant health problems and measure disease severity accurately. Based on the ground-check results, both blight and spot diseases were dominant in Ciherang and Ciliwung.

Table 2. Percentage of disease severity based on the average DGCI index of leaves of Ciherang and Ciliwung rice varieties in each observation subplots

Subplots	Ciherang						Ciliwung			
	Plot 1		Plot 2		Plot 3		Plot 1		Plot 2	
	DGCI	DS (%)	DGCI	DS (%)	DGCI	DS (%)	DGCI	DS (%)	DGCI	DS (%)
1	0.396	20	0.348	30	0.376	20	0.345	30	0.505	0
2	0.339	30	0.344	30	0.390	20	0.470	0	0.404	20
3	0.389	20	0.387	20	0.397	20	0.396	20	0.369	20
4	0.244	60	0.317	40	0.358	30	0.414	10	0.358	30
5	0.360	30	0.342	30	0.390	20	0.402	20	0.327	30
6	0.332	30	0.355	30	0.449	0	0.292	40	0.404	20
Averages		31.67		30.00		18.33		20.00		20.00
± SD		± 14.72		± 6.32		± 9.83		± 14.14		± 10.95
Friedman test (p-value)						7.96^{ns}				

Note: DS: disease severity, ns: not significant, SD: standard of deviation

DGCI in ground-check activities showed that blight disease relatively had a greater impact on leaf damage compared to spot, characterized by lower DGCI value. This disparity was attributed to the different morphology of symptoms, with blight disease distributed evenly from the tip to the base of leaf. Meanwhile, spot disease caused damage unevenly distributed, leaving many healthy areas.

Damaged plant leaf tissue depletes chlorophyll thereby inhibiting the absorption of sunlight for photosynthesis in the damaged area. Specifically, in this study, the damaged leaf area cannot absorb red light based on RGB profile graph, possibly because chlorophyll a was damaged. Chlorophyll a absorbs the red-orange light spectrum, while chlorophyll b mainly absorbs the blue-violet light spectrum. Damage to chlorophyll a will affect the total amount of leaf chlorophyll content (Chl a + b) and the ratio (Chl a/b), thereby disrupting the photosynthesis process (Li et al. 2018).

Based on NDVI, Ciherang in the field had a greater proportion of diseased plants compared to Ciliwung. However, DGCI after a ground-check showed that the average level of damage was statistically the same. Ciliwung appeared to have a relatively higher level of resistance to disease infection compared to Ciherang based on the high average percentage of severity. Disease severity in Ciliwung varied compared to Ciherang based on the high standard deviation value. This suggests the presence of clusters belonging to Ciliwung with low disease severity and some even tend to be healthy. As stated in a previous study, Ciherang is a variety susceptible to bacterial leaf blight caused by Xoo (Joko et al. 2019), but is quite resistant to several races of *P. oryzae* (Fitriah et al. 2019). Meanwhile, no clear information has been found regarding the resistance of Ciliwung to these two diseases.

The relatively higher resistance of Ciliwung to disease infection compared to Ciherang had a positive relationship with NDVI. This correlation was evident in the result of image analysis using NDVI, where the proportion of diseased rice field in Ciliwung was lower than in Ciherang. A previous study also reported a positive and strong correlation between DGCI and NDVI (Caturegli et al. 2020). However, in the present study, a relatively low correlation value was obtained between the two vegetation indexes. This discrepancy was attributed to the number of samples used to measure disease severity through DGCI during ground-check activities, which did not represent plant population estimated using NDVI.

The challenge of estimating plant population in each field (plot) due to the scattering system used by farmers complicates the determination of representative samples. Furthermore, the lack of clear planting distances and unknown plant populations hinder the achievement of accurate estimates. The focus on assessing only blight and spot diseases is suspected to contribute to low correlation value, even though rice plants in the field can also be attacked by several pests such as stem borers and rice leaf folder pests, or a lack of nutrition. All of these factors are causes of plant health problems associated with low NDVI values.

In conclusion, NDVI and DGCI were found to be valuable methods for determining disease severity in rice or other plants. The digital image processing method based on NDVI showed that the proportion of healthy field in Ciliwung was greater than in Ciherang. Based on DGCI, Ciliwung had a relatively lower level of disease severity than Ciherang, although the resistance level was not statistically different. The image processing results showed that blight disease caused more severe damage to rice leaf samples than spot. The increase in DGCI correlated positively with NDVI but the correlation value was relatively low. This was presumably because the number of samples assessed for disease severity using DGCI did not represent plant population. Therefore, further studies are recommended to use more plant samples in assessing disease severity. Future studies should also consider using DGCI to assess diseases caused by pests or nutritional disorders in rice plant to provide comprehensive health assessment results.

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