Asian Journal of Plant Sciences

ISSN 1682-3974

OPEN ACCESS **Asian Journal of Plant Sciences**

ISSN 1682-3974
DOI: 10.3923/ajps.2024.88.97

Research Article
Interaction of Principal Component Analysis and Normalized Difference Vegetation Index (NDVI) Using Drone in Evaluation of the Vegetative Phase of Rice

[1]Andi Isti Sakinah, [2]Muh Farid, [2]Yunus Musa, [2]Nasaruddin Nasaruddin, [2]Muhammad Fuad Anshori and [2]Hari Iswoyo

[1]Agricultural Systems, Graduate School Hasanuddin University, Makassar 90245, Indonesia
[2]Department of Agronomy, Faculty of Agriculture, Hasanuddin University, Makassar 90245, Indonesia

Abstract
Background and Objective: The use of Normalized Difference Vegetation Index (NDVI) with drone technology has proven effective in crop assessment. However, integration with morphological features is needed. This study aims to explore the interplay between morphological characters and NDVI in evaluating rice cultivation during the vegetative phase. **Materials and Methods:** The experiment conducted across two proximate locations using a nested randomized complete group design, with replications nested in the environment, the study involved 10 genotypes. The NDVI and morphological data obtained were analyzed using analysis of variance and principal components. **Results:** Findings reveal the efficacy of integrating NDVI and principal component-based morphological characters. This combined approach effectively stratifies varieties into two distinct groups: Six varieties in the first group and three in the second. Notably, genotypes Inpago 15, IR20 and Way Apo Buru exhibit favorable phenotypes concerning shoot fresh weight, shoot dried weight and NDVI. Conversely, Inpari 29 showcases a lower vegetative index but demonstrates commendable plant height. **Conclusion:** These results underscore the potential of this interaction concept, especially for studies emphasizing vegetative traits.

Key words: Precision agriculture, multivariate analysis, *Oryza sativa*, Unmanned Aerial Vehicle (UAV), vegetative index

Citation: Sakinah, A.I., M. Farid, Y. Musa, N. Nasaruddin, M.F. Anshori and H. Iswoyo, 2024. Interaction of principal component analysis and Normalized Difference Vegetation Index (NDVI) using drone in evaluation of the vegetative phase of rice. Asian J. Plant Sci., 23: 88-97.

Corresponding Author: Muh Farid, Department of Agronomy, Faculty of Agriculture, Hasanuddin University, Makassar 90245, Indonesia

Competing Interest: The authors have declared that no competing interest exists.

Data Availability: All relevant data are within the paper and its supporting information files.

INTRODUCTION

Developing rice crops is one of the priorities in many countries, especially in Asia. This plant is one of the main staple crops for most of the world's communities, including Indonesia[1]. It can be seen as evidenced by the high per capita consumption of rice and the increase in population, which is correlated with the increase in rice commodities[2]. On the other hand, the increase in land expertise and climate change causes rice production not to increase significantly, even though sometimes it has decreased[3-5]. Rice development through the intensification process is the best solution to overcome the demand gap. One type of rice intensification is the development of rice varieties.

The development of rice varieties does not escape the development of technology and data analysis. It aims to increase the effectiveness and efficiency of the development process. Several studies have reported using the latest technology and precise data analysis to increase the effectiveness of the plant breeding process[6], including rice. One of the technologies developed in the agricultural era 4.0 was using drones in crop evaluation[7,8]. Drones are unmanned rudders flown to assess plant conditions at certain heights[9]. In addition, this tool can also be integrated into the fertilization process and control of pests and plant diseases[10,11]. The effectiveness of using drones in the evaluation process has been reported by several studies[7], particularly in predicting plant growth[6,12,13]. The results of drone observations through vertical shooting were analyzed using image processing[9]. One form of image processing analysis is the Normalized Difference Vegetation Index (NDVI).

The NDVI can be defined as the ratio between the reflectance of red and Near-Infrared (NIR) light waves used to monitor plant growth[14-17]. The NDVI has been used as remote sensing in distinguishing vegetation and other materials in satellite photos[17-19]. Several studies have widely reported the effectiveness of NDVI results in measuring growth, biomass and productivity[17,20-24]. However, the use of NDVI is highly dependent on the stage of plant development. It is because NDVI only focuses on green[25], so plants that have experienced senescence will have low NDVI[14,26,27]. Therefore, the use of NDVI is very identical to the vegetative phase.

The effectiveness of the NDVI assessment needs to be combined with other morphological characters, especially characters related to the vegetative phase. In general, vegetative characters are characters that play a role in the process of biomass formation[28]. This biomass will support their reproductive processes[29], so it is critical to study vegetative growth in more depth. In addition, some growth characteristics cannot be observed by NDVI analysis, especially in conditions of high canopy density[30]. Based on this, it is essential to observe several vegetative morphological characters. The combination of NDVI and these morphological characters can complement each other to make the assessment more accurate. The combination of the two characters in the evaluation has also been reported by Cal *et al.*[31] on rice plants. However, evaluation based on morphological characters requires precise analysis so that bias can be minimized in the assessment process[1], especially for multi-characters. The principal component analysis is one of the multi-character analyzes that can increase the precision of the analysis.

The principal component analysis is one of the multivariate analyses used to compress big data's diversity into a simpler one while retaining most of the diversity of its primary data[32-34]. This analysis will generate a new parameter called PC. The PC is a combination of the variability between the observed variables[32,35,36]. In addition, this PC has non-overlapping diversity between these components[1,34,36], so the assessment becomes more effective. Several studies have widely reported the effectiveness of this analysis, both in the field of agronomy in general and in the field of plant breeding in particular[37-42]. Based on this, the combination of vegetative morphological character analysis, principal component-based analysis and NDVI analysis became interesting to research in increasing the effectiveness of the evaluation or selection of lines. Therefore, this study aimed to identify the interaction between morphological characters based on principal component analysis and NDVI analysis on the evaluation of rice cultivation in the vegetative phase.

MATERIALS AND METHODS

This study was conducted in Maros City, South Sulawesi Province, Indonesia from May-October, 2021. This study was conducted in two adjacent locations. This is intended to see the interaction of the environment and genetics on the morphological characteristics of the vegetative phase.

This study was designed with a nested randomized complete group design, where the replicates were nested in the environment. The number of genotypes used consisted of 10 varieties obtained from Indonesian Center of Rice Research (BB Padi) and Indonesian local variety, namely Inpari 34 Salin Agritan (V1), Inpari 29 (V2), Mekongga (V3), Inpari 42 (V4), Inpago 15 (V5), Pokkali (V6), Ciherang (V7), Jeliteng (V8), IR20 (V9) and Way Apo Buru (V10). The variety was repeated 3 times, so there were 27 experimental units per environment.

Experimental design and procedures: This research was carried out using the general method of rice cultivation. Tillage is carried out by inundating and plowing the land to a depth of 20 cm using a tractor. After the first plowing, the rice fields were left alone for 2 days and then a second plowing was carried out to make the fields more suitable for rice with harrowing for leveling and puddling. Subsequently, 24 plots were made according to the number of experimental plots. The size of each plot is 4×4 m (16 m^2) with a distance between plots of 150 cm. Nurseries were carried out side by side with experimental land separated by rice fields. The nursery land was processed perfectly and then leveled and made 8 plots with a size of 2×2 m and a distance between plots of 30 cm. The seeds are soaked for 3×12 hrs and then soaked in sacks for 3×12 hrs. The day before the seeds were sown, the land was sprayed with a molluscicide with the active ingredient fentin acetate 60% with a concentration of 1 g/L. After the seedlings are 15 days old, the seedlings are transplanted into land with a spacing of 25×25 cm. The number of seeds planted in one planting hole is three seeds. Fertilization is done by giving urea fertilizer 200 kg/ha and NPK fertilizer 400 kg/ha given 3 times and SP-36 fertilizer 100 kg/ha given 1 time. Maintenance of rice plants includes embroidery, weeding, fertilization, irrigation, pest and disease control. Embroidery is done at the age of seven days after planting when there are dead plants and then replaced with new plants taken from the rest of the nursery. Weeding is done after the rice plants are about 30 days after planting, done by removing weeds that grow in each experimental plot. The first fertilization was carried out at the age of seven days after transplanting with 100 kg/ha urea, 200 kg/ha NPK fertilizer and 100 kg/ha SP-36 fertilizer and the second fertilization was given 30 days after planting. Transplanting with urea fertilizer 50 kg/ha NPK fertilizer 100 kg/ha. The third fertilization was given at the age of 45 days after planting with urea fertilizer 50 kg/ha, NPK fertilizer 100 kg/ha. Irrigation was carried out intermittently by giving water as high as ±10 cm above the soil surface and left until the soil dries, then watering was carried out under the same conditions until the plants were 45 DAP. Pest control was carried out in the morning by spraying insecticide with the active ingredient fipronil with a concentration of 1 ml/L of water evenly in each experimental plot at the age of 72 and 75 DAP. Harvesting is done when 80% of the panicles have entered the physiological ripe phase (yellowing of the straw) and the rice grains at the base of the panicles have hardened. Harvesting is carried out according to the harvest criteria for each variety.

Observation and data analysis: Observations were made on the character of plant height, number of tillers, number of panicles, flag leaf length, shoot fresh weight and shoot dry weight. In addition, the NDVI parameters are carried out using the Inspire 2 UAV (Unmanned Aerial Vehicle) drone which is equipped with an RGB camera with a 20-megapixel resolution with a 4/3 in sensor, 20 mm focal length and a capture speed of 1/16 sec. Each flight will contain about 1000 images or 3000-4000 images for mapping an area of 100 ha. The shooting height is 50 m above ground level. Flights are carried out at 11.00-12.00 am in clear weather conditions.

The observed data were analyzed by analysis of variance. Then, the parameters that are significant to the variety and interactions are continued in the principal component analysis. Principal component analysis was carried out on each environment and the interaction between the 2 environments. The appropriate PC proceeds to the conversion stage of the varietal growth character values into PC parameters. The analysis of variance and principal component analysis using STAR 2.01 software. Then the selected PCs (PC1 and PC2) are combined with standardized NDVI to form a 3D plot. The 3D plot formation using R-Studio 3.6 software.

RESULTS

The results of the ANOVA showed that the effect of the research location was insignificant for almost all characters except for the flag leaf length (Table 1). The effect of varieties significantly affected all vegetative characters, including NDVI. Meanwhile, the interaction effect between location and variety significantly affected almost all characters except for NDVI.

The PCA analyzed all vegetative characters. The analysis was carried out independently per environment and interactions between environments. All environments have reached an 80% cumulative proportion on PC2. As for the interaction analysis, PC2 has a cumulative proportion of 75%. However, the two are selected PCs with an eigenvalue of more than 1. Based on the results of PCA in environment 1 (Table 2), the number of tillers (0.5285), number of panicles (0.4796), shoot fresh weight (0.4026) and shoot dry weight (0.4037) have high positive eigenvectors on PC1 and shoot fresh weight (0.5122) and shoot dry weight (0.4934) have high positive eigenvectors on PC2. On the other hand, the character of plant eight (-0.3139) and flag leaf length (-0.62) are characters with the highest negative eigenvector values on

Table 1: Analysis of variance on the vegetative character of rice

	Pr (<F)			
Character	E	V	E×V	CV
PH	0.2617	0.0000	0.0339	3.55
SFW	0.2538	0.0017	0.0002	19.18
SDW	0.2736	0.0027	0.0009	21.14
NT	0.6417	0.0000	0.0050	16.92
NP	0.9207	0.0000	0.0514	18.92
FLL	0.0000	0.0000	0.0000	8.47
NDVI	0.3527	0.0002	0.275	14.01[tr]

E: Environment, V: Variety, CV: Coefficient of variation, PH: Plant height, SFW: Shoot fresh weight, SDW: Shoot dry weight, NT: Number of tillers, NP: Number of particles, FLL: Flag leaf length and NDVI: Normalized Difference Vegetation Index

Table 2: Principal component analysis in each planting environment and the interactions between the environments

	E1		E2		Interaction	
Character	PC1	PC2	PC1	PC2	PC1	PC2
PH	-0.3139	0.1611	-0.0345	0.7089	-0.1451	0.5521
SFW	0.4026	0.5122	-0.4933	0.1659	0.3909	0.5188
SDW	0.4037	0.4934	-0.4596	0.2747	0.4206	0.3976
NT	0.5285	-0.1352	-0.5031	-0.1524	0.5457	-0.1371
NP	0.4796	-0.2559	-0.5111	-0.1014	0.5243	-0.1611
FLL	0.2591	-0.6200	0.173	0.6008	0.2765	-0.4725
Proportion of variance	0.5589	0.2414	0.591	0.2807	0.5137	0.2424
Cumulative proportion	0.5589	0.8004	0.591	0.8718	0.5137	0.7561
Eigenvalues	3.3537	1.4486	3.5462	1.6843	3.0821	1.4547

E: Environment, PC: Principal component, PH: Plant height, SFW: Shoot fresh weight, SDW: Shoot dry weight, NT: Number of tillers, NP: Number of particles and FLL: Flag leaf length

PC1 and PC2, respectively. Meanwhile, shoot fresh weight and shoot dry weight characters consistently have high and positive eigenvectors on both PCs.

The PCA results in the 2nd environment show that flag leaf length is the only character with a positive eigenvector value, 0.173, on PC1 (Table 2). On PC2, the characters with high eigenvector values are plant height (0.7089) and flag leaf length (0.6008). On the other hand, characters with high negative eigenvectors on PC1 are fresh shoot weight (-0.4933), shoot dry weight (-0.4596), number of tillers (-0.5031) and number of panicles (-0.5111). Characters with high negative eigenvectors on PC2 are the number of tillers (-0.1524) and panicles (-0.1014). The characters with consistent eigenvectors on both PCs are the number of tillers, panicles and flag leaf length.

The PCA results show that the number of tillers and the number of panicles have the most significant eigenvector values above 0.5 on PC1. In contrast, TTV is the only character with negative eigenvectors (-0.1451). On PC2, the characters' plant height, shoot fresh weight and shoot dry weight have positive and relatively high eigenvectors, namely 0.5521, 0.5188 and 0.3976. On the other hand, the characters' number of tillers, number of panicles and flag leaf length have negative eigenvectors, namely -0.1371, -0.1611 and -0.4725, respectively. The characters with stable eigenvectors are fresh shoot weight and shoot dry weight characters.

The results of the analysis of the conversion of vegetative characters into PC values and normalization of NDVI values for both environments and their interactions were shown in Table 3. Based on the table, genotypes V8, V10 and V9 are genotypes that have the most significant index values for the parameters PC1 (1.50), PC2 (0.45) and NDVI (1.36), respectively, in the first environment. On the other hand, genotypes 5 (0.47), 3 (-0.41) and 1 (0.82) were genotypes that had the most significant negative index values on PC1, PC2 and NDVI, respectively. In environment 2, genotype V2 was the genotype with the most considerable positive index value for PC1 (0.95) and genotype V5 for PC2 (0.53) and NDVI (1.21). On the other hand, genotype V8 is the genotype with the highest negative index value on PC1 (0.77) and PC2 (-0.57) and genotype V2 on NDVI characters (0.82). As for the interactions, genotypes V7, V10 and V9 are the genotypes that have the most significant positive index values for the parameters PC1 (1.71), PC2 (0.42) and NDVI (1.25), respectively. On the other hand, genotypes V5, V3 and V2 were the genotypes that had the most significant negative index values for the parameters PC1 (0.27), PC2 (-0.46) and NDVI (0.51).

The results of the combination of the three parameters are shown in the form of a vegetative index (Fig. 1). The group division is based on a value of 0. Based on Fig. 1a, genotypes with an index above 0 are genotypes V3, V5, V7, V4, V10 and V9. On the other hand, genotypes V2, V1 and V8 are genotypes

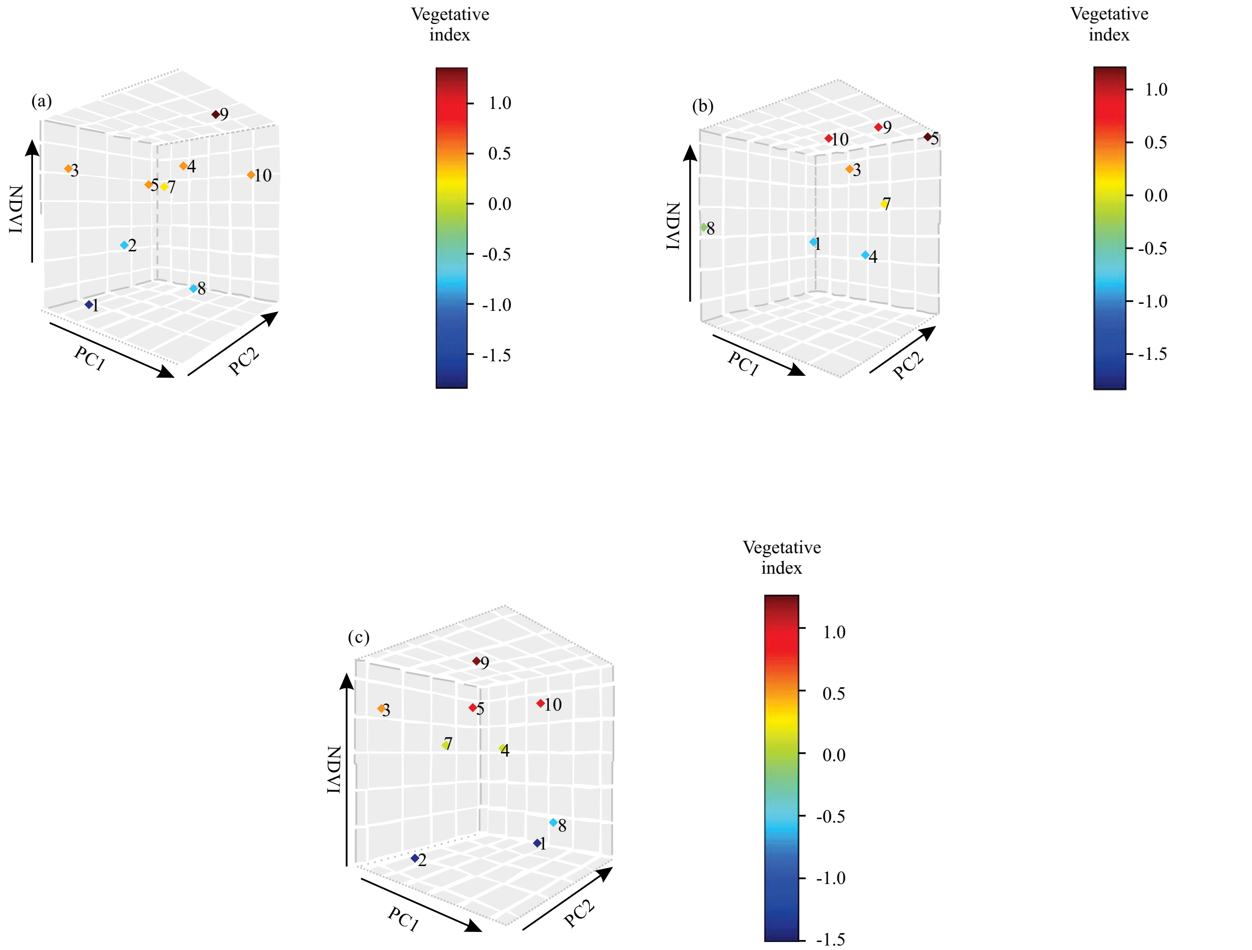

Fig. 1(a-c): Vegetative index based on 3D plot analysis, (a) Index value above 0, (b) Index value below 0 and (c) Positive index value

Table 3: PC and NDVI values in each environment and interactions between environments

	E1			E2			Interaction		
Genotype	PC1	PC2	NDVI	PC1	PC2	NDVI	PC1	PC2	NDVI
V1	-1.06	-0.20	-1.82	-1.93	0.51	-0.68	0.55	0.27	-1.37
V2	-0.63	-0.07	-0.78	0.95	-0.08	-1.82	-0.88	-0.21	-1.51
V3	-0.61	-0.41	0.47	0.30	-0.14	0.51	-0.53	-0.46	0.53
V4	0.38	0.05	0.58	-0.08	0.26	-0.80	0.48	-0.01	0.06
V5	-1.47	0.38	0.45	0.75	0.53	1.21	-1.27	0.36	0.86
V7	-0.06	0.06	0.27	0.81	-0.10	0.01	-0.51	-0.10	0.13
V8	1.50	-0.32	-1.05	-1.77	-0.57	-0.31	1.71	-0.18	-0.75
V9	0.96	0.07	1.36	0.90	-0.21	0.95	0.12	-0.08	1.25
V10	0.99	0.45	0.51	0.06	-0.21	0.93	0.34	0.42	0.81

E: Environment, PC: Principal component and NDVI: Normalized Difference Vegetation Index

that have an index value below 0. In Fig. 1b, genotypes with positive index values are genotypes V7, V3, V10, V9 and V5, while genotypes V8, V1, V4 and V2 have negative index values. Meanwhile, based on Fig. 1c, the genotypes with a positive index value are V4, V7, V3, V5, V10 and V9. On the other hand, the genotypes in the negative index area are V2, V1 and V8.

DISCUSSION

The interaction test is divided into two concepts: Vegetative morphology and NDVI. The NDVI analysis represents the chlorophyll potential analyzed vertically via drone[25,43,44]. Based on the ANOVA results (Table 1), the diversity of varieties and their interactions with the environment significantly affect the productivity character. It indicates that the evaluation assessment based on morphological vegetative characters is practical. The use of this concept was also reported by Farid *et al.*[36,45] on wheat, Abduh *et al.*[46] on maize and Laraswati *et al.*[47] on rice. In contrast, the use of NDVI is only influenced by the influence of varieties[18,21]. This indicates that the appearance of vertical photos is relatively the same between the two optimal environments, so the use of NDVI is independent of its morphological character in assessing the effectiveness of genotype evaluation. Further, morphological characters were analyzed in-depth with multivariate analysis, such as principal component analysis.

Assessment of PC effectiveness in principal component analysis depends on the total variance collected for each PC[36,45]. The optimal PC assessment is based on cumulative proportions and eigenvalues[32,33,40,48,49]. According to Jolliffe and Cadima[32] and Farid *et al.*[36], the optimal cumulative proportion value is 0.8, so the optimal number of PCs is the PC that reaches the value of 0.8 the first time. In addition, according to Anshori *et al.*[1] and Jolliffe and Cadima[32], the optimal PC assessment can be based on an eigenvalue of more than 1. Based on this, the PC used in this study only focused on PC1 and PC2, independent of each environment and the interaction between these environments.

Based on the PCA analysis in environment 1 (Table 2), the higher the PC1 value in a genotype, the higher the diversity of fresh shoot weight, shoot dry weight, number of tillers and number of panicles characters. On the other hand, the lower the PC1 value, the lower the four characters and the higher the plant height. The concept is also the same as PC2, where the higher the PC2 value, the correlation with the fresh shoot weight and shoot dry weight values, while the lower the PC2 value, the correlation with the high diversity of flag leaf length and the number of panicles. Based on this, the combination of interactions between the two PCs is positive. It is determined by the diversity of fresh shoot weight and shoot dry weight, which is dominant compared to other characters. Yang *et al.*[33] further supported this notion, highlighting the positive interactions between PCs, specifically providing a foundation for understanding the dynamics of diversity within genotypes based on PCA outcome.

The results of the PCA analysis in environment 2 (Table 2) also show a pattern of grouping the diversity of characters relatively the same as in environment 1. However, these characters' positive and negative directions are different from environment 1. According to Jollife and Cadima[32] and Fadhli *et al.*[50], positive and negative directions only show the position of the director in a variety and not absolute. Based on this analysis, the higher PC1 value indicates the high diversity of flag leaf length and plant height and the low diversity of other characters. The lower PC1 value indicates the high diversity of fresh shoot weight, shoot dry weight, number of tillers and number of panicles. As for PC2, the higher PC value indicates high diversity in flag leaf length and plant height, while the lower PC value indicates high diversity in the number of tillers and panicle characters. Based on the combination of PC1 and PC2, the character of flag leaf length in environment 2 is the dominant character of positive diversity. On the other hand, the characters' number of tillers and the number of panicles are the characters that dominate the negative diversity in PC2.

The results of PCA analysis on environmental interactions have the same pattern and direction of diversity as the first environment. In general, the diversity between environments 1 and 2 is relatively the same. This was also supported by environmental diversity, which does not significantly affect almost all characters[51,52]. However, based on this interaction analysis, the pattern and direction of diversity refer more to the first environment. Meanwhile, the contribution of the second environment is not too enormous in influencing the eigenvector values on PC1 and PC2 in the interaction of the two environments. Therefore, PCA can be focused on the first environment and its interaction in the second environment. In addition, shoot fresh and dry-weight characters are dominant characters in controlling genotype diversity. However, further analysis of the index of the combination of PC and NDVI is also an essential reference in the assessment.

The results of PC1, PC2 and NDVI were used to form the vegetative index. This index is an unweighted combination of the three parameters that have been normalized. The concept of using the index in an evaluation assessment was also reported by Anshori *et al.*[1], Laraswati *et al.*[47], Okasa *et al.*[53] and Farid *et al.*[54] on rice. The index interaction assessment can be visualized as graphs and plots. This was also reported by Okasa *et al.*[53] and Farid *et al.*[54] on rice, Fadhli *et al.*[38] on maize and Farid *et al.*[36] on wheat. Based on the research concept, the results of this study use a 3D plot. This 3D plot analysis was directed towards grouping genotypes based on a threshold 0. This concept was also reported by Peternelli *et al.*[55], Fadhli *et al.*[38] and Anshori *et al.*[1]. Based on threshold 0, environment 1 and the interaction between the environments have genotype diversity which is distributed between 3D plot spaces. In contrast, environment 2 has a data distribution centred on the positive quadrant of the combination of all parameters. This confirms that the assessment of interactions in the vegetative phase should focus on environment 1 and the interaction between the two environments.

Based on 3D plots in both environmental approaches, genotype grouping against the threshold is more strongly determined by NDVI. Consistent with findings from previous studies[1,55], the strong influence of NDVI serves as a powerful indicator for characterizing and discriminating genotypes in 3D plots under different environments. This is because NDVI has a large diversity in this study. Moreover, the diversity of PCs, especially PC1, divides the pattern of subgroups in each group.

Based on the division of genotype groups, genotypes V5, V9 and V10 are consistently high or have a value above 0.5. This indicates that these three genotypes have a relatively high diversity of fresh shoot weight, shoot dry weight and NDVI characters. It aligns with Schaefer *et al.*[19] who showed that increased NDVI values often correspond to increased diversity in shoot characters. On the other hand, genotype V2 is a genotype that consistently has a negative vegetative index. Negative NDVI values can be indicative of specific phenotypic traits[45], such as reduced biomass and lower overall plant vigor. This means that genotype V2 has a relatively low phenotype for the four characters but a high phenotype for the plant height characters.

Based on the index character grouping, the NDVI parameter has a direction of diversity that is relatively positive about shoot fresh and dry weight. The relationship between NDVI parameters on biomass was also reported by Jin *et al.*[21] and Prabhakara *et al.*[22] on grassland or cover crops, Marín *et al.*[56] on turfgrass and Ryu *et al.*[23], Choudhury *et al.*[24] on rice. On the other hand, NDVI has a consistent negative direction on rice plant height. Although according to Choudhury *et al.*[24], there is a significant plant height on NDVI. However, the NDVI measurement of rice plants in this study was carried out when the plants had passed the heading phase so that there were overlapping leaves and began to experience a greenish decline. This causes the measurement of NDVI is not optimal or has a low correlation to some vegetative characters[14,26,57]. Therefore, based on the overall results, the use of NDVI in this study is in line with the development of fresh shoot weight and shoot dry weight characters.

CONCLUSION

The interaction of the Normalized Difference Vegetation Index (NDVI) and the principal component-based morphological characters in this study was considered adequate. These interactions can describe the distribution of diversity and group the varieties combined into a vegetative index. Environment 1 and the interaction of the two environments is an approach with an excellent varietal vegetative index distribution. Meanwhile, the grouping of varieties in this study was divided into two main groups, which were dominated by NDVI diversity. In contrast, the diversity of PCs, particularly PC1, determines the subgroups of the leading group. The first group consisted of varieties Inpari 42 (V4), Ciherang (V7), Mekongga (V3), Inpago 15 (V5), Way Apo Buru (V10) and IR20 (V9), while the second group consisted of Inpari 34 Salin Agritan (V1), Inpari 29 (V2) and Jeliteng (V8). Based on the subgrouping, genotypes Inpago 15 (V5), IR20 (V9) and Way Apo Buru (V10) were genotypes that consistently had an excellent vegetative index or were explicitly related to the shoot fresh weight, shoot dry weight and NDVI characters. On the other hand, Inpari 29 (V2) is a genotype with a low vegetative index but has a good plant height phenotype. Based on the results of this study, interaction analysis of morphological characters based on principal component analysis and NDVI can select genotypes with good vegetative characters so that this concept can be recommended for research focused on vegetative characters.

SIGNIFICANCE STATEMENT

Rice crops in a vegetative phase were observed to identify the interaction between morphological characters based on PCA and NDVI. It was found that this approach was effective in stratifying varieties into two different groups: Six varieties in first group and three varieties in second group. In particular, the genotypes Inpago 15, IR20 and Way Apo Buru show favorable phenotypes in terms of fresh shoot weight, dry shoot weight and NDVI. Conversely, Inpari 29 shows a lower vegetative index but a good height. Therefore, this approach can describe the distribution of diversity and group the varieties combined into one vegetative index, which is useful for selecting genotypes with good vegetative traits, so this concept can be recommended for research focused on vegetative traits.

ACKNOWLEDGMENT

The authors acknowledge the Ministry of Education, Culture, Research, Technology and Higher Education, Republic of Indonesia for the PMDSU research grant with grant Number 2402/UN4.22/PT.02.00/2021.

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