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INTEGRATED CORN CULTIVATION TECHNOLOGY BASED ON MORPHOLOGY, DRONE IMAGING, AND PARTICIPATORY PLANT BREEDING

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SUMMARY

The evaluation of a cultivation technology would be more efficient when the technology assessment is based on various approaches like conventional morphological approaches, the use of drone's normalized difference vegetation index (NDVI) imaging, and participatory plant breeding (PPB). The recent study aimed to assess the effectiveness of the combination of morphological approaches, drone imaging, and participatory plant breeding in selecting the best corn cultivation technology package. This research conducted in a randomized complete block design (RCBD) with one factor from March to December 2021 at the Village Taroang, Takalar Regency, South Sulawesi, Indonesia. The factor is 40 cultivation technology packages. The treatments were replicated three times, thus having 120 experimental units. For plant participation, the investigations were conducted with 56 farmers on their corn fields through quantitative surveys in the targeted area. For NDVI, the observation was recorded 70 days after planting using a DJI Inspire two unmanned aerial vehicles equipped with a multi-spectral camera. Based on the results of the study, the combined strategy of different approaches like morpho-physiological, drone's NDVI, and participatory plant breeding is found effective in evaluating the corn production technology. The yield, plant height, percentage of net yield, and cob weight were good selection criteria for the morphology approach in evaluating corn cultivation. The NDVI could be recommended in helping the morphology evaluation and PPB, especially in a large-scale evaluation. Based on a combined assessment of the different approaches, the maize cultivar Pioneer-27 combined with 'Legowo' spacing technology, NPK fertilizer ratio of 200:100:50, KNO_3 at the rate of 25 kg, and application of biofertilizer 'Eco farming' @ 5 cc L^{-1}, was recommended as the best corn production technology package in the Village Taroang, Takalar Regency, South Sulawesi, Indonesia.

Keywords: Corn cultivation, NDVI, PPB, morphological approach, multivariate analysis

Key findings: Conventional morpho-physiological, drone NDVI, and participatory plant breeding approaches were used in a combined strategy to evaluate the maize production technology. Based on this study, this combination was found very effective in determining the best corn production technology. The combination of all approaches was formulated in the form of evaluation indices, i.e.,

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morphological index (0.539), NDVI (- 0.553), and PPB (0.635). The morphological index values for yield-related traits were, i.e., yield, plant height (0.06), percentage of net yield (0.20), and cobs weight (0.47). Based on the evaluation index analysis, maize cultivar Pioneer-27 was recommended with 'Legowo' spacing technology, NPK fertilizer ratio of 200:100:50, KNO_3 @ 25 kg, and biofertilizer 'Ecofarming' @ 5 cc L^{-1} as the best corn production technology package, especially in the Village Taroang, Takalar District, Takalar Regency, South Sulawesi, Indonesia.

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INTRODUCTION

The increasing huge world population has become a challenge for food security in the future. According to Adam (2021), the world population will reach 9.7 billion in 2070, which indicates that food stability and security will be the main issue in many countries (Walker, 2016). In general, the concept of resilience relies more on the sustainable increase in the production of major cereals such as corn, wheat, and rice. Maize is a food and feed commodity, and has an important and vital role in maintaining the balance in world food security (Bahtiar *et al.,* 2020; Abduh *et al.,* 2021). Therefore, the increase in corn production has been a priority in many countries, including Indonesia.

In Indonesia, plans to increase corn production is still considered ineffective, where it remains at 3.91% per year, and the production rise was relatively due to an increase in cultivation area. On the contrary, the maize production increase at 0.27% was achieved through cultivation technology intensification (Ministry of Agriculture, 2018). Therefore, it is a clear indication that the corn intensification concept needs further effective development and improvement. In general, the development of production intensification is possible through two approaches, namely, environmental management and genetic engineering (Chozin and Sudjatmiko, 2019; Abduh *et al.,* 2021). Simultaneous improvement and development of the two approaches can be an effective solution to increase corn yield in Indonesia.

Environmental engineering is possible and can be used via different plant spacing and fertilization levels (Abduh *et al.,* 2021). In Indonesia, there are two common types of spacing, namely, square spacing and 'legowo' spacing (Padjung *et al.,* 2020). The 'legowo' spacing is an innovation to improve the air cycle and reduce competition among plants, receiving their needed benefits even when positioned as a border plant (Portes and Melo, 2014; Kurt *et al.,* 2017; Alimuddin *et al.,* 2020). This spacing can increase the potential cob size and fill as it gives a trigger to increase the maize prolific (Al-Naggar *et al.,* 2017). The spacing technology also increases the effectiveness of fertilizer applications in corn.

Fertilization is a major factor in providing nutrients for plants (Jjagwe *et al.,* 2020; Nascimento *et al.,* 2020). There are three types of fertilizers, namely, chemical, organic, and biofertilizer (Hasnain *et al.,* 2020; Abduh *et al.,* 2021). However, among them, the biofertilizer has a significant effect to improve the biological soil characteristic (Nascimento *et al.,* 2020; Gubali and Abdullah, 2021). Generally, the biofertilizer contains bacteria and hormones that can stimulate plant growth (Rahimi *et al.,* 2019; Nascimento *et al.,* 2020). However, the effectiveness of biological fertilizer is largely determined by the type of bacteria and its accompanying content, as well as, the application method (Gubali and Abdullah, 2021; Padjung *et al.,* 2021). The combination of plant spacing and chemical and biological fertilizers is possible and applicable through environmental engineering.

Generally, the genetic engineering of corn is to develop open-pollinated and hybrid varieties (Kutka, 2011; Fromme *et al*., 2019). Yet, hybrid varieties are mostly used in corn cultivation. The hybrid cultivar has a high heterosis ability to increase its yield, thus, chosen by farmers (Hake and Ross-Ibarra, 2015; Fadhli *et al*., 2020). Alternatively, the open-pollinated has an advantage in adapting to marginal conditions, so this cultivar is the potential to develop in suboptimal environments (Jaradat *et al.,* 2010; Wolde *et al.,* 2018). Based on that, the genetic potential is dependent on the existing environment and its interaction (Acquaah, 2007). Therefore, the combination of genetic factors and cultivation technology is important in inducing optimal yield in maize. Moreover, the evaluation of the combined genetic factors and cultivation technology has several observational approaches, such as conventional morphological traits, drone technology, and social approaches through participatory plant breeding.

The drone technology and participatory plant breeding (PPB) have not been optimized in evaluating corn cultivation as opposed to conventional morphological approaches. Drones are smart farming technology used in monitoring and predicting crop performance, as well as, the need and impact of fertilization and pesticides (Ahirwar *et al.,* 2019; Khoirunisa and Kurniawati, 2019). Drone technology provides analytical information related to the crop status through aerial imaging, and such evaluation is easier and more efficient (Rokhmana, 2015). Meanwhile, the core components of PPB include the identification of community, crop, and needs of local farmers, and the selection of promising genotypes based on their performance in the farmer's field (Ceccarelli and Grando, 2019; Colley *et al.,* 2021). The PPB can help the researcher know the farmer's needs. Besides that, the PPB concept can increase the farmer's adoption of the disseminated technology (Morris and Bellon, 2004; Colley *et al.,* 2021, 2022). This concept is considered more effective in the dissemination process of the selected lines and their adaptability to formulate the best corn production technology (Casals *et al.,* 2019; Hairmansis *et al.,* 2019). However, the scope of this approach is limited and the level of farmer knowledge is also limited scientifically. Therefore, the combination of morphology, drone, and PPB is deemed the most fitting solution for a more precise and accurate approach than having a single approach.

Based on that, as the combined strategy of morphological approach, drone technology, and PPB is considered important in assessing the best production technology for corn, the latest study aimed to assess the effectiveness of these combined strategy for the best corn production technology selection.

MATERIALS AND METHODS

The recent study was carried out from March to December 2021 in the Village Taroang, South Galesong District, Takalar Regency, South Sulawesi, Indonesia. The study combined plant morphology observations with participatory plant breeding (PPB). For the PPB concept, the study involved several parties such as university researchers, local agriculture officials, village heads, agricultural extension workers, and farmer's groups to evaluate the treatment.

Experimental design

The recent study focused on forming a selection model through an index so that the role of combination is prioritized over the influence of a single factor among cultivar or production technology. Based on that, the research set up randomized complete block design (RCBD) with one factor. The factor is the combination of five corn varieties and eight cultivation technology packages, hence, 40 combination levels. The treatments were replicated three times, for a total of 120 experimental units. Table 1 shows the detail of the combinations. Each experimental unit had a plot size of 5 m × 5 m. The RCBD formula is shown below:

$$Y_{ij} = \mu + \tau_i + \beta_j + \varepsilon_{ij}$$

where

Y_{ij} = the j^{th} observation of the i^{th} treatment,

μ = the population mean,

τ_i = the treatment effect of the i^{th} treatment,

β_j = the rep effect of the j^{th}, replicate, and

ε_{ij} = the random error.

Evaluation based on morpho-physiological characters

Observations for morphological data based on plant growth and production traits were performed following the guidelines for corn cultivation (Abduh *et al*., 2021; Padjung *et al*., 2021). The component traits were plant height, stem diameter, cob height off ground, number of leaves, male and female flowering age, anthesis-silking interval, cob diameter, cob length, seed rows per cob, closure of cob, and cob weight. As for the physiological characteristics, these are absorption, reflection, transmission, leaf SPAD, green value, chlorophyll a and b, total chlorophyll, and the number of stomata. The types of equipment used in the observations were a miniature leaf spectrometer CI-710 type (absorption, reflection, and transmission), and a microscope.

Table 1. Treatment details of cultivars and cultivation packages.

Cultivar	Detail treatment	Cultivation package	Detail treatment
V1	NASA-29	P1	square spacing of 75 cm × 20 cm with NPK fertilizer ratio of 225:100:75 (P1)
V2	JH-37	P2	square spacing of 75 cm × 20 cm, with NPK fertilizer ratio of 200:100:50, plus 25 kg of KNO_3, and biofertilizer 'Biotany' application @ 5 cc L^{-1}
V3	Bisi-2	P3	'Legowo' spacing (50 + 100) × 20 cm, with NPK fertilizer ratio of 225:100:75
V4	Bisi-18	P4	'Legowo' spacing (50 + 100) × 20 cm, with NPK fertilizer ratio of 200:100:50, plus 25 kg of KNO_3, and biofertilizer 'Biotany' application @ 5 cc L^{-1}
V5	Sinhas-1	P5	'Legowo' spacing (50 + 100) × 20 cm, with NPK fertilizer ratio of 200:100:50, plus 25 kg of KNO_3, and biofertilizer 'Ecofarming' application @ 5 cc L^{-1} (P5).
V6	NK-7328		
V7	Pioneer-27		
V8	ADV-JOSS		

Evaluation based on drone's aerial imaging

The data were recorded 70 days after planting using a DJI Inspire 2 unmanned aerial vehicles (UAV) equipped with a multi-spectral camera. The captured aerial photo data was processed using the agisoft metashape application to obtain normalized difference vegetation index (NDVI) data of the corns. NDVI is an algorithm that uses near-infrared light (NIR) and red visible light I to determine the pattern of plant development in terms of plant density and health (NDVI = [NIR – R]/[NIR + R]). NDVI ranges from -1 to 1 where the closer the value to unity (1) the healthier the plants by having a higher density. On the contrary, when the value is closer to -1 the plant is suspected to be unhealthy or even dead. The NDVI value in this article focuses on comparing growth and the yield in each combination of different treatments in corn production technology.

Observation of participatory plant breeding

The concept of participatory plant breeding was emphasized in farmers' assessment of corn plantations through quantitative surveys. The farmers' participation in this study referred to the fourth type by Morris and Bellon (2004), where farmers evaluate finished corn cultivation on station or in scientists' managed on-farm trials, and help select corn cultivation to distribute. There were 56 farmers involved in this survey. The survey was conducted during the generative stage by observing each plot. Each farmer marked the five most preferred plots without ranking. All the marks were counted and then, presented as participatory plant breeding qualitative data.

Data analysis

The morpho-physiological data were systematically analyzed through analysis of variance (ANOVA), factor analysis, and path analysis (Farid *et al*., 2020). The results of the paths become the basis for the formation of a morpho-physiological index. Drone aerial data presented in the NDVI, along with other data (morphological index analysis and participatory plant breeding) were standardized before being combined (Peternelli *et al*., 2017). The whole approach was analyzed by principal component analysis (PCA). The results of the eigenvectors in the PCA were used as an evaluation index of the corn cultivation technology packages. Overall, the data were analyzed using several softwares including STAR 2.0.1, MS Excel 2016, and Minitab version 17 (Anshori *et al.,* 2019, 2021).

RESULTS

The analysis of variance revealed that almost all the morphological characters were significantly affected by the different corn cultivation technology packages (Tables 2 and 3). However, in the case of physiological characters, the number of stomata was the only character that was significantly affected by the corn cultivation technology packages.

Table 2. Analysis of variance of morphological characters.

SV	Pr(>F)								
	PH	SD	CH	NL	MFA	FFA	ASI	CD	CL
Package	0	0.168	0.202	0.001	0.000	0.000	0.000	0.000	0.000
CV	5.56	14.49	10.73	6.86	1.33	1.24	19.52	3.35	2.89
SV	Pr(>F)								
	SRC	CC	Prolifik	PNY	1000-GW	CW	The yield	-	-
Package	0	0.008	0.000	0.003	0.000	0.000	0.000	-	-
CV	4.17	33.01	18.47	4.45	4.6	9.8	8.31	-	-

Note: SV = source of variance; CV= coefficient of variance, PH = plant height, SD= stem diameter, CH = cob's height, NL = number of leaves, MFA =male flowering age, FFA = female flowering age, ASI = anthesis-silking interval, CD = cob's diameter, CL = cob's length, SRC = seed rows per cob, CC = closure of cobs, PNY = percentage of net yield, 1000-GW = 1000-grain weight, CW = cobs weight.

Table 3. Analysis of variance of physiological characters.

SV	Pr(>F)							
	Leaf absorption	Leaf reflection	Leaf transmission	Green value	Chl.a	Chl.b	Chl.Tot	NS
Package	0.70	0.96	0.08	0.17	0.56	0.58	0.56	0.0**
CV	24.99	15.21	14.14	3.85	10.17	14.17	4.56	12.78

Note: SV = source of variance; CV = coefficient of variance, Chl = Chlorophyll, NS = number of stomata

The morphological and physiological characteristics, which have a significant impact on different production technology packages, were further combined for advanced analysis through factor analysis.

The factor analysis results are given in Table 4. The diversity of factor one was strongly influenced by the prolific character (0.301). However, the diversity of factor two was influenced by the diversity of plant height (-0.319), cobs weight (-0.315), and yield (-0.367). The diversity of factor three was influenced by the cultivar yield (-0.487) and 1000-seed weight (0.311). The diversity of factor four was determined by the diversity of the number of leaves (-0.463) and anthesis-silking interval (0.567). The diversity of factor five was determined by the number of stomata (-0.683) and the cob's length (-0.486). However, the diversity of factor six was prejudiced by the closure of the cob (0.888). Based on these results, all the characteristics that affect the various dimensions of the factors can be continued in the next path analysis.

Before path analysis, all the selected characters in factor analysis were correlated to yield. Based on the results of the Pearson correlation to yield (Table 5), the characters. i.e., plant height, cob weight, percentage of net yield, and 1000-seed weight were found significantly correlated with the yield. Therefore, these characters were brought further for path analysis.

The path analysis results are shown in Table 6. The analysis produced a determination with a total diversity value 52.55%. Based on the direct effects, the traits, cob weight, percentage of net yield, and plant height, had a direct positive effect of 0.89, 0.39, and 0.11, respectively. However, the 1000-seed weight had a direct negative effect of -0.23. Therefore, the trait, 1000-seed weight, was not continued in the index formation. Three characters that have a direct positive effect on yield were used as selection characters along with yield in forming a morphological index.

The results of the PCA analysis of the three observational approaches are shown in Table 7 where PC1 was found as best with an eigenvalue of 1.72. However, the PC2 and PC3 had eigenvalues of 0.7665 and 0.51, respectively. Based on PC1, the morphological index (0.539) had eigenvectors in the same direction as participatory plant breeding (0.635). But, the drone's NDVI had a negative eigenvector value (-0.553).

The results of the evaluation index are shown in Table 8. Eighteen treatments had a positive evaluation index. Cultivars V7 (Pioneer-27), V8 (ADV-JOSS), and V6 (NK-7328) showed the most positive evaluation index values. Meanwhile, P5V7 (package five with cultivar Pioneer-27) (2.90) was the best

Table 4. Factor analysis to significant characters based on analysis of variance.

Variables	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Factor 6
PH	0.034	-0.319	-0.137	-0.242	0.175	-0.043
NL	0.009	-0.029	0.125	-0.463	0.003	-0.038
NS	-0.136	0.053	-0.152	-0.049	-0.683	-0.181
MFA	0.237	-0.016	0.211	0.109	-0.090	-0.016
FFA	0.198	-0.017	0.175	-0.012	-0.145	-0.008
ASI	0.132	-0.033	0.088	0.567	0.158	0.036
CD	-0.192	-0.054	0.147	0.022	-0.137	-0.104
CL	-0.020	-0.049	0.066	-0.078	-0.486	0.183
SRC	-0.275	0.004	0.046	-0.049	-0.176	0.026
CC	-0.047	-0.022	-0.038	0.051	0.038	0.888
Prolific	0.301	-0.103	-0.167	0.053	0.218	-0.154
PNY	-0.062	-0.111	-0.487	0.000	-0.157	0.138
Yield	0.063	-0.367	-0.223	0.110	0.046	0.035
1000-GW	-0.050	-0.169	0.311	-0.007	-0.116	0.185
CW	0.039	-0.315	0.100	0.055	-0.057	-0.040

Note: PH = plant height, NL = Number of leaves, NS = number of stomata, MFA =male flowering age, FFA = female flowering age, ASI = anthesis-silking interval, CD = cob's diameter, CL = cob's length, SRC = seed rows per cob, CC = closure of cobs, PNY = percentage of net yield, 1000-GW = 1000-grain weight, CW = cobs weight

Table 5. Pearson correlation analysis to selected characters from factor analysis.

Variables	PH	NL	NS	ASI	CL	CC	Prolific	PNY	Yield	1000-GW
NL	0.26									
NS	-0.09	-0.22								
ASI	-0.21	-0.50**	0.01							
CL	-0.14	0.23	0.22	-0.08						
CC	-0.03	0.04	-0.04	-0.12	0.15					
Prolific	0.05	0.17	0.20	-0.14	0.37*	0.05				
PNY	-0.01	-0.09	0.26	-0.02	0.07	0.08	0.18			
Yield	0.54**	-0.17	-0.04	0.23	0.09	-0.13	0.05	0.32*		
1000-GW	0.34*	0.10	-0.18	0.17	-0.03	-0.01	-0.37*	-0.29	0.31*	
CW	0.57**	-0.09	-0.08	0.23	0.11	-0.21	-0.11	-0.15	0.74**	0.69**

Note: PH = plant height, NL = number of leaves, NS = number of stomata, ASI = anthesis-silking interval, CL = cob's length, CC = closure of cobs, PNY = percentage of net yield, 1000-GW = 1000-grain weight, CW = cobs weight

Table 6. Path analysis based on the significant correlation to the yield.

Characters	Direct Effect	Indirect Effect				Residual
		PH	PNY	1000-GW	CW	
PH	0.11		0.00	-0.08	0.51	0.23
PNY	0.39	0.00		0.07	-0.13	0.23
1000-GW	-0.23	0.04	-0.11t		0.62	0.23
CW	0.89	0.06	-0.06	-0.16		0.23

Notes: R^2= 52.55% (0.5255), PH = plant height, PNY = percentage of net yield, 1000-GW = 1000-grain weight, CW = cobs weight

Table 7. Principal component analysis of the three observational approaches.

Characters	PC1	PC2	PC3
Morpho	0.539	-0.733	-0.416
NDVI	-0.553	-0.680	0.481
PPB	0.635	0.029	0.772
Proportion of Variance	0.575	0.256	0.170
Cumulative Proportion	0.575	0.830	1.000
EigenValues	1.724	0.767	0.510

Note: NDVI = normalized difference vegetation index, PPB = participatory plant breeding

Table 8. Standardization value and evaluation index of corn cultivation technology package.

Combination	Morpho	NDVI	Sum_PPB	PPB (%)	Morpho	NDVI_z	PPB_z	Evaluation index
P5V7	1.79	0.70	17	6.07	1.79	-1.23	1.98	2.90
P2V7	1.92	0.71	13	4.64	1.92	-1.09	1.18	2.39
P1V7	2.25	0.65	7	2.50	2.25	-1.96	-0.01	2.29
P4V7	0.80	0.73	18	6.43	0.80	-0.79	2.18	2.25
P3V8	1.89	0.76	15	5.36	1.89	-0.36	1.58	2.22
P3V7	1.98	0.74	13	4.64	1.98	-0.65	1.18	2.18
P2V8	1.10	0.73	15	5.36	1.10	-0.79	1.58	2.04
P3V6	0.31	0.60	9	3.21	0.31	-2.69	0.39	1.90
P4V8	2.43	0.83	14	5.00	2.43	0.66	1.38	1.82
P5V8	1.94	0.81	12	4.29	1.94	0.37	0.99	1.47
P1V6	-0.68	0.71	12	4.29	-0.68	-1.09	0.99	0.86
P4V6	-1.38	0.70	14	5.00	-1.38	-1.23	1.38	0.82
P5V6	-0.55	0.73	12	4.29	-0.55	-0.79	0.99	0.77
P2V6	-1.04	0.71	11	3.93	-1.04	-1.09	0.79	0.54
P1V3	1.22	0.80	7	2.5	1.22	0.23	-0.01	0.53
P3V3	1.62	0.81	4	1.43	1.62	0.37	-0.61	0.28
P4V4	1.39	0.81	5	1.79	1.39	0.37	-0.41	0.28
P1V8	1.49	0.76	0	0.00	1.49	-0.36	-1.40	0.11
P5V2	0.29	0.74	2	0.71	0.29	-0.65	-1.01	-0.12
P3V1	0.25	0.75	2	0.71	0.25	-0.50	-1.01	-0.23
P3V2	-0.30	0.78	6	2.14	-0.30	-0.07	-0.21	-0.26
P1V1	0.00	0.76	2	0.71	0.00	-0.36	-1.01	-0.44
P2V1	0.49	0.81	3	1.07	0.49	0.37	-0.81	-0.46
P2V2	-0.99	0.76	6	2.14	-0.99	-0.36	-0.21	-0.47
P1V4	-0.04	0.89	9	3.21	-0.04	1.54	0.39	-0.63
P4V3	0.20	0.89	5	1.79	0.20	1.54	-0.41	-1.00
P2V3	-0.25	0.89	6	2.14	-0.25	1.54	-0.21	-1.12
P3V4	-0.10	0.87	4	1.43	-0.10	1.25	-0.61	-1.13
P5V1	-0.53	0.81	2	0.71	-0.53	0.37	-1.01	-1.13
P5V3	0.33	0.89	3	1.07	0.33	1.54	-0.81	-1.18
P4V1	-0.62	0.80	1	0.36	-0.62	0.23	-1.20	-1.22
P4V2	-2.23	0.79	6	2.14	-2.23	0.08	-0.21	-1.38
P1V2	-2.08	0.79	5	1.79	-2.08	0.08	-0.41	-1.43
P5V4	-0.07	0.86	0	0.00	-0.07	1.10	-1.40	-1.54
P2V5	-1.07	0.86	4	1.43	-1.07	1.10	-0.61	-1.57
P3V5	-1.83	0.80	3	1.07	-1.83	0.23	-0.81	-1.62
P2V4	-1.37	0.89	6	2.14	-1.37	1.54	-0.21	-1.72
P4V5	-2.99	0.78	3	1.07	-2.99	-0.07	-0.81	-2.08
P1V5	-2.35	0.87	6	2.14	-2.35	1.25	-0.21	-2.09
P5V5	-3.24	0.81	0	0.00	-3.24	0.37	-1.40	-2.85

Note: z = standardization

treatment combination among all other treatments. Inversely, the P5V5 (package five with cultivar Sinhas-1) treatment was the lowest treatment in this experiment.

DISCUSSION

The morpho-physiological approach is more complex than the drone's NDVI and participatory plant breeding. This approach summarizes in detail all the important characteristics of plants in supporting their yield potential. It also becomes essential since an assessment based solely on the yield will confer a high error (Araya-Alman *et al.,* 2019; Laraswati *et al.,* 2021; Zafar *et al.,* 2021). Grain yield is a quantitative and polygenic character which cannot be separated from environmental influences and interactions (Kassahun *et al.*, 2013; Fellahi *et al.*, 2018; Farid *et al.*, 2020). Anshori *et al.* (2021) mentioned that the assessment of a crop yield potential should include secondary characters, especially if the evaluation is carried out only at one location (environment). Therefore, the morpho-physiological characters were analyzed systematically and advanced by focusing on the yield as the basis for assessing secondary characters in selection. Yet, based on the analysis of variance in this study, the combination of different technology packages had more influence on morphological characters than physiological characters. So, further analysis was focused on morphological characters.

Factor analysis and path analysis are multivariate analyses that are useful to detect the secondary character or the supporting yield characters (Farid *et al*. 2020; Arifuddin *et al*. 2021). The factor analysis plays an important role in identifying large internal covariance between the characters in a dimension of variance (Dormann *et al.,* 2013; Momen *et al.,* 2020). It becomes important to predict the main characters that affect the total variance, hence, this step can reduce the less optimal characters in selection (Filipović *et al.,* 2014; Rocha *et al.,* 2018; Arifuddin *et al.,* 2021). Several studies have reported the effectiveness of this analysis in determining the selection criterion (Rocha *et al.,* 2018; Arifuddin *et al.,* 2021; Kahveci and Acar, 2021). In the latest study, the determination of the important characters in each factor dimension was identified by the loading factor value which reaches 0.3. Although, according to Yong and Pearce (2013) and Farid *et al.* (2020), the determination was based on principal component analysis when the loading factor was more than or equal to 0.32. However, the value of 0.3 was considered representative to distinguish the determinants of variance and characters that do not have high covariance. Based on factor analysis, there were six optimal dimensions and 11 characters that have a significant diversity of these six dimensions. Therefore, the 11 characters were analyzed further on the yielding character as the main variable. One other possible analysis for this purpose is path analysis.

Path analysis is a development of correlation and multiple regression analysis (Streiner, 2005; Singh and Chaudhary, 2007; Du *et al.,* 2021). Path analysis was performed by partitioning a correlation value into direct and indirect effects. This direct effect becomes the main indicator of a character in influencing the total variance of its main characters (Olivoto *et al.*, 2017; Anshori *et al.,* 2021). However, path analysis with many variables is considered less effective, so it needs to be reduced by correlation analysis. The characters with significant correlation to the yield were progressed to path analysis. This step will minimize bias in predicting or projecting supporting characters that directly affect the yield (Alsabah *et al.,* 2019; Akbar *et al.,* 2021; Karima *et al.,* 2021). The same concept was also reported by Farid *et al.* (2020, 2021a) in wheat, Anshori *et al.* (2019, 2021) in rice, Fadhli *et al.* (2020), and Padjung *et al.* (2021) in maize crop. Based on the correlation analysis, plant height, cob weight, percentage of net yield, and 1000-seed weight were found significantly correlated with yield. The positive correlation of yield with plant height and 1000-seed weight was also reported by Munawar *et al.* (2013) and Padjung *et al.* (2021), with cob weight by Fadhli *et al.* (2020), and 1000-seed weight by Agbaje *et al.* (2000). Therefore, the four morphological characters have proceeded in the path analysis.

Based on the path analysis, the traits of plant height, percentage of net yield, and cob weight became the supporting characters for yield. The positive direct effect of these traits has also been reported by Crevelari *et al*. (2018) and Abduh *et al*. (2021) for plant height, and Fadhli *et al.* (2020) for cob weight. These three supporting characters can be combined and formulated into a selection index. The selection index is a selection method for multiple characters using multiple regression formulation accompanied by weighting characters (Acquaah, 2007; Singh and Chaudhary, 2007; Islam *et al.*, 2016). The regression values were ranked as the basis of the selection process. The use of this concept has also been reported by Anshori *et al.* (2019), Akbar *et al.* (2021), Farid *et al.* (2021a), and Karima *et al.* (2021). The formation of this index was highly dependent on the weighting character's values (Anshori *et al.,* 2021). According to Sabouri *et al.* (2008), and Alsabah *et al.* (2019), the direct effect of path analysis is a practical basis for the formation of a selection index. Yet, the use of this direct effect also needs to be corrected with the determination of the path analysis. As a result, the formed selection index is:

Morphological index = Yield + (0.11× 0.5255) plant height + (0.39 × 0.5255) Percentage of Net Yield + (0.89 × 0.5255) cobs weight

Morphological index = Yield + 0.06 (plant height) + 0.20 {Percentage of Net Yield) + 0.47 (cobs weight)

The morphological selection index was then combined with the results of the analysis of standardized NDVI and participatory plant breeding (PPB). This concept can also detect the variance direction of NDVI and PPB toward morphological traits. The combination of three approaches must be standardized to equalize the variance among the approaches. This standardization concept has also been used and reported in past studies on sugarcane (Peternelli *et al.*, 2017) and rice (Anshori *et al.*, 2021). For the morphological approach, it has been standardized independently among selection characters, so it does not need to be standardized again (Anshori *et al.,* 2019; Farid *et al.,* 2021a, b). The combination of these three approaches also took the concept of the index value. Yet, the weighting used principal component analysis (PCA). PCA can provide information on the pattern of diversity of a particular variable against other variables in a certain dimension (Jolliffe and Cadima, 2016; Zafar *et al.,* 2021). PC1 was the dimension with the highest diversity (Evgenidis *et al.,* 2011; Jolliffe and Cadima, 2016; Farid *et al.,* 2021a, b), Therefore, this PC is an indicator in seeing the diversity between the three variables. Based on PCA analysis, the formulation of the evaluation index of the three approaches was:

Evaluation index = 0.539 (morphological index) - 0.553 (NDVI) + 0.635 (PPB)

The results of the evaluation index showed that the morphological index had the same direction as the PPB. However, the NDVI has a negative value compared to the other two approaches. It is an indication that the high NDVI value of corn cannot be a general basis for increasing yield. However, it did not also indicate a very low NDVI value which means a very high yield because the NDVI value has been standardized. Wahab *et al.* (2018) also concluded the low yield correlation (0.393) with maize NDVI. However, according to Herrmann *et al.* (2020), the use of super spectral cameras can increase the correlation of NDVI to the yield (0.69). The use of this type of camera, therefore, can increase the chances of NDVI accuracy. In the latest study, the optimal NDVI value was in the range of 0.7 to 0.8. According to Zaman-Allah *et al.* (2015), the optimal NDVI range was from 0.4 to 0.6 as per the nitrogen stress test. According to Zhang *et al.* (2019), the optimal NDVI was in the range of 0.8 which also confirms the previous statement. The lush leaf stands will reduce the effectiveness of photosynthesis since shaded leaves have a low photosynthetic process. Similarly, this had relatively the same energy and enzyme consumption as the un-shaded leaves which decreased the net photosynthate. Therefore, for the study, the NDVI range was applicable as a reference in the use of NDVI for corn.

NDVI in the latest study is potential to use in participatory plant breeding concept and morphology evaluation. The NDVI eigenvector is not relatively very different from the morphological index and PPB. It indicates that the use of NDVI could increase the effectiveness of evaluation through cultivation on a large scale. Several studies have effectively reported the use of NDVI drones to evaluate corn cultivation in a wide area (Hall *et al*., 2018; Tirado *et al*., 2020; Burns *et al*., 2021). Besides that, this approach can give a correction to the result of human measurement to plant growth traits and yield (Panday *et al*. 2020; Tirado *et al*., 2020; Castro *et al*., 2021), so that the evaluation by researchers and farmers could be corrected to select the best lines or cultivation technology. Hence, the NDVI could be recommended in helping the morphology evaluation and PPB.

The latest study revealed that the farmers were able to identify the potential of a corn production technology. It was indicated by the diversity of eigenvectors in PCA analysis, where the eigenvector value of PPB had a value that was in the same direction and greater than the morphological index. The success of the PPB concept was also reported by Casals *et al.* (2019), where farmer's assessments had a high correlation with morphological observations. According to Ceccarelli and Grando (2019) and Colley *et al.* (2021, 2022), the effectiveness of PPB occurs when farmers understand the characteristics of plants that produce significantly high yield. Therefore, based on these findings the PPB model was effective to be practiced in the process of evaluating the potential for corn cultivation technology packages in the Village Taroang, Takalar Regency, South Sulawesi, Indonesia. In addition, the PPB data were also found effective in combination with other approaches. The evaluation index results also showed that cultivars six (NK-7328), seven (Pioneer-27), and eight (ADV-JOSS) were found more dominant than the selected technology package. It means that the influence of cultivars was more dominant than the cultivation technology. However, the use of 'legowo' spacing can increase the potential of these cultivars to be more optimal (P3, P4, and P5). The addition of KNO_3 fertilizer and biological fertilizer was relatively specific for certain corn cultivars, including P5V7, which was identified as the best cultivation technology package. Based on the results, the P5V7, P3V8, and P3V6 were recommended for corn cultivation in the Village Taroang, Takalar Regency, South Sulawesi, Indonesia, and other areas with considerable similarities.

Based on this study, the morphological index, drone's NDVI, and PPB are very helpful to use. All approaches relatively have great eigenvector value, and they can be used independently. However, each approach has advantages and disadvantages in evaluating corn cultivation, and their combination can cover the disadvantages of each approach. Therefore, the evaluation of corn cultivation should include the NDVI and PPB approaches to help the morphology or agronomy approach.

CONCLUSIONS

The combination of morphological approaches, drone imaging, and participatory plant breeding is effective in selecting the best corn production technology. The yield, plant height, percentage of net yield, and cob weight are the good selection criteria of the morphology approach in evaluating corn cultivation. The NDVI could be recommended in helping the morphology evaluation and PPB, especially in a large-scale evaluation. The combination of the three approaches was formulated in the form of an evaluation index, namely, evaluation index = 0.539 (morphological index) - 0.553 (NDVI), and 0.635 (PPB). The evaluation index analysis recommended maize cultivar Pioneer-27 with 'legowo' spacing technology, NPK fertilizer ratio of 200:100:50, plus KNO_3 @ 25 kg, and 'biofertilizer' Ecofarming @ 5 cc L^{-1}, and found this as the best corn cultivation technology package, especially in the Village Taroang, Takalar District, Takalar Regency, South Sulawesi, Indonesia.

REFERENCES

Abduh ADM, Padjung R, Farid M, Bahrun AH, Anshori MF, Nasaruddin, Ridwan I, Nur A, Taufik M (2021). Interaction of genetic and cultivation technology in maize prolific and the yield increase. *Pak. J. Biol. Sci.* 24(6): 716-723.

Acquaah G (2007). *Principles of Plant Genetics and Breeding*. Blackwell Publishing, Oxford, United Kingdom, pp. 130-134.

Adam D (2021). How far will the global population rise? *Nature* 597: 463-465.

Agbaje GO, Abayomi YA, Awoleye F (2000). Grain yield potential and associated traits in maize (*Zea mays* L.) varieties in the forest zone of Nigeria. *Ghana J. Agric. Sci*. 33: 191-198.

Ahirwar S, Swarnkar R, Bhukya S, Namwade G (2019). Application of drone in agriculture. *Int. J. Curr. Microbiol. Appl. Sci.* 8(1): 2500-2505.

Akbar MR, Purwoko BS, Dewi IS, Suwarno WB, Sugiyanta, Anshori MF (2021). Agronomic and yield selection of doubled haploid lines of rainfed lowland rice in advanced yield trials. *Biodiversitas* 22(7): 3006-3012.

Alimuddin S, Musa Y, Azrai M, Asrul L (2020). Effect of double rows plant system on plant growth, yield components, and grain yield in prolific and non-prolific hybrid maize. *IOP Conf. Series: Earth Environ. Sci.* 473: 012013.

Al-Naggar AMM, El-Salam RMA, Badran AEE, El-Moghazi MMA (2017). Molecular differentiation of five quinoa (*Chenopodium quinoa* Willd.) genotypes using inter simple sequence repeat (ISSR) markers. *Biotechnol. J. Int.* 20: 1-12.

Alsabah R, Purwoko BS, Dewi IS, Wahyu Y (2019). Selection index for selecting promising doubled haploid lines of black rice. *SABRAO J. Breed. Genet.* 51(4): 430-441.

Anshori MF, Purwoko BS, Dewi IS, Ardie SW, Suwarno WB (2019). Selection index based on multivariate analysis for selecting doubled-haploid rice lines in lowland saline prone areas. *SABRAO J Breed Genet.* 51(2): 161-174.

Anshori MF, Purwoko BS, Dewi IS, Ardie SW, Suwarno WB (2021). A new approach to select doubled haploid rice lines under salinity stress using an indirect selection index. *Rice Sci.* 28(4): 368-378.

Araya-Alman M, Leroux C, Acevedo-Opazo C, Guillaume S, Valdés-Gómez, H, Verdugo-Vásquez N, Pañitrur-De la Fuente C, Tisseyre B (2019). A new localized sampling method to improve grape yield estimation of the current season using yield historical data. *Precision Agric.* 20: 445-459.

Arifuddin M, Musa Y, Farid M, Anshori MF, Nasaruddin N, Nur A, Sakinah AI (2021). Rice screening with hydroponic deep-flow technique under salinity stress. *SABRAO J. Breed. Genet.* 53(3): 435-446.

Bahtiar B, Zanuddin B, Azrai M (2020). Advantages of hybrid corn seed production compared to corn grain. *Int. J. Agric. Syst.* 8: 44-56.

Burns BW, Green VS, Hashem AA, Massey JH, Shew AM, Borbe MAAA, Milad M (2021). Determining nitrogen deficiencies for maize using various remote sensing indices. *Precision Agric*. Doi.org/10.1007/s11119-021-09861-4.

Casals J, Rull A, Segarra J, Schober P, Simó J (2019). Participatory plant breeding and the evolution of landraces: A case study in the organic farms of the Collserola Natural Park. *Agron.* 9(9): 486.

Castro AID, Shi Y, Maja JM, Pena JM (2021). UAVs for vegetation monitoring: Overview and recent scientific contributions. *Remote Sens.* 13: 1-13. Doi.org/10.3390/rs13112139.

Ceccarelli S, Grando (2019). Participatory plant breeding: Who did it, who does it and where?. *Exp. Agric.* 2019: 1-11.

Chozin M, Sudjatmiko S (2019). Combining ability analysis of ear characteristics of sweet corn hybrids suitable for organic crop production. *J. Hort. Res.* 27: 81-90.

Colley MR, Dawson JC, McCluskey C, Myers JR, Tracy WF, Van-Bueren ETL (2021). Exploring the emergence of participatory plant breeding in countries of the Global North – a review. *J. Agric. Sci.* 159: 320-338.

Colley MR, Tracy WF, van Bueren ETL, Diffley M, Almekinders CJM (2022). How the seed of participatory plant breeding found its way into the world through adaptive management. *Sustainability* 14: 2132. Doi: 10.3390/su14042132.

Crevelari JA, Durães NNL, Bendia LCR, Vettorazzi JCF, Entringer GC, Júnior JAF, Pereira MG (2018). Correlations between agronomic traits and path analysis for silage production in maize hybrids. *Bragantia, Campinas* 77(2): 243-252.

Dormann CF, Elith J, Bacher S, Buchmann C, Carl G, Carré G, Marquéz JRG, Gruber B, Lafourcade B, Leitão PJ, Münkemüller T, McClean C, Osborne PE, Reineking B, Schröder B, Skidmore AK, Zurell D, Lautenbach S (2013). Collinearity: A review of methods to deal with it and a simulation study evaluating their performance. *Ecography* 36: 27-46.

Du Y, Du J, Liu X, Yuan Z (2021). Multiple-to-multiple path analysis model. *PLoS ONE* 16(3): e0247722.

Fadhli N, Farid M, Rafiuddin, Effendi R, Azrai M, Anshori MF (2020). Multivariate analysis to determine secondary traits in selecting adaptive hybrid corn lines under drought stress. *Biodiversitas* 21: 3617-3624.

Farid M, Nasaruddin N, Musa Y, Anshori MF, Ridwan I, Hendra J, Subroto G (2020). Genetic parameters and multivariate analysis to determine secondary traits in selecting wheat mutant adaptive on tropical lowlands. *Plant Breed. Biotechnol.* 8(4): 368-377.

Farid M, Nasaruddin, Anshori MF, Musa Y, Iswoyo H, Sakinah AI (2021b). Interaction of rice salinity screening in germination and seedling phase through selection index based on principal components. *Chile J. Agric. Res.* 81(3): 368-377.

Farid M, Nasaruddin, Musa Y, Ridwan I, Anshori MF (2021a) Effective screening of tropical wheat mutant lines under hydroponically induced drought stress using multivariate analysis approach. *Asian J. Plants Sci*. 20(1) 172-182.

Fellahi ZEA, Hannachi A, Bouzerzour H (2018). Analysis of direct and indirect selection and indices in bread wheat (*Triticum aestivum* L.) segregating progeny. *Int. J. Agron.* 8312857: 1-11.

Filipović M, Babić M, Delić N, Bekavac G, Babić V (2014). Determination of relevant breeding criteria by the path and factor analysis in maize. *Genetika* 46(1): 49-58.

Fromme DD, Spivey TA, Grichar WJ (2019). Agronomic response of corn (*Zea mays* L.) hybrids to plant populations. *Int. J. Agron.* 2019: 3589768.

Gubali H, Abdullah N (2021). The effectivity testing bio-organic fertilizer toward the plant's growth and production of water spinach (*Ipomoea reptans* Poir). *IOP Conf. Series: Earth Environ. Sci.* 681: 012010.

Hairmansis A, Supartopo, Yullianida, Warsono, Manzanilla D, Cruz CMV, Jamil, Suwarno (2019). Upland rice breeding lines adapted to high elevation areas selected through participatory approaches. *SABRAO J. Breed. Genet.* 49(3): 248-257

Hake S, Ross-Ibarra J (2015). Genetic, evolutionary, and plant breeding insights from the domestication of maize. *eLife* 4: e05861.

Hall O, Dahlin S, Marstorp H, Bustos MFH, Oborn I, Jirstrom M (2018). Classification of maize in complex smallholder farming systems using UAV imagery. *Drones* 2(22): 2-8.

Hasnain M, Chen J, Ahmed N, Memon S, Wang L, Wang Y, Wang P (2020). The effects of fertilizer type and application time on soil properties, plant traits, yield and quality of tomato. *Sustainability* 12(21): 9065.

Herrmann I, Bdolach E, Montekyo Y, Rachmilevitch S, Townsend PA, Karnieli A (2020). Assessment of maize yield and phenology by the drone-mounted super spectral camera. *Precision Agric.* 21: 51-76.

Islam MR, Kayess MO, Hasanuzzaman M, Rahman MW, Uddin MJ, Zaman MR (2016). Selection index for genetic improvement of wheat

(*Triticum aestivum* L.). *J. Chem. Biol. Phys. Sci.* 7: 1-8.

Jaradat AA, Goldstein W, Dashiell K (2010). Phenotypic structures and breeding value of open-pollinated corn varietal hybrids. *Int. J. Plant Breed.* 4: 37-46.

Jjagwe J, Chelimo K, Karungi J, Komakech AJ, Lederer J (2020). Comparative performance of organic fertilizers in maize (*Zea mays* L.) growth, yield, and economic results. *Agron.* 10(1): 69.

Jolliffe IT, Cadima J (2016). Principal component analysis: A review and recent developments. *Phil. Trans. R. Soc. A.* 374: 20150202.

Kahveci H, Acar C (2021). Determination of selection criteria of plants in urban coastal landscapes: An example of the eastern black sea coast, Turkey. *Forestist* doi: 10.5152/ forestist.2021.21019.

Karima AW, Putri RK, Purwoko BS, Dewi IS, Suwarno WB, Kurniawati A (2021). Selection of doubled haploid black rice lines in advanced yield trial based on multivariate analysis. *Biodiversitas* 22(2): 5425-5431.

Kassahun BM, Alemaw G, Tesfaye B (2013). Correlation studies and path coefficient analysis for seed yield and yield components in Ethiopian coriander accessions. *Afr. Crop Sci. J.* 21(1): 51-59.

Khoirunisa H, Kurniawati F (2019). The use of drones in applying pesticides in the Sungai Besar Area, Malaysia. *Jurnal Pusat Inovasi Masyarakat* 1(1): 87-91.

Kurt C, Bakal H, Gulluoglu L, Arioglu H (2017). The effect of twin-row planting pattern and plant population on yield and yield components of peanut (*Arachis hypogaea* L.) at main crop planting in Cukurova region of Turkey. *Turk. J. Field Crops* 22: 24-31.

Kutka F (2011). Open-pollinated vs. hybrid maize cultivars. *Sustainability* 3: 1531-1554.

Laraswati AA, Padjung R, Farid M, Nasaruddin N, Anshori MF, Nur A, Sakinah AI (2021). Image-based phenotyping and selection index based on multivariate analysis for rice hydroponic screening under drought stress. *Plant Breed. Biotechnol.* 9(4): 272-286.

Ministry of Agriculture (2018). Agricultural database. Available at https://aplikasi2.pertanian.go.id/bdsp (Access: January 1, 2022)

Momen M, Bhatta M, Hussain W, Yu H, Morota G (2020). Modeling multiple phenotypes in wheat using data-driven genomic exploratory factor analysis and Bayesian network learning. *Plant Direct* 2021(00): e00304.

Morris ML, Bellon MR (2004). Participatory plant breeding research: Opportunities and challenges for the international crop improvement system. *Euphytica* 136: 21-35.

Munawar M, Shahbaz M, Hammada G, Yasir M (2013). Correlation and path analysis of grain yield components in exotic maize (*Zea mays* L.) hybrids. *Int. J. Sci. Basic Appl. Res.* 12(1): 22-27.

Nascimento AdM, Maciel AM, Silva JBG, Mendonça HV, de Paula VR, Otenio MH (2020). Biofertilizer application on corn (*Zea mays*) increases the yield and quality of the crop without causing environmental damage. *Water Air Soil Pollut.* 231: 414.

Olivoto T, de Souza VQ, Nardino M, Carvalho IR, Ferrari M, de Pelegrin AJ, Szareski VJ, Schmidt D (2017). Multicollinearity in path analysis: A simple method to reduce its effects. *Agron. J.* 109(1): 131-142.

Padjung R, Farid M, Musa Y, Anshori MF, Nur A, Masnenong A (2021). Drought-adapted maize line based on a morpho-physiological selection index. *Biodiversitas* 22(9): 4028-4035.

Panday US, Pratihast AK, Aryal J, Kayastha RB (2020). A review on drone-based data solutions for cereal crops. *Drones* 4(41): 1-29.

Peternelli LA, Moreira ÉFA, Nascimento M, Cruz CD (2017). Artificial neural networks and linear discriminant analysis in early selection among sugarcane families. *Crop Breed. Appl. Biotechnol.* 17(4): 299-305.

Portes TDA, Melo HCD. (2014). Light interception, leaf area, and biomass production as a function of the density of maize plants analyzed using mathematical models. *Acta Sci.* 36(4): 457-463.

Rahimi A, Siavash Moghaddam S, Ghiyasi M, Heydarzadeh S, Ghazizadeh K, Popović-Djordjević J (2019). The influence of chemical, organic, and biological fertilizers on agrobiological and antioxidant properties of Syrian cephalaria (*Cephalaria Syriaca* L.). *Agric.* 9(6): 122.

Rocha JRDASDC, Machado JC, Carneiro PCS (2018). Multitrait index based on factor analysis and ideotype-design: Proposal and application on elephant grass breeding for bioenergy. *Bioenergy* 10: 52-60.

Rokhmana CA (2015). The potential of UAV-based remote sensing for supporting precision agriculture in Indonesia. *Procedia Environ. Sci.* 24: 245-253.

Sabouri H, Rabiei B, Fazlalipour M (2008). Use of selection indices based on multivariate analysis for improving grain yield in rice. *Rice Sci.* 15(4): 303-310.

Singh RK, Chaudhary BD (2007). *Biometrical Methods in Quantitative Genetic Analysis*. Kalyani Publisher, New Delhi, India pp. 69-78.

Streiner DL (2005). Finding our way: An introduction to path analysis. *Can. J. Psychiatry* 50: 115-122.

Tirado SB, Hirsch CN, Springer NM (2020). UAV-based imaging platform for monitoring maize growth throughout development. *Am. Soc. Plant Biol.* 4: 1-11. DOI: 10.1002/pld3.230.

Wahab I, Hall O, Jirström M (2018). Remote sensing of yields: Application of UAV imagery derived NDVI for estimating maize vigor and yields in complex farming systems in Sub-Saharan Africa. *Drones* 2(3): 28.

Walker RJ (2016). Population growth and its implications for global security. *Am. J. Econ. Soc.* 75(4): 980-1004.

Wolde L, Tolera K, Berhanu T, Gezahegn B, Adefris TW, Beyene A (2018). Mega environment targeting of maize varieties using Ammi and GGE bi-plot analysis in Ethiopia*. Ethiopian J. Agric. Sci.* 28: 65-84.

Yong AG, Pearce S (2013). A beginner's guide to factor analysis: Focusing on exploratory factor analysis. *Tutor. Quant. Methods Psychol*. 9(2): 79-94.

Zafar MM, Manan A, Razzaq A, Zulfqar M, Saeed A, Kashif M, Khan AI, Sarfraz Z, Mo H, Iqbal MS, Shakeel A, Ren M (2021). Exploiting agronomic and biochemical traits to develop heat resilient cotton cultivars under climate change scenarios. *Agron.* 11: 11091885.

Zaman-Allah M, Vergara O, Araus JL, Tarekegne A, Magorokosho C, Zarco-Tejada PJ, Hornero A, Albà AH, Das B, Craufurd P, Olsen M, Prasanna BM, Cairns J (2015) Unmanned aerial platform-based multi-spectral imaging for field phenotyping of maize. *Plant Methods* 11: 35.

Zhang L, Zhang H, Niu Y, Han W (2019). Mapping maize water stress based on UAV multispectral remote sensing. *Remote Sens.* 11(6): 605.