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# SELECTED AGRONOMIC TRAITS AND DRONE APPLICATION IN CORN YIELD PREDICTION

**M. FIKRI[1], M. FARID[2*], Y. MUSA[2], M.F. ANSHORI[2], and A. NUR[3]**

[1]Agriculture System Study Program, Graduate School, Hasanuddin University, Makassar, Indonesia
[2]Department of Agronomy, Faculty of Agriculture, Hasanuddin University, Makassar, Indonesia
[3]Indonesian Cereal Testing Instrument standard Institute, Jl. Maros, South Sulawesi, Indonesia
*Corresponding author's email: farid_deni@yahoo.co.id
Email addresses of co-authors: muhfikri23al@gmail.com, 54.yunusmusa@gmail.com, fuad.anshori@unhas.ac.id, iceriamin76@gmail.com

## SUMMARY

Selected agronomic traits are the conventional approach to evaluating corn plantings. However, this approach is only some-encompassing for planting plots; hence, needing a more precise method for the evaluation. Unmanned aerial vehicles (UAVs) or drones are precision technologies that provide detailed information regarding cropping status through image analysis to make the assessment and prediction process more efficient. Therefore, using agronomic traits and drones together is a necessary approach to take. Presented research aimed to develop a productivity prediction model based on selective and precision secondary characters. The experiment happened from September to December 2021 in Tarowang Village, Takalar Regency, South Sulawesi, Indonesia. Eight maize cultivars, i.e., ADV1, Pioneer 1, Pioneer 2, NK, Bisi 18, Sinhas 1, NASA 29, and ADV2, grown and evaluated in a randomized completely block design with three replications, served as the main factor. Based on the results, the weight of 1000 grains, was a recommended agronomic trait in the evaluation and prediction of corn planting. In addition, normalized difference vegetation index (NDVI)-UAV, as part of 'Technology 4.0', considerably showed effectiveness in predicting maize productivity. Meanwhile, combining two variables notably have the highest accuracy in predicting corn productivity compared with their independent predictions. However, the advanced research still needs optimizing by using more maize genotypes and locations to increase the accuracy and forecast of the model.

**Keywords:** Agronomic traits, multivariate regression, NDVI, Technology 4.0, *Zea mays*

**Key findings:** Combining a selective agronomic trait (weight of 1000 grain) and NDVI-UAV revealed more effectiveness in evaluating the maize genotypes. This combined strategy can enhance the accuracy and precision of corn yield prediction. The multiple regression formulation from combining the two characters was 17.0486 NDVI + 0.038 weight of 1000 grain - 20.244. Moreover, the maize cultivar NK-7328 proved to be the best for cultivation in Takalar Region, Indonesia.

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## INTRODUCTION

Corn (*Zea mays* L.) is an important food crop after rice and wheat. Increasing corn raw material demand is inevitable yearly for food and feed industries (Amzeri, 2018). The corn demand is proportional to increasing population and improving people's purchasing power, so an enhancement in production is a dire need (Kayad *et al*., 2021; Wicaksana *et al*., 2022). However, in the last seven years, corn production has decreased to target since 2016 in Indonesia (Directorate General of Food Crops, 2020). Therefore, efforts should move toward enhancing corn production as intensification innovation continues the attempt to resolve the gap in demand and production of corn. Developing superior corn cultivars is one of the central determining factors in increased corn production.

Developing high-yielding maize cultivars can be through improving the genetic makeup of populations with free pollination and hybrids (Farid *et al*., 2022). Generally, both concepts have very different genetic constitutions. However, both have the same direction by optimizing the genetic combinations to support yield (Fromme *et al*., 2019; Farid *et al*., 2022). The current development of hybrid cultivars prioritizing heterosis has dominated the concept of optimizing the genetic base (Wicaksana *et al*., 2022; Bahtiar *et al*., 2023). However, free-pollinating cultivars with specific environments can still show their genetic potential for significant share and support in national corn production (Kutka, 2011; Wolde *et al*., 2018). Therefore, comprehensive and systematic genetic development of maize genotypes is in dire need for maize yields' significant increase. Although, this concept can also succeed by using secondary characters in the evaluation.

Corn population evaluation requires promising and precise secondary characters. Mainly, the secondary characters used for improvement are agronomic characters related to grain yield in corn (Padjung *et al*., 2021; Dermail *et al*., 2022; Farid *et al*., 2022). However, with technological developments, paying attention to a precision approach in evaluating corn genotypes is necessary. Several past studies have also reported the effectiveness of using 'Technology 4.0' to support maize cultivation and production (Walter *et al*., 2017; Kayad *et al*., 2021; Al-Naggar *et al*., 2022; Chaiyaphum *et al*., 2022). This utilization can support increased production by minimizing the gap by efficiently using the existing resources. Meanwhile, one of the 4.0 technologies to employ in evaluating corn plantings is Unmanned Aerial Vehicle (UAV) drones.

The development of drone-based evaluation is one of the efforts to increase accuracy in assessing complex technological combinations, including corn. Drones are a smart farming technology used in various processes of monitoring and predicting a crop with the need for fertilizing and spraying pesticides (Ahirwar *et al*., 2019; De-Castro *et al*., 2021). Furthermore, in the monitoring and prediction process, drone technology will provide detailed information regarding planting status through imagery (Neupane and Baysal-Gurel, 2021), including corn (Ali et al., 2022). This can also facilitate the evaluation process on a broader scale in the farming community (Walter *et al*., 2017). Furthermore, using drones in agriculture will save energy and time supporting agricultural production (Rejeb *et al*., 2022). This advantage can be an additional solution in assessing corn plantings, particularly in predicting the planting potential per hectare. Therefore, the advanced research aimed to develop a yield prediction model based on drones and selective secondary characters in maize.

## MATERIALS AND METHODS

### Breeding material and procedure

The research ran from September to December 2021, in Tarowang Village, South Galesong District, Takalar Regency, South Sulawesi, Indonesia, with an altitude of 18.3 masl (coordinates of 5°$^3$6'32.2" S, 119°$^4$0'31.8" E). The experiment, laid out in a randomized completely block design (RCBD) with three replications, used the maize cultivars as the main factor. The eight maize cultivars comprised ADV1, Pioneer 1, Pioneer 2, NK-7328, Sinhas-1, NASA-29, ADV2, and Bisi-18. All these cultivars had three replications to adjust them in 24 experimental units.

The research procedure started with tillage and making experimental unit plots. Each experimental unit had a plot size of 4 m x 4 m, with a distance of 1 m between beds, and 7 m between replications. After that, planting pure seeds of each cultivar received a fungicide (metalaxyl) application to prevent downy mildew. The seeds had a planting spacing of 70 cm x 20 cm, and each planting hole consisted of two seeds. Then, the maintenance of maize plants until harvest, included replanting, weeding, thinning, fertilizing, heaping, and watering. Stitching also followed on plants that do not grow, die, or were late in growth, made in the first/second week after the first sowing. Thinning proceeded in the second week after planting in each hole where two plants grew. Around the corn plants underwent the manual weeding in the first/second week after planting and periodically in the following weeks as required.

Fertilization ensued three times, namely, at 10 days after planting (DAP), 30 DAP, and 45 DAP, with a dose of Nitrogen: Phosphate: Potassium = 200:100:50 kg $ha^{-1}$. Fertilizers were NPK Phonska, SP-36, and Urea (Abduh *et al*., 2021). Hoarding followed after the second fertilization, using a hoe for raising the mounds and loosening the soil for better aeration. Watering used a water pump machine and a water hose, with the watering done by inundating the plots and wetting up to the bed's height. At physiological maturity, after the appearance of a black coating on the back side of the seeds, manual harvesting took place.

**Evaluation based on the use of drones**

The Unmanned Aerial Vehicle (UAV) drone monitoring and mapping activities transpired using the Inspire 2 drone, equipped with aircraft controls that can shoot an area of 30–40 ha in one flight. The research images taken employed two flights with an overlay data acquisition system. The said drone can also take pictures in offline internet mode. Flight planning occurred in 1200–1400 h in acceptable weather conditions. The UAV image data collection proceeded in three phases of plant age, namely, 35, 75, and 105 DAP. Image acquisition data analysis through the Normalized Difference Vegetation Index (NDVI) formula succeeded. NDVI is an index that describes the level of the greenness of a plant, and the vegetation index is a mathematical combination of the red band and the Near-Infrared Radiation (NIR) band. The use of NDVI values further analyzed corn seed production.
NDVI calculation used the following equation:

$$NDVI = \frac{\text{IMD}-\text{M}}{\text{IMD}+\text{M}} \quad \ldots\ldots\ldots\ldots(1)$$

Where:
M = Red
IMD = Near Infrared

**Recorded observations and data analysis**

The observed data included plant height, leaves per plant, stem diameter, cob height, peeled cob weight, cob diameter, cob length, seed rows per cob, total chlorophyll, seed yield, weight 1000 grain, grain yield, and NDVI (Abduh *et al.*, 2021). The data of these parameters underwent analysis of variance and heritability. Then, the study continued with a correlation analysis of morphological and physiological characters. Meanwhile, the NDVI character was first in the regression analysis to get the peak point of the observation. The basis for forming the regression formula used characters related to grain yield and NDVI. The method focused on predicting the potential of grain yield. The regression analysis includes linear and multiple regressions (Budiarto *et al.*, 2021). Also, validating the regression results consisted of a determined value ($R^2$), the root of mean square error (RMSE), and mean relative error (MRE). A high value indicates a good formulation performance on $R^2$ and a low value on RMSE and MRE. The entire validation formulas used were as follows:

$$R^2 = 1 - \frac{\sum_i (x_i - y_i)^2}{\sum_i (x_i - \bar{x}_i)^2} \quad \ldots\ldots(2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (x_i - y_i)^2}{n}} \quad \ldots\ldots(3)$$

$$MRE = \frac{\sum_{i=1}^{n} |x_i - y_i|}{n \times x_i} \quad \ldots\ldots(4)$$

Where:
$x_i$ = the yield predicted
$y_i$ = the actual yield and the means of the yield predicted.

**RESULTS AND DISCUSSION**

The analysis of variance revealed that maize genotypes significantly impact the growth characters (Table 1). In addition, the results also showed a low coefficient of variance. The coefficient value aligns with the repeatability value, which was above 50% for all characters except stem diameter (39.80). Meanwhile, the recorded cob height and weight of 1000 grain had a heritability value above 90%. The entire maize genotypes can be help in in-depth character evaluation based on these results.

**Table 1.** Analysis of variance and character heritability of maize planting evaluation.

| Traits | Genotype | Error | CV | Vg | Vp | Heritability |
|---|---|---|---|---|---|---|
| Plant height | 185.86** | 23.76 | 2.10 | 54.03 | 77.79 | 69.46 |
| Leaves plant$^{-1}$ | 3.24* | 0.22 | 3.60 | 1.01 | 1.23 | 81.94 |
| Stem diameter | 14.36** | 4.81 | 10.50 | 3.18 | 8.00 | 39.80 |
| Cob height | 313.96** | 4.55 | 2.20 | 103.14 | 107.68 | 95.78 |
| Peel cob weight | 9901.75** | 1512.32 | 6.30 | 2796.48 | 4308.80 | 64.90 |
| Cob diameter | 9.74** | 0.43 | 1.50 | 3.10 | 3.54 | 87.72 |
| Cob length | 2.17** | 0.11 | 2.20 | 0.69 | 0.80 | 85.91 |
| Grain rows cob$^{-1}$ | 2.02** | 0.43 | 4.00 | 0.53 | 0.96 | 55.13 |
| Total chlorophyll | 3257.37** | 529.36 | 5.00 | 909.33 | 1438.70 | 63.21 |
| Seed yield | 0.001** | 0.000 | 1.00 | 0.00030 | 0.00034 | 88.19 |
| weight of 1000 grain | 609.91** | 18.98 | 1.40 | 196.98 | 215.96 | 91.21 |
| Grain yield | 7.65** | 0.37 | 6.30 | 2.43 | 2.80 | 86.63 |

Notes: CV= Coefficient of variance, Vg = Genetic variance, Vp = Phenotypic variance.

The influence of the maize genotype forms the basis for evaluating the character and technology of maize cultivation (Abduh *et al*., 2021; Farid *et al*., 2022). The evaluation process was more effective, with high heritability for almost all the traits. According to Anshori *et al*. (2022) and Farid *et al*. (2022), repeatability and heritability are supporting factors for a character to be used as a selective character in evaluating genotypes and plant cultivation technology. Therefore, the findings of the analysis of variance and repeatability can serve as a true basis for the in-depth assessment of plantings.

The correlation analysis showed that grain yield had positively correlated with weight of 1000 grains (0.58) significantly (Table 2). However, the number of leaves (-0.45) and stem diameter (-0.58) were significantly negatively correlated with grain yield. In addition to grain yield, the weight of 1000 grains has a significant positive correlation with the grain yield (0.43). Overall, the correlation focuses more on the core character, the grain yield. Based on the correlation, the weight of 1000 grain was the only character having a significant positive correlation with grain yield. The same type of positive correlation also came out from studies in the same traits of maize genotypes (Aman *et al*., 2020; Rafique *et al*., 2020; Farid *et al*., 2022). Although, several studies also showed contradictory findings in maize (Nemati *et al*., 2009; Sumange *et al*., 2021). However, in general, the weight of 1000 grains is a representative indicator of seed size, quality, and seed vigor. The potential of this parameter will indirectly affect the yield potential in maize genotypes (Wu *et al*., 2018; He *et al*., 2020). Therefore, the said parameter can serve as an indicator for evaluating the reproductive phase of the maize genotypes.

The regression analysis using three different periods appears in Figure 1. Based on the regression analysis results, the character of the NDVI formula has a quadratic curve with the formula y = -0.0001 day 2 + 0.0191 days + 0.0088 NDVI. Observation of 70 days after planting (HST) showed the peak point of the NDVI value. Generally, NDVI is one of the commonly used index vegetation formulations in evaluating a plantation based on image analysis through drones, satellites, and other digital sensors (Aryal *et al*., 2022; Xu *et al*., 2022). This index was closely related to the greenness of the leaves in a planting plot (García-Martínez *et al*., 2020; Panday *et al*., 2020), so the NDVI curve will decrease when the generative phase is quadratic. It is because the leaves of corn plants experience chlorosis when entering the seed-filling process (Song *et al*., 2016; Sadras *et al*., 2000). Therefore, NDVI testing should proceed during the peak vegetative phase and when the corn is experiencing male flower anthesis. These findings also agree with the past research by Farid *et al*. (2022), who observed NDVI around 60 HST, and García-Martínez *et al*. (2020) recorded around 79 HST. This study recommends NDVI observations at 70 HST for evaluating and predicting maize grain yield.

Based on these assumptions, two essential traits, namely, weight of 1000 grains and NDVI, were of greater concern in evaluating and predicting corn grain yield. Although, this study did not include NDVI in the correlation analysis. However, according to Maresma *et al*. (2020), the NDVI indicated more relevant and effective in predicting maize grain yield. The basis was also on the far-reaching capacity of NDVI in observing plots of maize planting. Therefore, NDVI and weight of 1000 grains observations emerged as representatives of evaluating the maize planting conditions.

**Table 2.** Correlation analysis between characters in corn planting evaluation.

| Traits | PH | LP | SD | CH | PCW | CD | CL | NKRC | Tot. Cl | SY | W1000G | GY |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| PH | 1.00 | -0.10tn | 0.27tn | 0.81** | 0.49** | 0.35* | -0.55** | 0.40* | 0.42* | -0.03tn | -0.42* | -0.20tn |
| LP | | 1.00 | 0.53** | -0.06tn | 0.28tn | -0.20tn | -0.09tn | -0.25tn | -0.51** | 0.34* | -0.07tn | -0.45* |
| SD | | | 1.00 | 0.40* | 0.48** | 0.28tn | -0.07tn | 0.05tn | -0.26tn | 0.10tn | -0.36* | -0.58** |
| CH | | | | 1.00 | 0.48** | 0.52** | -0.41* | 0.48** | 0.32tn | -0.19tn | -0.65** | -0.29tn |
| PCW | | | | | 1.00 | 0.14tn | -0.15tn | 0.33tn | -0.16tn | 0.16tn | -0.17tn | -0.09tn |
| CD | | | | | | 1.00 | 0.20tn | 0.27tn | 0.31tn | 0.21tn | -0.46* | -0.10tn |
| CL | | | | | | | 1.00 | -0.25tn | -0.24tn | -0.11tn | -0.14tn | 0.02tn |
| NKRC | | | | | | | | 1.00 | 0.32tn | -0.02tn | -0.02tn | 0.30tn |
| Tot. Cl | | | | | | | | | 1.00 | -0.14tn | -0.21tn | 0.21tn |
| SY | | | | | | | | | | 1.00 | 0.43* | 0.09tn |
| 1000GW | | | | | | | | | | | 1.00 | 0.58** |
| GY | | | | | | | | | | | | 1.00 |

Notes: numbers followed by signs are significantly different from table r 0.05 = 0.34 (*); r 0.01 = 0.47 (**), PH = Plant height, LP= Leaves per plant, SD = Stem diameter, CH = Cob height, PCW = Peel cob weight, CD = Cob diameter, CL = Cob length, NKRC = Number of kernel rows per cob, Tot.Cl = Total chlorophyll, SY = Seed yield, 1000-GW = weight of 1000 grains, GY = Grain yield.

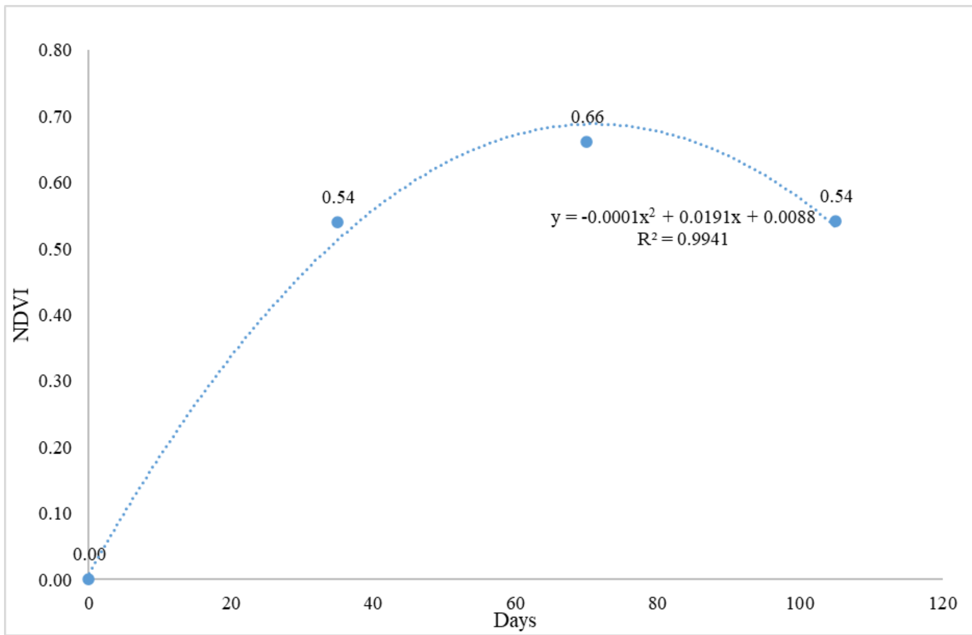


**Figure 1.** Graph of the normalized difference vegetation index (NDVI) on the development of corn plantation.

**Table 3.** Linear and multiple regression analysis in predicting maize yield.

| Formulation | $R^2$ | RMSE | MRE |
|---|---|---|---|
| 29.528 NDVI - 9.7692 | 0.27 | 1.28 | 0.120 |
| 0.0746 W1000G - 13.098 | 0.44 | 1.11 | 0.098 |
| 17.0486 NDVI+0.038 W1000G - 20.244 | 0.52 | 1.04 | 0.087 |

Notes: NDVI = Normalized Difference Vegetation Index, W1000G = Weight 1000 grains, $R^2$ = the determination value, RMSE = the root of mean square error, MRE = mean relative error.

**Table 4.** Mean yield and yield predicted from NDVI and weight of 1000 grains.

| Genotypes | NDVI | W1000G (g) | Yield predicted | | | Grain yield (ton ha$^{-1}$) |
|---|---|---|---|---|---|---|
| | | | NDVI | W1000G | NDVI + 1000-GW | |
| ADV1 | 0.67ab | 305.17b | 10.01 | 9.67 | 9.82 | 9.50c |
| Pioneer-1 | 0.68ab | 312.03ab | 10.31 | 10.18 | 10.41 | 11.30ab |
| Pioneer-2 | 0.66abc | 318.07a | 9.72 | 10.63 | 10.44 | 9.38c |
| NK-7328 | 0.69a | 321.57a | 10.61 | 10.89 | 11.17 | 12.80a |
| Sinhas-1 | 0.61c | 312.77ab | 8.36 | 10.23 | 9.33 | 9.72bc |
| NASA-29 | 0.63bc | 284.73c | 8.74 | 8.14 | 7.84 | 7.60d |
| ADV2 | 0.66abc | 284.90c | 9.82 | 8.16 | 8.47 | 9.04cd |
| Bisi-18 | 0.69a | 313.60ab | 10.61 | 10.30 | 10.68 | 8.83cd |

Notes: NDVI = Normalized Difference Vegetation Index, W1000G= Weight 1000 grains.

Evaluation and prediction of corn yield can also be through using regression analysis. Combining the analysis with the determination value ($R^2$), the root of mean square error (RMSE) and mean relative error (MRE) was part of the validation (Table 3). Based on these results, multiple linear regressions have better determination values (0.52), RMSE (1.04), and MRE (0.087) compared with a single linear regression. In contrast, the NDVI character independently has a low determination value with high RMSE and MRE values compared with the other two formulas. In general, three validation formulas require usage in assessing the model's accuracy (Ren *et al*., 2023). Some studies only use the value of determination in testing model validation.

However, the determination value was still less convincing, especially for small samples. According to Chai and Draxler (2014), RMSE is a validation standard for analyzing various models. The RMSE concept will provide a variance penalty for a high absolute error rather than a low absolute error. The MRE is a validation tool used to measure the error rate of an estimate, a model from an estimator, and a small sample (Widiarti *et al*., 2018). RMSE and MRE analyses have the same scoring concept, and where both values are low can achieve better accuracy of the model (Chai and Draxler, 2014). Therefore, using RMSE and MRE is necessary for strengthening model validation.

From the validation results, the weight of 1000 grains has better prediction accuracy than NDVI. It may be due to NDVI still basing on the RGB sensor. RGB-based sensors are the only approach to achieving NDVI values (Zhang *et al*., 2019; Herrmann *et al*., 2020). It contrasts with several past studies using cameras with multispectral sensors (García-Martínez *et al*., 2020; Johnson *et al*., 2021). However, combining NDVI results with the weight of 1000 grains can increase the accuracy of predictions compared with forecasts based on the weight of 1000 grains alone. These results also align with the findings of Farid *et al*. (2022) and Djufry *et al*. (2022); hence, the NDVI approach is still relevant as a reinforcement of the weight of 1000 grains. Therefore, recommending weight of 1000 grains and NDVI in predicting and evaluating maize grain yield is high.

Based on selected evaluation characters, maize cultivar NK-7328 emerged as the best genotype in this study (Table 4). Rifai *et al*. (2020) have also reported similar results that the cultivar NK-7328 has greater yield and stability. Therefore, highly recommend the said maize cultivar for use in the Takalar region, Indonesia. Yet, the concept of the presented research still needs improvement and confirmation with a more significant number of genotypes and locations. Another recommendation is the further conduct of the said study in a broader area for better validation and prediction concepts.

## CONCLUSIONS

Combining conventional and drone approaches in evaluating and predicting corn planting is considerably adequate. The recommended weight of 1000 grains is an essential yield component in assessing and estimating corn planting. NDVI-UAV, as part of Technology 4.0, is quite effective in predicting maize grain yield. The combination of NDVI-UAV and the 1000-seed weight has the highest accuracy in forecasting maize grain yield compared with their independent predictions. The recommendation of maize cultivar NK-7328 for cultivation resulted from selected agronomy characters and NDVI. However, this research further needs optimization using more maize genotypes and locations. It will further improve the accuracy and prediction of the combined model.

## 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. 2*4(6): 716-723.

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

Ali AM, Abouelghar M, Belal AA, Saleh N, Yones M, Selim AI, Amin MES, Elwesemy A, Kucher DE, Maginan S, Savin I (2022). Crop yield prediction using multi-sensors remote sensing (review article). *Egypt. J. Remote Sens. Space Sci.* 25: 711-716.

Al-Naggar AMM, Soliman AM, Hussien MH, Mohamed AMH (2022). Genetic diversity of maize inbred lines based on morphological traits and its association with heterosis. *SABRAO J. Breed. Genet*. 54(3): 589-597. http://doi.org/10.54910/sabrao2022.54.3.11.

Aman J, Bantte K, Alamerew S, Sbhatu DB (2020). Correlation and path coefficient analysis of yield and yield components of quality protein maize (*Zea mays* L.) hybrids at Jimma, western Ethiopia. *Int. J. Agron.* 2020: 1-7.

Amzeri A (2018). Tinjauan perkembangan pertanian jagung di Madura dan alternatif pengolahan menjadi biomaterial. *Rekayasa* 11(1): 74-86. (in Indonesian).

Anshori MF, Purwoko BS, Dewi IS, Suwarno WB, Ardie SW (2022). Salinity tolerance selection of double-haploid rice lines based on selection index and factor analysis. *AIMS Agric. Food.* 7(3): 520-535.

Aryal J, Sitaula C, Aryal S (2022). NDVI threshold-based urban green space mapping from sentinel-2a at the local government area (LGA) level of Victoria, Australia. *Land* 11: 351. https://doi.org/10.3390/ land11030351.

Bahtiar, Arsyad M, Salman D, Azrai M, Tenrirawe A, Yasin M, Gaffar A, Sebayang A, Ochieng PJ (2023). Promoting the new superior variety of national hybrid maize: Improve farmer satisfaction to enhance production. *Agriculture* 13: 174. https://doi.org/ 10.3390/agriculture13010174.

Budiarto R, Poerwanto R, Santosa E, Efendi D, Agusta A (2021). Short communication: Allometric model to estimate bifoliate leaf area and weight of kaffir lime (*Citrus hystrix*). *Biodiversitas* 22(5): 2815-2820.

Chai T, Draxler RR (2014). Root mean square error (RMSE) or mean absolute error (MAE)?– Arguments against avoiding RMSE in the literature. *Geosci. Model Dev.* 7(3): 1247-1250.

Chaiyaphum A, Chankaew S, Falab S, Sukto S, Sanitchon J, Lertrat K, Suriharn K (2022). Improvement of large-seeded waxy corn (*Zea mays* L. var. 'Ceratina Kulesh') populations for food and industrial purposes. *SABRAO J. Breed. Genet.* 54(1): 99-112. http://doi.org/10.54910/ sabrao2022.54.1.10.

De-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.

Dermail A, Fuengtee A, Lertrat K, Suwarno WB, Lübberstedt T, Suriharn K (2022). Simultaneous selection of sweet-waxy corn ideotypes appealing to hybrid seed producers, growers, and consumers in Thailand. *Agronomy* 12: 87. https://doi.org/10.3390/agronomy12010087.

Directorate General of Food Crops (2020). Guidelines for Implementation of Corn Activities in 2017. Directorate General of Food Crops, Jakarta, Indonesia.

Djufry F, Farid M, Musa Y, Anshori MF, Yassi A, Nasaruddin, Aqil M, Adzima AF, Iswoyo H, Jamil MH, Pati S (2022). Normalized difference vegetation index analysis to evaluate corn cultivation technology based on farmer participation. *Indonesian J. Geogr.* 54(3): 247-253.

Farid M, Djufry F, Yassi A, Anshori MF, Musa Y, Nasaruddin, Aqil M, Adzima AF, Iswoyo H, Jamil MH, Pati S (2022). Integrated corn cultivation technology based on morphology, drone imaging, and participatory plant breeding. *SABRAO J. Breed. Genet*. 54(2): 267-279. http://doi.org/10.54910/sabrao2022.54.2.5.

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

García-Martínez H, Flores-Magdaleno H, Ascencio-Hernández R, Khalil-Gardezi A, Tijerina-Chávez L, Mancilla-Villa OR, Vázquez-Peña MA (2020). Corn grain yield estimation from vegetation indices, canopy cover, plant density, and a neural network using multispectral and RGB images acquired with unmanned aerial vehicles. *Agriculture* 10: 277. doi:10.3390/agriculture10070277.

He H, Hu Q, Li R, Pan X, Huang B, He Q (2020). Regional gap in maize production, climate and resource utilization in China*. Field Crops Res.* 254: 107830.

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. https://doi. org/10.1007/s11119-019-09659-5.

Johnson DM, Rosales A, Mueller R, Reynolds C, Frantz R, Anyamba A, Pak E, Tucker C (2021). USA crop yield estimation with MODIS NDVI: Are remotely sensed models better than simple trend analyses? *Remote Sens.* 13: 4227. https:// doi.org/10.3390/rs13214227.

Kayad A, Sozzi M, Gatto S, Whelan B, Sartori L, Marinello F (2021). Ten years of corn yield dynamics at field scale under digital agriculture solutions: A case study from North Italy. *Comp. Electr. Agric.* 185: 106126

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

Maresma A, Chamberlain L, Tagarakis A, Kharel T, Godwin G, Czymmek KJ, Shields E, Ketterings QM (2020). Accuracy of NDVI-derived corn yield predictions is impacted by the time of sensing. *Comput. Electron. Agric.* 169: 105236.

Nemati A, Sedghi M, Sharifi RS, Seiedi MN (2009). Investigation of correlation between traits and path analysis of corn (*Zea mays* L.) grain yield at the climate of Ardabil Region (Northwest Iran). *Not. Bot. Hortic. Agrobot. Cluj-Nap.* 37(1): 194-198.

Neupane K, Baysal-Gurel F (2021). Automatic identification and monitoring of plant diseases using unmanned aerial vehicles: A review. *Remote Sens.* 13(19): 3841. https:// doi.org/10.3390/rs13193841.

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(3): 41.https://doi.org/10.3390/drones4030041.

Rafique M, Shahzad A, Mallhi AR, Abbas M, Mughal KM, Yousaf MI (2020). Assessment of heritability, correlation, and path coefficient analysis for yield-associated traits in newly synthesized corn (*Zea mays* L.) hybrids. *J. Agric. Res.* 58(4): 233-237.

Rejeb A, Abdollahi A, Rejeb K, Treiblmaier H (2022). Drones in agriculture: A review and bibliometric analysis. *Comput. Electron. Agric.* 198: 107017.

Ren Y, Li Q, Du X, Zhang Y, Wang H, Shi G, Wei M (2023). Analysis of corn yield prediction potential at various growth phases using a process-based model and deep learning. *Plants* 12: 446. https://doi.org/10.3390/ plants1203044.

Rifai A, Nurlaily R, Setiapermas MN (2020). Analisis usahatani jagung pada perlakuan pemupukan, varietas dan jarak tanam di agroekosistem lahan kering. In *Prosiding Seminar Nasional Kesiapan Sumber Daya Pertanian dan Inovasi Spesifik Lokasi Memasuki Era Industri 4.0.* Agricultural Ministry of Indonesia, Semarang, pp. 667-672 (in Indonesian).

Sadras VO, Echarte L, Andrade FH (2000). Profiles of leaf senescence during reproductive growth of sunflower and maize. *Ann. Bot.* 85(2): 187-195.

Song Y, Zhang Z, Tan X, Jiang Y, Gao J, Lin l, Wang Z, Ren J, Wang X, Qin L, Cheng W, Qi J, Kuai B (2016). Association of the molecular regulation of ear leaf senescence/stress response and photosynthesis/metabolism with heterosis at the reproductive stage in maize. *Sci. Rep.* 6:29843. doi:10.1038/srep29843.

Sumange L, Rahman S, Yasin HM, Mustari K (2021). The correlation of variables affecting yield on anthocyanins corn. *IOP Conf. Ser.: Earth Environ. Sci.* 911(1): 012050.

Walter A, Finger R, Huber R, Buchmann N (2017). Opinion: Smart farming is key to developing sustainable agriculture. *Proc. Natl. Acad. Sci. USA.* 114(24): 6148-6150. doi:10.1073/pnas.1707462114.

Wicaksana N, Maulana H, Yuwariah Y, Ismail A, Ruswandi YAR, Ruswandi D (2022). Selection of high yield and stable maize hybrids in mega-environments of Java island, Indonesia. *Agronomy* 12: 2923. https://doi.org/10.3390/agronomy12122923.

Widiarti, Adityawati N, Nusyirwan (2019). Bootstrap method in estimation of mean squared error of the beta-bernoulli model. *IOP Conf. Series: J. Physics* 1338: 012039.

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.

Wu W, Zhou L, Chen J, Qiu Z, He Y (2018). GainTKW: A measurement system of thousand kernel weight based on the Android platform. *Agronomy* 8: 178. doi:10.3390/agronomy8090178.

Xu Y, Yang Y, Chen X, Liu Y (2022). Bibliometric analysis of global NDVI research trends from 1985 to 2021. *Remote Sens.* 14: 3967. https://doi.org/10.3390/ rs14163967.

Zhang L, Zhang H, Niu Y, Han W (2019). Mapping maize water stress based on UAV multispectral remote sensing. *Remote Sens.* 11(6): 605. https://doi. org/10.3390/ rs11060605.