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Research Article
Evaluation of Nitrogen Fertilizer Doses on Several Corn Varieties Using UAV-Based Multi-Sensor Imagery

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Abstract
Background and Objective: Unmanned Aerial Vehicles (UAVs), widely known as drones, have proven to be very effective in assessing crops or cultivating crops. The UAVs can generate drone-based vegetation algorithms, which reflect leaf greenness, a parameter related to photosynthesis and plant productivity, especially in the evaluation of nitrogen dosage. Therefore, the aim of this research was to determine the effectiveness of using UAVs in administering nitrogen doses to several varieties. **Materials and Methods:** The research was conducted in Bajeng District, Gowa Regency, South Sulawesi, Indonesia. The trial was set using a factorial split plot design with a randomized block design as the environmental design. The factors used were nitrogen dose (7 levels) and corn varieties (5 varieties) repeated 3 times resulting in a total of 105 experimental units. Observations focused on productivity, chlorophyll content and drone-based vegetation index. Four drone vegetation index used were NDVI, GNDVI, Clre and NDRE. **Results:** The drone-based vegetation index effectively evaluated chlorophyll and corn yield. Chlorophyll characteristics also had a significant correlation with the vegetation indices NDVI (0.796), GNDVI (0.774), Clre (0.810) and NDRE (0.713). Meanwhile, productivity correlation only focused on Clre (0.410) and NDRE (0.430). The NDRE has the highest corn yield accuracy compared to other drone-based vegetation. The V2 variety was the effective variety to be evaluated using the NDRE approach. **Conclusion:** Therefore, the NDRE index can be recommended in evaluating corn plantings, especially in evaluating corn productivity and chlorophyll. However, this development still needs to be optimized through a more complex approach to increase model efficiency.

Key words: Drone, interaction analysis, nitrogen dosage, vegetation index, *Zea mays*

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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

The production of corn (*Zea mays* L.), which serves as both the primary food source and animal feed, has a significant impact on the economic stability of many nations, including Indonesia[1-3]. However, the instability of corn production is influenced by changes in land use and global warming[4-6]. In order to address the difficulties of sustained corn production in Indonesia, increasing corn production should be focused on the idea of intensification.

According to Saeri *et al.*[7], the national maize productivity still relatively low and cannot meet with needs of consumers. This productivity is less than the variety's described output potential (10-12 ton/ha), which is lower. This phenomena suggests that Indonesia's efforts to improve maize production have not been successful due to a lack of fertilizer and farmers' over use of it, especially nitrogen fertilizer doses[8-11]. Therefore, one of the keys to raising maize output is boosting nitrogen fertilization.

Macro fertilizer containing nitrogen is crucial for the growth and production of maize[12,13]. Low nitrogen levels will affect the generation of chlorophyll pigments and low rubisco enzymes, resulting in low photosynthetic rates in plants, which will have an effect on reducing plant growth and output[13,14]. On the other hand, elevated nitrogen levels will affect the inefficiency of photosynthesis, susceptibility to lodging pest organisms and lower product quality[15,16]. Therefore, one of the keys to enhancing maize productivity in accordance with its potential yield is to apply the proper dose of nitrogen fertilizer. However, conventional morphology-based nitrogen dose evaluation has obstacles in conducting thorough and comprehensive observations in a crop evaluation, so the use of precision technology is important for this evaluation. One of which is through the use of Unmanned Aerial Vehicle (UAV) drones.

The UAV drone imagery can be used to maximize the effectiveness of nitrogen fertilization and irrigation. In general, the use of UAV drones in agriculture can aid in the processes of monitoring planting conditions, caring for plants and projecting plant growth and productivity[17-19]. This benefit can be used to assess the efficiency of nitrogen fertilizer for corn[20-22]. However, this idea needs to be backed by a precise and accurate data base and vegetation index algorithm, also known as drone-based vegetation index[23-25]. Several researchers have created a drone-based vegetation index for corn nitrogen fertilization using different approaches[11,26-30]. However, the research concept was carried out in a subtropical climate with relatively uniform and monoculture agroecosystems and cultures. This condition is very different from Indonesia, where Indonesia has a tropical climate with very diverse agro-ecosystems and cultures[31,32]. This indicates that the drone-based vegetation index that has been developed cannot be applied optimally in Indonesia. Therefore, the Drone-Based Vegetation Index model for nitrogen fertilization for maize in Indonesia still needs to be developed. The aim of this research was to identify the effectiveness of using UAVs to administer nitrogen doses to several varieties.

MATERIALS AND METHODS

Study area: The research was carried out in Bajeng Sub-District, Gowa Regency, South Sulawesi Province. This study followed the corn period from June to October, 2023. Meanwhile, the details of experimental research are explained below.

Study design: Activities were focused on developing a database for the Drone Vegetation Index model for corn plantings. Data development was carried out by combining several corn varieties at various nitrogen fertilization doses. A split plot design was employed with a completely randomized design used as the environmental design. The main plot was treated with N fertilizer doses consisting of 7 doses (0, 50, 100, 150, 200, 250 and 300 N kg/ha). On the other hand, the treatment of corn varieties consisting of 5 varieties [Sinhas (V1), Nasa 29 (V2), JH 36 (V3), Bisi 18 (V4) and Pioner 27 (V5)] was used as a subplot. Each combination of the two treatments was repeated three times, resulted in 108 experimental units. Each experimental unit used a 15 m^2 size plot.

Experimental procedures: The study used the standard procedure of corn cultivation[33]. The research was started by planting the seed according to the variety treatment. Each hole was planted with 2 seeds and Furadan application to avoid pest attack. The plan spacing was general for all treatment as double row systems or Legowo systems ((50+100)$\times$20 c). At 35 days after planting (DAP), each plant was fertilized according to the N dose treatment. For urea doses, the fertilizer was applied gradually with two steps on 35 and 50 DAP, whereas the N were applied in one section at 35 DAP. Liquid organic fertilizers were applied according to recommendation company, both of doses or the spread intensity. The other of plant maintenance were irrigating, weeding, covering and thinning. The harvest time was conducted at physiology maturity.

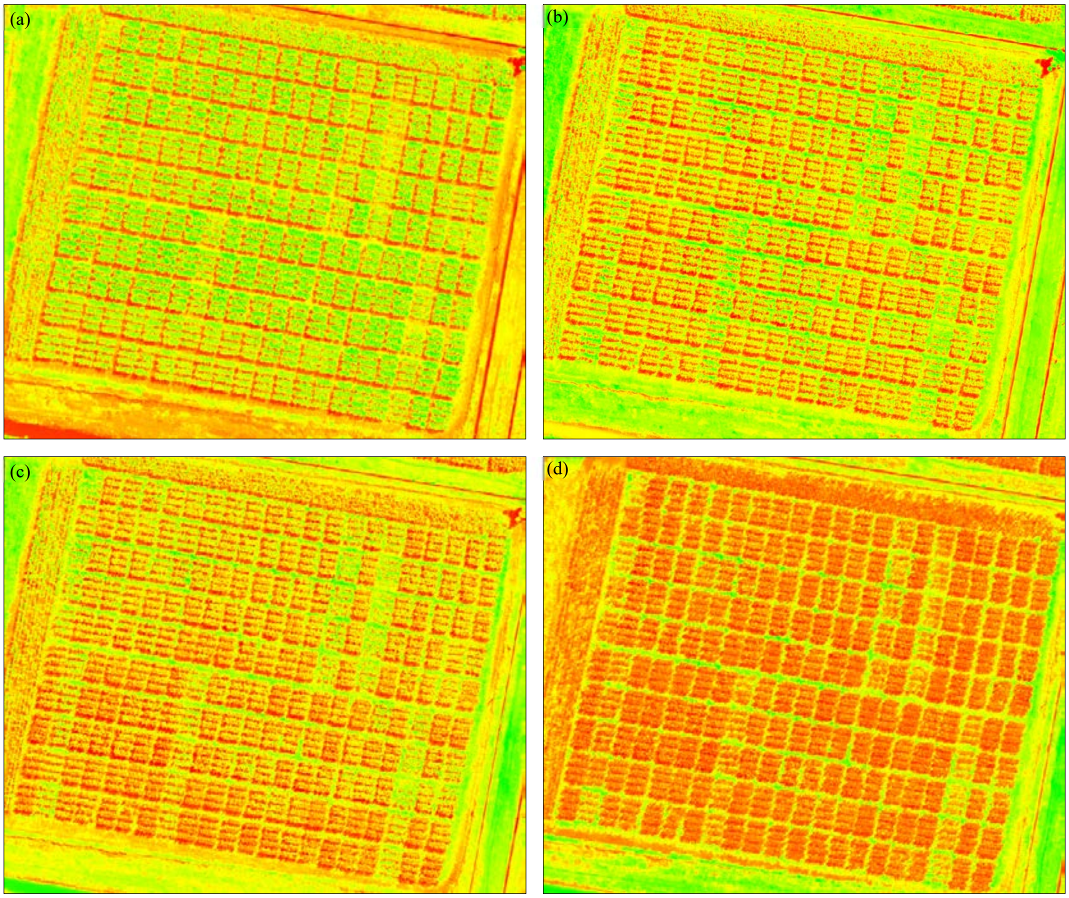

Fig. 1(a-d): Results of (a) NDVI, (b) GNDVI, (c) Clre and (d) NDRE analysis

Observation and data analysis: Observation of the mother-plot treatment focused on three characters: UAV-derived NDVI, GNDVI, Clre and NDRE, total chlorophyll (measured with CCM-200 chlorophyll content meter) and yield. Several analyses were performed on the data: Analysis of Variance (ANOVA) and Duncan's Multiple Range Test (DMRT) at 5% level in STAR 2.0.1 software, regression analysis in Minitab v.17 and 3D plot analysis in RStudio 3.6.1. The research focused on the regression analysis between NDVI, GNDVI, Clre, NDRE and yield.

Drone based vegetation indices

Data collection and analysis: Drone based vegetation data were collected in a field survey and converted from remote sensing products, i.e., aerial photos captured with a DJI Phantom 4 Multispectral (P4M) UAV equipped with the real-time kinetic (RTK) system. Images of the field were taken when the corn plants were at 80 days after transplanting (DAT) (Fig. 1a-d). These images were then processed in Agisoft Metashape Professional program to generate NDVI data. Afterward, the NDVI values were classified using the scheme adopted, which divides the category of plant density into four classes: <0.20 is classified as no vegetation cover, 0.21-0.40 as low-density vegetation cover, 0.41-0.60 as medium-density and 0.61-0.90 as high-density. The class of density is also often used to assess plant health levels.

RESULTS

The results of the correlation analysis were shown in Table 1. Based on this Table 1, all vegetation indices had a significant correlation between these indices. On the other hand, chlorophyll characteristics also had a significant correlation with the vegetation indices NDVI (0.796), GNDVI (0.774), Clre (0.810) and NDRE (0.713). However, the different responses in productivity traits did not correlate much with various vegetation indices. Productivity correlation only focused on Clre (0.410) and NDRE (0.430). In addition, productivity also did not have a significant correlation with corn chlorophyll.

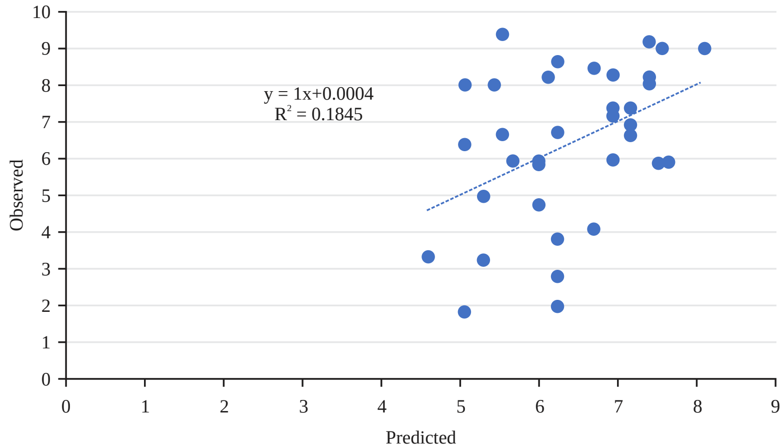

Fig. 2: Productivity prediction graph based on stepwise regression analysis of observed yields

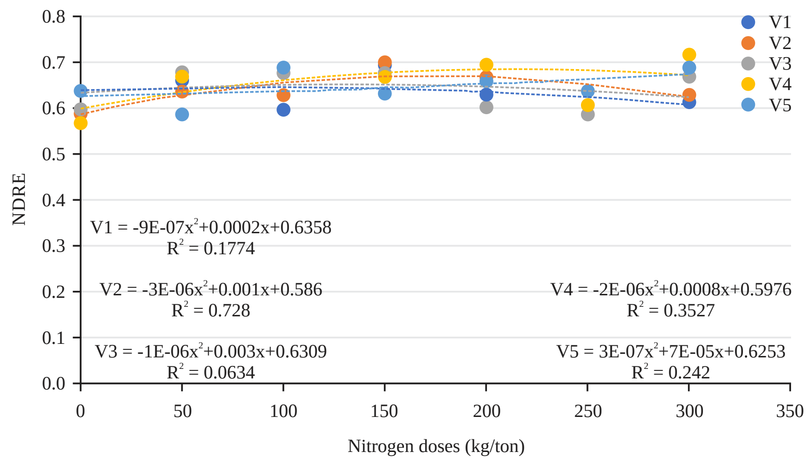

Fig. 3: Graph of interaction between varieties and nitrogen fertilization doses on NDRE parameters

Table 1: Correlation analysis between drone vegetation indices of chlorophyll and corn yield

Component	NDVI	GNDVI	Clre	NDRE	Chlorophyll	Productivities
NDVI	1.000					
GNDVI	0.745**	1.000				
Clre	0.583**	0.678**	1.000			
NDRE	0.582**	0.810**	0.664**	1.000		
Chlorophyll	0.796**	0.774**	0.810**	0.713**	1.000	
Productivities	-0.203^{ns}	0.227^{ns}	0.410*	0.430*	0.219^{ns}	1.000

*Significant correlation at 5% error level and **Significant correlation at 1% error level, ns: No significant effect

Table 2: Stepwise regression analysis of productivity

Component	Estimate	Std. error	t value	Pr(>|t|)	F value	Pr(>|F|)
Intercept	-8.647	5.508	-1.57	0.126	4.317	0.022*
NDRE	23.384	8.557	2.733	0.01*		

*Significant effect at 5% error level

The results of the stepwise regression analysis were shown in Table 2 and visualized in Fig. 2. Based on this Table 2, the NDRE character is the only character that can significantly predict productivity character, as the main character. This can be clearly seen from the t test on characters and the F test on the same model which both have a $p<0.05$. However, the determination value of this model is considered very low, namely 0.1845.

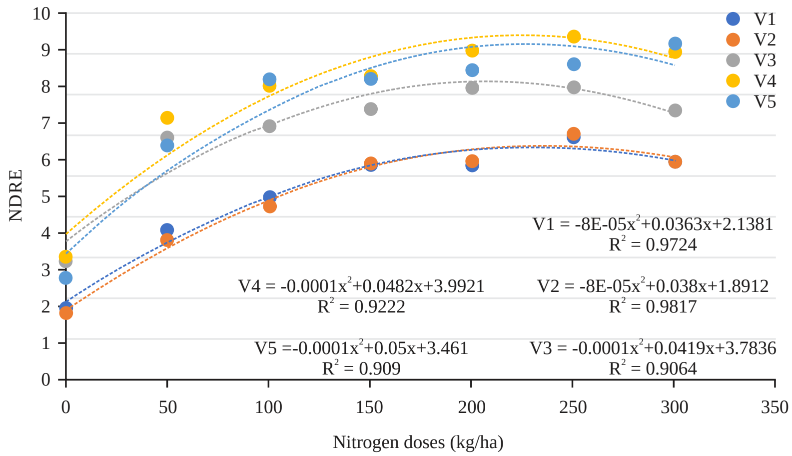

Fig. 4: Graph of interaction between varieties and nitrogen fertilization doses on corn yield parameters

The results of the interaction analysis between variety and nitrogen dose on NDRE characteristics and productivity were shown in Fig. 3 and 4, respectively. Based on Fig. 3, the V2 variety is the only variety that has a quadratic NDRE graph with a high determination value (0.728) for nitrogen dosage. On the other hand, other varieties have a quadratic graph with a determination value below 0.5 for the nitrogen dose. As in Fig. 4, all quadratic graphs of varieties show high determination values above 0.9 for nitrogen dosage. In particular, variety 1 has the highest determination value, namely 0.97. Varieties V1 and V2 are varieties that have a sloping graph for nitrogen fertilizer doses with low productivity potential. On the other hand, varieties V4 and V5 are varieties that have good nitrogen dose response graphs on productivity.

DISCUSSION

The results of the correlation analysis show that productivity and chlorophyll did not have a significant relationship between the parameters. In contrast, chlorophyll was highly correlated with all vegetation indices. In general, the vegetation index detects the potential of a plant through color, so that chlorophyll as a green leaf pigment has a close relationship with the vegetation index[27,34-37]. However, chlorophyll is not the main character or has economic value in a plant, hence this character becomes a secondary character in plant evaluation. However, in several studies, chlorophyll has a strong relationship in predicting the potential for corn productivity, especially the potential for applying nitrogen doses[36,38]. Despite this, in this study this relationship did not occur. This is because nitrogen not only plays a role in the status of chlorophyll pigments, but also plays a role in other functions such as amino acids, proteins, plant hormones and reactions in the photosynthesis process[14,39]. Apart from that, each genotype has a different ability to absorb and allocate nitrogen or nitrogen use efficiency (NUE)[12,13]. These two assumptions can cause discrepancies in the relationship pattern between chlorophyll and productivity in this study. However, there are two characters that have a good correlation between them, namely Clre and NDRE. These results are also supported by the research results of Torino *et al.*[40] which focused on estimating planting status and corn productivity. These two indices can be candidates for connecting the optimization of increasing chlorophyll with increasing productivity. This is very important in the efficient process of automated nitrogen fertilization in supporting corn productivity. Nevertheless, the use of a correlation basis is still considered rough, so the use of multiple regression for both is a strengthening basis in optimizing the formation of the corn yield prediction model.

Based on the results of the step wise regression analysis, the Clre character did not significantly influence the productivity prediction model, only the NDRE character is believed to have strong power in predicting corn productivity. Although based on this analysis, NDRE also has a low determination value in the prediction model. In general, NDRE is a vegetation index that focuses on transitional red light between visible red light and infrared light[36,41]. This method is considered very suitable for identifying chlorophyll properties in leaves, including corn[36]. This makes many studies of nitrogen doses use this approach, where nitrogen is one of the main constituents in the formation of leaf chlorophyll[12,14]. Therefore, the estimation of nitrogen doses is always related to this vegetation index. This was also concluded by Santana *et al.*[27], where the use of the NDRE index has a very significant correlation with corn productivity. Apart from that, the study also concluded that NDRE has better effectiveness than NDVI in evaluating corn, especially in evaluating nitrogen dosing. This was also confirmed by researchers[36,42,43], who assessed NDRE as more effective than several vegetation indices in assessing corn biomass and productivity potential. Based on this, NDRE is suitable to be used as a secondary character and evaluation in predicting productivity. However, the low model determination value in this study means that evaluations are still carried out independently between NDRE and the corn yield.

The results of evaluating the interaction between variety and nitrogen dose on NDRE and productivity show that the two relative parameters have different interaction patterns. Most of the varieties' responses to fertilizer doses in the NDRE character did not follow the quadratic pattern which is the general response of the yield character. This phenomenon further strengthens the reason that NDRE is more correlated with chlorophyll than corn productivity. Chlorophyll potential based on NDRE in some varieties is relatively unaffected by differences in nitrogen dosage. This confirms that the majority of plants will optimize the potential of their leaf chlorophyll in low nitrogen conditions as a form of adaptability, even though the phenomenon of morphological and agronomic performance is significantly reduced. This was also reported by Wu *et al.*[44], which shows that the amount of chlorophyll in low N sensitive plants is greater than in low N tolerant plants in low N environmental status. Therefore, the NDRE approach alone cannot be a guarantee in assessing potential productivity through vegetation indices, so it requires other approaches in the process of assessing and predicting potential yields in corn, such as canopy area and plant height.

Although in general in this research the NDRE approach cannot be a strong basis for predicting productivity. However, especially for the variety (V2), this approach can still be compatible for application. Quadratic graphs with strong determination values for this variety are the basis for utilizing NDRE parameters. However, the difference between the NDRE values at each fertilizer dose is relatively not too different. This is also closely related to the degree of deviation of the NDRE which has a narrow interval like other vegetation indices, where the interval of the vegetation index ranges from 0-1[36,43]. Therefore, the NDRE approach for this variety also requires other considerations in the evaluation process, especially in predicting productivity. However, in general, the potential response from NDRE V2 and productivity for all characters is found at a dose of 250 kg/ha. This dose can be a recommendation for nitrogen fertilization, especially for the V2 variety based on NDRE and productivity parameters.

CONCLUSION

The recent study has shown the effective use of vegetative indices in adequately evaluating corn plantings. The NDRE vegetation index is the best Unmanned Aerial Vehicle (UAV)-based vegetation index related to chlorophyll and can predict the potential productivity of corn crops. Nevertheless, the development of the NDRE still needs to be optimized further. Based on the NDRE and corn yield models, a nitrogen dose of 250 kg/ha is the optimal dose for corn planting.

SIGNIFICANCE STATEMENT

This research focuses on developing an evaluation of the effectiveness of nitrogen fertilizer doses on several corn varieties based on UAV-based multisensor imagery. We know that nitrogen fertilizer has a significant effect on corn growth and yield. However, the conventional approach carried out with eyes has many biases or errors and is not a completely accurate evaluation. Therefore, the use of UAVs can help the evaluation process in detecting the best nitrogen fertilizer dose.

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