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RESEARCH ARTICLE

Normalized Difference Vegetation Index Analysis to Evaluate Corn Cultivation Technology Based on Farmer Participation

Fadjry Djufry[1], Muh Farid[2*], Yunus Musa[2], Muhammad Fuad Anshori[2], Amir Yassi[2], Nasaruddin[2], Muhammad Aqil[3], Ahmad Fauzan Adzima[4], Hari Iswoyo[2], Muhammad Hatta Jamil[5] and Sakka Pati[6]

[1]Indonesian Agency for Agric. Res. and Dev., Ministry of Agriculture of the Republic of Indonesia, Jakarta, Indonesia
[2]Department of Agronomy, Hasanuddin University, Makassar, South Sulawesi, Indonesia
[3]Indonesian Cereal Research Institute, Ministry of Agriculture of the Republic Indonesia, Maros, South Sulawesi, Indonesia
[4]Department of Soil Science, Hasanuddin University, Makassar, South Sulawesi, Indonesia
[5]Department of Socio-Economics of Agriculture, Hasanuddin University, Makassar, South Sulawesi, Indonesia
[6]Department of Civil Law, Hasanuddin University, Makassar, South Sulawesi, Indonesia

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Correspondent email:
farid_deni@yahoo.co.id

Abstract. An unmanned aerial vehicle (UAV), widely known as a drone, proves very effective in assessing cropping or crop cultivation conditions. Using UAV to evaluate various corn cultivation technology systems is feasible when based on farmers' participation. UAV can generate the Normalized Difference Vegetation Index (NDVI) algorithm that reflects the greenness of leaves, a parameter related to photosynthesis and plant productivity. Therefore, this study aimed to evaluate whether the farmer participation-based UAV-derived NDVI could be effectively used to assess and determine the appropriate corn cultivation technology. The research was conducted in Tarowang Village in Galesong Selatan District, Takalar Regency, South Sulawesi, Indonesia. A mother and baby trial system was employed: the mother trial used a randomized complete block design (RCBD) with eight packages of corn cultivation technology implemented by the researchers, whereas the baby trial consisted of eight corn plots cultivated by farmers. In the latter, each farmer received one package of the cultivation technology. The results indicated that NDVI and yield could effectively evaluate corn cropping. Consistently good outcomes made three packages, i.e., P1, P4, and P5, recommended for corn cultivation, especially in the village observed. Nevertheless, the treatment combinations in the three packages are expected to also apply to other South Sulawesi districts to promote improvement in corn production.

1. Introduction

Land resources for agriculture are increasingly depleting year by year. It poses a major problem in meeting the food demands of the world population that continues to grow significantly. According to FAO, by 2050, the world population will have increased 35% from its current size (Tarancón, 2011). Developing countries are predicted to be the biggest contributor to this population increase. Multiplying food production on a large scale is thereby a solution to meet human needs in the future.

Corn is one of the main food crops and the best cereal globally besides wheat and rice (García-Martínez et al., 2020). Corn has excellent potential as an export commodity. Based on data from BPS-Statistics Indonesia (2019), corn production sharply increased from 19 million tons/ha in 2014 to 30 million tons/ha in 2018. However, it was still far below the average national corn demand. Climate change is believed to exacerbate the scarce supply, for it can significantly reduce crop yields (Cervantes et al., 2014; Moore et al., 2015). Therefore, innovations to multiply corn yields are constantly developed to maintain food security and the national economy.

Innovations can be introduced to different aspects of corn cultivation in various ways, one of which is by optimizing the cultivation technology package offered to farmers. For example, Abduh et al. (2021) have found several packages optimal for growing this crop. However, farmers' participation in harnessing the technology is a concept that needs to be incorporated into its application. In optimizing the roles of farmers and researchers, participatory research that shares some similarities with participatory plant breeding (PPB) can be conducted in two ways: mother trials and baby trials (Snapp et al., 2002; Merga, 2017; Najeeb et al., 2018; Lyon et al. 2020; Tyack et al. 2020). Researchers plant a predefined variety in the mother trial, while farmers are responsible for the breeding in the baby trial. Generally, a mother trial is a principal experiment to evaluate the best variety or cultivation technology, and a baby trial is a supplement to this evaluation (Lyon et al. 2020; Tyack et al. 2020). It means that combining both trials can increase the effectiveness of selecting the best-adapted variety or cultivation and that analyzing the trial results can determine the optimal technology and varieties to develop in an area. However, it is crucial to also optimize the assessments necessary for the evaluation analysis. The optimization can involve, for instance, smart farming with unmanned aerial vehicles (UAVs) or drones (Durlo et al., 2015; de Castro et al., 2021; Neupane & Gurel, 2021).

UAV is a solution in smart farming activities that focuses on data precision (Radoglou et al., 2020). It produces data that can be processed into various algorithms, one of which is the Normalized Difference Vegetation Index (NDVI). NDVI is correlated with biophysical nature, like biomass, leaf area index (LIA), and vegetation condition (Jiang et al. 2006), which makes it currently the most widely used algorithm for vegetation analysis (Weier & Herring 2000). Some studies have also reported the effectiveness of NDVI for corn (Wahab et al. 2018; García-Martínez et al. 2020; Panday et al. 2020). It is thereby interesting to study whether the UAV-derived NDVI that involves farmers' participation or PPB can be used to assess corn cultivation technology. This is a new concept or method that integrates UAV and NDVI technologies to evaluate crops. Accordingly, the research was intended to measure the effectiveness of the NDVI in assessing and determining the appropriate technology for corn cultivation.

2. The Methods

This research area is Tarowang Village, Galesong Selatan District, Takalar Regency, South Sulawesi, Indonesia (Figure 1). The minimum and maximum average temperatures are 27.14 °C and 31.44 °C, respectively. The PPB type used in this study was the sixth-level method based on Morris and Bellon (2004). The mother and baby trial design was employed to evaluate the corn cultivation technologies implemented from September until December 2021. Corn-cultivated plots were subjected to either the mother trial or the baby trial. The mother trial with a randomized complete block design (RCBD) introduced eight packages of corn cultivation technology, as presented in detail in Table 1. The eight packages or treatments were repeated to obtain triplicate measurements, creating a total of 24 experimental units. The plot size of each unit was 8 m x 8 m. Farmers were responsible for cultivating eight corn plots in the baby trial; each received one package of corn cultivation technology.

The Experimental Procedure

The study used the standard corn cultivation procedure (Abduh et al. 2021). It started by planting the seed according to the variety treatment. In each hole made in the soil, two seeds were sown and Furadan was applied for pest control. The crops in all the treatments were spaced with a double row planting system, locally known as *legowo* ((50+100) x 20 c). At 35 days after planting (DAP), the crops were fertilized with different N:P:K

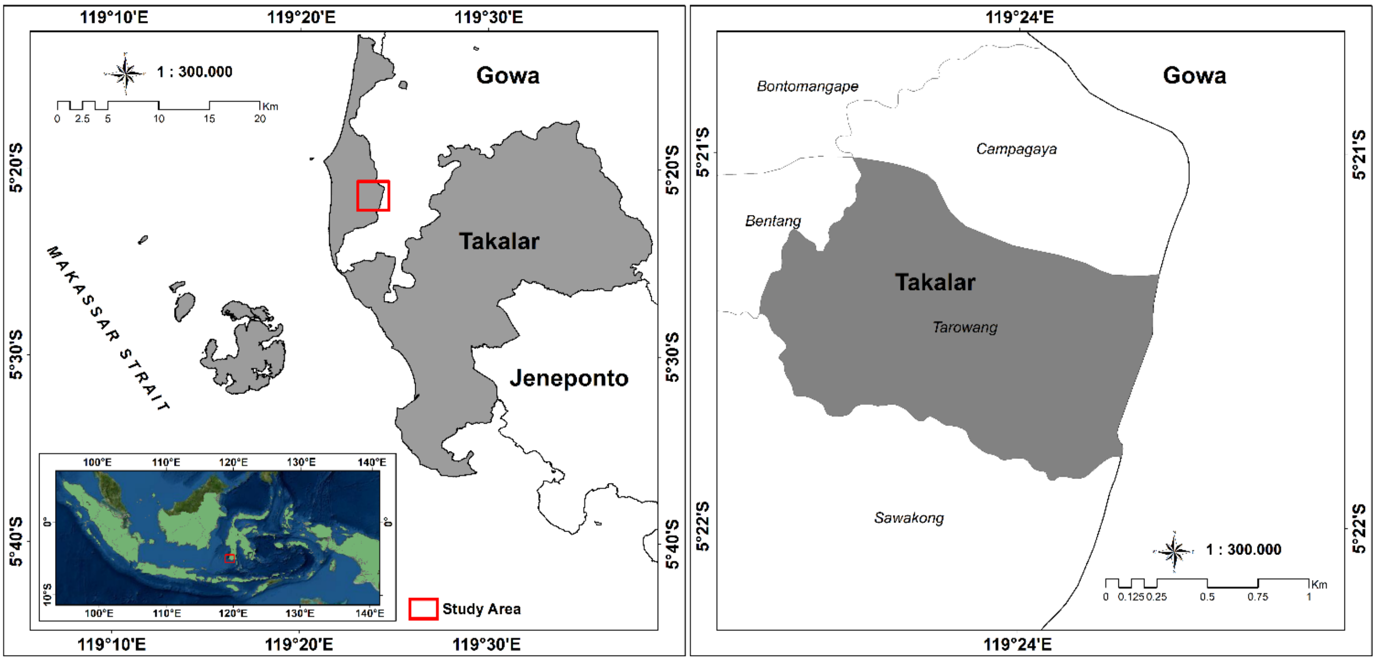

Figure 1. Research location.

Table 1. Description of the eight packages of corn cultivation technology.

Label	Corn Cultivation Technology
P1	Pioner variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5cc/L of Biotani biofertilizer
P2	Pioner variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5cc/L of Ecofarming biofertilizer
P3	ADV variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 225:100:75 ratio
P4	NK3728 variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5 cc/L of Biotani biofertilizer
P5	ADV variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5 cc/L of Biotani biofertilizer
P6	BISI 18 variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 225:100:75 ratio
P7	SINHAS 1 variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5cc/L of Ecofarming biofertilizer
P8	NASA 29 variety, double row spacing system ((50+100) x 20 cm) and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5cc/L of Ecofarming biofertilizer

doses depending on their variety (see Table 1). Urea fertilizer was applied gradually, i.e., at 35 and 50 DAP, whereas NPK and SP-36 (P_2O_5 fertilizer) were given to one section at 35 DAP. Liquid organic fertilizers were added to the plots following the dose and spread intensity recommended by the producer companies. Other crop treatments included irrigation, weeding, mulching, and thinning. Corns were harvested at physiological maturity.

Observation and Data Analysis

The mother trial's plot observation focused on three characters: UAV-derived NDVI, total chlorophyll (measured with CCM-200 chlorophyll content meter), and crop yield. In the baby trial, only NDVI and yield data were collected and observed in detail. The mother trial data were analyzed using analysis of variance (ANOVA) and Duncan's multiple range test (DMRT) at a 5% significance level in STAR 2.0.1 software, regression analysis in Minitab v.17, and 3D plot analysis in RStudio 3.6.1. In the baby trial, regression analysis between NDVI and yield was conducted.

Normalized Difference Vegetation Index (NDVI): Data Collection and Analysis

NDVI 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 a real-time kinetic (RTK) system. Images of plots in the mother and baby trials were taken when the crops were 80 days after transplanting (DAT) (Figures 2 and 3). The images were then processed in Agisoft Methashape Professional program to generate NDVI data. Afterward, the NDVI values were classified using the scheme from Al-doski et al. (2013) to divide plant density into four classes: no vegetation cover (<0.20), vegetation cover of low density (0.21–0.40), medium density (0.41–0.60), and high density (0.61–0.90). These classes of density are also often used to assess plant health levels.

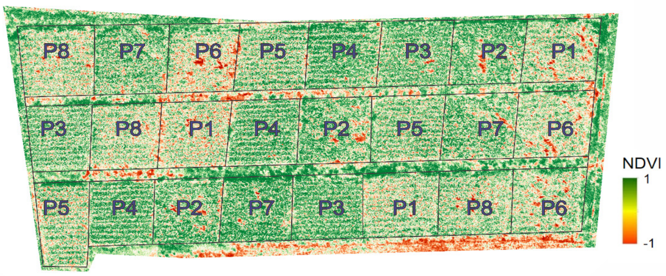

Figure 2. NDVI analysis results of the plots in the mother trial.

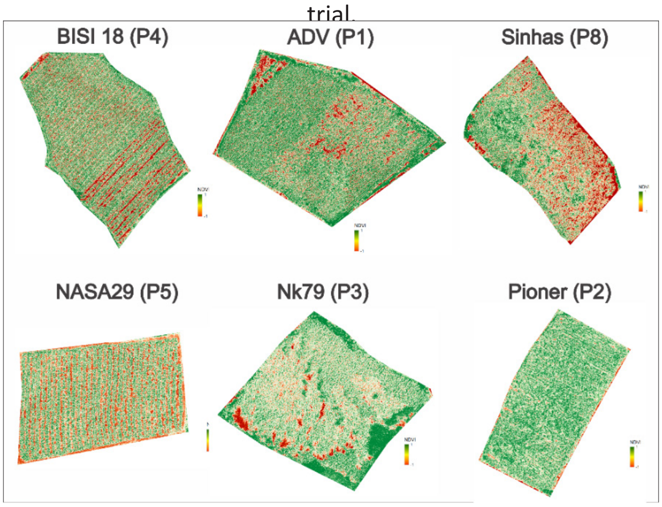

Figure 3. NDVI analysis results of the plots in the baby trial.

3. Results and Discussion

Plot Analysis in the Mother Trial

The analysis of variance (ANOVA) of the mother trial data revealed that differences in the applied cultivation technology packages strongly influence the NDVI, total chlorophyll, and yields (Table 2). P4 was the package with the best NDVI value (0.658), although not significantly different from that of P1 (0.628), P3 (0.587), and P6 (0.605). In addition, all packages resulted in a relatively similar amount of chlorophyll, except for P8, whose average chlorophyll content was 28.95. Likewise, they also produced somewhat identical yields, except for P7 and P8, which had the lowest yields of 9.67 tons/ha and 8.78 tons/ha.

Table 2. Analysis of variance of the three characters: NDVI, chlorophyll content, and yield.

P	NDVI	Chlorophyll	Yield
P1	0.628ab	41.05a	11.30a
P2	0.560bc	35.75ab	9.99abc
P3	0.587abc	41.28a	10.47ab
P4	0.658a	39.48a	10.60ab
P5	0.563bc	40.10a	10.99ab
P6	0.605abc	34.52ab	10.14abc
P7	0.530c	35.71ab	9.67bc
P8	0.519c	28.96b	8.78c
Average	0.581	37.106	10.24
Pr(> F)	0.0009**	0.0023**	0.0018**
CV	5.27	8.04	5.33

Notes: **: Significant effect at a 1% significance level (P≤0.01); CV = coefficient of variance; the values with the same letter in a column are not significantly different based on Duncan's multiple range test at a 5% significance level.

The ANOVA results also showed that NDVI, total chlorophyll, and yield could determine the effectiveness of a corn cultivation technology package. NDVI is a character associated with the green density of an image and is one of the parameters used in evaluating cropping conditions. According to Mahlein (2015) and Messina (2020), NDVI can be used to assess changes in plant physiology due to cropping treatments or environments. Chlorophyll is a physiological character widely used to examine cropping conditions (Nishant et al. 2016; Kapoor et al. 2020; Azzawi et al. 2020). This character is closely related to photosynthetic potential and indirectly affects productivity (Széles et al. 2012; Brito et al. 2019, Kapoor et al. 2020; Yan et al. 2021). Its use as a basis for evaluation has been reported by Xiang et al. (2013), Karimpour et al. (2019), Padjung et al. (2021), and Shin et al. (2021). Finally, yield is the main character observed in the economic valuation of crop cultivation (Anshori et al. 2019, 2021a). Based on the DMRT analysis, the three characters appeared in different patterns across the applied cultivation technologies. Therefore, they were combined to assess and evaluate the effectiveness of a particular corn cultivation technology.

Figure 4 shows the results of two separate regression analyses in the mother trial between NDVI and the other two characters, i.e., chlorophyll content and yield. As seen in the line plots, the samples in both regressions were still within the range of the prediction interval. However, the NDVI-yield analysis showed a higher coefficient of determination (42.0%) than NDVI-chlorophyll (28.9%).

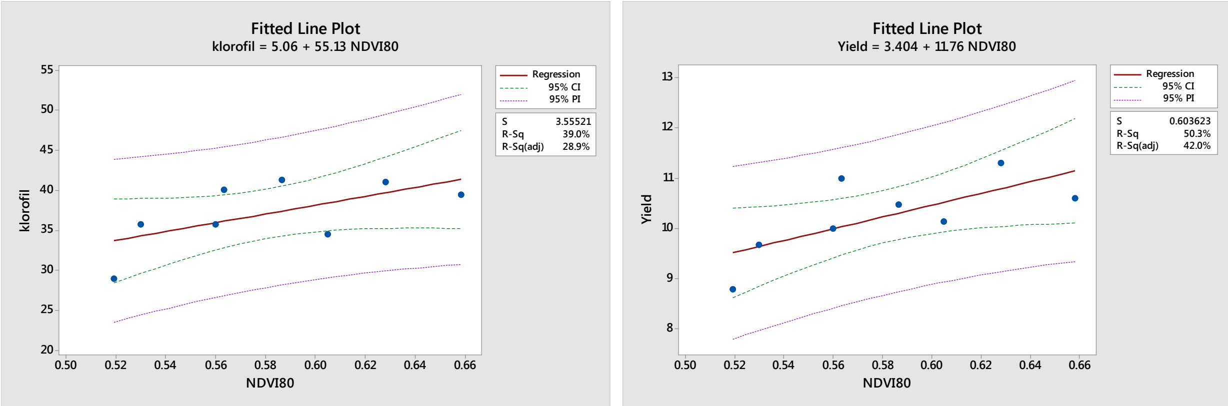

Figure 4. Regression analysis results between NDVI and yield (A) and chlorophyll (B) in the mother trial

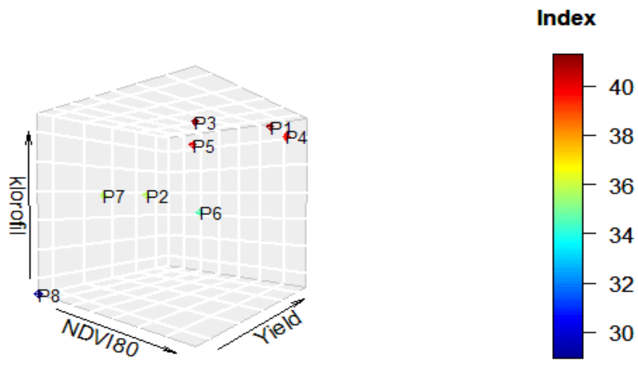

Figure 5. 3D analysis of the three main characters observed in the mother trial.

Furthermore, based on the regression analysis, NDVI effectively predicted chlorophyll content and yield. These results correspond to Benincasa et al. (2017), Janoušek et al. (2021), and Kim et al. (2021) for the NDVI-chlorophyll relationship and to Wahab et al. (2018), Guan et al. (2019), Herrmann et al. (2020), and Perros et al. (2021) for the capacity of NDVI to predict crop yield. In general, assessing chlorophyll fluorescence using the NDVI obtained with multispectral cameras offers more advantages than relying on the RGB-based color analysis alone (Zaman-Allah et al. 2015; Zhang et al. 2019; Herrmann et al. 2020). However, it was found that NDVI determined yields better than chlorophyll contents because the NDVI was measured at 70 DAP when the leaf senescence started, resulting in a lower determination value than the crop yield. Although NDVI increases precision in evaluating crop cultivation and determining the most effective cultivation, incorporating various aspects in the assessment remains a practical step in such evaluation so as to deal with or find the solution for any identified drawbacks or weaknesses.

The 3D plot of the mother trial data shows three groups of technology packages (Figure 5). The first group with a high composite index value consisted of four treatments: P1, P3, P4, and P5. The second group consisted of P7, P2, and P6, whose genotype members had a medium index value. The third group had only one package, P8, with the lowest index value.

The 3D plot shows the position of the cultivation technology packages relative to NDVI, chlorophyll, and yield. Evaluation using the three characters could clearly distinguish between the packages, as indicated by the three different colors (see Figure 5). This finding corresponds to the previous regression analysis where the three characters showed the same direction of selection. 3D plot analysis is widely used to simplify the interaction between multiple aspects, thereby allowing for more effective assessment (Paulus 2019; Farid et al. 2020, 2021; Anshori et al. 2021b). However, the 3D concept is based on degrees of equality among the aspects observed; hence, no aspect is dominant (Paulus 2019). In conclusion, farmers are recommended to implement all four packages of corn cultivation technology, which had the high composite index values in the 3D plot analysis, namely P1, P3, P4, and P5.

Plot Analysis of the Baby Trial

In the baby trial, only NDVI and yield were tested because the regression analysis of the mother trial data revealed that NDVI and chlorophyll had the same direction of selection. In addition, NDVI had a high coefficient of determination when analyzed against yield, creating a sufficient basis for their assessment in the baby trial. NDVI values collected in the baby trial ranged between 0.46 and 0.56, with the highest value shown by P2 (0.56) (Table 3). Meanwhile, P1 produced the highest corn yield, 10.71 tons/ha. The average NDVI and yield in the baby trial were relatively lower than in the mother trial. This result is considered reasonable because the plots in the mother trial were researcher-designed and supervised, while the experiment in the baby trial involved farmers who drew upon their agricultural experience and tended to follow certain cultures and characters (Najeeb et al. 2017). Nevertheless, the average NDVI and yield in the baby trial were not substantially different from those of the mother trial, meaning that the former can adequately validate the analysis in the latter.

Table 3. Mean NDVI values and yields of corns cultivated in the baby trial.

Treatment	Variety	NDVI	Yield (ton/ha)
P1	ADV	0.53	10.71
P2	Pioner 1	0.56	10.14
P3	NK79	0.49	8.82
P4	Bisi 18	0.53	10.41
P5	Nasa 29	0.53	10.40
P6	ADV 1	0.40	8.27
P7	Pioner 2	0.51	8.04
P8	Sinhas 1	0.46	7.85
Average		0.50	9.33

Figure 6 depicts the regression analysis results between NDVI and yield in the baby trial. It showed a high coefficient of determination, R^2 = 0.528 (Figure 4). Furthermore, the NDVI-yield plots categorized the implemented technology packages into three groups: P1, P2, P4, and P5 in the first group, P3 and P7 in the second group, and P6 and P8 in the third group.

The regression analysis of the baby trial data produced similar results to the mother trial despite some differences in the treatments. However, P1, P4, and P5 were the corn cultivation technology packages with consistently good outcomes. These results support the previous statement by Lyon et al. (2020) and Tyack et al. (2020) that the baby trial can substantially increase the effectiveness of selection in the mother trial evaluation. Therefore, P1, P4, and P5 are recommended for corn production, especially in Tarowang Village, Galesong Selatan District. Besides, the local farmers can be part of a pilot project on corn production improvement in the district. This study is a stepping stone in developing corn cultivation and recommending relevant policies in many regions in Indonesia; thus, comprehensive experiments that integrate various cultivation aspects, physical environments, and farmers' participation are necessary.

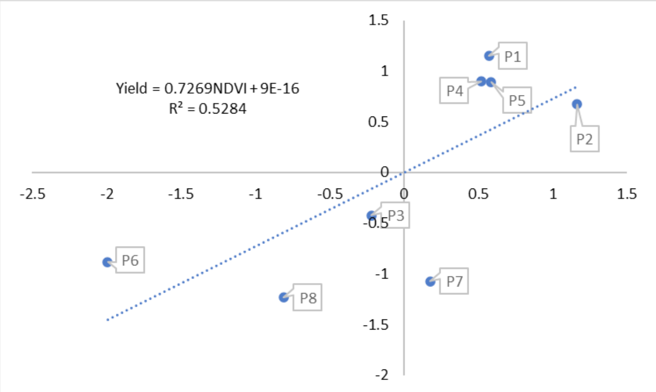

Figure 6. Regression analysis of NDVI and yield in the baby trial.

4. Conclusion

This research has found that NDVI and yield can effectively evaluate corn cultivation conditions. Farmers' participation, like participatory plant breeding, is a good concept for disseminating corn cultivation technology. The farmers in Tarowang Village can be part of a pilot project aimed at multiplying corn production in the district. Three technology packages produce consistently good outcomes: Pioneer variety, double row spacing system ((50+100) x 20 cm), and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5 cc/L of Biotani biofertilizer (P1); NK3728 variety, double row spacing system ((50+100) x 20 cm), and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5 cc/L of Biotani biofertilizer (P4); and ADV variety, double row spacing system ((50+100) x 20 cm), and NPK fertilizer with a 200:100:50 ratio + 25 kg of KNO3 fertilizer + 5 cc/L of Biotani biofertilizer (P5). However, it is necessary to test these packages further in several other districts to see their effectiveness in broader geography.

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