Optimizing soybean management with UAV RGB and multispectral imagery: A Neural Network method and image processing

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Abstract.

Precision agriculture (PA) has emerged as a fundamental approach in contemporary agricultural management, aimed at maximizing efficiency in the use of resources and improving crop productivity. The transition to so-called "agriculture 4.0" represents a revolution in the way technology is applied in the field, with an emphasis on digital and automated solutions such as UAVs (Unmanned Aerial Vehicles). These devices offer new capabilities for capturing high-resolution images, enabling detailed analysis of agronomic variables at plot level. This study focused on evaluating the accuracy of counting soybean plants (Glycine max (Linnaeus) Merrill) at different stages of development and sowing speeds, using images obtained by RPAs equipped with RGB and multispectral sensors. The project was carried out at Ben Hur Research Farm, located in the United States in Baton Rouge, LA, to evaluate the performance of the sensors under real conditions, and determine the most efficient sensor for accurately counting soybean plants. Through advanced analysis, including Neural Networks and image processing with R Language and the FIELDimageR package, this study identified RGB technology as highly accurate in classifying the number of soybean plants. However, image processing presented challenges in environments with high plant overlap, resulting in reduced accuracy in estimating the number of plants. These results highlight the importance of proper sensor selection and timing of image capture to obtain accurate plant count estimates in different agronomic conditions. Furthermore, they suggest the need to explore new techniques and approaches to improve the accuracy of image processing in challenging environments, such as areas with high plant population density. These findings have significant implications for the practice of precision agriculture, providing valuable insights for efficient crop management, optimizing the use of *resources and increasing productivity in soybean crops. The study contributes to the advancement of scientific knowledge in this constantly evolving field, paving the way for future research and practical applications in modern agriculture.*

Keywords.
soybean, density plant, machine learning, artificial intelligence, UAV.

1. Introduction

Precision agriculture (PA) optimizes resource use and maximizes crop productivity through advanced information and communication technologies (SBCS, 2021). Agriculture 4.0 integrates digital technologies like AI, UAVs, GIS, and sensors to enhance agricultural processes (Araújo et al., 2021). PA practices improve crop yields, reduce costs, and optimize inputs by managing nutrients, pests, weeds, and sowing gaps (Wrigley, 2015; Nukala et al., 2016). UAVs with digital cameras are crucial in precision agriculture for crop phenotyping and digital image processing (Maes and Steppe, 2019; Valente et al., 2020; Yang, 2020).

Stand assessments in early soybean growth stages (VC to V3) ensure optimal plant populations, facilitating timely replanting if necessary (Carver et al., 2018; Licht, 2020). Delays in sowing reduce yield potential (Egli and Cornelius, 2009; Salmeron et al., 2014; Nleya et al., 2020), and replanting must balance costs and benefits (Pathak et al., 2022). The optimum agronomic plant population (AOPP) for soybeans is about 247,000 plants per hectare (Epler and Staggenborg, 2008; Gaspar and Conley, 2015). Manual counting methods, although accurate, are labor-intensive and error-prone (Pathak et al., 2022). Advanced technologies like LIDAR, high-resolution imaging, and smartphone apps offer precise alternatives (Shi et al., 2013; Jia and Krutz, 1992; Shrestha and Steward, 2003; Tang and Tian, 2008; Smith et al., 2019).

UAVs enable high-resolution imagery for detailed field analysis (Hunt et al., 2005). RGB and multispectral cameras on UAVs facilitate vegetation indices like NDVI for crop health assessment (Prakash, 2000; Rouse et al., 1974). RGB-derived indices are useful for early-stage monitoring and stand counts (Woebbecke et al., 1995; Vong et al., 2021; Fan et al., 2018).This study evaluates and compares the accuracy of soybean plant counts using RGB and multispectral images to enhance agricultural management and productivity.

2. Materials and Methods

The experiment was conducted starting May 19, 2023, at Ben Hur Research Farm, Baton Rouge, LA, to identify the most efficient sensor for counting young Roundup Ready 2 Xtend soybean plants and determining the optimal phenological stage for accurate crop population estimation. The experimental area measured 90 x 15 meters, with a sowing rate of 326,000 seeds per hectare and row spacing of 0.99 meters. Sowing speeds were 1.1 m/s, 1.6 m/s, and 2.2 m/s, with 60 one-meter samples marked for visualization.

Images were captured using a DJI Matrice 300 UAV with DJI Zenmuse H20 and Micasense Red-Edge-MX sensors at three soybean stages: cotyledon (VC), first node (V1), and second node (V2). Each stage required one flight per sensor, totaling six flights. The UAV operated at 15 meters altitude with 80% overlap, achieving GSDs of 0.5 cm (RGB) and 1.0 cm (multispectral). Data processing was conducted at LSU and UConn laboratories. Orthomosaics were created using Agisoft Metashape, producing six orthomosaics (three RGB, three multispectral). The steps included image addition, alignment, DEM creation, and orthomosaic construction. A total of 360 image samples were cropped for analysis. Neural Networks classified plant counts using Orange software and pre-trained Inception v3 networks. The analysis involved 220 selected images.

The R language and FIELDimageR package were employed for further image analysis. FIELDimageR counted plants in each of the 60 marked samples, totaling 360 images. Soil removal and vegetation indices were applied during processing to enhance accuracy. Model performance was evaluated using AUC, Precision, Accuracy, Conformal Recall, and F1 Score. The estimated plant counts were compared with field counts. Both RGB and multispectral images were validated using R^2 and MAE metrics, comparing UAV-derived estimates with field and manual counts.

3. Results and Discussion

The Neural Network's classification performance for RGB and multispectral images is shown in Table 1. The RGB model achieved an AUC of 0.969, an accuracy of 80%, and an F1 score of 0.803. For multispectral images, the AUC was 0.942, accuracy 71.8%, and F1 score 0.713. Precision and recall were 82.5% and 80% for RGB, and 71.8% and 70% for multispectral, respectively. These results indicate a strong classification ability, although increasing the number of images per class could further improve accuracy. The confusion matrices showed that the Neural Network had an error rate of 20% for RGB images and 28% for multispectral, misclassifying 22 and 31 images, respectively.

Table 1 - Neural Network classification result

Model	AUC	CA	F1	Precision	Recall
RGB	0.969	0.800	0.803	0.827	0.800
Multiespectral	0.942	0.718	0.713	0.718	0.705

Vegetation indices GLI for RGB and CIG for multispectral images were effective for plant counting, with MAE values of 0.057 and 0.292, respectively, in the VC stage. These indices reduced noise and improved accuracy.Comparisons of plant number estimates from orthomosaic images processed with R and manual counts indicated estimation challenges due to plant overlap, especially at later growth stages. The model showed the highest accuracy with RGB images at the VC stage (R^2 = 0.38), but overall accuracy was low due to overlap, leading to undercounting.

Without overlapping, the model's accuracy was high for both RGB and multispectral images at the VC stage (R^2 = 0.92 and 0.72). Accuracy decreased with advancing vegetative stages, but remained better in the VC and V1 stages (R^2 = 0.92 and 0.88, respectively). The lowest MAE was achieved with the RGB sensor at the VC stage (MAE = 0.057) under non-overlapping conditions, as shown in Table 2.

Table 2 - Mean absolute errors (MAE) between the number of plants estimated and the number of plants in the field and in the orthomosaic cut-outs for each vegetative stage and for each sensor (RGB and multispectral)

Soybean stage	MAE			
	RGB		Multispectral	
	Field	Orthomosaic	Field	Orthomosaic
VC	0.382	**0.057**	0.519	0.156
V1	0.464	0.096	0.572	0.152
V2	0.471	0.195	0.596	0.321

Pixel size and plant development stages impacted plant counting accuracy. Larger pixel sizes reduced resolution, complicating soil and vegetation differentiation. Despite these challenges, the Neural Network showed high accuracy even with overlapping plants and varying resolutions. The RGB sensor outperformed the multispectral sensor due to its higher resolution (0.5 cm per pixel), resulting in more accurate counts (R^2 = 0.92) and lower error (MAE = 0.057).

Accurate plant stand counts are crucial for evaluating harvest yields and optimizing the sowing process, directly affecting crop yield and quality. Factors such as nutrient and water availability, sowing depth, herbicide effects, climatic conditions, pest infestations, and sunlight exposure significantly influence plant density and uniformity, impacting overall yield and production quality.

5. Conclusion

Explored in the study was the impact of optimal conditions and plant overlap on vegetation estimation accuracy. Results underscored the significance of selecting suitable sensors and timing for image acquisition. Estimating plants up to the VC stage notably minimized errors. RGB technology exhibited high accuracy in soybean plant classification using Neural Networks, whereas image processing struggled with accuracy, particularly in environments with dense plant overlap, suggesting the need for alternative approaches.

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