Computer vision by UAVs for estimate soybean population across different physiological growth stages and sowing speeds

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A paper from the Proceedings of the
16th International Conference on Precision Agriculture
21-24 July 2024
Manhattan, Kansas, United States

Abstract.

Soybean (Glycine max (Linnaeus) Merrill) production in the United States plays a crucial role in agriculture, occupying a considerable amount of cultivated land. However, the costs associated with soybean production have shown a notable increase in recent years, with seed-related expenses accounting for a significant proportion of the total. This increase in costs is attributed to a number of factors, including the introduction of patented and protected genetic traits, as well as inflationary pressures. Accurate counting of the number of soybean plants per unit area is essential for monitoring emergence and losses in plant population density, playing a critical role in agricultural science and practice. However, traditional manual counting methods are inefficient and subject to inaccuracies, due to variables such as plant density, limitations in human visual perception and the representativeness of the samples collected. This study investigated the feasibility of using Unmanned Aerial Vehicle (UAV) to monitor the population density of soybean plants at different phenological stages. The experiment was conducted at Ben Hur Research Farm, located in the southern United States, using UAV images and advanced image processing techniques to count plants. The results showed that the VC phenological stage had the highest accuracy, due to the increased visibility of the plants as they grow. In addition, the influence of sowing speed on plant counting accuracy was examined. It was observed that increasing the sowing speed resulted in a decrease in the model's accuracy, due to the greater overlap between plants. However, when excluding overlapping plants, the accuracy of manual counting using the UAV image was high at the VC stage. This project contributes to the advancement of scientific knowledge by providing insights into the dynamics between soybean phenological stages, sowing speed and plant counting techniques. The integrated approach using UAV and image processing *technologies offers an effective way to optimize plant counting in the soybean crop, providing valuable information to improve agricultural practices and maximize production. These results not only enrich the scientific literature, but also have significant practical implications for precision agriculture and crop management*

Keywords.
soybean, number of plants, growth stages, remote sensing, UAV.

1. Introduction

Soybeans (Glycine max) are crucial to US agriculture, covering 36.8 million hectares in 2022 (USDA-NASS, 2022). Seed costs, which have risen over 200% from 2000 to 2021, now account for 32% of production expenses due to patented traits, genetic improvements, and inflation (Bergada et al., 2015; Chen; Wiatrak, 2011; Lee et al., 2008; USDA-NASS, 2022).

Manual plant density assessments are time-consuming and inaccurate (Li et al., 2019; Xu et al., 2020; Wei and Molin, 2020). UAVs offer a scalable solution for monitoring plant populations (Li, Wang, and Huang, 2022).While digital imaging for plant stands varies by crop (Pathak et al., 2022), UAV technology shows promise in soybean assessments. Studies like Yang et al. (2024) and Randelović et al. (2020) have used UAV images and advanced algorithms for detecting soybean seedlings, though plant overlap at high densities presents challenges.

Seeding speed affects plant distribution and operational capacity (Bortoli, 2021; Bertelli et al., 2016; Pacheco et al., 1996). Improved methods for stand evaluation are needed for high-density crops like soybeans (Pathak et al., 2022). This study explores the interplay between soybean growth stages, seeding speed, UAV imaging, and plant counting to optimize plant counting efficiency and improve agricultural practices.

2. Materials and Methods

The experiment took place at the Ben Hur Research Farm, Baton Rouge, Louisiana, 8 km south of the LSU campus. The region's humid subtropical climate is suitable for agricultural research. Soybeans were sown on May 19, 2023, at three speeds: 1.1 m/s, 1.6 m/s, and 2.2 m/s, with four rows per speed, totaling 12 rows over 0.13 hectares. A randomized design with 60 samples (each 1 meter wide) was used. The variety planted was Roundup Ready 2 Xtend, at 326,000 seeds per hectare, with 0.99 m row spacing, following a corn crop.

Data collection occurred at the cotyledon (VC), first node (V1), and second node (V2) stages, as per Fehr and Caviness (1977), chosen to ensure full plant emergence while minimizing overlap (Matias et al., 2020; Ranđelović et al., 2020; Yang et al., 2024). Images were captured using a DJI Matrice 300 UAV with a 20 MP Zenmuse H20 RGB camera at 15 m altitude, achieving a 0.5 cm GSD and 80% overlap. Collections occurred at the VC stage (May 29, 2023), V1 stage (June 2, 2023), and V2 stage (June 6, 2023), between 9:30 a.m. and 2:30 p.m. under clear skies.

Image processing was conducted at LSU and UConn using Agisoft Metashape 2.1.1 for orthomosaic creation and QGIS 3.28.11 for sample delineation. The R software environment (version 4.3.1) facilitated area extraction. The FIELDimageR package in R, utilizing EBImage, was employed for plant population analysis. Vegetation indices were used to filter non-crop elements (Ranđelović et al., 2020; Matias et al., 2020). Automated plant counting was performed with the Fieldobject package in R, validated against manual counts. Model performance was evaluated using the coefficient of determination (R^2) and Mean Absolute Error (MAE) to compare UAV estimates with manual counts.

3. Results and Discussion

The analysis of orthomosaic cutouts revealed that increased sowing speeds resulted in fewer plants observed in the field. At 1.1 m/s, the number of plants per sample ranged from 4 to

30, which was higher than at 1.6 m/s and 2.2 m/s, indicating a negative correlation between sowing speed and plant count. In the orthomosaic cutouts, fewer plants were counted due to overlap, affecting the accuracy of manual counts (Table 1). This suggests that higher sowing speeds may cause seeds to fall unevenly, impacting plant emergence and distribution.

Table 6 - The Mean Absolute Error (MAE) between the number of plants estimated in the orthomosaic cut-outs and the number of plants counted manually in the field and in the orthomosaic cut-outs for each vegetative stage.

Growth Stage	Sowing speeds (mph)	MAE (compare by number of plants in the field)	MAE (number of plants in the orthomosaic cut-outs)
VC	3	0.333	0.025
VC	4	0.366	0.038
VC	5	0.382	0.102
V1	3	0.550	0.069
V1	4	0.561	0.113
V1	5	0.590	0.116
V2	3	0.598	0.176
V2	4	0.629	0.186
V2	5	0.659	0.239

Data collected at various growth stages allowed for a comprehensive assessment of soybean plant density. The Green Leaf Index (GLI) was the most effective vegetation index for plant count estimation, showing the lowest MAE across all stages: VC (MAE = 0.057), V1 (MAE = 0.096), and V2 (MAE = 0.195). The accuracy of plant count estimates decreased with advancing growth stages, with the highest accuracy at the VC stage ($R^2 = 0.92$) and lowest at the V2 stage ($R^2 = 0.46$). This decline is due to increased plant overlap at later stages, complicating individual plant identification.

Accurate plant counting is challenged by overlapping plants and uneven emergence (García-Martínez et al., 2020). This study highlighted the impact of phenological stages and sowing speeds on plant count accuracy using orthomosaic cutouts. Higher sowing speeds and advanced growth stages decreased accuracy due to increased overlap (Kurachi et al., 1989). Optimal image acquisition times and sowing speeds are crucial for minimizing errors (Luna and Lobo, 2016; De Souza et al., 2017).

Overlapping leaves and contact between plants in later growth stages reduced the visible area for individual identification, leading to underestimation of plant counts (Keller et al., 2018; García-Martínez et al., 2020). Early stages (VC) showed lower error rates, indicating better precision. However, early-stage imaging might face challenges due to lower plant emergence and smaller plant size, complicating identification.

This research underscores the importance of selecting appropriate phenological stages and sowing speeds for accurate plant count estimation. Incorporating vegetation indices and UAV-based image processing can enhance accuracy, though challenges like overlap remain significant (Ranđelović et al., 2020). Accurate plant population estimates are vital for assessing emergence uniformity and overall productivity, with implications for current and future crop management.

The findings suggest that while the current methodology is robust, improvements are needed to address limitations such as early-stage overlap in dense plant populations. This approach, although focused on soybeans, can be adapted for other crops, considering specific growth characteristics to optimize estimation accuracy.

5. Conclusion

This study explored how soybean phenological stage and sowing speed impact plant number estimation. By integrating these factors, correlations between estimates from orthomosaic cutouts and actual field observations were established. Results underscore the critical importance of carefully selecting phenological stages and optimal image capture times, considering specific environmental conditions like sowing speed.

The VC stage and a sowing speed of 1.1 m/s showed superior accuracy due to increased vegetation overlap as plants mature, diminishing estimation precision. Higher speeds led to decreased homogeneity, affecting area coverage and potentially resulting in plant overlap. Despite these challenges, manual counts via orthomosaic cutouts achieved high accuracy at the VC stage and 1.1 m/s speed.This research deepens our understanding of soybean phenological stage, sowing speed, and plant number estimation in orthomosaics, paving the way for future studies and practical applications in agriculture.

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