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Establishment of a Canola Emergence Assessment Methodology using Image-based Plant Count and Ground Cover Analysis

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Abstract.

Manual assessment of emergence is a time-consuming practice that must occur within the short time-frame of the emergence stage of canola (Brassica napus). Unmanned aerial vehicles (UAV) may allow for a more thorough assessment of canola emergence by covering a wider scope of the field in a more timely manner than in-person evaluations. This research aimed to calibrate the relationship between manual emerging plant population counts and UAV imagery-based emergence measurements. The field trial took place at the University of Saskatchewan Kernen Research Farm, SK, Canada in the 2021 growing season. The experiment used an RCBD study combining six row spacing treatments and eight seeding density treatments to factor in growth variability. At emergence, the two center rows of each plot underwent a manual plant population count. The same day each plot was imaged from the height of two meters with a Mavic 2 Pro UAV using a RGB camera. The low altitude, high resolution imagery was used to calculate emergence ground cover using the excess green (ExG) index. The UAV imagery was also used in plant population counts derived from deep learning software. Several model architectures using different sized models were compared. Accuracy of count and model efficiency were used to select the model to be applied to the whole dataset of images for the generation of plant population counts. Comparing emergence ground cover to computer generated and manual emergence plant population counts may express the value of using UAV imagery in emergence scouting and the opportunity for this imagery to be applied in precision agriculture.

Keywords.
UAV, Unmanned aerial vehicle, low altitude imagery, high resolution imagery, subsample imagery, plant population count, ground cover, crop emergence measurement, canola, precision agriculture

Introduction

A gap in the current models of precision agriculture takes place at the emergence stage of a crop, as there is a lack of field wide data being collected. Industry standard for measuring canola emergence can be subject to human error and is biased by both the ability to access subsample sites and the number of subsamples collected (Sankaran et al., 2015). An alternative is to use UAV imagery to efficiently survey a large number of subsamples across a field and apply computer-based plant counts and ground cover values to provide producers with unbiased usable information for early growing season decision making (Li et al., 2019). The objectives of this research were to (1) calibrate the accuracy of UAV subsampling at canola emergence by applying imagery of different plant densities and (2) determine whether computer-based plant counts or ground cover measurements are more accurate at representing plant population emergence.

Materials and Methods

This research took place on a previously established canola row spacing study at the University of Saskatchewan Kernen Crop Research Farm (52.158201°N, 106.520850°W). To factor in growth variabilities, the study design combined six row spacing treatments and eight seeding density treatments in a Random Complete Block Design (RCBD) with four replicates of the 12 m^2 plots. The site was located within the dark brown soil zone with fine with clay to clay-loam textured soils. The surface slope was 0.5-2%, and the agricultural capability of the area has moderate limitations (Class 2) according to the Saskatchewan Soil Information System (SKSIS).

The plant population in the two center rows of each plot were manually counted at emergence, when seedlings were at the cotyledon to first-leaf stage on June 1, 2021. The same day, each plot was imaged from a height of two meters with a DJI Mavic 2 Pro UAV using a visible-light RGB camera. An image that accounted for 1 m x 1.5 m of the plot was taken as a subsample of each plot. The manual counts provided a ground truth of the industry standard emergence evaluation for the image-based ground cover evaluation with the UAV imagery.

The raw RBG images were processed using a model pipeline created in ArcGIS Pro to determine ground cover percentage. Within the pipeline, the red, green, and blue bands were separated through a raster iterator, then in a raster calculator the Excess Green Index (ExG) was applied [1] to the individual bands, the output was then extracted and reclassified as a new raster layer. The pixel count from the extracted ExG layer was used to calculate the ground cover percentage of each plot. ExG was the chosen vegetation index for this research as it was the most applicable index that could work with the limited three available bands from a true colour image. The raw RGB imagery was also processed through deep learning model architectures to train, validate, and test the model counting of canola seedlings. Annotations of canola seedlings by hand took place on 20% of the dataset. Three models were trained and applied to the dataset to compare model counting consistency and a mean model plant count was calculated from the results. These models identified canola seedlings at a 0.5 confidence level to count them. An optimum confidence level was found to be at 0.62 when compared to the annotated images, and a second count was taken at this confidence level and a mean plant count calculated. The computer-based plant population counts were then compared to the ground cover percentages and manual plant counts for analysis.

$$ExG = 2 * G - R - B \tag{1}$$

Where: ExG = Excess Green, G = Green waveband, R = Red waveband, B = Blue waveband.

Results and Discussion

When analyzed, the three models for the computer-based plant population count were all found to be highly correlated (r=1.00), and therefore the mean value of the computer-based plant counts was used for further analysis. The optimum confidence level (0.62) computer-based plant count was applied in the scatter plots to represent the computer-based plant counts as it had plant population numbers most closely related to the annotated plant population numbers. Manual plant counts were most highly correlated with image-based ground cover percentages (r=0.75), but also significantly correlated with the computer-based plant count (r=0.70) and the optimum confidence computer-based plant count (r=0.69) (Figure1). Ground cover and computer-based plant counts at both confidence levels having stronger correlations than those with the manual plant population count (r=0.89, r=0.88, respectively), could be due to the number of volunteer canola seedlings that were visible between the planted rows. The ground cover ExG raster layer and the plant population counting computer models both included volunteer canola seedlings outside of the rows

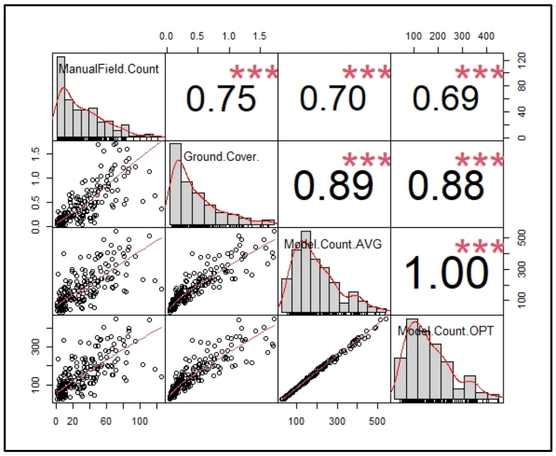

Fig 1. Correlation Chart of the relationships between a manual plant population count (plants/m^2), image-based ground cover (%) for an area of 1.5 m^2, and computer-based plant count (plants/ 1.5m^2) averaged across the three models at a confidence level of 0.50 and at the optimum confidence level of 0.62. Histograms of each variable are on the diagonal, with their correlated scatter plots to the left and correlation coefficient values (r) on the right.

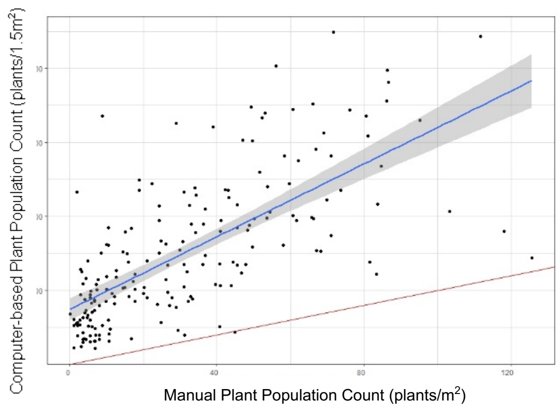

Fig 2. A scatterplot of manual plant population count (plants/m^2) and computer-based plant counts (plants/ 1.5m^2) averaged across the three models at the optimum confidence level of 0.62, with a regression line in blue with standard error in gray shade. The theoretical linear relationship of 1:1 is shown in red.

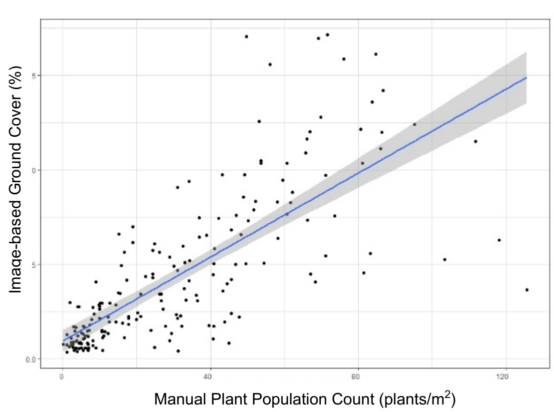

Fig 3. A scatterplot of manual plant population count (plants/m^2) and image-based ground cover (%) for an area of 1.5 m^2, with a regression line in blue with standard error in gray shade.

which were counted manually. This, along with the knowledge that each image covered a 1.5 m^2 area while being compared to a 1 m^2 area of manually counted plants would assist in the explanation of why the regression line is much higher than the theoretical linear relationship (Figure 2). It can also be seen that ground cover and the computer-based count relate very similarly to manual plant counts, but with less error in the lower ground cover values. Increased error with increased plant populations could also have to do with seedling overlap resulting in object occlusion that was difficult for the computer models to differentiate. While volunteer canola was counted, other weeds with unique leaf shapes were not included in the counts. Therefore, the over estimation that took place in this trial would not be of such concern when imaging in a field as plants between rows contribute to yield as well, but it does cause difficulty in trial plant counts. An area of future research could include the addition of row lines so that only those plants within the crop row are included in the population count.

Conclusion

The results suggest that image-based ground cover and computer-based plant counts could both be applied to measure canola at emergence, as they are both highly correlated with manual plant population counts. While over estimation occurred in the trial, this error would be less evident in a field environment. Preliminary results for the computer models differentiating between canola and other weed seedlings was favorable, as well as its ability to recognize canola from cotyledon to two-leaf stage. These early findings show promise in the ability to apply precision agriculture at the emergence stages of a canola crop.

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