Canola Agronomic Research Program (CARP)
FINAL REPORT

The Final Report should fully describe the work completed for the year and note the personnel involved. It should also note any deviations from the original plan and next and/or corrective steps as may be required if deviations are noted. A complete statement of expenses should be included. In the event of major changes within the budget, supporting notes should be included. The report should capture a complete summary of activity for the final year and an overview of the entire project.

Project Title: How does in-row seed spacing and spatial pattern affect canola yield?

Research Team Information

Lead Researcher:		
Name	***Institution***	***Project Role***
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Project Start Date: March 30, 2018 **Project Completion Date: March 31, 2023**

Reporting Period: April 1, 2022 to March 31, 2023

CARP Project Number: 2018.41

Instructions: This Final Project Report shall be completed and submitted on or about March 31st of the fiscal year that the agreement is in effect (upon completion of the project). The Lead Researcher of the project in question shall complete and submit the report on behalf of his/her complete research team.

This Report is a means by which to provide a detailed account upon completion of the project.. Final project financial reporting should be provided at this time.

The following template is provided to assist you in completing this task. Please forward the completed document electronically to the CCC contact listed below.

In addition, a Final Extension Report is due upon completion of the project, maximum 2-3 pages, to be used for publication on the Funders' websites and in the *Canola Digest*. Content will be used in extension material, for consumers and/or industry. Include an Executive Summary, brief project description, key findings and conclusions (with a summary graph/table or supporting image for the project), translation of key findings into best management practices and/or relevance to the canola sector and future research, and funding acknowledgment as determined in the grant award letter. The Final Extension Report is intended to support messaging to all audiences. Information needs to be clear, concise and in "grower-friendly" language.

Please include the funding acknowledgements outlined in your research agreement in all deliverables (publications, presentations, etc.) from this project.

1. Date of completion & status of activity (please check one)

Date of completion: March 31, 2023 (change if require an extension)

_____ Ahead of Schedule _____ On Schedule __Yes___Behind Schedule _____ Completed

Comments:

2. Abstract/Summary - Maximum of one page. This must include project objectives, results, and conclusions for use on the Funders' websites. (refer to template)

This research found that canola yield is maximized when seeding rate and row spacing result in the longest duration of vegetative ground cover. It also confirmed that existing recommendations to establish 5 – 8 seedlings per square foot with row spacings of 12" are adequate to achieve maximum yield.

The overall hypothesis of this research is that optimal seeding rate and row spacing affect seed yield in canola by maximizing the ground cover through the growing season. To test this hypothesis the following sub-objectives were tested:

Objective 1: Determine plant distribution, survival, branching, ground cover, and yield in response to row width & seeding density.

Objective 2: Develop and apply image analysis techniques to track space occupied by individual plants over time in different planting arrangements.

Objective 3: Study and validate plant growth responses to planting arrangements through simulation modeling.

A replicated, factorial field experiment that varied seeding rate and row spacing over a wide range was used. This research was conducted in small plots (2 x 6 m) using equipment similar to field scale equipment. It was conducted at Saskatoon (Dark Brown Soil Zone, semi-arid climate) and Carman (Black Soil Zone, sub-humid climate) from 2019 – 2022.

The growing conditions during these field trials resulted in below optimal seed yield in canola and may have influenced the results. This was due to drought and heat stress that occurred at both the Saskatoon and Carman locations. Despite these stresses and sub-optimal yields we believe these results are still valid as plant population effects often have greater proportional effects in dry years.

To maximize yield in canola growers should seed at least 60 seeds /m2 (5.5 seeds/ft) and have row spacing of 30 cm (12") or less. Canola was able to compensate for low seeding rates by increasing branching and number of pods but this delayed flowering. The row spacing effect was minimal compared to seeding rate however wider row spacings always trended to lower maximum yields than narrower row spacing.
Crop yield in canola is highly associated with the space that the crop canopy occupies over time. The highest yielding treatments were the ones that most rapidly achieved and maintained full canopy coverage. The practical agronomic message of this model is that canola yield is not able to compensate for reduced ground cover from poor stands. To manage canola for highest seed yield requires agronomic practices including seeding rates and row spacings, that result in rapid canopy closure.

3. Introduction – Brief project background, rationale, and objectives.

The study examine how the canola canopy develops with varied planting arrangements through field experimentation and simulation modeling, with the goal of understanding crop productivity. To facilitate study of plant growth in different arrangements over time, new methodologies will be developed to track and quantify canola plant sizes using UAV and ground-based images.

Canola is Canada's most valuable crop, generating one-quarter of all farm cash receipts. Canola stands are often below the recommended 45 plants m^{-2} threshold to maximize yield, but farmers are reluctant to increase planting densities due to the high cost of hybrid canola seed. In previous studies, narrow rows (20-30cm) and uniform intra-row spacing increased crop yield when a constant planting density was used. Thus, we hypothesize that the economic planting density of canola will be lower than the current recommendation of 45 plants m-2 if seeds are arranged optimally.

Currently farmers interested in seeding canola with uniform intra-row spacing use wide row planters (40-100cm) designed for seeding corn and soybean. No equipment is currently capable of varying the row width of uniformly planted canola to study the combined effects of row width, uniformity, row orientation, and seeding density. Furthermore, while there have been empirical studies of canola row width and planting uniformity on yield, none of these studies were of high enough spatial or temporal resolution to track individual plant responses to their neighbours over time. We aim to further previous studies by Optimizing canola spatial relationships. This model will enable prediction of canola survival, growth and yield responses to simulated plant arrangements that are not currently possible to test in the field. To develop a model of this nature, information is required of how the proximity and relative size of neighbouring plants influences the fate of each individual canola plant as the crop grows. While older studies of the Asteraceae family have tracked plant survival outcomes in response to area occupied, neighbour size, and cotyledon opening time, no similar studies exist for canola. Furthermore, the effects of the changing canopy light environment on floral branching as the canola crop grows are ambiguous and require further investigation to understand how canola will respond to simulated planting arrangements.

The study will consist of three field experiments and one growth chamber experiment, which will generate varying inter- and intra-row distances between plants, and canopy light environments. The goal of testing these different variables is to elicit different canola growth responses that can be quantified and attributed to spatial and environmental cues. These experiments will form the basis for UAV and ground-based imagery that will be used to develop automated techniques to track and quantify individual plant area, volume, and branching. These image analysis techniques will then be applied to the experimental images to study individual plant responses to their neighbours and light environment as the canopy grows. Imagery data will be used to develop and validate simulation models of canola seed survival, plant and canopy development in order to predict the most efficient planting arrangements. The results will be used to improve seed distribution with CNH Industrial, an industry leader in seeder technology. This will allow canola growers to seed at lower planting densities than are currently recommended without sacrificing crop yield.

4. Methods – Include approaches, experimental design, methodology, materials, sites, etc. Major changes from original plan should be cited and the reason(s) for the change should be specified.

To overcome the challenges of studying canola planting arrangement we propose an approach that combines direct experimentation to elicit different plant growth responses, with modeling to simulate arrangements that cannot be tested in the field. Image analysis techniques will be developed in order to track plant and canopy growth in images collected using UAVs. Our combined approach of field experimentation and simulation modeling will allow us to identify efficient planting arrangements, including those that may not currently be possible to test in the field. It will also contribute to the fundamental understanding of processes affecting plant development, morphology, interaction with the environment, and yield, and determine optimum canola phenotypes for canola breeders to select for. We will Identify efficient planting arrangements for canola production by addressing the following sub-objectives:

OBJ 1: Determine plant distribution, survival, branching, ground cover, and yield in response to row width, planting uniformity, seeding density, light quality and intensity

OBJ 2: Develop and apply image analysis techniques to track space occupied by individual plants over time in different planting arrangements

OBJ 3: Study and validate plant growth responses to planting arrangements through simulation modeling.

The experimental site, study design, and data collection

The experiment was conducted at the Saskatoon, Saskatchewan and Carman Manitoba Canada in 2018 to 2022. The trial used the commercially available canola variety (Ex-Dekalb -TFLL 21SC), and it was seeded in the spring of each year. The field design was a two-factor factorial split-plot design with four replicates (Figure 1). The trial has row spacing (main plot factor) and seeding density (subplot factor) as factors influencing the growth variability associated with the ground cover accumulation and yield. The row spacing had six different factor levels 15, 30, 45, 60, 75, and 90 cm in Saskatchewan and 19, 38, 57, and 76 cm in Manitoba which were randomised within each block. The seeding density had eight different factor levels that are 5, 10, 20, 40, 60, 80, 100, and 140 targeted plants per square meter randomised within each main plot factor. Each pass (Figure 1 rows) corresponds to the main-plot factor and randomly allocated seeding densities in each plot within the pass correspond to the subplot factor. Canola emergence was manually assessed by counting all the plants in the two centre rows for the entire plot length at the cotyledon stage as well as the one to two leaf stages. Canola grain yield was determined by harvesting one or two center rows with a plot harvester to avoid the edge effect influence on the final harvest.

Intensive Harvest component analysis

For this 2019 year at Carman and Saskatoon, the yield component data were collected close at maturity. In individual plots, 5 plants sample were randomly selected to obtain the yield component data which include number of branches plant^{-1}, number of siliques plant^{-1} and thousand seed weight (TSW) and phenological traits like biomass, start of flowering and end of flowering. The number of branches was collected in two of the four-site years. This data was collected by counting the number of branches on the 5 plant-sampled for biomass data, including the main stem from individual plots. The number of siliques per plant was collected in two of the four-site years. This data was collected by counting the number of siliques present on 5 plants collected in individual plot.

TSW was collected only in Kernen location in 2018 and 2019. The TSW data was collected from seed yield by weighting one thousand clean seeds in individual plots. It was measured in grams.

Start of flowering data was collected at all of the four-site years. The start of flowering was recorded on the day when fifty percent of plants had begun flowering in individual plots. It was measured in Julian date. End of flowering data was collected in all of the four site years. This data was recorded on the day when ninety percent of plants had begun to end flowering in individual plots. It was measured in Julian date.

Individual plant biomass data was collected in Kernen 2019, the biomass sample was collected prior to seed harvest at physiological maturity. Biomass was determined by randomly collecting 5 plants from individual plots and bagged. The samples were air-dried to avoid damaging the seeds with heat. About a week later, the plant was weighed.

The relationship between row spacing, seeding rate, and its interaction with the yield components was first analyzed using Analysis of Variance (ANOVA) across all site-year. We considered the generalized additive mixed (GAM) model for further analysis. Generalized additive mixed (GAM) models were used to determine the effects of row spacing, seeding rate, biomass, start of flowering, end of flowering, thousand seed weight, number of siliques per plant, and number of branches per plant. The GAM model was fit for this study using the R program for statistics (Version 1.3.1056) and the gam function from mgcv package (Wood, 2017; R Development Core Team, 2019). GAM model was selected because, unlike other methods, it gives a modified solution when your model includes nonlinear effects. GAM models were fit for each response variable. Replication was included in all models as a random factor to account for the replication effect within each site to filter experimental noise.

We used the function 'AIC', Akaike's Information Criterion (AIC) is used to compare different possible models to select the best fit model. Row spacing and seeding rates were considered continuous predictors (fixed factors) and replication was considered the random effect.

Field imaging

Figure 1 shows the ariel view of the study site. We used a DJI Matrice 600 (SZ DJI Technology Co., Shenzhen, China) Unoccupied Arial Vehicle (UAV) to mount imaging sensors. A MicaSense multispectral camera (AgEagle Sensor Systems Inc., Seattle, Unites States) was capable of one capture per second of 12-bit RAW images. The camera captured five different electromagnetic regions of the reflectance, including blue (475 nm centre, 32 nm bandwidth), green (560 nm centre, 27 nm bandwidth), red (668 nm centre, 14 nm bandwidth), red edge (717 nm centre, 12 nm bandwidth), and near-infrared (842 nm centre, 57 nm bandwidth). The UAV followed a pre-set flight path at 20m above ground level to reach the ground sampling distance of ~ 1.36cm. The sensor captured images at nadir with 70% forward and side image overlap. The experimental layout had six ground control points (GCPs) for geo-referencing imagery. All GCPs were permanently mounted at the field to avoid image-to-image geo-referencing disparities and were manually geo-referenced using Trimble GeoExplorer 2008 Global Positioning System (Trimble Inc., Sunnyvale, California, United States). The study site was imaged weekly (weather permiting) to capture crop growth and phenological development over time.

Image processing and thresholding

Images were preprocessed in Pix4Dmapper photogrammetry software (Pix4D Inc., California, United States). The stitching process aligned images based on the specified forward and side overlap percentages and common features to generate the geo-referenced whole-site orthomosaics (World Geodetic System 1984/WGS84). We used physically mounted Micasense reflectance panels as geo-reference points to implement geometric calibration. The same panels were used to implement radiometric calibration to enhance spectral consistency between images acquired on different dates throughout the season. All final stitched image pixels contained reflectance that was used for further analysis.

Further processing and the analysis of images occurred in ArcGIS 10.5 software (ArcGIS Desktop: Release 10.5, Environmental Systems Research Institute, Redlands, CA). The plot segmentation was manually implemented for each image date individually to improve the data extraction accuracy of target plots. Our study used variable-size plots based on the row spacing of the plot to avoid the edge effect from plants growing on edge rows. The plot width was calculated as a function of row spacing (row spacing *(number of rows -2)). The calculation of the Visible Band Difference Vegetation Index (VDVI) distribution across the experimental layout was implemented in the ArcGIS 10.5 software environment. Literature suggests that the thresholding at 0.00 is sufficient for green vegetation extraction. However, the thresholding at zero likely increased the shadow-picking risk in our analysis. Therefore, the VDVI thresholding was done at 0.1 across all image dates to extract the ground cover while reasonably controlling the influence of shadow-picking. The ground cover estimates were converted to percent ground cover as a normalisation process to make comparisons reasonable across different plot sizes and image dates. Each plot's cumulative ground cover model was based on ten image dates acquired throughout the growing season.

$$\text{Visible Band Difference Vegetation Index } (VDVI) = \frac{2 * \rho_{green} - \rho_{red} - \rho_{blue}}{2 * \rho_{green} + \rho_{red} + \rho_{blue}}$$

2.3.1 Experimental Design

This research took place on previously established canola-based studies at the University of Saskatchewan. To factor in growth variabilities, in 2021 the study design combined six row spacing treatments and eight seeding density treatments. An RCBD experiment design was used, with four replicates and 192 -12 m^2 plots in total. Two site-years of the 192-plot trial were planted adjacent to one another, with perpendicular seeding directions. In 2022, the row spacing trial consisted of five row spacing treatments and eight seeding density treatments, with four replicates and 160 -12 m^2 plots in total. A second canola-based trial was also imaged, this was a RCBD combined with a specialized systematic design nitrogen-rate canola trial. It had 11 treatments with 20 replicates for a total of 220 -22.5 m^2 plots.

3.3.2 Site Description

The canola trials took place at the University of Saskatchewan Kernen Crop Research Farm with the 2021 site-year locations: Brown (52.158201°N, 106.520850°W) and Nasser (52.158201°N, 106.520521°W) (Figure 1). The 2022 site locations: Nasser2 (52.165492°N, 106.514169°W) was the row spacing trial and LowN (52.158267°N, 106.525754°W) was the nitrogen-rate trial. The sites were located within the dark brown soil zone, with a Class 2 slope (0.5-2%), and had a Class 2 agricultural capability (*SKSIS*, n.d.). The surface texture was fine with clay to clay-loam soils on this glaciolacustrine plain parent material. The salinity levels were very slight (Class 1) and there was some alkaline soils with a pH class of C5 (*SKSIS*, n.d.).

a)

b) **c)**

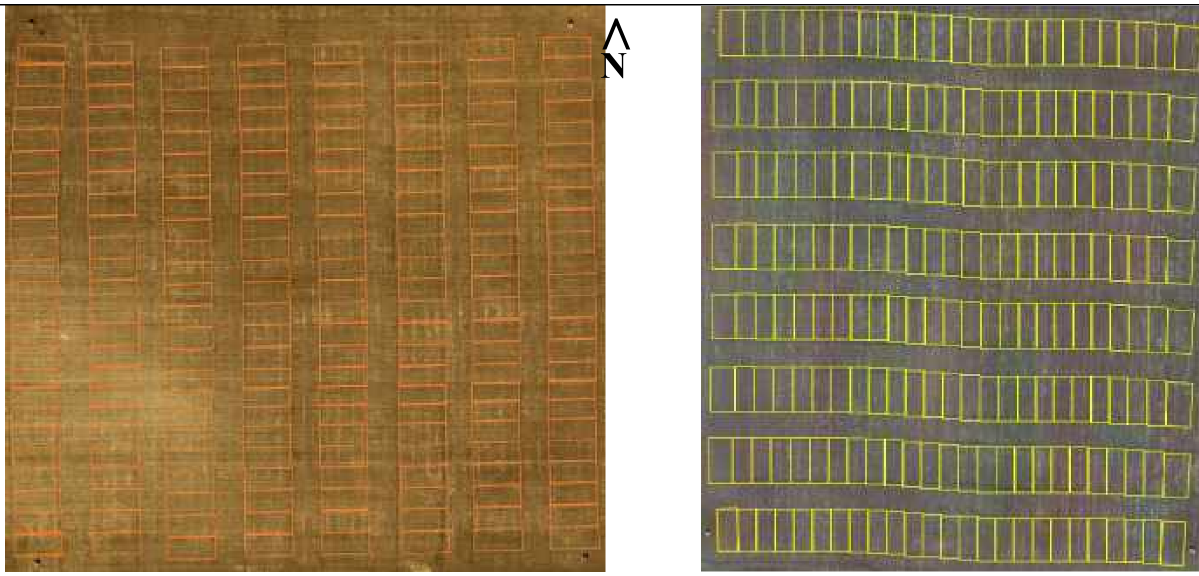

Figure 2. 1. a) A map showing the University of Saskatchewan Kernen Crop Research Farm in reference to the city of Saskatoon, SK. b) An othomosaic of the Brown site of the canola-based trial taken on June 1, 2021 with individual plots outlined in orange. c) An othomosaic of the Nasser site of the canola-based trial taken on June 1, 2021 with individual plots outlined in yellow.

2.3.3 Experimental Methodology

In the row spacing trials, the two center rows of each plot underwent a manual plant population count at emergence, when seedlings were at the cotyledon to first-leaf stage. For the nitrogen-rate trial, 1 m into the seed row at a 1 m length was counted on the front of the second and third rows and the back of the fourth and fifth rows of each plot at the cotyledon to first-leaf stage of the canola. Each plot had 6 rows. For all the trials, each plot was imaged from a height of two meters with a DJI Mavic 2 Pro UAV using a visible-light RGB camera on the same day as the manual count. This mimicked the imaging process of the waypoint surveying software that will be applied in Chapter 2 and 3, but with greater location accuracy for the smaller plots in close proximity to one another. An image that accounted for 1.5 m^2 of the plot was taken as a survey point at the center of each plot. The manual count and UAV imaging were repeated one week later to account for delayed emergence in 2021.

2.3.4 Image Processing

2.3.4a Preprocessing

Preprocessing for the point sample surveyed image sets consisted of sorting images into folders by research block ID and date imaged. The point sample image sets were then uploaded to the Canola Counter web interface to be processed.

2.3.4b Building the Canola Count model

Deep learning-based object detection networks were applied to the point sample images to determine emergence counts for the plant population. A partnership was formed with a MSc candidate from the University of Saskatchewan Department of Computer Science to train, validate, and test the counting of canola seedlings. They compared and contrasted a number of deep learning model architectures in order to determine the most suitable design to be used across the project data. Hand annotating of canola seedlings within 177 images took place in 16 image sets that were set aside to create a base model for the Canola Counter interface. This included a total of 839 images that were used for the training and testing of the Canola Counter base model. During training, the model was periodically tested on images in the validation set in order to monitor its ability to successfully detect canola seedlings in images it had not been trained on. The test set was used to establish the quality and precision of the system once the training was complete. The Canola Counter web interface that was created allowed for annotations of image sets to take place, execution of plant population estimates using the base model, training and testing of annotated images within image sets, execution of plant population estimates with image set training applied, and determination of ground cover percentage set using a filter to manually set the threshold. The ground cover percentage in the Canola Counter web interface was created using the Excess Green (ExG) vegetative index (Equation 1). A threshold can be set on each image or across an image set for what value is to be considered at minimum to be plant material. The number of pixels included in the ExG layer is then divided by the total possible number of pixels to find the percentage ground cover.

$$\text{Excess Green} = 2 * \text{Green Band} - \text{Red Band} - \text{Blue Band} \qquad [1]$$

2.3.4c CNN used to Determine Plant Population Counts

The 6 point sample image sets from the pre-existing canola trials were uploaded into the Canola Counter web interface. This included two image sets from 2021, Nasser and Brown, that were flown twice, June 1, 2021 and June 8, 2021. As well as two image sets from 2022 that were flown once each, Nasser2 on June 2, 2022 and LowN flown on June 4, 2022. Each image set had 15 total images annotated: 10 for testing, and 5 for fine-tune training of the image set. Plant population estimates were created using the baseline model for each trial. Model training was applied to each image set using the 5 annotated images. A new plant population estimate was collected after each additional image was trained to compare the results of the further fine tuning of the model. Plant population counts were gathered at two confidence threshold values for comparison: the average (0.50) and the optimum confidence value recommended by the computer science student for these image sets at (0.62). The confidence threshold being how confident the computer model is that an object is a canola seedling.

2.3.4d ExG Applied to Collect Ground Cover Percentage

Excess Green vegetation index was applied to each image of the 6 point sample image set uploaded into the Canola Counter web interface. Vegetation was separated from background at a threshold pixel value of 0.30. Pixels with values above this threshold were separated into their own class. The number of pixels in this class were divided by the total number pixels making up the image to result in the ground cover percentage of the image, presented as a decimal value (0.0 - 1.0).

<u>2.3.5 Statistical Analysis</u>

R Studio was the statistical program used for analysis, unless otherwise noted. Linear regression models were utilized to present the relationship between plant population predictions and image annotation values when the base model was applied, between plant population predictions and image annotation values when fine-tuning of the model occurred, between image annotations and manual field counts, and between plant population predictions and manual field counts. Linear regression models were graphed between plant population predictions and image annotation values after each added training image for model fine tuning from one to five to see the progression of the training process. A correlogram of manual field counts, image annotations, plant population predictions when the base model was applied, and plant population predictions when fine-tuning of

the model occurred to look for correlations between them. A correlogram was also used to determine the correlations of different models that could used as a base model.
An accuracy assessment was completed using a single-class confusion matrix to compare annotations to predictions, using Mircosoft Excel. A single-class, or binary, confusion matrix results in a F1 score statistic (Vanacore et al., 2022). This value was found by using the annotated plant bounding boxes as validation for the predicted plant bounding boxes which are the object classification. If the canola plant was in a bounding box for both the annotation and prediction it was considered a true positive. If the canola plant was in a bounding box for an annotation but was not identified as a canola plant by the prediction, then it was a false negative. If an area that was not annotated as canola with a bounding box was identified as a canola plant by the prediction, then it was a false negative. True negative values are not used in a single-class confusion matrix, because with one class it is classified as "present" or "absent" and areas where there was no canola was not bound and labeled as such but rather left as is. True positive and false positive values were used to find Precision (Equation 3). True positive and false negative values were used to determine Recall, or Sensitivity (Equation 4). Using Precision and Recall the F1 score of the single-class confusion matrix was calculated (Figure 2).

$$F1 = 2 * Precision * Recall / (Precision + Recall) \quad [2]$$

$$Precision = True\ Positives / (True\ Positives + False\ Positives) \quad [3]$$

$$Recall = True\ Positives / (True\ Positives + False\ Negatives) \quad [4]$$

Statistical modelling

The experiment was initially analysed using generalised linear mixed modelling ANOVA to determine the seeding density and row spacing effect on yield. The model specification followed the two-factor factorial split-plot design with four replicates. The random influence from the landscape was partitioned as a blocking factor to account for the influence on experimental subjects. All ANOVA models were ran in R statistical analysis platform:lme4 package (R Core Team, Vienna, Austria). Simple linear and non-linear regression was essential to the analysis illustrating the yield response with various predictive variables. The yield was specifically modelled versus the seeding rate and actual plant count to determine the seeding rate that produces 95% of the maximum yield (SR95) to compare with ground cover simulation models. The analysis was implemented in drc package in R statistical analysis platform. The asymptotic regression model is a three-parameter model using an exponential function: $\text{Yield}\ (Y) = a - (a - b)\ exp^{(-c\,X)}$, where a is the maximum attainable Y, b is Y at x=0, and c is proportional to the relative rate Y increase while X increases. Simple linear and non-linear regression was used to model the yield response with various predictive variables. Image-based percent ground cover accumulation from each plot was regressed against time (Julian date), and the integral of the function was used to calculate the area under the curve representing the cumulative ground cover. The Locally Weighted Scatter Plot Smoothing (LOESS) technique was used to develop a non-linear regression model to illustrate the ground cover phenology over time. The 2020 data was used as a training dataset to build the relationship between the cumulative ground cover and the yield. The modelled relationship was cross-validated using the 2021 independent data set to illustrate the robustness of the trained model.

5. Results – Present and discuss project results, including data, graphs, models, maps, design, and technology development.

Combined analysis of both MB ane SK data are presented. The emergence and early season growth were moderately affected by the drought conditions in certain years and trials did not respond well to the drought conditions that prevailed throughout the growing season. As a result, yields variations were expected to be much higher in the analysis.

Row spacing vs yield,

Row spacing influence on the yield is not distinct along all years in Saskatchewan (Figure 1). Manitoba field trials show a yield-decreasing trend when the spacing increases (Figure 2). A similar random trend is apparent in all years combined from Saskatchewan and Manitoba field trials, showing a decreasing trend with increasing row spacings (Figure 3).

Seeding rate vs yield

We used the Asymptotic Regression Model to demonstrate the seeding density influence on the yield. Our asymptotic regressions across all spacing categories at Saskatchewan sites indicate parallel response curves, with 0.3m, 0.45m, and 0.6m row spacing having the highest d (max yield) value (Figure 5 and Table 1). The SR95 estimates show precise results indicating seeding rates ranging from 46 to 62 seeds m^{-2}, providing sufficient plant densities to achieve 95% maximum yield. (Table 1). Similarly, Manitoba sites indicate parallel response curves, with 0.76m row spacing having the lowest max yield (Figure 6 and Table 2). The SR95 estimates show precise results indicating seeding rates ranging from 20 to 23 seeds per m^{-2}, providing sufficient plant densities to achieve 95% maximum yield (Table 2). Overall, for all site years together, the maximum attainable yield in relation to seeding rates is 1.2428 tons ha^{-1} where 95% of the maximum yield is at 42.25 seeds m^{-2} (Figure 9).

Actual plant count vs yield

A similar response pattern is also apparent between yield and actual plant counts. The asymptotic regression of Saskatchewan data shows that the maximum yield response ranges between 0.9 to 1.4 t ha^{-1}, with the lowest maximum yield reported from 0.15m, 0.75m, and 0.9m row spacing (Table 3). The SR-95 on actual plant counts ranges between 14 to 23 plants m^{-2} (Table 3). The Manitoba results show a maximum yield response ranges between 1.2 to 1.7 t ha^{-1}, with the lowest maximum yield reported from 0.76m row spacing (Table 4). The SR-95 on actual plant counts ranges between 44 to 67 plants m^{-2} (Table 4). Overall, for all site years together, the maximum attainable yield in relation to actual plant counts is 1.2635 tons ha^{-1} where 95% of the maximum yield is at 23.20 seeds m^{-2} (Figure 9).

The study observed a linear tendency ($\rho=0.4777, p\leq0.0000, R^2=0.2282$) between actual plant counts and the seeding densities used (Figure 10). The slope parameter clearly illustratess the plant's success rate of ~59% in all site years. Its about ~53% in Saskatchewan and ~ 78% in Manitoba.

ANOVA - generalized linear mixed modelling

Saskatchewan all site years generalised mixed model ANOVA showed that the interaction effect between row spacing and seeding density was not significant based on the null probability of 0.1371 (Table 5). Both main effects, row spacing ($p<0.0000$) and seeding rate ($p<0.0000$), appeared significant at 0.05 significance level (Table 5), confirming at least one level in each factor in consideration is different from another. All means of both factors are presented in Table 5, and the grouping of means refers to no significant difference between means that share the same letter. A graphical illustration of mean comparison, pair-wise assessment and contrasts is available in Figure 11 and Figure 12. Based on the mean comparison, the row spacing effect on yield is apparently random, although 0.3m and 0.6m are slightly different from the rest. The mean comparison of the seeding rate suggests a significant mean difference among the seeding rates in comparison. The results clearly highlight, irrespective of row spacing, that an adequate number of plants can easily achieve the maximum yield and the yield response is directly associated with either seeding densities or actual plant count.

Manitoba all site years generalised mixed model ANOVA analysis revealed that the interaction effect between row spacing and seeding density was not significant based on the null probability of 0.8517 (Table 6). Both main effects, row spacing ($p<0.0000$) and seeding rate ($p<0.0000$), appeared significant at 0.05 significance level (Table 6), confirming at least one level in each factor in consideration is different from another. All means of both factors are presented in Table 6, and the grouping of means refers to no significant difference between means that share the same letter. A graphical illustration of mean comparison, pair-wise assessment and contrasts is available in Figure 13 and Figure 14. Based on the mean comparison, the row spacing effect on yield is significant at Manitoba sites, and it reflects lower yields when spacing is increased. The mean comparison of the seeding rate suggests a significant mean difference among the seeding rates in comparison. The results clearly highlight, that an adequate number of plants can easily achieve the maximum yield and the yield response is tightly associated with either seeding densities or actual plant count.

Pooled analysis of Saskatchewan and Manitoba data using generalised mixed model ANOVA analysis revealed that the interaction effect between row spacing and seeding density was not significant based on the null probability of 0.7954 (Table 7). Both main effects, row spacing ($p<0.0000$) and seeding rate ($p<0.0000$), appeared significant at 0.05 significance level (Table 7), confirming at least one level in each factor in consideration is different from another. Please note that the pooled analysis of both provinces treated the row spacing as a continuous variable for all site-year assessments due to differences in factor levels between Saskatchewan and Manitoba trials. Based on the analysis, the row spacing effect on yield is significant at 0.05 significance level, and it reflects a significant slope parameter where lower yields when spacing is increased. The mean comparison of the seeding rate suggests a significant mean difference among the seeding rates in comparison. The results clearly highlight that an adequate number of plants highly influence the maximum yield and the yield response is tightly associated with either seeding densities or actual plant count.

Pass \ Row	1	2	3	4	5	6	7	8	
1	S90D140	S90D100	S90D40	S90D10	S90D20	S90D5	S90D60	S90D80	Rep-1
2	S75D80	S75D20	S75D100	S75D40	S75D10	S75D140	S75D5	S75D60	
3	S30D60	S30D10	S30D5	S30D80	S30D40	S30D20	S30D140	S30D100	
4	S15D80	S15D100	S15D10	S15D20	S15D60	S15D5	S15D40	S15D140	
5	S45D140	S45D60	S45D40	S45D10	S45D5	S45D20	S45D100	S45D80	
6	S60D40	S60D10	S60D5	S60D20	S60D100	S60D80	S60D60	S60D140	
7	S30D20	S30D40	S30D140	S30D100	S30D80	S30D60	S30D10	S30D5	Rep-2
8	S60D5	S60D100	S60D140	S60D80	S60D40	S60D10	S60D20	S60D60	
9	S15D80	S15D20	S15D40	S15D60	S15D100	S15D5	S15D140	S15D10	
10	S45D5	S45D140	S45D10	S45D20	S45D60	S45D40	S45D80	S45D100	
11	S90D100	S90D5	S90D40	S90D80	S90D140	S90D20	S90D10	S90D60	
12	S75D140	S75D40	S75D10	S75D20	S75D100	S75D5	S75D60	S75D80	
13	S15D40	S15D100	S15D80	S15D5	S15D60	S15D10	S15D140	S15D20	Rep-3
14	S45D20	S45D140	S45D40	S45D80	S45D100	S45D60	S45D10	S45D5	
15	S90D5	S90D60	S90D140	S90D20	S90D40	S90D10	S90D80	S90D100	
16	S75D40	S75D10	S75D5	S75D100	S75D60	S75D140	S75D20	S75D80	
17	S60D80	S60D100	S60D40	S60D10	S60D140	S60D5	S60D60	S60D20	
18	S30D40	S30D80	S30D140	S30D5	S30D60	S30D100	S30D20	S30D10	
19	S45D140	S45D60	S45D5	S45D80	S45D10	S45D20	S45D40	S45D100	Rep-4
20	S30D100	S30D140	S30D40	S30D20	S30D80	S30D10	S30D5	S30D60	
21	S60D20	S60D40	S60D140	S60D60	S60D5	S60D100	S60D80	S60D10	
22	S90D5	S90D80	S90D40	S90D10	S90D20	S90D60	S90D100	S90D140	
23	S75D40	S75D60	S75D5	S75D140	S75D80	S75D100	S75D20	S75D10	
24	S15D60	S15D80	S15D40	S15D10	S15D100	S15D20	S15D5	S15D140	

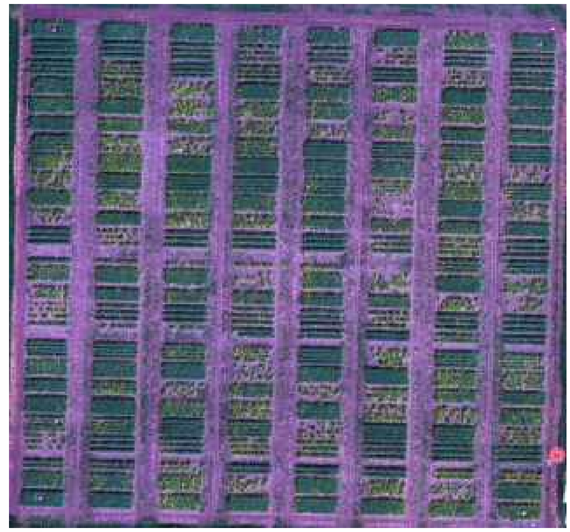

Figure 1: a) Treatment distribution layout with row spacing (15, 30, 45, 60, 75, and 90 cm) and seeding density (5, 10, 20, 40, 60, 80, 100, and 140 targets plants m^{-2}) as factors that influence spatial aspects of plant growth (2020 field trial). The field design was a two-factor factorial split-plot design with four replicates. Row spacing was the main-plot factor, and seeding density was the subplot factor according to the field design principles. The experimental layout enables us to precisely evaluate the variability associated with ground cover accumulation over time together with yield. The notation of the treatment layout S90D140 (pass-1, row-1) refers to the spacing=90cm and the seeding density=140 targeted plants per square meter b) A mid-season areal view of the field site imaged on June 29th, 2020.

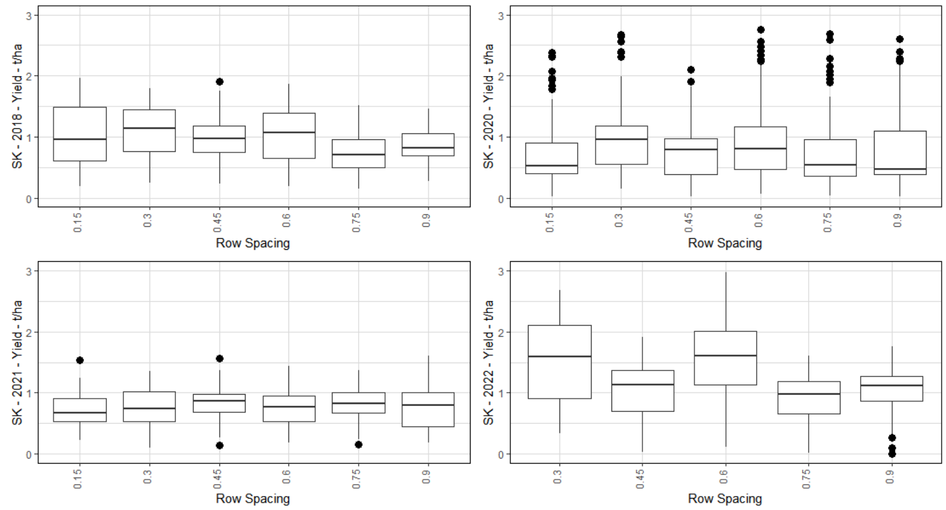

Figure 2. Canola yield distribution of among row spacing categories for Saskatchewan segregated by each year.

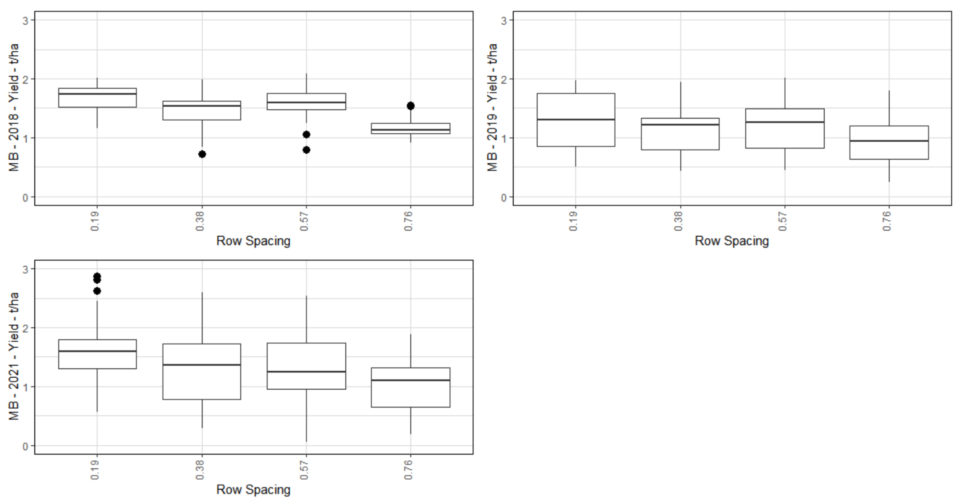

Figure 3. Canola yield distribution of among row spacing categories for Manitoba segregated by each year.

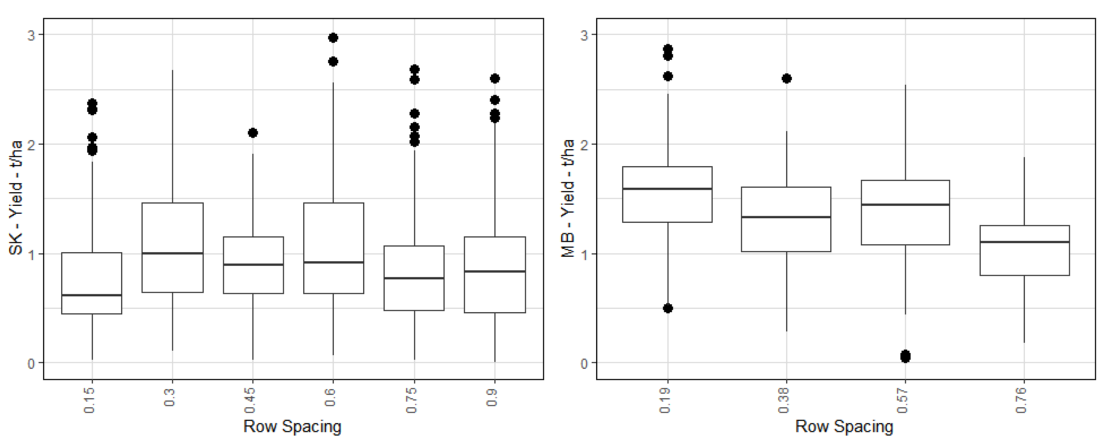

Figure 4. Canola yield distribution of all site-years among row spacing categories used in the study. SK stands for Saskatchewan, and MB stands for Manitoba.

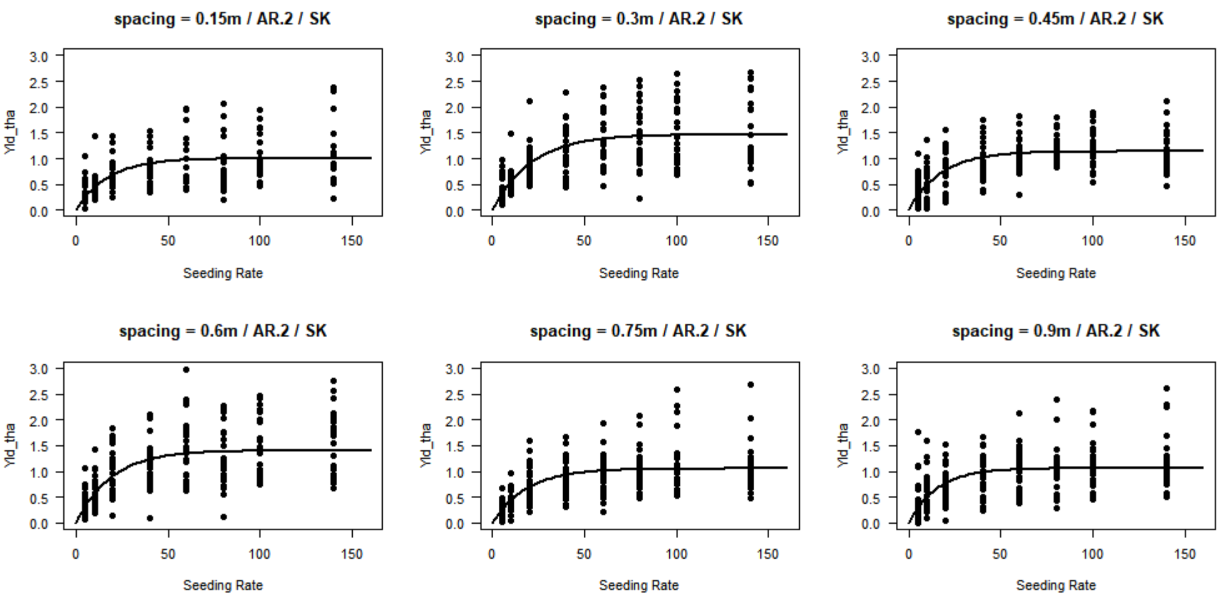

Figure 5: Yield (tons per hectare) response model against the seeding rates used in the study. Six panels represent different spacing categories. The asymptotic regressions (AR.2) across all spacing categories indicate closely parallel response curves, with max yield ranging 1-1.5 tha^{-1}. The SR95 estimates show precise results indicating seeding rates ranging from 46 to 62 seeds m^{-2}, providing sufficient plant densities to achieve 95% maximum yield. Field trial location is Saskatchewan.

Table 1: Parameter estimates of seeding rate effect on canola yield at varying row spacings. Parameters in the table: d = upper limit, e = relative rate of Y increase as X increases, SR95 = seeding rate required to achieve 95% of maximum yield. Field trial location is Saskatchewan.

	Row spacing (m)					
	0.15m	**0.3m**	**0.45m**	**0.6m**	**0.75m**	**0.9m**
d(upper limit)	1.0024***	1.4649***	1.1366***	1.4015***	1.0514***	1.0583***
e(relative slope)	17.0907***	20.9771***	17.2281***	18.9212***	18.2906***	15.2711***
SR-95	51.19	62.84	51.61	56.68	54.79	45.74

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

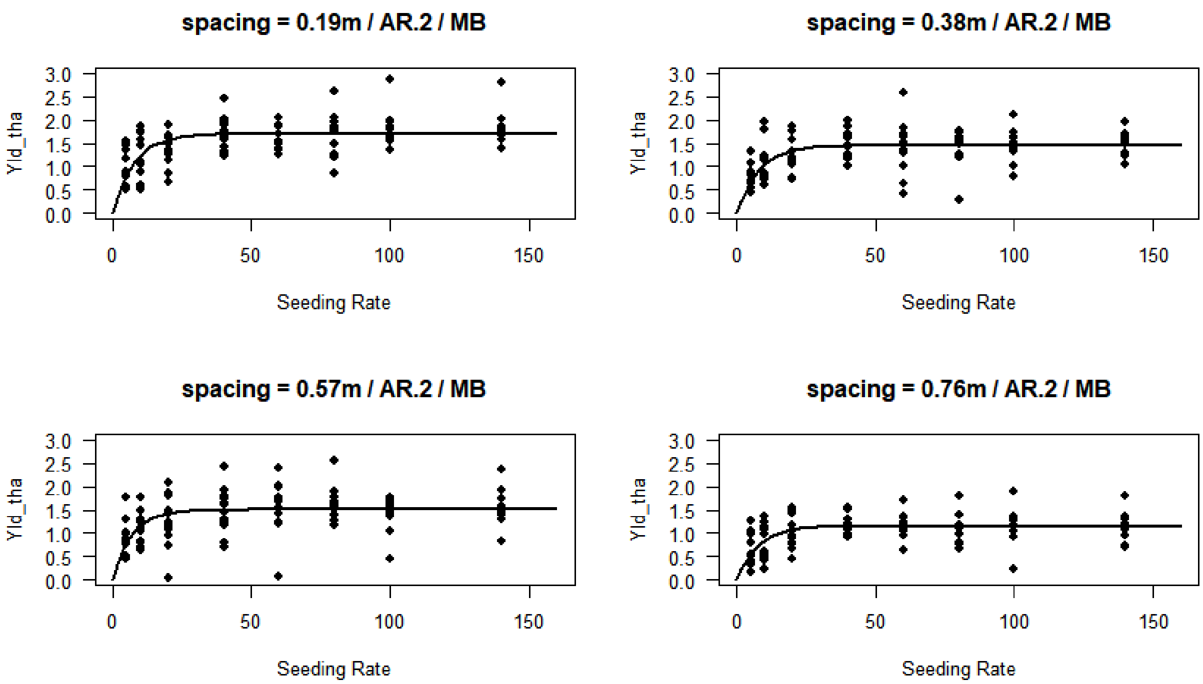

Figure 6: Yield (tons per hectare) response model against the seeding rates used in the study. Four panels represent different spacing categories. The asymptotic regressions (AR.2) across all spacing categories indicate parallel response curves, with 0.76m row spacing having the lowest max yield. The SR95 estimates show precise results indicating seeding rates ranging from 20 to 23 seeds per m^{-2}, providing sufficient plant densities to achieve 95% maximum yield. Field trial location is Manitoba.

Table 2: Parameter estimates of seeding rate on canola yield at varying row spacings. Parameters in the table: d = upper limit, e = relative rate of Y increase as X increases, SR95 = seeding rate required to achieve 95% of maximum yield. Field trial location is Manitoba.

	Row spacing (m)			
	0.19m	**0.38m**	**0.57m**	**0.76m**
d(upper limit)	1.7034***	1.4477***	1.5025***	1.1542***
e(relative slope)	7.7825***	7.6923***	6.8706***	7.4856***
SR-95	23.31	23.04	20.58	22.42

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

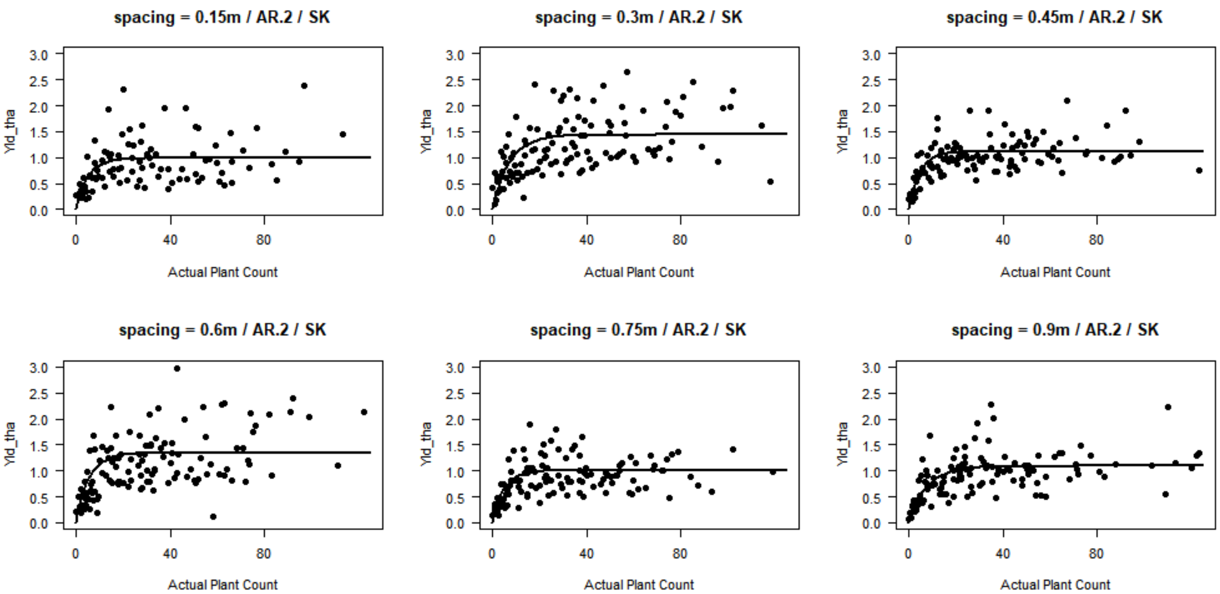

Figure 7: Yield (tons per hectare) response model against the actual plant count observed during the field season. Six panels represent different spacing categories used in the study design. The SR95 based on the asymptotic regressions on actual plant counts ranges between 14 to 23 plants m^{-2}. It shows the maximum yield can be reached by an adequate number of plants, 22 plants per m^{-2}. Field trial location is Saskatchewan.

Table 3: Parameter estimates of actual plant count effect on canola yield at varying row spacings. Parameters in the table: d = upper limit, e = relative rate of Y increase as X increases, SR95 = seeding rate required to achieve 95% of maximum yield. Field trial location is Saskatchewan.

	Row spacing (m)					
	0.15m	**0.3m**	**0.45m**	**0.6m**	**0.75m**	**0.9m**
d(upper limit)	0.9848***	1.4380***	1.1107***	1.3443***	1.0067***	1.0897***
e(relative slope)	5.0062***	7.2566***	4.6467***	5.4864***	4.9072***	7.6876***
SR-95	14.99	21.74	13.92	16.43	14.70	23.03

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

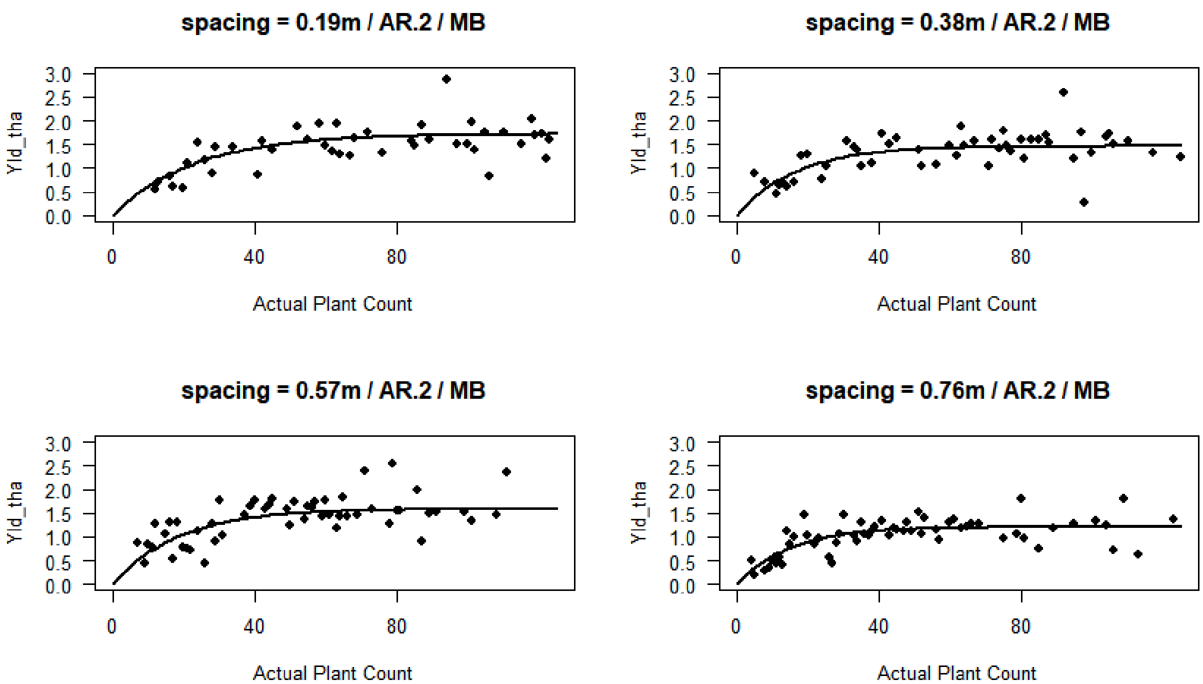

Figure 8: Yield (tons per hectare) response model against the actual plant count observed during the field season. Four panels represent different spacing categories used in the study design. The SR95 based on the asymptotic regressions on actual plant counts ranges between 44 to 67 plants m^{-2}. It shows the maximum yield can be reached by 67 plants m^{-2}. Field trial location is Manitoba.

Table 4: Parameter estimates of actual plant count on canola yield at varying row spacings. Parameters in the table: d = upper limit, e = relative rate of Y increase as X increases, SR95 = seeding rate required to achieve 95% of maximum yield. Field trial location is Manitoba.

	Row spacing (m)			
	0.19m	**0.38m**	**0.57m**	**0.76m**
d(upper limit)	1.7174***	1.4653***	1.5892***	1.2105***
e(relative slope)	22.5759**	16.5362***	18.2715***	14.7016***
SR-95	67.63	49.53	54.73	44.04

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

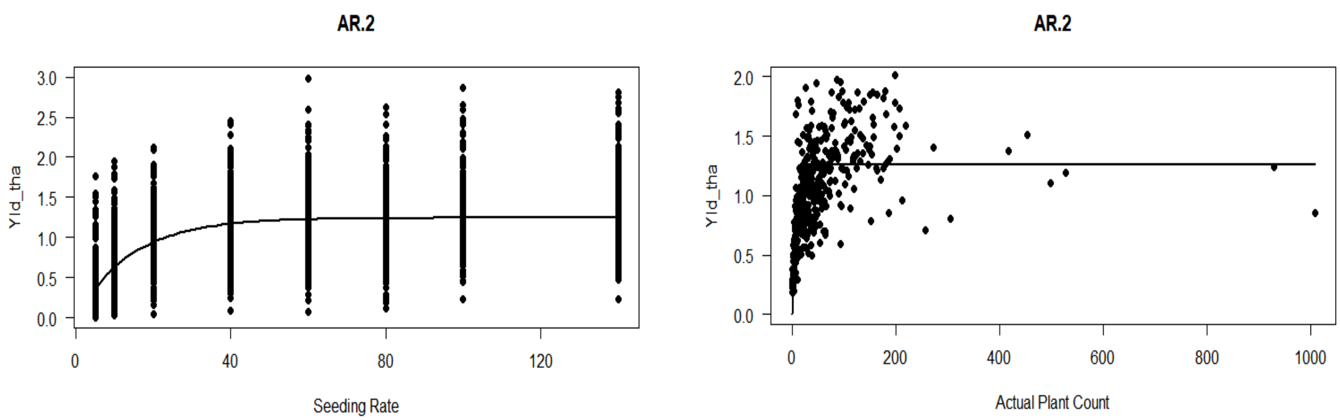

Figure 9: Yield (tons ha^{-1}) response model against the seeding rates used in the study and the actual plant count observed during the field season. The asymptotic regressions (AR.2) across both variables indicate closely parallel response curves. The maximum attainable yield in relation to seeding rates is 1.2428 tons ha^{-1} where 95% of the maximum yield is at 42.25 seeds m^{-2}. The maximum attainable yield in relation to actual plant count is 1.2635 tons ha^{-1} where 95% of the maximum yield is at 23.20 plants m^{-2}. The results are from both Saskatchewan and Manitoba field trial locations across all years.

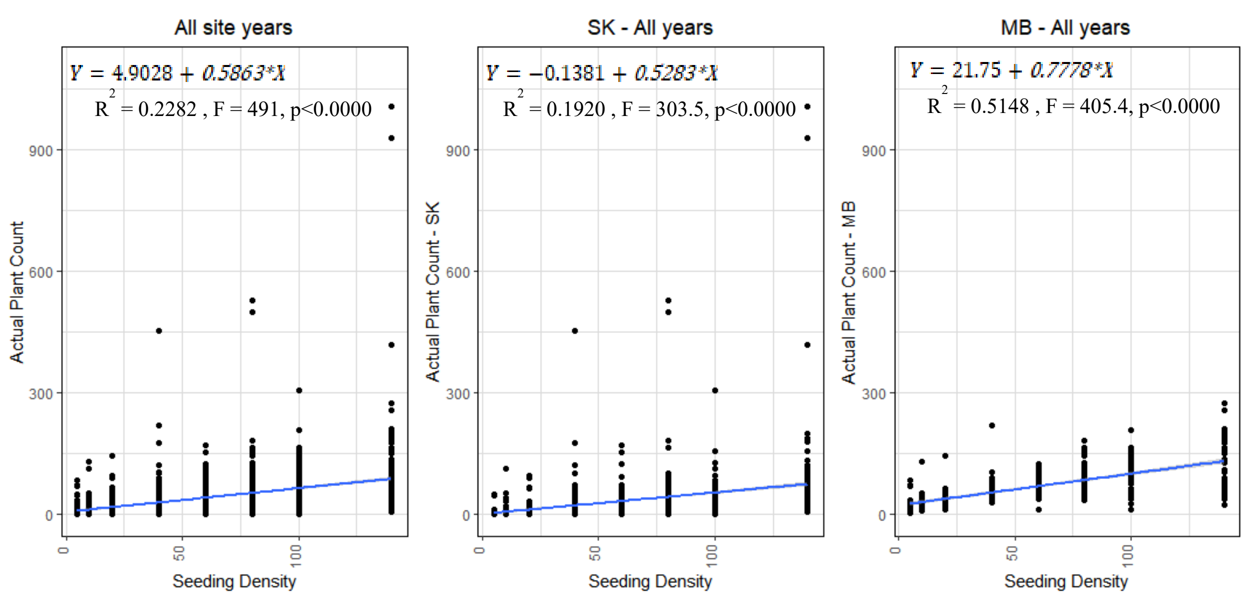

Figure 10. Trend analysis of seeding density vs actual plant count. Each panel illustrates the relationship between seeding density and actual plant count, and the linear regression between the two variables for all site years together, and each province separate.

Table 5: Analysis of variance (ANOVA) and post hoc multiple comparisons of means for canola yield for

Saskatchewan trials. The analysis of variance is based on the type-III Wald F test with Kenward-Rogers degree of freedom. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Means followed by the same letter do not differ significantly.

Factors	**ANOVA p-value**		**Fixed factor levels**	**Mean canola yield (t ha^{-1})**	**Standard Error**	**Mean comparison**
Row Spacing - RS (m)	p<0.0000	Interaction p=0.1371	0.15m	0.89	0.057	A
			0.3m	1.10	0.054	B
			0.45m	0.89	0.054	A
			0.6m	1.08	0.054	B
			0.75m	0.81	0.054	A
			0.9m	0.85	0.054	A
Seeding Rate – SR (Plnt/m^2)	p<0.0000		5 Plnt m^{-2}	0.39	0.056	A
			10 Plnt m^{-2}	0.54	0.056	B
			20 Plnt m^{-2}	0.81	0.056	C
			40 Plnt m^{-2}	0.99	0.056	D
			60 Plnt m^{-2}	1.12	0.056	E
			80 Plnt m^{-2}	1.15	0.056	EF
			100 Plnt m^{-2}	1.24	0.056	EF
			140 Plnt m^{-2}	1.27	0.056	F

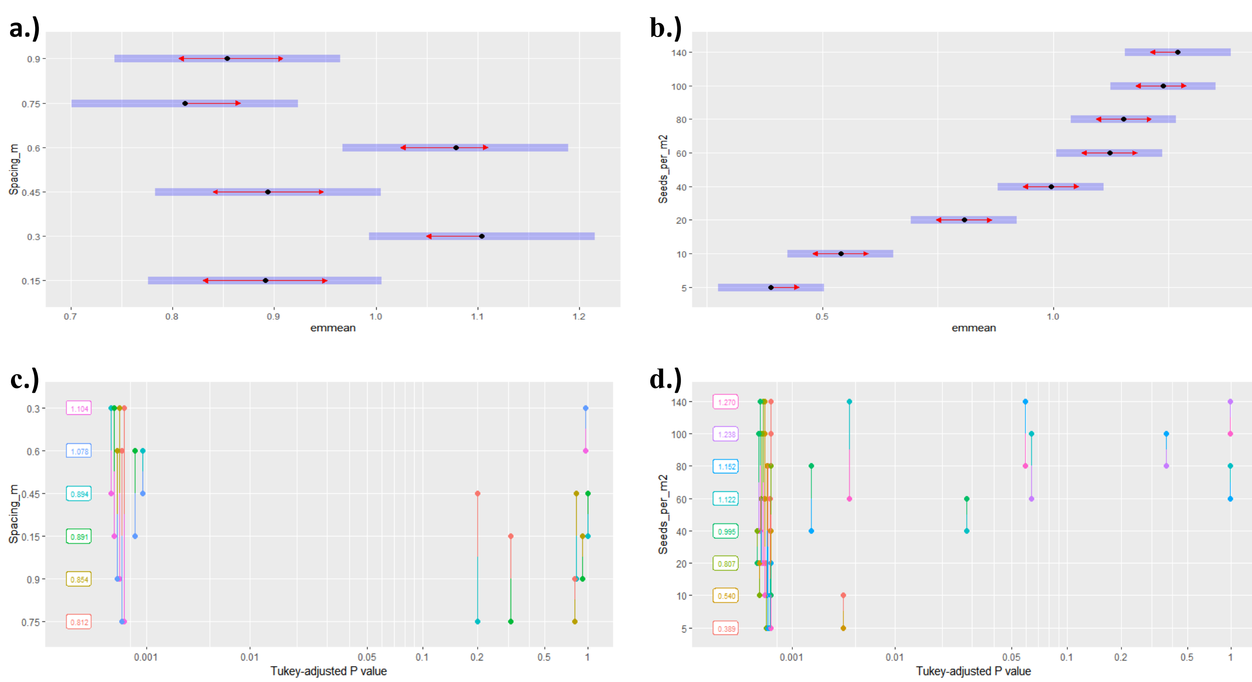

Figure 11: Post hoc multiple comparisons of means for canola yield by row spacing and seeding rate

categories. Field trial location is Saskatchewan. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Panel a.) and b.) blue bars represent confidence intervals for the means, and the red arrows compare the difference among them. If an arrow from one mean overlaps an arrow from another group, the difference is not "significant" . Panel c.) and d.) represents all pairwise mean comparisons and whose horizontal position determines the p-value of the comparison.

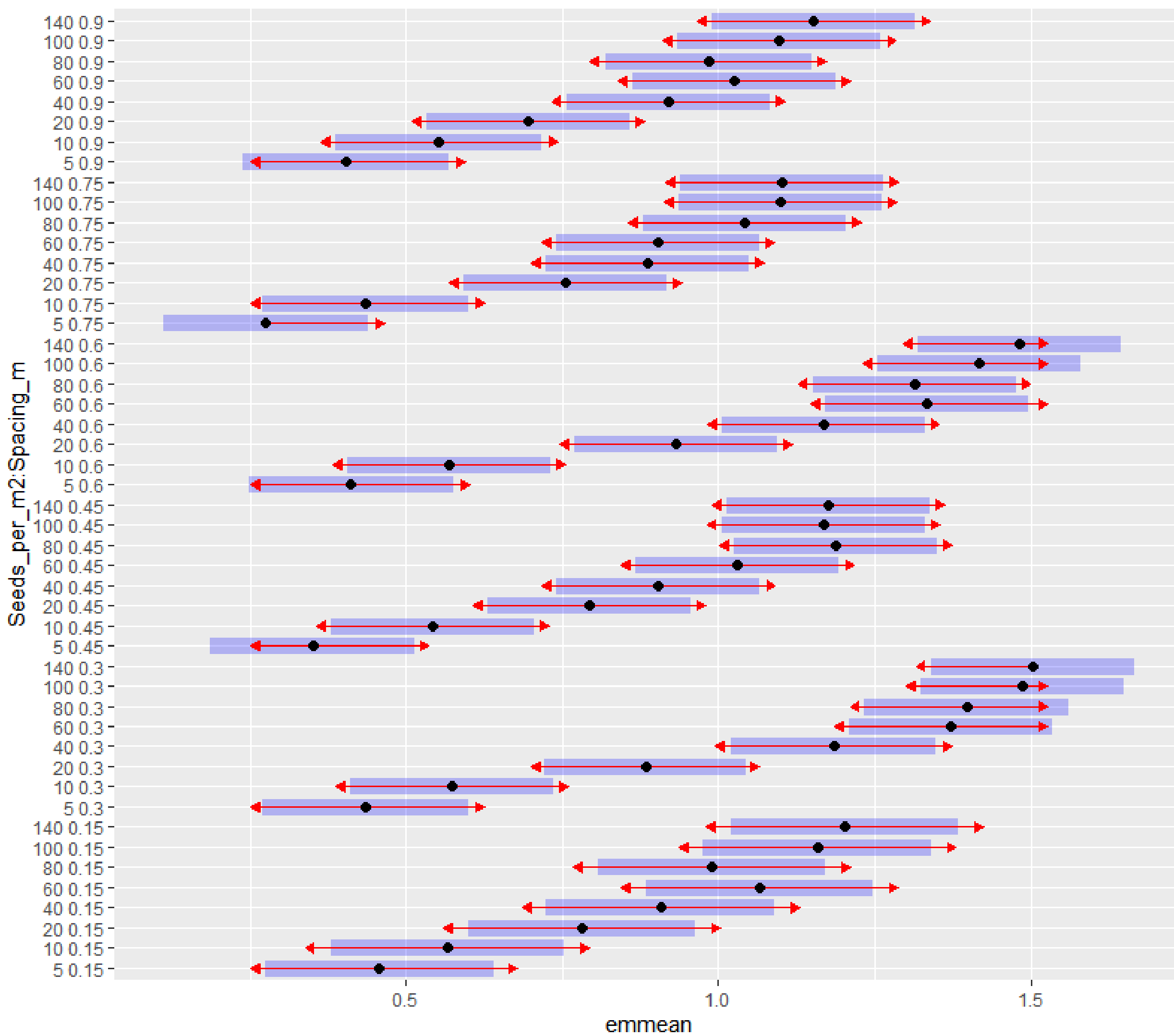

Figure 12: Post hoc contrasts multiple comparisons of means for canola yield. The figure contrasts means across all seeding rate under each row spacing. Field trial location is Saskatchewan. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Blue bars represent confidence intervals for the means, and the red arrows compare the difference among them. If an arrow from one mean overlaps an arrow from another group, the difference is not "significant".

Table 6: Analysis of variance (ANOVA) and post hoc multiple comparisons of means for canola yieldfor Manbitoba. The analysis of variance is based on the type-III Wald F test with Kenward-Rogers degree of freedom. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Means followed by the same letter do not differ significantly.

Factors	**ANOVA p-value**		**Fixed factor levels**	**Mean canola yield (t ha^{-1})**	**Standard Error**	**Mean comparison**
Row Spacing - RS (m)	p<0.0000	Interaction p=0.8517	0.19m	1.52	0.070	C
			0.38m	1.29	0.070	B
			0.57m	1.36	0.070	B
			0.76m	1.03	0.070	A
Seeding Rate – SR (Plnt/m^2)	p<0.0000		5 Plnt m^{-2}	0.82	0.077	A
			10 Plnt m^{-2}	1.02	0.077	A
			20 Plnt m^{-2}	1.23	0.077	B
			40 Plnt m^{-2}	1.47	0.077	C
			60 Plnt m^{-2}	1.43	0.077	C
			80 Plnt m^{-2}	1.46	0.077	C
			100 Plnt m^{-2}	1.47	0.077	C
			140 Plnt m^{-2}	1.50	0.077	C

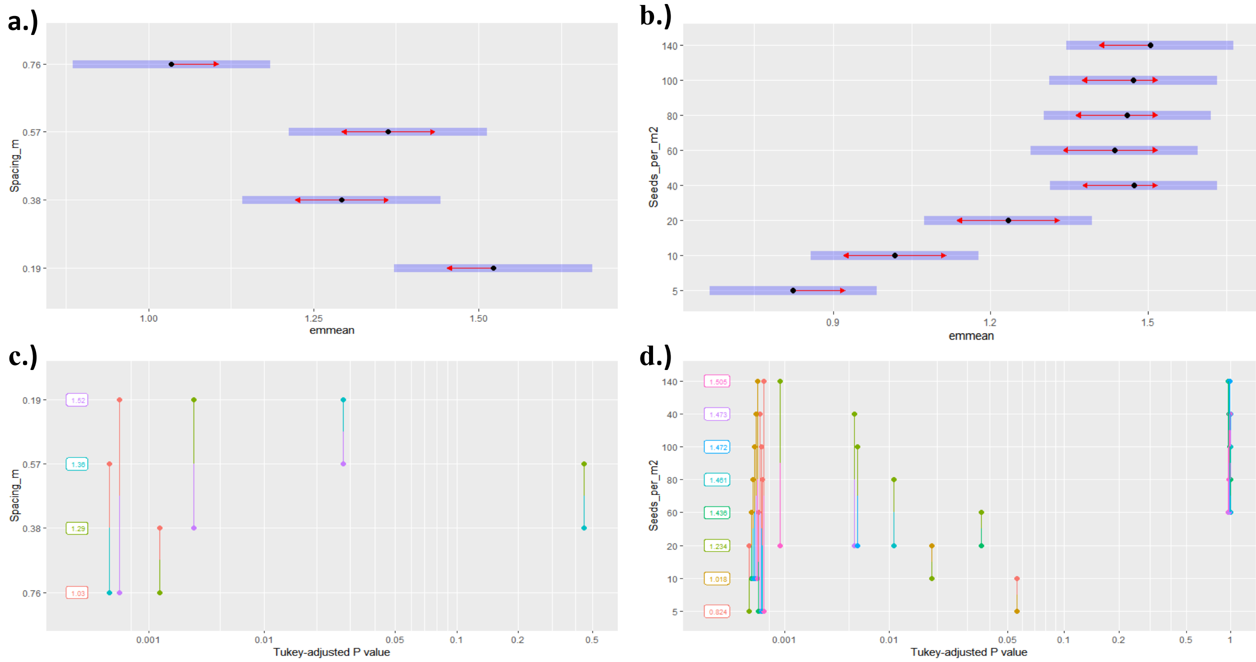

Figure 13: Post hoc multiple comparisons of means for canola yield by row spacing and seeding rate categories. Field trial location is Manitoba. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Panel a.) and b.) blue bars represent confidence intervals for the means, and the red arrows compare the difference among them. If an arrow from one mean overlaps an arrow from another group, the difference is not "significant" . Panel c.) and d.) represents all pairwise mean comparisons and whose horizontal position determines the p-value of the comparison.

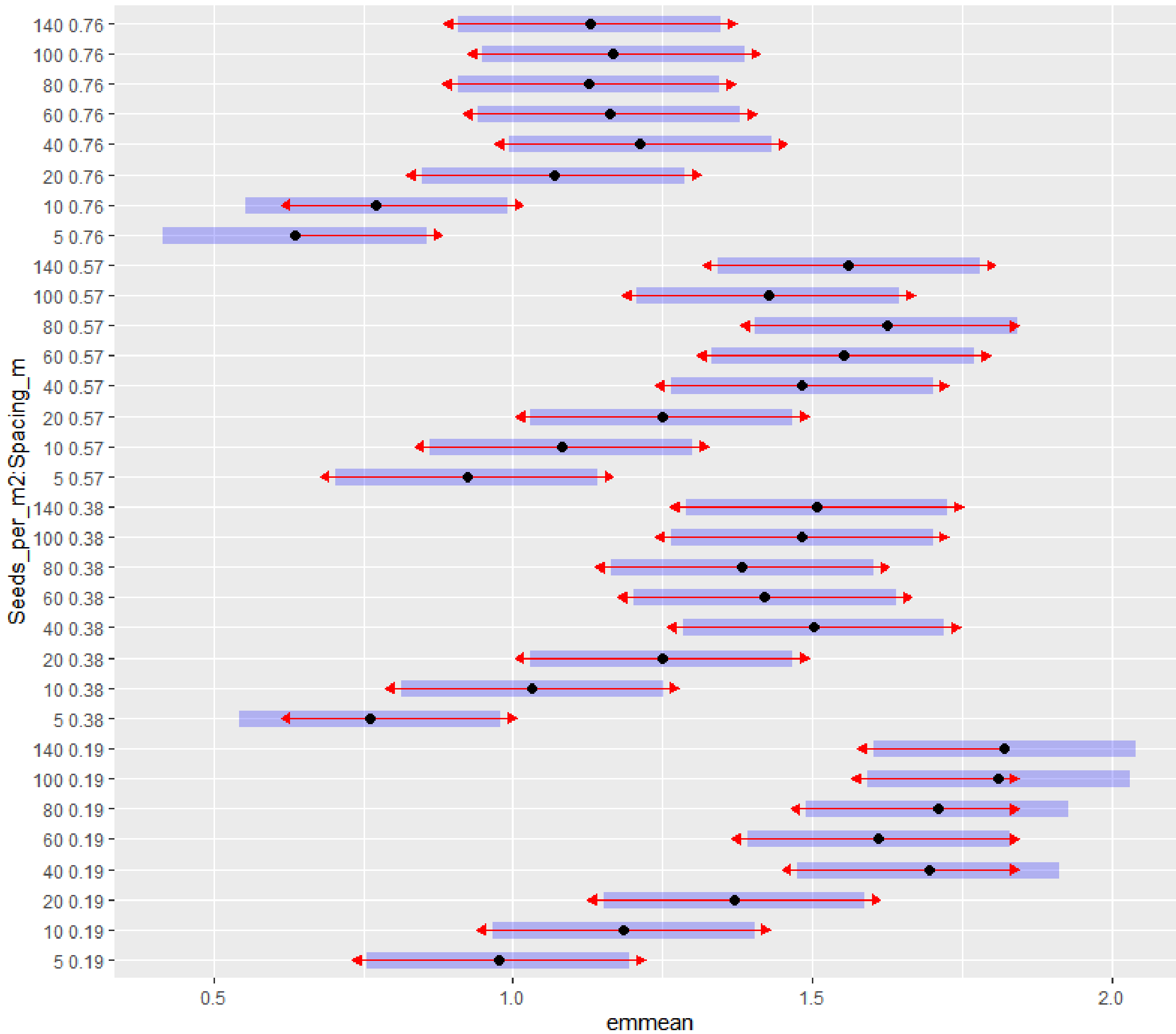

Figure 14: Post hoc contrasts multiple comparisons of means for canola yield. The figure contrasts means across all seeding rate under each row spacing. Field trial location is Manitoba. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Blue bars represent confidence intervals for the means, and the red arrows compare the difference among them. If an arrow from one mean overlaps an arrow from another group, the difference is not "significant".

Table 7: Analysis of variance (ANOVA) and post hoc multiple comparisons of means for canola yield. Field trial location is both Saskatchewan and Manitoba. The analysis of variance is based on the type-III Wald F test with Kenward-Rogers degree of freedom. The multiple comparisons of means are based on Tukey's post hoc method, which used a 0.95 confidence level and a 0.05 significance level for the testing. Means followed by the same letter do not differ significantly.

Factors	**ANOVA p-value**		**Fixed factor levels**	**Mean canola yield (t ha^{-1})**	**Standard Error**	**Mean comparison**
Row Spacing - RS (m)	$p<0.0000$	Interaction $p=0.7954$	The variable was treated as a continuous variable for all site-year analysis due to differences in factor levels between Saskatchewan and Manitoba trials.			
Seeding Rate – SR (Plnt/m^2)	$p<0.0000$		5 Plnt m^{-2}	0.56	0.104	A
			10 Plnt m^{-2}	0.73	0.104	B
			20 Plnt m^{-2}	0.98	0.104	C
			40 Plnt m^{-2}	0.19	0.104	D
			60 Plnt m^{-2}	1.25	0.104	DE
			80 Plnt m^{-2}	1.28	0.104	DEF
			100 Plnt m^{-2}	1.33	0.104	EF
			140 Plnt m^{-2}	1.36	0.104	F

Objective 1b. Canola yield compensation for row spacing and seeding rates.

1b.1 Introduction

Seed yield is a function of population density, number of pods per plant, number of seeds per pod, and seed weight (McGregor, 1987). According to Diepenbrock (2000), the number of siliques plant $^{-1}$ can influence the seed yield of individual plants. The number of pods plant $^{-1}$ is measured by the survival of branches, buds, flowers, and young pods during development (McGregor, 1987; Tayo & Morgan, 1979; Bouttier & Morgan, 1992; Diepenbrock, 2000). During crop development, variation in environmental conditions, seed genetics, and source-sink relationships affect the potentially obtainable yield factors (Keiller & Morgan, 1988; Habekotté, 1993). In canola development, flowering is a critical phase that influences pods and ultimately seed formation. Lardon and Triboi-Blondel, (1995) reported that in a frost occurrence at the start of flowering, branches increased and the flowering period lasted longer, which resulted in more poorly filled pods. The yield is compensated by pods of the lower branches, which yield relatively low. Plant growth is a function of a series of metabolic processes affected by distinct environmental factors (Ma et al., 2016).

The yield component factors provide insight into understanding yield formation. Wayne Adams hypothesized that component compensation resulted from limiting nutrient-metabolite availability to support developing reproductive structures (Sinclair TR, 2020). Each yield component is susceptible to environmental and management factors within a specific time. These periods correlate to the stages of development during which a component's potential is determined and subsequently achieved (McMaster & Wilhelm, 2020).

The effects of seeding rate on canola yield, yield component, oil, and protein concentration are variable and inconclusive in many studies. Tayo and Smith (1992) reported that increasing seeding rates did not significantly affect canola yield; however, we observed in other studies that the yield component could be altered with more seeds from the branch racemes (Angadi et al., 2003), late and prolonged anthesis, delayed crop maturity (Yang et al, 2014), more branches (Ma et al, 2016) leading to higher seed moisture at harvest.

According to a report from Chris Holzapfel, IHARF research manager, wider row spacing may have some advantages in improving the yield potentials of major crops. The advantages of wide row spacing include; reduced initial operational costs, lower maintenance costs, and less wear and tear on the equipment. With wider row spacing, growers can use less horsepower to pull drills, consume less fuel, and speed up seeding. Although there may be a minor yield loss every few years, slight adjustments in row spacing can erase some of the issues of no-till seeding into heavy residue (Fleury, 2017).

Similarly, the effect of row spacing on canola yield and yield component varies most especially when geographic location, environmental and climatic conditions are considered factors in the experiment. Haliloğlu, & Beyyavaş (2019) reported that row spacing effect on winter canola yield and its yield component experiment indicated that the number of branches per plant, the number of pods per plant, the number of seeds per pod, and 1000 seed weight increased with increased inter-row spacing. Others demonstrated improved yield with narrowing row spacing. Morrison et al. (1990) reported that plants seeded in 15-cm rows yielded more per area, produced more pods per plant, and lodged less than those in 30-cm rows, which lowered intra-row plant competition and reduced competition mortality and crop lodging at harvest. They also reported that the interaction between row spacing and seeding majorly influences phenological traits in canola plant.

An important yield component of canola is the number of siliques (pods) plant^{-1} (Bennett et al., 2011). It is an important yield component is the number of siliques (pods) plant^{-1}. Thousand Seed weight (TSW) is an important factor that contributes toward the final yield of a crop. Although seed size influences thousand seed weight, the average seed size in a canola field is typically significantly less than the seed lot due to small seed in late branches (Harker et al, 2015). Stresses such as hot and dry weather during seed filling can also lead to a lower thousand seed weight value.

In canola, the entire anthesis phase is a significant period for yield determination (Kirkegaard et al., 2018). The start and end of flowering are phenological traits influenced by environmental variation and ecological factors (Wang, 2020). Assimilate limitation on developing ovules causes pod abortion and limited potential for compensatory growth in surviving pods (Kirkegaard et al., 2018). Flowering is an important stage that can influence productivity in canola development. Canola plants experience indeterminate flowering; hence, they can produce new flowers in favorable conditions (Edwards, 2011).

The objective of this study is to determine how canola yield compensates for the effects of row spacing and seeding rates. Yield components considered in this research include the number of siliques, number of branches, and thousand seed weight. Phenological responses considered include individual crop biomass, the start of flowering, and the end of flowering.

1b.1 Yield Components Results and discussion

Table 1b.2: ANOVA table for all site years. The bolded font indicates significant p-values.

Variables	AnthS	AnthE	Biomass	Pods/plant	Branches/plant	TSW
Carman 2018						
Row spacing (RS)	0.496	0.731				
Seeding rate (SR)	NS	**<0.001**				
RS X SR	0.605	0.662				
Carman 2019						
Row spacing	**0.091**	0.764	0.852	0.525	0.815	
Seeding rate	0.179	**<0.001**	0.028	**<0.001**	**0.001**	
RS X SR	0.273	**<0.001**	0.32	0.41	0.498	
Kernen 2018						
Row spacing	**0.095**	0.651				0.934
Seeding rate	**0.019**	**<0.001**				**0.036**
RS X SR	**0.033**	0.694				**0.045**
Kernen 2019						
Row spacing	0.309	0.588	0.967	0.659	**0.001**	0.117
Seeding rate	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**
RS X SR	0.851	0.824	0.467	0.467	0.325	**<0.001**

AnthS = Start of flowering
AnthE = End of flowering

Table 1b.3: GAM model table for all site years. The bolded font indicates significant p-values.

Variables	Anthesis S	Anthesis E	Biomass	Siliques/plant	Branches/plant	TSW
Carman 2018						
Row spacing		**0.059**				
Seeding rate		**0.0001**				
RS X SR		**0.001**				
Reps		0.384				
Carman 2019						
Row spacing		**0.0504**		0.911	0.606	
Seeding rate		**<0.001**		**<0.001**	**<0.001**	
RS X SR		0.8485		0.310	0.465	
Reps		**0.0214**		0.354	0.468	
Kernen 2018						
Row spacing	0.3898	0.234				**0.01**
Seeding rate	0.1168	**<0.001**				**<0.00**
RS X SR	**0.0429**	0.539				0.10
Reps	0.4366	0.473				0.73
Kernen 2019						
Row spacing	0.361	**0.0495**	0.962	0.851	**<0.001**	**<0.00**
Seeding rate	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.001**	**<0.00**
RS X SR	0.629	**<0.001**	**<0.001**	**0.001**	0.559	**<0.00**
Reps	**0.0004**	**0.0214**	0.358	0.298	0.667	**0.02**

Table 1b.4: ANOVA model and GAM model comparison with AIC.

Variable	Model	AIC
Carman 2018		
End of flowering	ANOVA	508.7921
	GAM	452.5984
Kernen 2018		
TSW	ANOVA	-78.59440
	GAM	-96.45151
End of flowering	ANOVA	844.0036
	GAM	833.6333
Start of flowering	ANOVA	930.1427
	GAM	929.6810
Carman 2019		
End of flowering	ANOVA	488.3815
	GAM	475.4792
Pods	ANOVA	1821.049
	GAM	1806.116
Branches	ANOVA	786.5779
	GAM	774.9059
Kernen 2019		
Biomass	ANOVA	2475.459
	GAM	2372.424
Start of flowering	ANOVA	587.5574
	GAM	578.9915
End of flowering	ANOVA	1070.2185
	GAM	809.6004
Pods	ANOVA	3038.185
	GAM	2942.504
Branches	ANOVA	1070.219

	GAM	1027.920
TSW	ANOVA	-125.3523
	GAM	-184.9805

The ANOVA result indicates seeding rate significant effect on most of the yield component. GAM result indicates that seeding rate had a significant effect on most yield component and phenological traits. Furthermore, we noticed few significant effect of row spacing on yield component.

Although the ANOVA and GAM results were somewhat similar, AIC indicates that GAM model was better model for our analysis (Table 1b.4). GAM result indicates that treatment interaction and replication did not influence most of the yield components.

1b.6 Yield Components of Canola

1b.6.1 Number of branches per plant.

One of the primary yield components is the number of branches plant^{-1}. As expected, seeding rate had a significant impact on the number of branches plant^{-1} at Carman 2019 and Kernen 2019 (Table 1b.3). GAM model result is similar to the ANOVA analysis (Table 1b.2; Table 1b.3). There was a highly significant difference between row spacing at the Kernen 2019 (Table 1b.3). Furthermore, there was no significant seeding rate by row spacing interaction and replication effect at the two site years (Table 1b.3). The number of branches generated can be influenced by the plant's response to light interception, photosynthetic activities, and aeration.

In Carman 2019, the maximum average number of branches plant^{-1} was recorded at 5 seeds m^{-2} 26 branches plant^{-1}, followed by 25 branches plant^{-1} at 20 seeds m^{-2} (Figure 1b.2). The lowest average number of branches plant^{-1} (16 branches plant $^{-1}$) was recorded at a high seeding rate of 100 seeds m^{-2} (Figure 1b.2). In Kernen 2019, the maximum average number of branches plant $^{-1}$ was obtained at 10 seeds m^{-2} with 32 branches plant $^{-1}$ followed by 5 seeds m^{-2} with 31 branches plant^{-1}, while the lowest average number of branches 18 branches plant $^{-1}$ was recorded at 80 seeds m^{-2} where seeding density increased (Figure 1b.2). This result indicates that increasing seeding rate influenced the number of plant branches^{-1}. In both locations, the number of branches plant^{-1} reduced by increasing seeding rate, and this result is similar to Clarke et al. (1978) study on the effect of seeding method and seeding rate on canola. Their result indicated that irrespective of the method used to plant canola, increasing the seeding rate reduced the number of branches plant $^{-1}$. This decrease can be attributed to intra-row competition during crop development.

In Kernen 2019, the maximum average number of branches plant^{-1} was recorded at 15 cm and 30 cm at 27 branches plant^{-1} and 26 branches plant^{-1}, respectively (Figure 1b.1). The lowest average number of branches (22 branches plant $^{-1}$) were recorded in 90 cm rows at wide row spacing (Figure 1b.1). Previous research illustrated that row spacing positively influenced canola branching (Kondra, 1977; McGregor, 1987; Morrison et al., 1990; Holzapfel & May, 2016) and the flowering of canola plant (Holzapfel & May, 2016).

However, in Kernen 2019, the number of branches plant^{-1} linearly decreased as row spacing increased; linear regression best describes this (Figure 1b.1). In Carman and Kernen 2019, the number of branches plant^{-1} responded logarithmically to increasing seeding rate (Figure 1b.2).

It may be essential to consider primary and secondary branching in canola yield components and canola population density effect on branching for a study on yield components. Secondary branch production helps the crop compensate for poor stand establishment, hail, and pest damage (Canola Council of Canada, 2019).

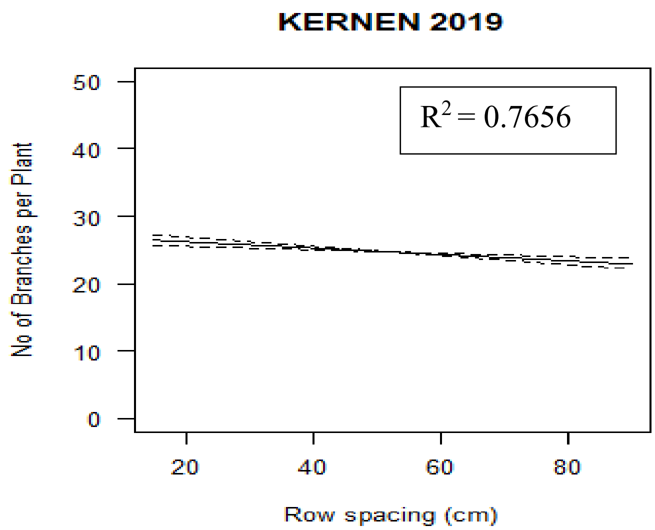

Figure 1b.1: Effect of row spacing (cm) on the number of branches at Kernen 2019. No number of branches data was not collected in 2018 growing season. Dark lines indicate the mean value for number of branches plant -1. Dotted lines indicate 95% confidence intervals around the predicted values.

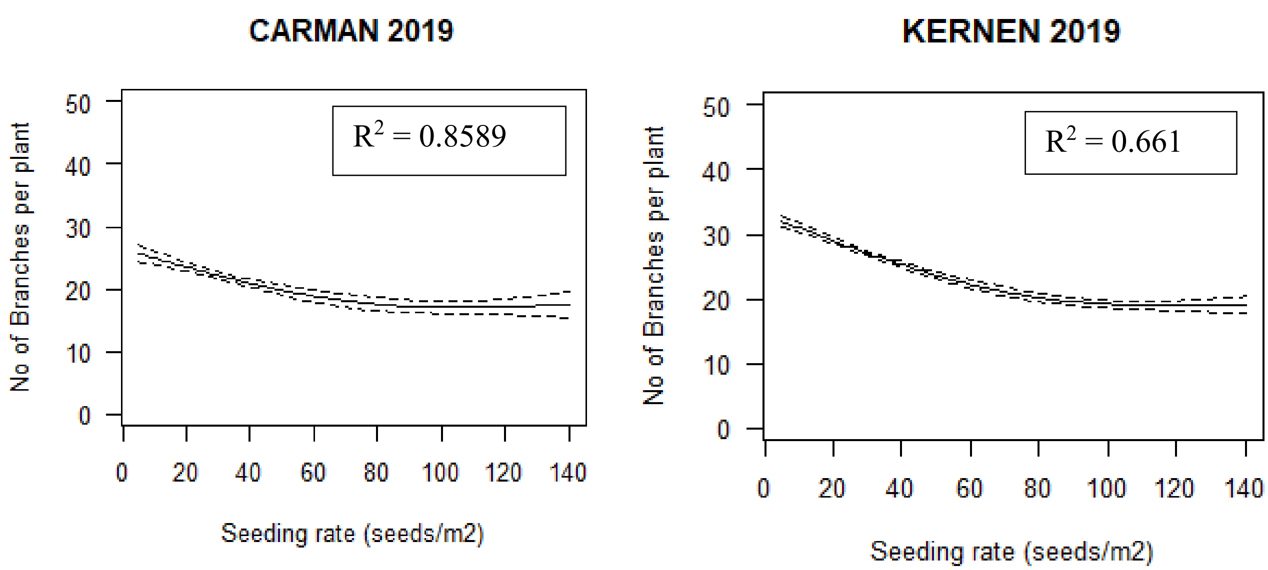

Figure 1b.2: Effect of seeding rate (viable seeds m-2) on the number of branches in 2019 at Carman and Kernen respectively. No number of branches data was not collected in 2018 growing season. Dark lines indicate the mean value for number of branches plant -1. Dotted lines indicate 95% confidence intervals around the predicted values.

1b.6.2 Number of siliques per plants.

The number of siliques plant $^{-1}$ significantly responded to seeding rate in the two site-year (Table 1b.3), while row spacing had no significant effect on the number of siliques^{-1} (Table 1b.3). However, in Kernen 2019, there was a significant interaction between row spacing by seeding rate (Table 1b.3). In Carman 2019, the number of siliques plant $^{-1}$ was not significantly affected by the interaction between row spacing and seeding rate. Lastly, the replication effect was not significant.

In the two site years, it was observed that the maximum average number of siliques plant $^{-1}$ was observed in a low seeding rate of 5 seeds m^{-2} with 1150 siliques in Carman 2019 and 3358 siliques in Kernen 2019. Followed by 10 seeds m^{-2} with 1072 siliques in Carman 2019 and 2783 siliques in Kernen 2019. The lowest number of siliques were recorded at 140 seeds m^{-2} with 559 siliques in Carman 2019 and Kernen 2019 (Figure 1b.4)

However, the number of siliques plant $^{-1}$ decreased as seeding rates increased (Figure 1b.4), confirming earlier results (Kondra, 1975; Clarke & Simpson, 1978; Degenhardt and Kondra l98l; McGregor, 1987; Morrison et al., 1990). This decrease could be attributed to a higher number of plants per unit area, resulting in competition for nutrients, light, space, and moisture during crop development (Siddique & Bultynck, 2004). The movement of nutrients during flowering influences the number of siliques plant^{-1} produced (Allen & Morgan, 1972). Previous studies also indicate that environment can determine the number of pods plant^{-1} (Olsson, 1960; Clarke & Simpson, 1978). According to Morrison et al. (1990) discovered that number of siliques plant^{-1} is the most affected yield component. The average number of siliques plant $^{-1}$ significantly decreased by 9.6 % as the seeding rate increased from 20 seeds m^{-2} to 40 seeds m^{-2}. This result is similar to Shahin and Valiollah (2009) report that as seeding rate from 4 to 6 kg ha^{-1}, the number of siliques plant^{-1} decreased by 8.7%.

Row spacing had no significant effect on the number of siliques plant^{-1} in the two site years; this result is similar to Morrison et al. (1990) and Shanin & Valiollah (2008) studies that row spacing did not affect the number of siliques plant^{-1}. Contrary to these findings, Uzun et al. (2012) observed that row spacing significantly influenced the number of siliques plant^{-1} of winter canola.

The interaction indicates a significant difference between row spacing or among seeding rate for the number of siliques plant^{-1} at Kernen 2019. There is no literature discussing the significance of the interaction of row spacing and seeding rate on the number of pods plant^{-1} produced in canola. We discovered that using a low seeding rate with wide row spacing influences the number of pods plant^{-1} (Figure 1b.3). These factors will improve and increase the number of siliques plant^{-1} produced.

Angadi et al. (2003) discovered that canola compensates for reduced plant population by increasing the number of siliques plant^{-1} produced. Growth factors influence this compensation. However, this study has shown that the number of siliques plant $^{-1}$ has the potential to compensate for the effect of row spacing and seeding rate on canola crops.

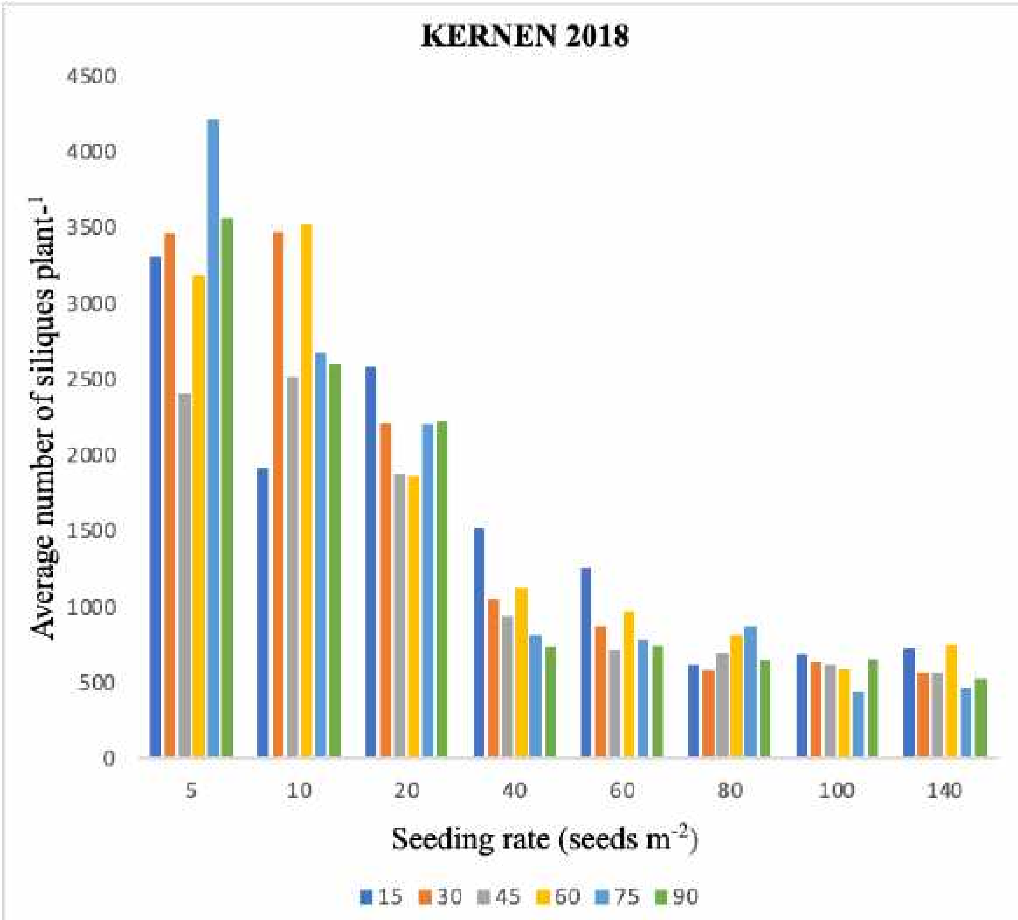

Figure 1b.3: The interaction effect of seeding rate (seeds m-2) and row spacing (cm) on the average number of siliques plant-1 from Kernen 2019.

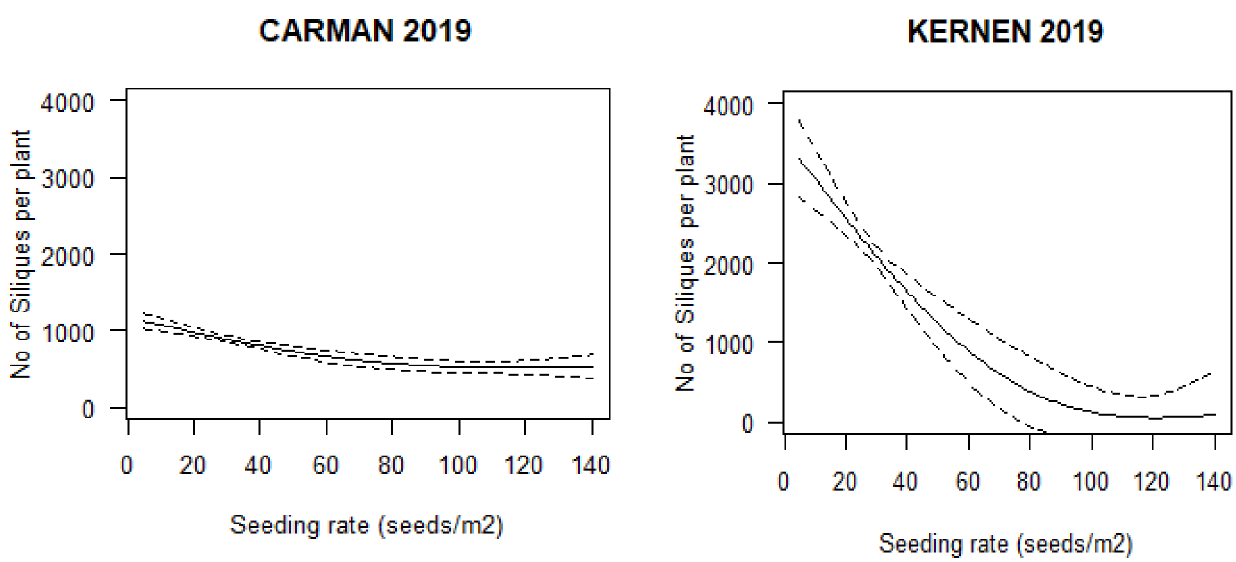

Figure 1b.4: Effect of seeding rate (viable seeds m-2) on the number of siliques from 2019 growing season, Carman, MB and Kernen, SK, respectively. No number of siliques data was collected in 2018 growing season. Dark lines indicate the mean value for number of siliques plant -1. Dotted lines indicate 95% confidence intervals around the predicted values.

1b.6.3 **Thousand Seed weight**

Row spacing significantly influenced thousand seed weight at Kernen 2018 and Kernen 2019 (Table 1b.3). As expected, there was an effect of seeding rate for the two site years. Furthermore, there was a significant seeding rate by row spacing interaction at one of the two site years (Table 1b.3). Additionally, in Kernen 2019, there was a significant replication effect. Data was not collected in Carman locations.

In Kernen 2018, row spacing influenced the thousand seed weight. The maximum average of thousand seed weight was recorded at 75 cm (3.41 g) row spacing followed by 60 cm (3.37 g) and the lowest at 15cm (3.24g). In Kernen 2019, row spacing had a highly significant effect on TSW. The maximum average of a thousand seed weight (3.74 g) was recorded in 90 cm row spacing, followed by 75 cm (3.67 g) and the lowest at 30 cm (3.49g). However, previous studies indicate that row spacing had no significant response to thousand seed weight (Morrison et al., 1990; Uzun et al., 2011) yet a significant response to intra-row spacing (Uzun et al., 2011). This study indicates that wide row spacing can improve the thousand seed weight obtained.

Thousand seed weight responded differently across site years. In Kernen 2018, thousand seed weight ranged from an average of 3.08g to 3.5 g. The maximum average of thousand seed weight was recoded at 80 seeds m-2 (3.5g) and the lowest at 5 seeds m-2 (3.08g) (Figure 1b.5). There was a positive relationship in Kernen 2018 as thousand seed weight increased with increasing seeding rate; this agrees with Clarke & Simpson (1978) and Clarke et al. (1978) that increasing seeding rate increased TSW. Harker et al. (2014) reported that thousand seed weight increased at a higher seeding rate. In contrast (Gross, 1963; Kondra, 1975; Degenhardt & Kondra, 1981) found that thousand seed weight had no significant influence on seeding rate. However, in other research, thousand seed weight positively correlated with yield (Ozer et al., 1999; Ivanovska et al., 2007).

In Kernen 2018, the average thousand seed weight increased until 80 seeds m-2, and there was barely any effect seeding beyond 80 seeds m-2 (Figure 1b.5). In Kernen 2019, TSW had a significant influence on seeding rate, yet a different response to increasing seeding rate. Data indicated that thousand seed weight ranged from an average of 3.49 to 3.74g. The maximum average of thousand seed weight was recoded at 5 seeds m-2 (3.94g) and the lowest at 140 seeds m-2 (3.44g) (Figure 1b.5). Thousand seed weight reduced as seeding rate increased, this trend has been observed in faba bean (Seitzer & Evans, 1973; López- Bellido et al., 2005). However, this result is similar to Harker et al., 2017 in two of the experimental locations of their seed size and seeding rate study, thousand seed weight decreased as seeding rate increased. Also, this response could be associated with variation in environmental conditions and abiotic stress. In this study, thousand seed weight decreased by 12 % from 5 seeds m-2 to 60 seeds m-2.

In Kernen 2019, the significant interaction indicates a significant difference between row spacing or the seeding rate for the thousand seed weight at Kernen 2019. Morrison et al. (1990) reported that row spacing, seeding rate, and interaction did not influence thousand seed weight. There are only a few literature to back up the interaction effect with other agronomic factors on thousand seed weight. The interaction indicated that decrease TSW was influenced at higher seeding rates and low row spacing (Figure 1b.6)

According to Adam (1967), major crop plants yield components observe negative correlations when exposed to various types of environmental stress. However, this correlation is based on crop development. This experiment indicates that thousand seed weight compensated for the effect of row spacing in canola development and environmental variation may have influenced the obtained seed weight.

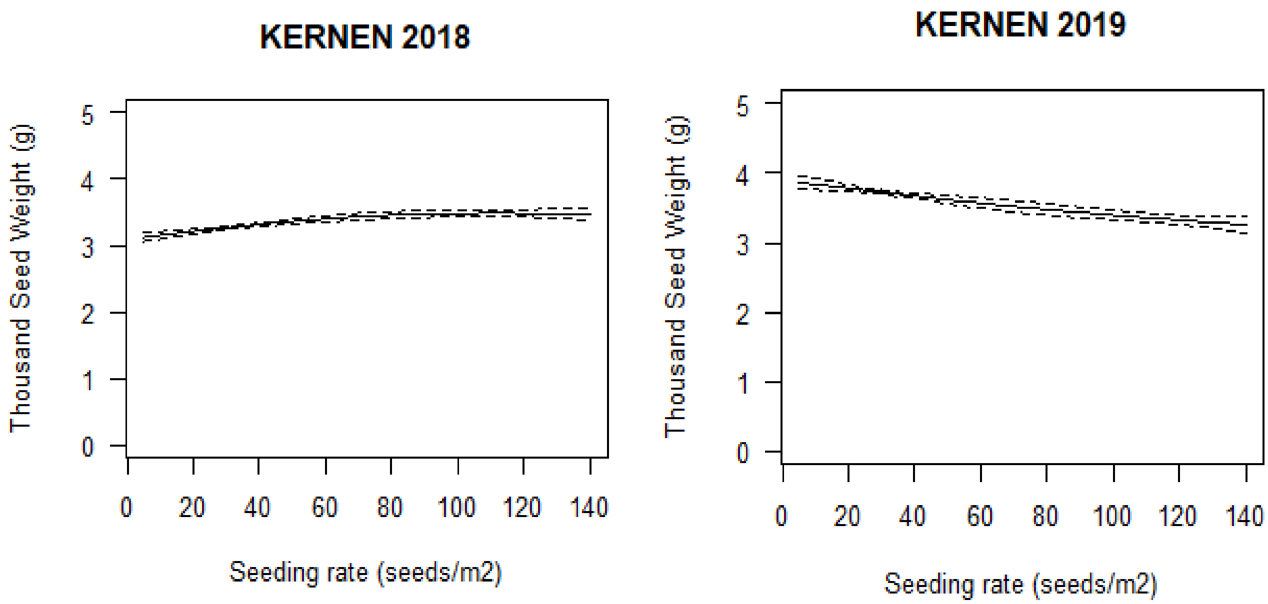

Figure 1b.5: Effect of seeding rate (viable seeds m-2) on thousand seed weight TSW (g) from 2018 and 2019 in Kernen, Saskatoon respectively. No TSW data was collected in Carman 2018 and Carman 2019. Dark lines indicate the mean value for Thousand Seed Weight. Dotted lines indicate 95% confidence intervals around the predicted values.

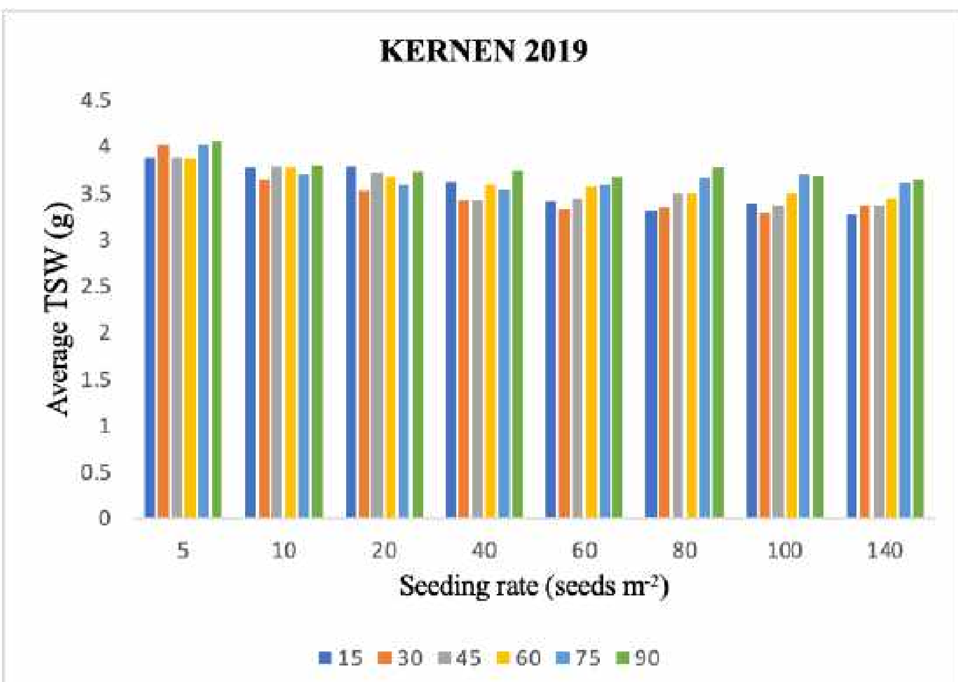

Figure 1b.6: The interaction effect of seeding rate (seeds m^{-2}) and row spacing (cm) on the number of siliques $plant^{-1}$ from Kernen 2019.

1b.7 Phenological Factors

1b.7.1 Start of flowering and End of flowering.

Start of flowering did not respond significantly to row spacing across site years (Table 1b.3). As expected, seeding rate significantly influenced end of flowering in all four site-years (Table 1b.3). End of flowering responded significantly to row spacing in three of the four site-years (Table 1b.3). There was significant row spacing by seeding rate interaction in two of four site-years (Table 1b.3). Nevertheless, there was a weak significant response to replication effect in two of four site years (Table 1b.3).

For Kernen 2019, the start of flowering was affected by seeding rate (Table 1b.3). Seeding rate is a factor known to influence the agronomic traits of plants generally. Furthermore, the result showed a significant random effect (replication) which indicates that the location of the plot has an influence on the result from the treatment (Table 1b.3). Row spacing and seeding rate interaction had weak significance in one of four site years which is likely due to environmental conditions (Table 1b.3).

There was a significant influence in flowering period using the GAM model (data not shown). Previous studies have only considered the influence of flowering period on crop productivity. In this field study, we observed delayed flowering in plots with wide row spacing and low seeding rate; this, in turn, influenced the time for harvest and the number of seeds obtained. Other plots completed flowering within an average of 13 to 22 days compared to an average of 17 to 25 days in Carman 2018 and 2019 respectively. In Kernen, flowering was completed in 16 to 27 days compared to 19 to 33 days in 2018 and 2019 respectively. It is important to note that the harvested seeds yield obtained from these delayed plots produced the lowest yield in this experiment. This result indicates that wide row spacing and low seeding rate have the potential to negatively influence obtainable canola yield. Seeding canola at narrow row spacing and high seeding rate should be considered for optimal crop production. However, this must be carefully designed and executed to avoid overcrowding, competition, and limited crop development resources. Flower abortion can be caused by abiotic stress during the early stages of flower development (Faraji et al., 2008).

The interaction in two of the four site-year indicates that the prolonged flowering period that occurred in plots with wide row spacing and low seeding rate.

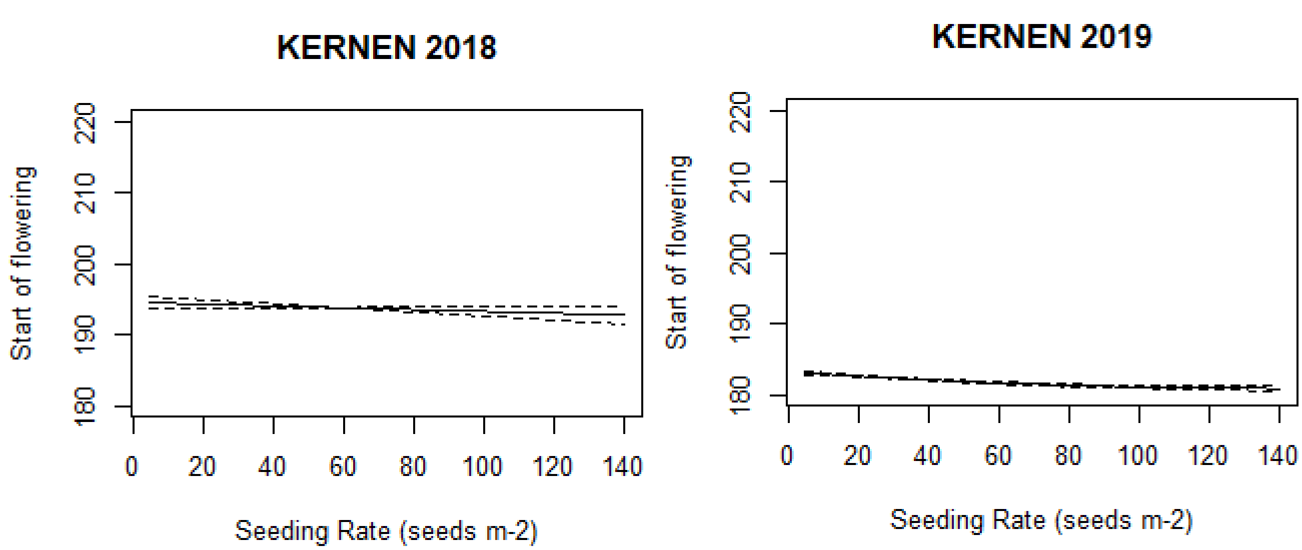

Figure 1b.7: Effect of seeding rate (viable seeds m-2) on start of flowering (Julian Date) from 2018 and 2019 in Kernen, Saskatoon respectively. Dark lines indicate the mean value for start of flowering. Dotted lines indicate 95% confidence intervals around the predicted values.

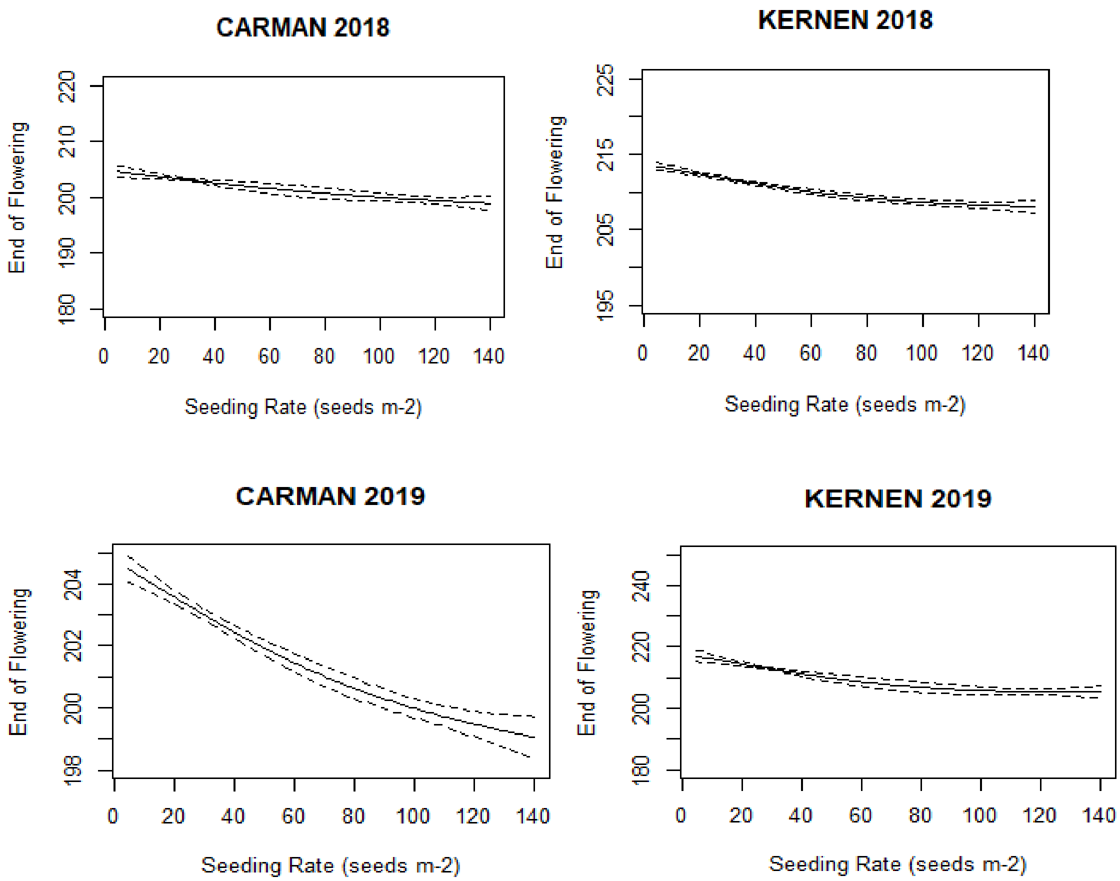

Figure 1b.8: Effect of seeding rate (viable seeds m-2) on end of flowering (Julian Date) from 2018 and 2019 in Kernen, Saskatoon respectively. Dark lines indicate the mean value for end of flowering. Dotted lines indicate 95% confidence intervals around the predicted values.

1b.7.2 Individual Plant Biomass

Individual plant biomass significantly responded to seeding rate (Table 1b.3). Furthermore, individual plant biomass was influenced by the interaction of row spacing and seeding rate (Table 1b.3). The lack of response to row spacing was expected based on earlier study. Individual plant biomass decreased as seeding rate increased, note that individual plant biomass was collected at maturity. However, Harker et al. (2014) discovered that early crop biomass increased at higher seeding rate. The relationship between biomass and increasing seeding rate is can be graphically described in a logarithmic fashion (Figure 1b.9).

There was no significant response to row spacing (Table 1b.3). Previous research reported that the crop lacks the ability to compensate for wider row spacing (Holzapfel & May, 2017). Furthermore, he discovered that canola is the least sensitive crop to wider row spacing among other crops such as wheat, oats and soybeans, where flax is the most sensitive (Holzapfel & May, 2017).

The significant row spacing and seeding rate interaction revealed that increasing seeding rate decreased individual plant weight across all row spacing (Figure 1b.10). There was a drastic decline of 53% in individual crop biomass from 20 to 40 seeds m^{-2} (Figure 1b.9). Previous research indicates that seeding rates had significant effect on biomass in an ideal growing condition (Angadi et al., 2003).

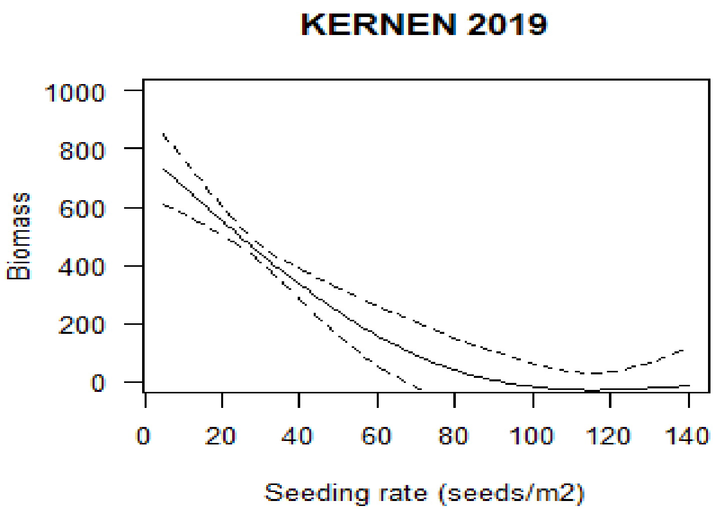

Figure 1b.9: Effect of seeding rate (viable seeds m^{-2}) on individual crop biomass (biomass 5plants^{-1}) in at Kernen, 2019. No biomass data was collected in 2018 growing season. Dark lines indicate the mean value for the biomass. Dotted lines indicate 95% confidence intervals around the predicted values.

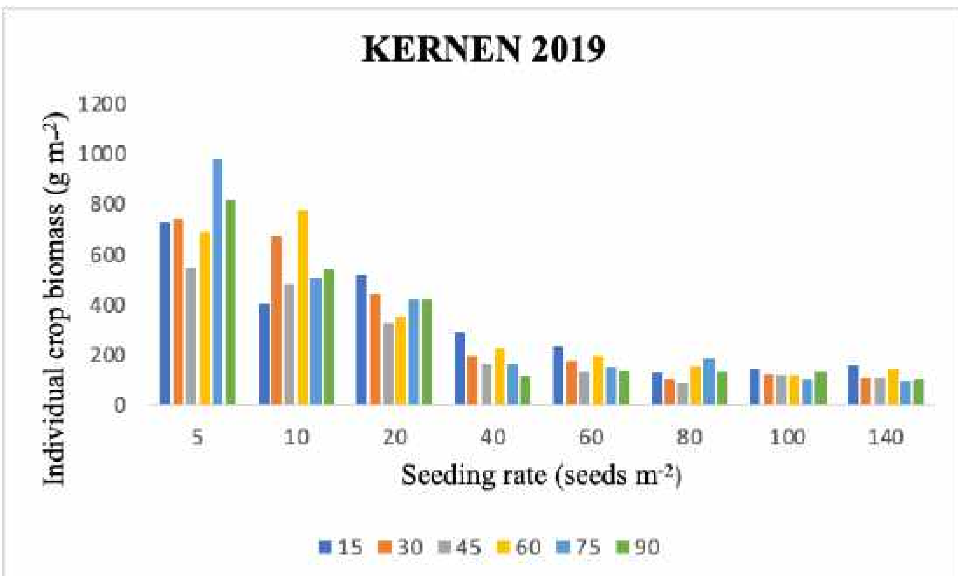

Figure 1b.10: The interaction effect of seeding rate (seeds m^{-2}) and row spacing (cm) on the number of siliques plant^{-1} from Kernen 2019.

1b.8 Conclusion

Across site-year, there was significant effect of row spacing and seeding rate and their interaction on yield component; however, these effects were negative on the component leading to a decrease in each yield component. Nevertheless, thousand seed weight in Kernen 2018 was the only yield component that increased with increasing seeding rate. The yield component compensation was primarily attributed to increased thousand seed weight as seeding rates increased in Kernen 2018 from 3.08g to 3.47g.

In both locations, the number of branches plant^{-1} and the number of pods plant^{-1} were reduced by increasing seeding rate. However, canola compensates for lower plant population by increasing the number of pods per plant through increased branching (Morrison et al., 1990; Angadi et al., 2003) and pod retention (Angadi et al., 2003).

Yield compensation can be influenced by temperature, soil moisture, and the duration of the stress

(Hertel & Edwards, 2011). Previous studies have shown that canola can compensate for decreasing plant density by increasing the number of pods plant^{-1} and increasing the number of branches plant^{-1} (Clarke and Simpson l978a; Clarke et al., 1978). However, (Morrison et al., 1990; Angadi et al., 2003) reported that canola compensates for lower plant population by increasing the number of pods plant^{-1} through increased branching and pod retention. This result is similar to the observation made on the field that there were more branches plants^{-1} in a few plots with wide row spacing and low seeding rates.

Seeding rate was the only factor that significantly influenced yield component and phenological traits. There was generally no significant row spacing effect on biomass and number of siliques plant$^{-1.}$ Their interaction also significantly influenced most but not all parameters and this can be associated with site-year variation.

Phenological traits also decreased as seeding rates increased. The start and end of flowering were influenced by seeding rates. We observed that plots with low seeding rate generally experience delayed start and end flowering.

We hypothesize to determine how canola compensate for the effects of row spacing and seeding rate. Our result indicates that canola compensated for increasing seeding rate with reduced compensatory branching and pods across both sites, and reduced thousand seed weight in one of two site-year. This variation may be attributed to environmental factor, as a result of drought in 2018 growing season. We observed that row spacing have slightly compensated for canola. The interaction effect indicated that canola compensates for increasing seeding rate and wide row spacing with decline in yield component and phenological traits.

Start and end of flowering also compensated for seeding rate and row spacing effect as we observed a delayed start of flowering and prolonged flowering period in plots with wide row spacing and low seeding rate. There was a reduced compensatory individual crop biomass has seeding rate increased.

Objective 2: Develop and apply image analysis techniques to track space occupied by individual plants over time in different planting arrangements.

2.1 Introduction

Seedling emergence counts are valued by field crop producers and plant breeders as a useful predictor of outcomes such as growth development and crop yield. However, collecting manual plant population counts is a tedious and error-prone task. In recent years, it has been shown that deep learning-based object detection models are capable of automatically detecting and counting plant seedlings in aerial images of early-season fields. Although these methods have the potential to alleviate considerable manual labour, they are also associated with challenges of their own. In particular, detection models must be trained on large quantities of annotated image data, which is time-consuming to prepare. It is therefore difficult to use deep learning-based detection models to generate count predictions in a timely manner, which limits the utility of the estimates for field crop producers. More timely data turnaround could assist in early growing-season decision making processes, such as reseeding if necessary. This chapter aimed at reducing annotation effort and providing accurate and timely counts for canola producers.

2.2 Hypothesis and Objectives

Hypothesis

- Ground truth plant counts, annotated plant counts, and computer model plant predictions will be highly correlated. A relationship between any two should be similar to a 1:1 linear relationship.
- Fine-tuned models with training images from the image set will greatly increase the accuracy of the results

Objectives

- To assess the accuracy of collecting plant population data from imagery as compared to manual ground truth data.
- To determine if a computer model is capable of generating reliable plant population predictions across diverse field conditions.

2.3 Materials and Methods

3.4 Results

The three base model options correlated completely (r=1.00) at both the average (0.50) and optimum (0.62) confidence thresholds, when compared to once another and to the annotated image values (Figure 2). This completely correlated result ensured that any of the 3 models could be used as a base model. It also showed that the average confidence threshold was as corelated as the optimum and therefore either could be applied for similar results when choosing a confidence threshold for the plant population estimations. Based on the findings of Figure 2, further results used the average of all 3 models, as all three used the same arictecture and were originally repeated for proof of stability. Manual field counts correlated consitently with all image analyses: ground cover (r=0.75), plant population prediction with average confidence threshold (r=0.70), and plant population prediction with optimum confidence threshold (r=0.69) (Figure 3). A stronger correlation was found between the ground cover and plant population predictions, average (r=0.89) and optimum (0.88).

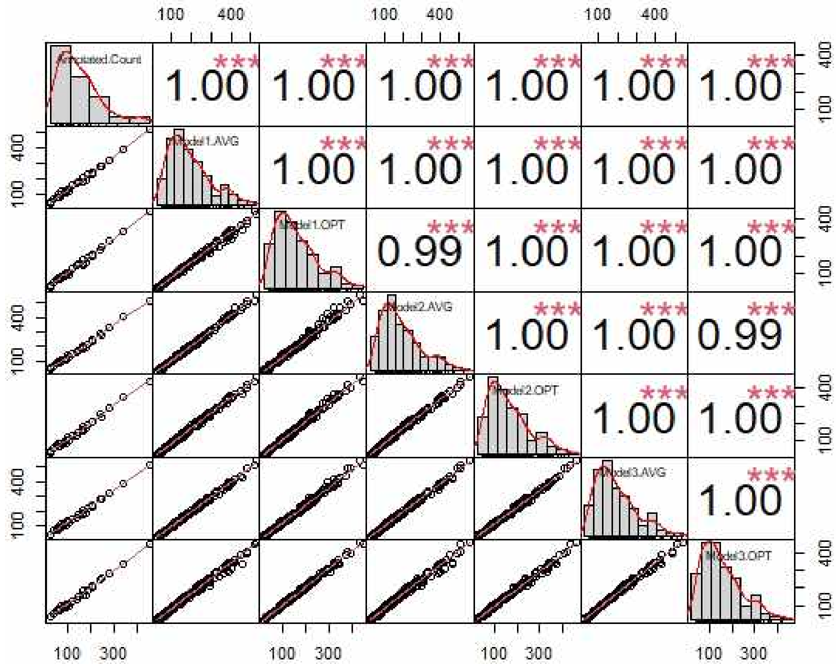

Figure 2. Correlogram of the relationships between manually completed plant population annotations and three computer-based plant population counting models at the confidence threshold average of 0.50 (model AVG), and the confidence threshold optimum of 0.62 (model OPT).

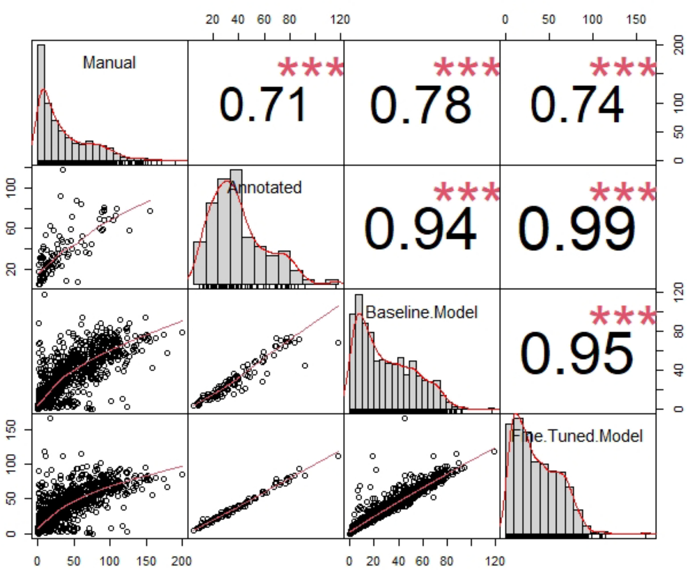

Figure 3. Correlation chart of the relationship between manual plant population densities (plants/m^2) and the annotated and predicted plant densities with no fine-tuning and after fine-tuning on five images. Correlation coefficient values (r) are shown on the right.

The computer model predictions using the average and optimum confidence thresholds correlated similarly with ground cover (r = 0.89 and 0.88, respectively) and the manual field count (r = 0.70 and 0.69, repectively) (Figure 4). The linear regression for the computer model predictions and manual counts was higher than the expected theoretical 1:1 relationship (Figure 5). Of the imagery collected, ground cover was the most correlated with manual field counts (r = 0.75) (Figure 4, Figure 6). The strongest r^2 value with the regression models was between computer model predictions and the ground cover at $r^2 = 0.77$ (Figure 7).

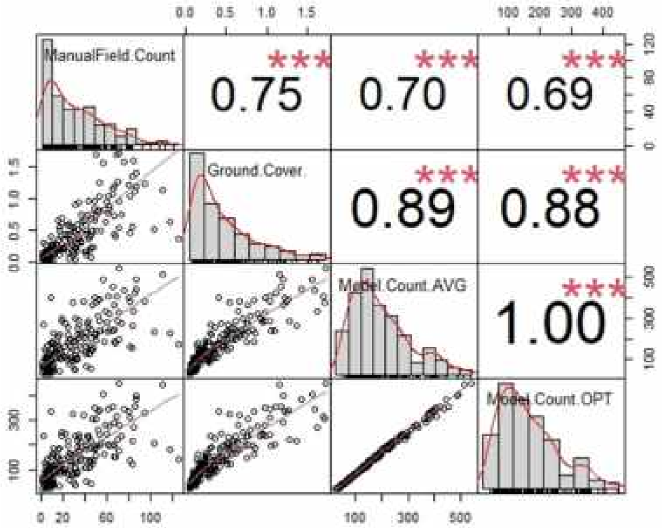

Figure 4. Correlogram of the relationships between manual plant population count (plants/m^2), image-based ground cover (%), and computer-model plant prediction (plants/m^2) at the average (0.50) and the optimum (0.62) model confidence thresholds.

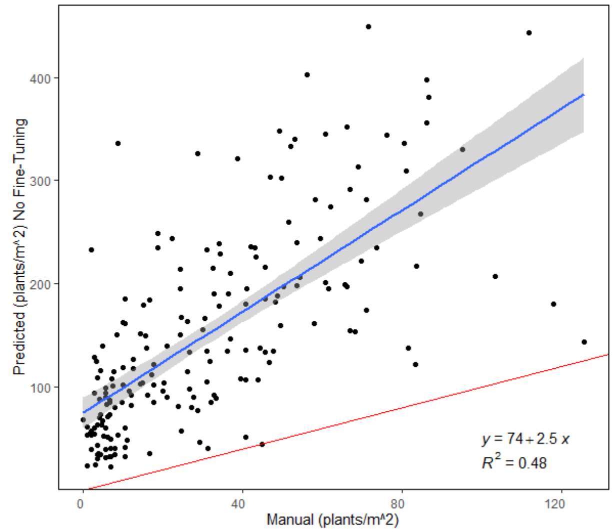

Figure 5. A scatterplot of manual plant population count (plants/m^2) and computer-model plant predictions (plants/m^2) averaged across the three models at the optimum confidence level of 0.62. A regression line is shown in blue with a confidence interval (0.95) in gray shade. The theoretical linear relationship of 1:1 is shown in red.

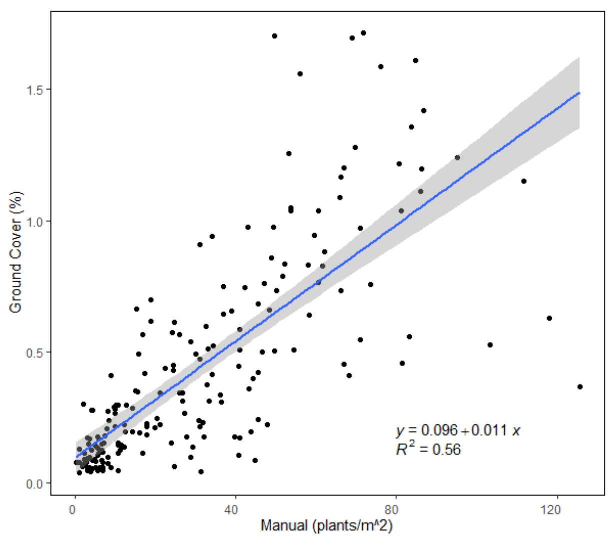

Figure 6. A scatterplot of manual plant population count (plants/m^2) and image-based ground cover (%). A regression line is shown in blue with a confidence interval (0.95) in gray shade.

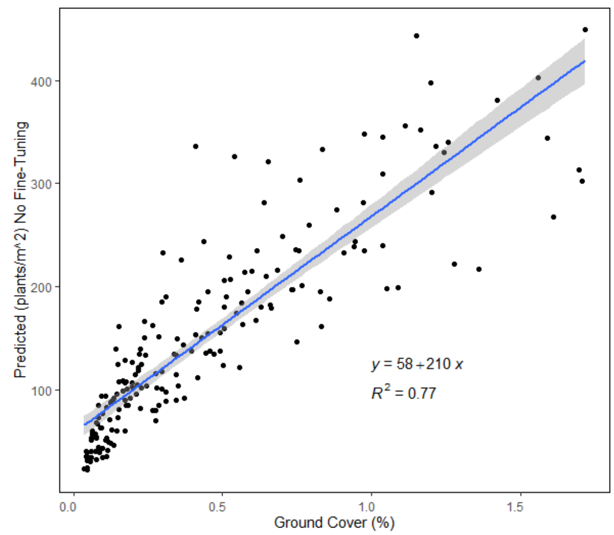

Figure 7. A scatterplot of image-based ground cover (%) and computer-model plant prediction (plants/ m^2) averaged across the three models at the optimum confidence level of 0.62. A regression line is shown in blue with a confidence interval (0.95) in gray shade

Fine tune training made a significant improvement on the correlation of the computer model plant predications to the testing annotations with an R^2 value increase of 0.09 with one imaged trained per image set (Figure 8 a., Figure 8 b.). The fine-tuned images all show a close relationship to the theoretical 1:1 linear relationship. The R^2 value maxes out at $R^2 = 0.99$ at three images trained per image set (Figure 8 d.), as the R^2 values for four and five images trained is the same (Figure 8 e., Figure 8 f.). The linear regression comparing annotated plant counts to manual plant counts and computer model predictions to manual plant counts are very similar to one another but much lower than their relationship to each other (Figure 9). Both show a linear relationship much lower than the theoretical 1:1 relationship, with annotated plant counts carrying a lower 95% confidence interval, as can be seen in the grey shade (Figure 9 a.).

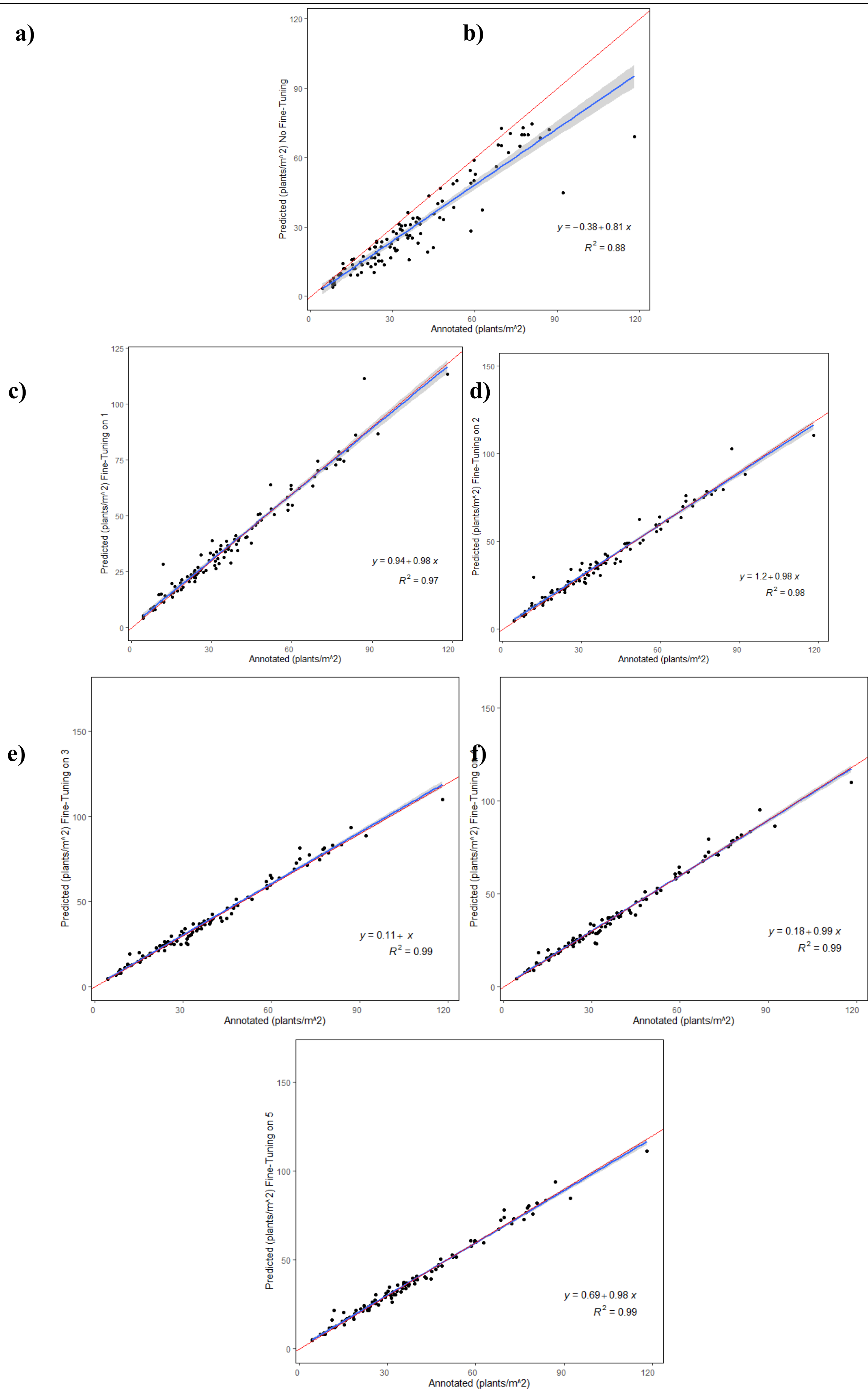

Figure 8. Regression line plotted for annotated images that were reserved for testing and predicted plant population densities

(plants/m^2) through different levels of fine-tuned training. Starting with (a) baseline model with no fine-tuned training, (b) fine-tuned with 1 training image, (c) 2 training images, (d) 3 training images, (e) 4 training images, (f) and 5 training images. Blue is the regression line with grey shaded confidence interval (0.95), red is the theoretical 1:1 relationship.

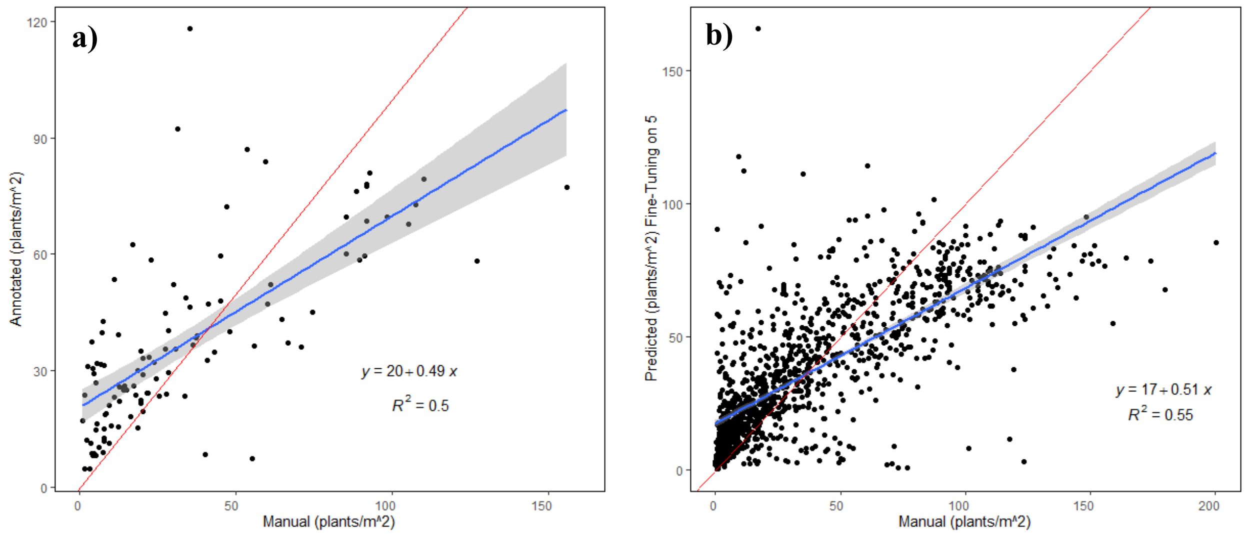

Figure 9. (a) Regression line plotted for annotated images that were reserved for testing and manual plant counts (plants/m^2). (b) Regression line plotted for predicted plant population densities fine-tuned with 5 training images and manual plant counts (plants/m^2). Blue is the regression line with grey shaded confidence interval (0.95), red is the theoretical 1:1 relationship.

Accuracy assessment confusion matrices increased from F1 = 0.886 with the baseline computer model that applied no fine-tuning to F1 = 0.999 with the fine-tuning of five training images (Table 1, Table 2). The false negatives, canola plant identified as present in annotations but absent in predictions, greatly decreased with the addition of fine-tuning, which increased the Recall values.

Table 1. Accuracy assessment confusion matrix to compare annotation values to baseline model predictions with no fine-tuned training. Test annotations taken on 10 images per set (5%). F1 Score = 0.886.

	Validation (Annotations)			
Classification (Predictions)	**Class**	Canola Present	Absent	**Precision**
	Canola Present	2230	0	1.0
	Absent	574		
	Recall	0.795		**F1 = 0.886**

Table 2. Accuracy assessment confusion matrix to compare annotation values to baseline model predictions with fine-tuned training on 5 images. Test annotations F1 Score = 0.999.

	Validation (Annotations)			
Classification (Predictions)	**Class**	Canola Present	Absent	**Precision**
	Canola Present	4004	0	1.0
	Absent	4.0		
	Recall	0.999		**F1 = 0.999**

Trial results of the methodological expansion of the yield model idea towards an optimization approach of ground cover and flowering phenology models to simulate canola yield for precision farming

Agronomic technological advancements provide more precise means to establish methodologies that can estimate crop response in many ways. A commonly used experimental response is yield, and recent imaging advancements provide ex-ante measurements that help make simulation-based crop response recommendations. Measurement of ground cover using imaging is very pragmatic and provides a framework for convenient assessment of foliage temporal dynamics (Arial view is available in Figure-15). Flowering intensity also another ex-ante representative of the yield. The study's objective was to evaluate the feasibility of using groundcover phenology as a proxy for estimating canola flowering and the yield response to row spacing and seeding density, which influence growth and spatial distribution. Using the Visible Band Difference Vegetation Index (VDVI) and Normalized Difference Yellowness Index (NDYI) from digital images, we estimated the ground cover and flowering change over time, and the integral of the ground/flower cover function was used to regress against yield.

The results indicate that the green ground cover accumulation overtime is sufficiently correlated with the yield ($F=368.8$, $p<0.0000$, $R^2=0.7$) (Figure 16, 17, and 18) in comparison to the flowering phenology model ($F=282.9$, $p<0.0000$, $R^2=0.6417$) (Figure 19, 20, and 21). Comparative analysis of ground cover and flowering phenology shows a similar trend with the yield (Figure 22). On the other hand, the Seeding rate and actual plant count relationship with the yield are very well mirrored with Canola's flowering and groundcover phenology as well. The evidence suggests that the ground cover phenology is an early predictor to identify the yield response of the crop. The analysis shows the higher seeding densities, 80 targeted plants m-2 and above, acquire biomass rapidly, and the most stable yield predictions with ground cover are likely reached at similar plant densities. It is evident that the variability observed with foliage at its early stages diminishes with time, and stable levels of the foliage are reached after ~30-35 days after emergence, representing ~0.90 percent cover at commonly used 0.3m spacing and >80 targeted plants m^{-2} seeding density. In general, the productivities of crops relate to their biomass, crop volume, leaf area index, etc., and are likely proportional to the final yield. Our findings suggest that the daily ground cover cumulation likely act as a proportional factor to three-dimensional space occupancy by the plant stand. The findings highlight that occupying space is crucial, and the possibilities using cumulative ground cover for yield simulations.

Figure 15: Field site areal view of row spacing by seeding rate trial on 2022-07-18. Field trial location is Saskatoon (Site Brown) Saskatchewan – 2022 field season.

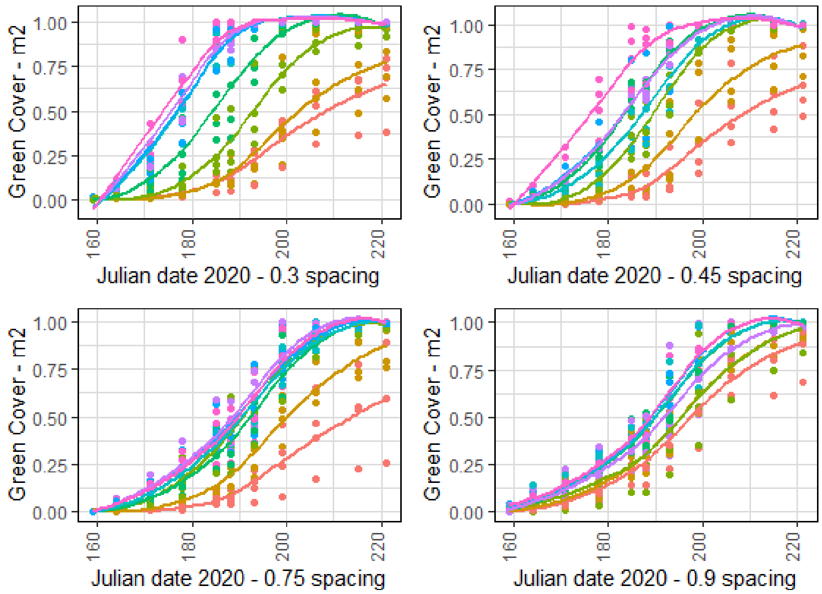

Figure 16: Canola ground cover temporal variation model based on the thresholded Visible Band Difference Vegetation Index (VDVI). Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season. Five panels represent different spacing categories (30, 45, 60, 75, and 90 cm) and each model corresponding to varying seeding rates (5, 10, 20, 40, 60, 80, 100, 140 targeted plants m^{-2}). The variations of fitted models are a result of experimental treatments (seeding rate x row spacing). The model is non-linear regression based on the Locally Weighted Scatter Plot Smoothing (LOESS) technique.

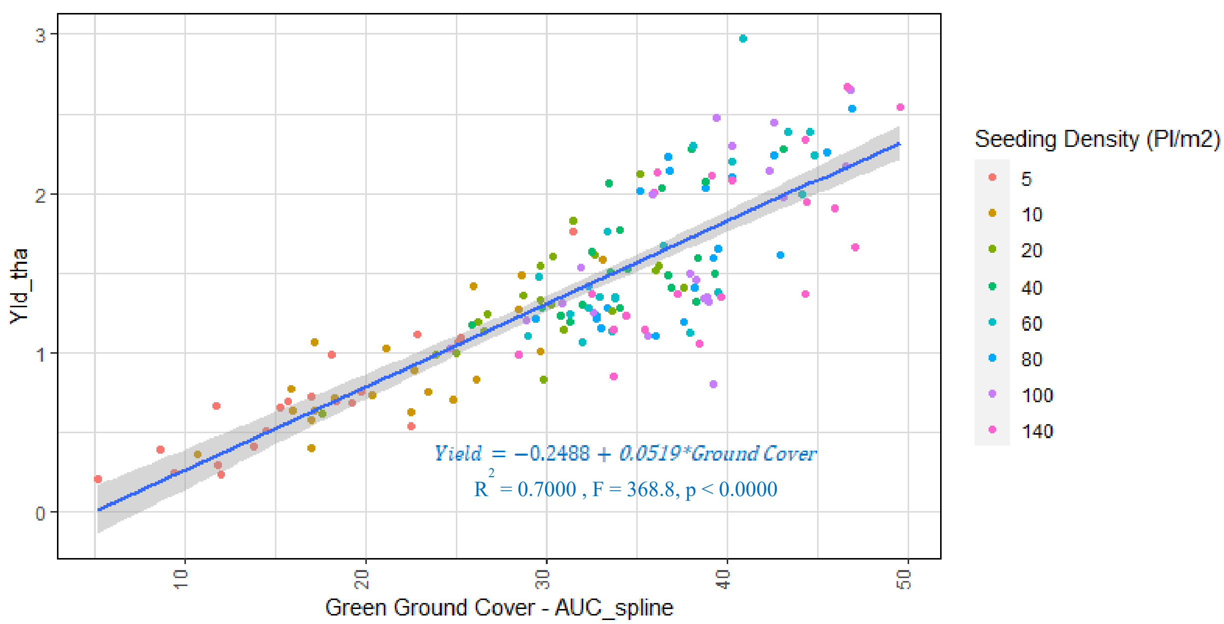

Figure 17: Relationship between canola yield vs ground cover accumulation over time. The scatter plot represents the yield distribution pattern among seeding densities used in the trial. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season.

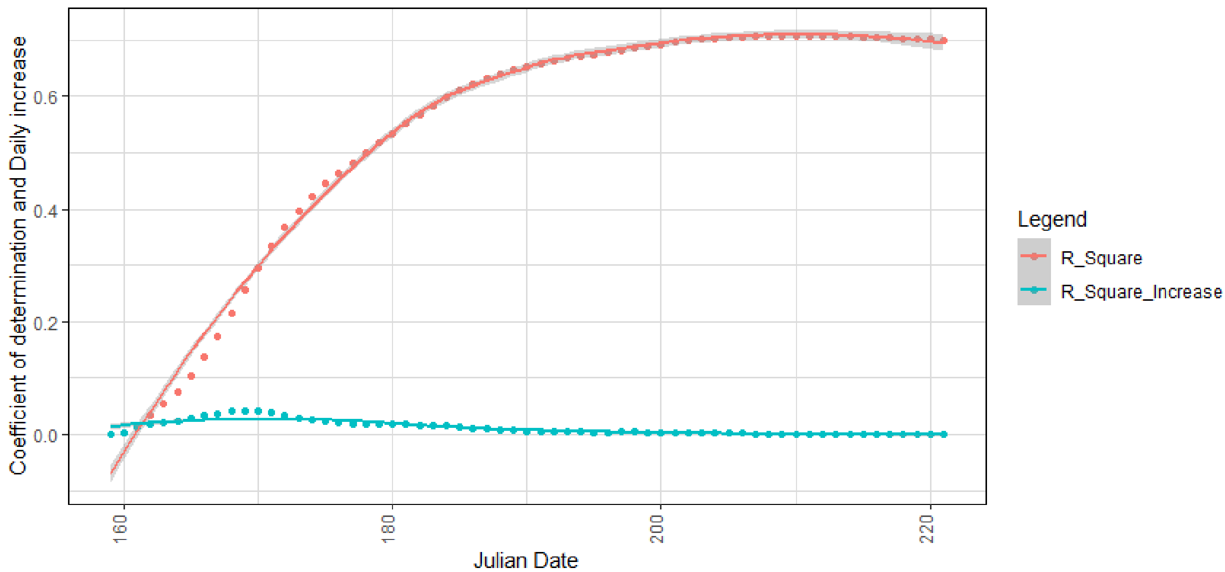

Figure 18: Illustration of coefficient of determination daily variation estimate between canola yield (tons per hectare) and the daily cumulative ground cover. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season. The ground cover change over time was modelled and integrated to calculate the daily area under the curve to estimate the cumulative ground cover change over time. The amount of ground cover accumulation for a given time is then regressed against yield to develop the final model and to calculate the coefficient of determination. The graph represents the coefficient of determination and the daily gain against the Julian date of the crop growing season.

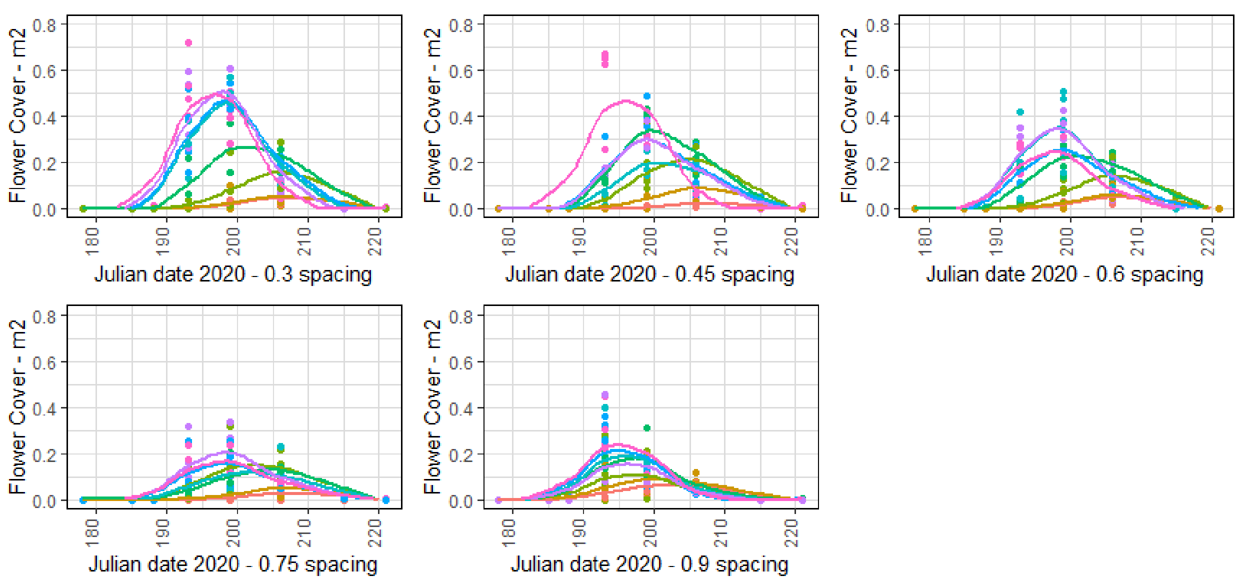

Figure 19: Canola flowering cover accumulation based on threshoulded Normalized Difference Yellowness Index (NDYI) over time for varying seeding rate combinations and row spacing categories. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season. Five panels represent different spacing categories (30, 45, 60, 75, and 90 cm) and each model corresponding to varying seeding rates (5, 10, 20, 40, 60, 80, 100, 140 targeted plants m^{-2}). The variations of fitted models are a result of experimental treatments (seeding rate x row spacing). The model is non-linear regression based on the Locally Weighted Scatter Plot Smoothing (LOESS) technique.

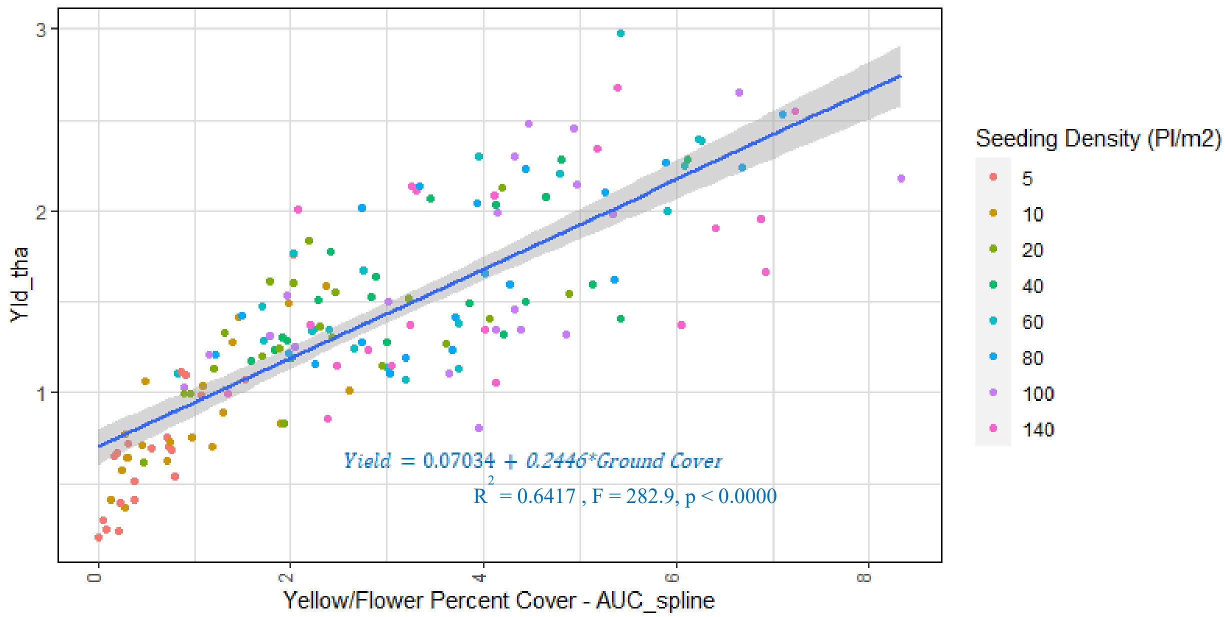

Figure 20: Relationship between canola yield vs flowering cover accumulation over time. The scatter plot represents the yield distribution pattern among seeding densities used in the trial. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season.

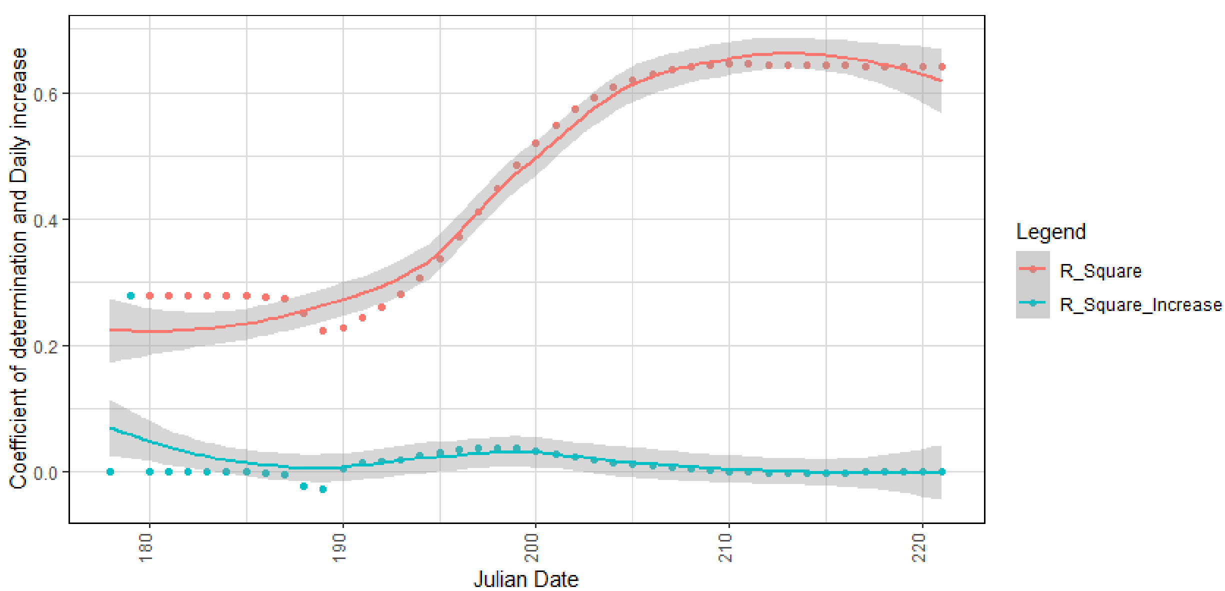

Figure 21: Illustration of coefficient of determination daily variation estimate between canola yield (tons per hectare) and the daily cumulative flowering cover. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season. The ground cover change over time was modelled and integrated to calculate the daily area under the curve to estimate the cumulative ground cover change over time. The amount of ground cover accumulation for a given time is then regressed against yield to develop the final model and to calculate the coefficient of determination. The graph represents the coefficient of determination and the daily gain against the Julian date of the crop growing season.

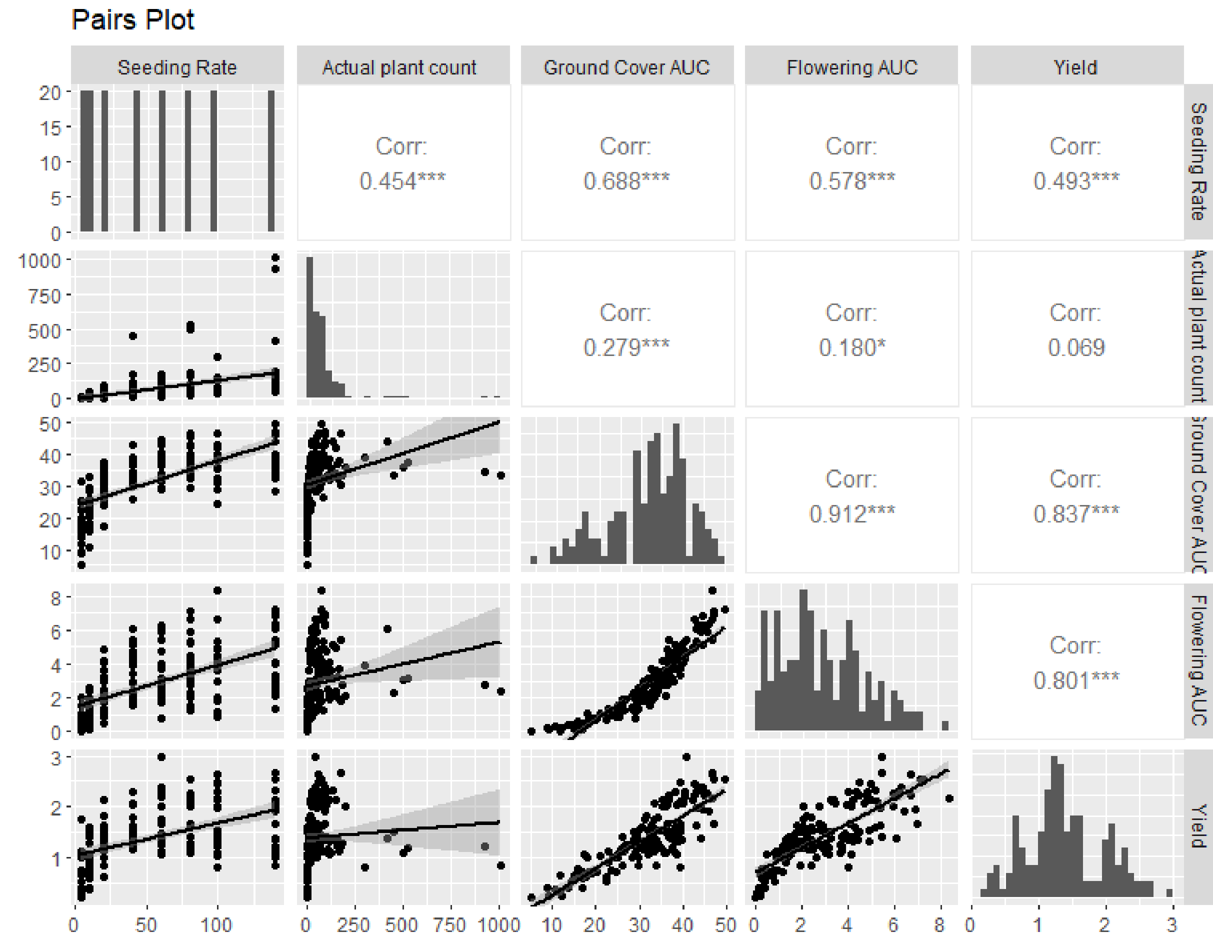

Figure 22: Grain yield relationship with fixed experimental factors and remotely sensed responses. The fixed experimental factors include seeding rate and actual plant count. Remotely sensed responses include ground cover accumulation and flowering area accumulation over time. Field trial location is Saskatoon (site Brown) Saskatchewan – 2022 field season.

6. Conclusions and Recommendations – Highlight significant conclusions based on the discussion and analysis provided in the previous section with emphasis on the project objectives specified above; also provide recommendations for the application and adoption of the project results and identify any further research, development, and communication needs, if applicable.

To maximize yield in canola growers should seed at least 60 seeds /m2 (5.5 seeds/ft) and have row spacing of 30 cm (12”) or less. Canola was able to compensate for low seeding rates by increasing branching and number of pods but this delayed flowering. The row spacing effect was minimal compared to seeding rate however wider row spacings always trended to lower maximum yields than narrower row spacing.

Crop yield in canola is highly associated with the space that the crop canopy occupies over time. The highest yielding treatments were the ones that most rapidly achieved and maintained full canopy coverage. The practical agronomic message of this model is that canola yield is not able to compensate for reduced ground cover from poor stands. To manage canola for highest seed yield requires agronomic practices including seeding rates and row spacings, that result in rapid canopy closure.

Objective 1: Determine plant distribution, survival, branching, ground cover, and yield in response to row width, planting uniformity, seeding density, light quality and intensity.

To maximize yield in canola growers should seed at least 60 seeds /m2 (5.5 seeds/ft) and have row spacing of 30 cm (12") or less. Canola was able to compensate for low seeding rates by increasing branching and number of pods but this delayed flowering. The row spacing effect was minimal compared to seeding rate however wider row spacings always trended to lower maximum yields than narrower row spacing.

Canola responded to both seeding rate and crop row spacing. The seeding rate which canola canola reached 95% of its maximum yield varied depending on location. However, canola always reached 95% of its maximum yield at seeding rates below 60 seeds per m2.

For most site years there was a trend to lower canola yield whenever the row spacing was increased beyond 19 cm (Manitoba) or 30 cm. (Saskatchewan). Higher seeding rates were unable to compensate for the increased row spacing as the maximum yield potential normally decreased with increased row spacing.

Yield compensation in canola for increased seeding rate in canola was driven largely by reduced compensatory branching and pod number with higher seeding rates. This occurred over a wide range of seeding densities as was responsible for the constant final yield observed in all trials

Objective 2: Develop and apply image analysis techniques to track space occupied by individual plants over time in different planting arrangements. We developed methodology to use UAV imagery to quantify development of canola groundcover over the season. This was used in the simulation modelling in Objective 3. The ambitious objective of tracking individual plants could not be used in the analysis of this data. We have worked with Ian Stavness of Computer Science to develop a program (Canola Counter) that utilizes a convolutional neural network that is capable of identifying and counting canola in high resolution UAV images. The network is quite accurate in counting canola seedlings when compared to manuals plant counts with an accuracy approaching 90%.

Objective 3: Study and validate plant growth responses to planting arrangements through simulation modeling. We have been able to successfully demonstrate that for a given location crop yield in canola is highly associated with the space that the crop canopy occupies over time. This model explains the reduced yield potential in low seeding rates and wide row spacings in canola. The delay in full ground cover with low seeding rates or wide row spacing always is the mechanism that results in reduced seed yield. The highest yielding treatments were the ones that most rapidly achieved and maintained full canopy coverage. The practical agronomic message of this model is that canola yield is not able to compensate for reduced ground cover. To manage canola for highest seed yield requires agronomic practices including seeding rates and row spacings, that ensure a rapid canopy closure.

Related research is currently being conducted. We are currently pursuing methodology to utilize UAVs to survey canola densities in fields to develop a sampling methodology to aid in the reseeding decisions.

7. Extension and communication activities: (e.g. extension meetings, extension publications, peer-reviewed publications, conference presentations, photos, etc).

1. **Gulden RH** (2018) Herbicide stewardship and low plant populations. Canola Discovery Forum, Canola Council of Canada, Banff, AB. Oct 23. *Invited*

2. **Steve Shirtliffe**, Hema Duddu, Menglu Wang, Ti Zhang, Kirstin Bett, Keegan Strubey, Anique Josuttes, Karsten Neilsen, Isobel Parkin, Sally Vail, Sajit Rajapaksa, Seungbum Ryu, Kevin Stanley, Ian Stavness, Shubhra Aich, Mark Eramian, Carl Gutwin & Co. Scott Noble Imaging Research in Canola. Canola Industry Roundtable Meeting. Feb. 4, 2019. Sasktoon SK.

3. **Steve Shirtliffe**, Hema Duddu, Menglu Wang, Ti Zhang, Kirstin Bett, Keegan Strubey, Anique Josuttes, Karsten Neilsen, Sally Vail, Sajit Rajapaksa, Seungbum Ryu, Kevin Stanley, Ian Stavness, Shubhra Aich, Mark Eramian, Carl Gutwin, Rob Gulden, Scott Noble. Reading the Leaves: Aerial Field Phenotyping for Plant Breeding and Agronomy. Department of Plant Science, University of Manitoba Seminar Series. Feb 14. 2019. Winnipeg, MB.

4. **Steve Shirtliffe**, Hema Duddu, Menglu Wang, Ti Zhang, Kirstin Bett, Keegan Strubey, Anique Josuttes, Karsten Neilsen, Sally Vail, Sajit Rajapaksa, Seungbum Ryu, Kevin Stanley, Ian Stavness, Shubhra Aich, Mark Eramian, Carl Gutwin, Rob Gulden, Scott Noble. Aerial Field Phenotyping for Plant Breeding and Agronomy. Department of Agronomy. Purdue University March 4, 2019. Purdue Indiana.

5. **Shirtliffe** 2019. Maximizing yield with crop inputs in canola. John Deere LEAD. Saskatoon. ~400 attended. January 2019. Invited presentation.

6. **Shirtliffe** 2019. Seeding rates in canola: What is best? Crop Opportunity. North Battleford March 13, 2019. ~100 attended. Invited presentation.

7. **Kanmi-Obembe, O.** 2020. Optimal Row Spacing and Seeding Rates to Improve Canola Yield. Corteva Agricultural Science Symposium Series. Nov. 17, 2020. University of Guelph, Canada. Poster Presentation

8. **Kanmi-Obembe, O.** 2020. The effect of row spacing and seeding rates on canola yield. Lagos State University (LASU) Faculty of Science International Virtual Conference (FOSIC2020). Dec. 2 - 4 2020. Lagos state, Nigeria. Oral Presentation.

9. **Kanmi-Obembe, O.** 2021. Utilizing UAV imagery to predict canola yield. North American Plant Phenotyping Network 1st Virtual Annual Conference . Feb. 16 - 19, 2021. Canada. Poster presentation.

10. **Kanmi-Obembe, O.** 2021. Effects of row spacing and seeding rates to obtain optimal canola yield. 36th edition of the Plant Science Graduate Student Symposium, 1st Virtual Annual Conference. March 5 - 6, 2021. Saskatoon, Canada. Oral Presentation.

11. **Kanmi-Obembe, O.** 2021. Optimal Row Spacing and Seeding Rates to Improve Canola Yield. Soils and Crops Conference. March 16 - 17, 2021. Saskatoon, Canada. Oral Presentation.

12. **Attanayake, A. 2021.** Rapid yield predictions for Canola: Temporal cumulative ground cover based

remote approach for precision agronomy. October 20-21, 2021. Saskatoon, Canada. Poster Presentation.

13. **Attanayake, A. 2022.** Image-based remote approach of Canola yield modelling with cumulative temporal ground cover for precision agronomy. The 2022 North American Plant Phenotyping Network (NAPPN) Annual Conference, February 22-25, 2022. Athens, USA. Oral Presentation.

14. **Attanayake, A. 2022.** Optimization of Ground Cover Phenology Models to Simulate Canola Yield for Precision Farming. March 8-9, 2022. Soils and Crops Annual Conference, 2022. Saskatoon, Canada. Oral Presentation.

15. **Attanayake, A. 2022.** Determination of agronomical dependencies and optimum timeframe for image-based Canola yield simulations using ground cover and flowering phenology. November 14-18, 2022. Canadian Weed Science Society and Canadian Society of Agronomy Annual Conference, 2022. Halifax, Canada. Oral Presentation.

8. Acknowledgements – Include actions taken to acknowledge support by the Funders.

The Canola Agronomic Research Program funding from the Canola Council was acknowledged in all presentations.

9. Literature Cited

Pereira, L.S., et al., Prediction of crop coefficients from fraction of ground cover and height. Background and validation using ground and remote sensing data. Agricultural Water Management, 2020. 241: p. 106197.

Xue, J. and B. Su, Significant Remote Sensing Vegetation Indices: A Review of Developments and Applications. Journal of Sensors, Hindawi, V2017. 2017: p. 17.

Boyd, N.S., R. Gordon, and R.C. Martin, Relationship between leaf area index and ground cover in potato under different management conditions. Potato Research, 2002. 45(2): p. 117-129.

Fernando, H., Ha, T., Attanayake, A., Benaragama, D., Nketia, K.A., Kanmi-Obembe, O. and Shirtliffe, S.J., 2022. High-Resolution Flowering Index for Canola Yield Modelling. *Remote Sensing*, *14*(18), p.4464.

Jimenez-Berni, J.A., et al., High Throughput Determination of Plant Height, Ground Cover, and Above-Ground Biomass in Wheat with LiDAR. Frontiers in Plant Science, 2018. 9(237).

Zhang, T., et al., Phenotyping Flowering in Canola (Brassica napus L.) and Estimating Seed Yield Using an Unmanned Aerial Vehicle-Based Imagery. Frontiers in Plant Science, 2021. 12(1178).

10. Other Administrative Aspects: HQP personnel (PhD and/or MSc students) trained and involved; equipment bought; project materials developed

Two HQPs spent significant time on this project. Olakorede Kanmi-Obembe completed her MSc using data from the 2019 and 2020 season. Anjika Attanayae was a post-doctoral fellow who worked extensively in the statistical analysis and modelling of the results of this project. Anjika and Ola made numerous presentations of the results. Experience on this project contributed to Anjika's current position as North American lead for canola phenotyping with BASF. Sengbum Ryu collected and processed aerial imaging. Eric Johnson and Shaun Campbell oversaw field work and organized data collection. Technical staff including Sydney Beresh, Racquelle Peters and numerous summer students.

11. Appendices - If necessary, include any materials supporting the previous sections, e.g. detailed data tables, maps, graphs, specifications.

12. Financial (to be provided to each Funding Agency (at the addresses indicated in 11.2) a. Comprehensive Financial Statement that summarizes the total income and expenditures to date attributable to the Funders' Funding. b. Explanation of variances from budget which are greater than 10%. c. An invoice for each Funding Agency

13. Final Report Posting Do you consent to a version of this Final Report (with sensitive information removed) to be posted on the funder's website?	___ Yes – this version can be posted ___ Yes – a modified version will be sent ___ No
14. Research Abstract Posting Do you consent to the 2-3 Research Abstract submitted with this Final Report to be posted on the funders and the Canola Council of Canada's website?	___ Yes ___ No

Please send an electronic copy of this completed document to:

Ellen McNabb
Research Administrator
Canola Council of Canada
400 – 167 Lombard Ave.
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Research Abstract Template
Canola Agronomic Research Program (CARP)

Research abstracts are utilized directly for the provincial grower associations on-line extension, the Canola Research Hub and annual Canola Digest Science Edition. Please follow the template for submission of your abstract. **Note- please submit as an editable (unlocked) Word document.**

Total length: About 500 words plus at least two supporting figures and/or tables that best demonstrate the project's key findings.

Project Name: How does in-row seed spacing and spatial pattern affect canola yield?
CARP Code: 2018.41
Principal investigator: Steven Shirtliffe, University of Saskatchewan
Co-investigators/collaborators: Rob Gulden, University of Manitoba
Funding Source: CARP
Project duration: March 30 2018 – March 31 2023

Extension Material: None.

Key Findings [~50 words]: What is the key message, considering the short- or long-term impact on canola growers and the canola industry. If the research did not make any major "new" discoveries, did it confirm an existing theory, prove that something did not work as expected, point to the need to further our understanding of the phenomenon?

This research found that canola yield is maximized when seeding rate and row spacing result in the longest duration of vegetative ground cover. It also confirmed that existing recommendations to establish 5 – 8 seedlings per square foot with row spacings of 12" are adequate to achieve maximum yield.

Translation of Key Findings to the applied community [~50 words]: How do the key findings of the study directly benefit farmers and/or agronomists?

This project provides evidence that current recommendations for seeding rates result in maximum crop yield. However, there was also evidence to suggest that row spacings wider than 12" (30 cm) increase the risk of reduced yields when crop emergence is low.

Catchy opening paragraph showing the benefit/impact of the project [~75 words]:

When it comes to canola seeding rate and row width, think of your crop as a solar panel. Using crop imagery, researchers have found that canola yields are maximized with seeding rates that result in early ground cover that is maintained throughout the growing season. Canola can compensate for lower seeding rates with increasing branching and podding but if that reduction slows canopy closure, or if wide row spacings do not fill in, then yield will be reduced.

Purpose/Objectives [~100 words]: Explain the importance of this research and what was being investigated?

The overall hypothesis of this research is that optimal seeding rate and row spacing affect seed yield in canola by maximizing the ground cover through the growing season. To test this hypothesis the following sub-objectives were tested:

Objective 1: Determine plant distribution, survival, branching, ground cover, and yield in response to row width & seeding density.

Objective 2: Develop and apply image analysis techniques to track space occupied by individual plants over time in different planting arrangements.

Objective 3: Study and validate plant growth responses to planting arrangements through simulation modeling.

Methodology [~75 words]: Focus on details that offer perspective on how the methodology might (or might not) influence how the results can be applied to farm / industry scenarios. Ex. Tools, plot size, locations (soil type), years, etc.

A replicated, factorial field experiment that varied seeding rate and row spacing over a wide range was used. This research was conducted in small plots (2 x 6 m) using equipment similar to field scale equipment. It was conducted at Saskatoon (Dark Brown Soil Zone, semi-arid climate) and Carman (Black Soil Zone, sub-humid climate) from 2019 – 2022.

Important conditions during the research [~50 words]: Such as weather conditions, production challenges, etc. Consider how these might (or might not) influence the results and their potential application moving forward.
The growing conditions during these field trials resulted in below optimal seed yield in canola and may have influenced the results. This was due to drought and heat stress that occurred at both the Saskatoon and Carman locations. Despite these stresses and sub-optimal yields we believe these results are still valid as plant population effects often have greater proportional effects in dry years.

Results [~150 words]: What is most relevant to canola growers / the canola industry? How did this research advance our knowledge?

To maximize yield in canola growers should seed at least 60 seeds /m2 (5.5 seeds/ft) and have row spacing of 30 cm (12") or less. Canola was able to compensate for low seeding rates by increasing branching and number of pods but this delayed flowering. The row spacing effect was minimal compared to seeding rate however wider row spacings always trended to lower maximum yields than narrower row spacing.
Crop yield in canola is highly associated with the space that the crop canopy occupies over time. The highest yielding treatments were the ones that most rapidly achieved and maintained full canopy coverage. The practical agronomic message of this model is that canola yield is not able to compensate for reduced ground cover from poor stands. To manage canola for highest seed yield requires agronomic practices including seeding rates and row spacings, that result in rapid canopy closure.

Figure/table/image: Provide at least two visuals to display the key findings

Figure 1: Field site aerial view of row spacing by seeding rate trial on 2022-07-18. Field trial location is Saskatoon (Site Brown) Saskatchewan – 2022 field season. The row spacing varied from 15cm – 90 cm and seeding rate from 5 – 140 seeds m^{-2}.

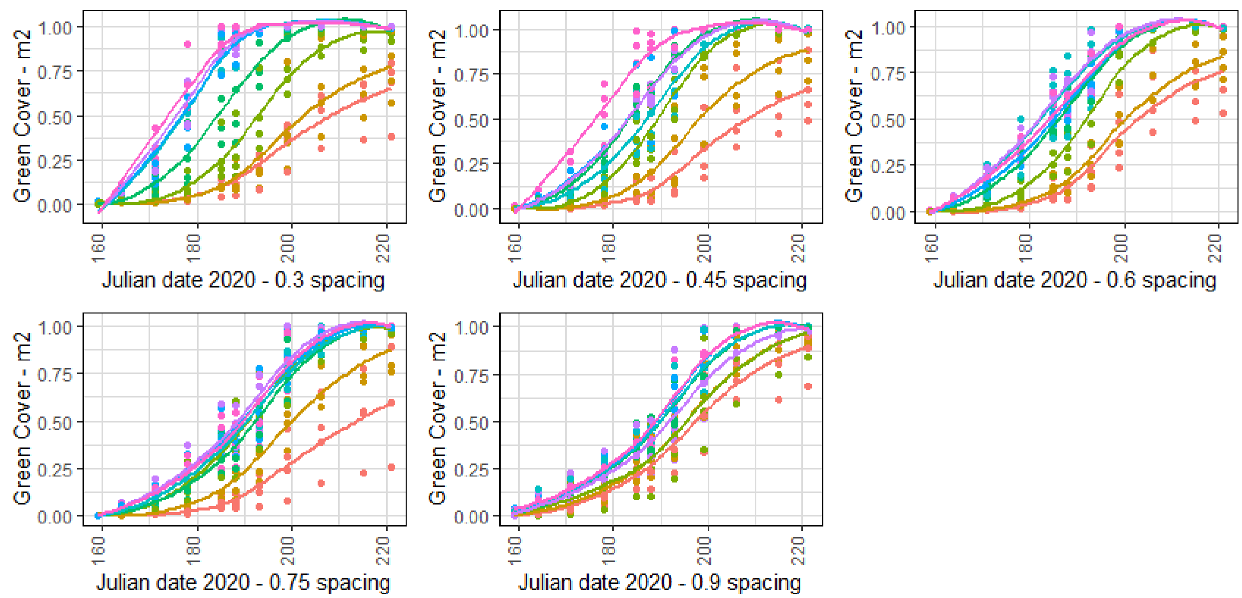

Figure 2: Canola ground cover as affected by seeding rate and row spacing. Five panels represent different spacing categories (30, 45, 60, 75, and 90 cm) and each model corresponding to varying seeding rates (5, 10, 20, 40, 60, 80, 100, 140 targeted plants m^{-2}). As the row width increases the time taken to achieve full ground cover for low densities increases.

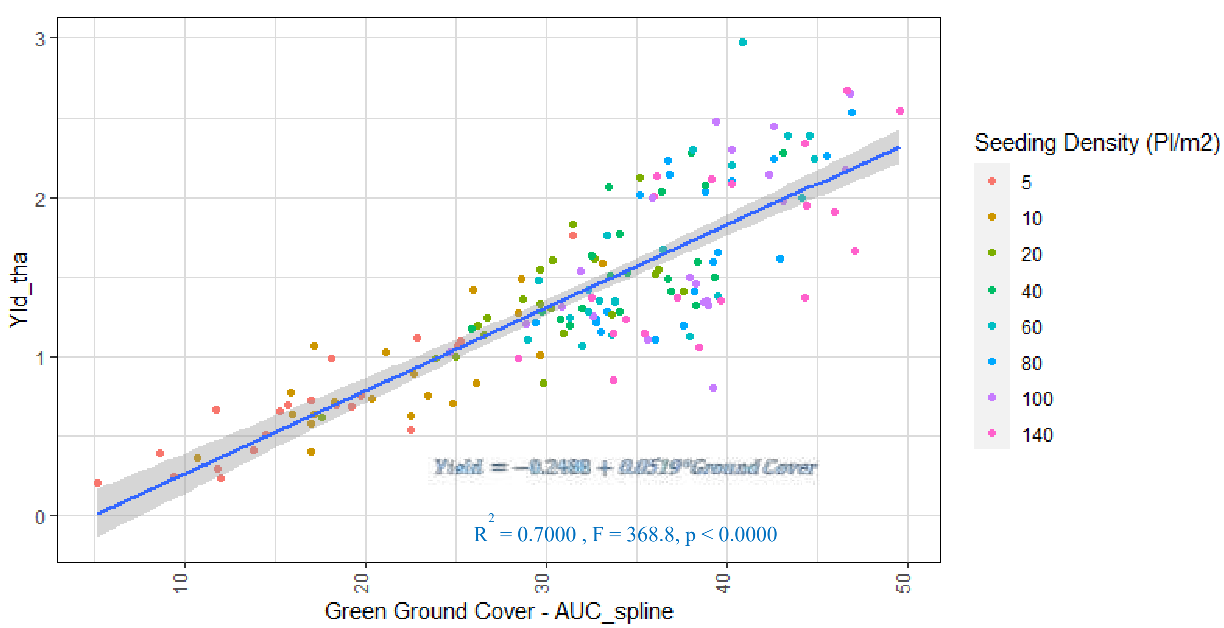

Figure 3: Relationship between canola yield vs ground cover accumulation over time for all row spacing and density combinations. The scatter plot represents the yield distribution pattern among seeding densities used in the trial.

Highly Qualified Personnel (HQP) [100 words]: Was a HQP (graduate student, post-doc, etc) assigned to the project? To what extent did they work on this project? Was some (or all) of the extension messaging prepared and delivered by the HQP?

Two HQPs spent significant time on this project. Olakorede Kanmi-Obembe completed her MSc using data from the 2019 and 2020 season. Anjika Attanayae was a post-doctoral fellow who worked extensively in the statistical analysis and modelling of the results of this project. Anjika and Ola made numerous presentations of the results. Experience on this project contributed to Anjika's current position as North American lead for canola phenotyping with BASF. Sengbum Ryu collected and processed aerial imaging. Eric Johnson and Shaun Campbell oversaw field work and organized data collection. Technical staff including Sydney Beresh, Racquelle Peters and numerous summer students.

Acknowledgements:

Credit for this funding was presented in all presentations. Hansanee Fernando used imagery from this experiment to develop a canola flowering index.

References:

Fernando, H., Ha, T., Attanayake, A., Benaragama, D., Nketia, K.A., Kanmi-Obembe, O. and Shirtliffe, S.J., 2022. High-Resolution Flowering Index for Canola Yield Modelling. *Remote Sensing*, *14*(18), p.4464.

Two other publications are currently being edited.