ESTIMATION OF COTTON PICKING LOSSES USING RGB UAV IMAGERY

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Abstract

Although technologies such as yield monitors are equipped on many current-generation cotton pickers, limited research has been conducted to quantify the amount of cotton that remains unharvested after a picker has passed through a field. Combined with tighter environmental regulations, higher operating, labor, seed, and land costs mean that now more than ever, it is vital to ensure cotton is being harvested as completely and efficiently as possible. This study aims to develop linear regression models which can be used to predict cotton losses using low altitude, RGB imagery captured from a consumer level UAV, or drone. Median seed cotton prediction error from one of the models developed was 27 kg ha^{-1} (24 lb ac^{-1}), with 90% of the prediction errors being less than 63 kg ha^{-1} (56 lb ac^{-1}), and a model R^2=0.842. It is foreseeable that these and similar models can be implemented into real-time systems, which would allow operators to get instant feedback, as well as make in-field adjustments to minimize losses.

Introduction

Use of Unmanned Aerial Vehicles, or "UAV" in the field of Precision Agriculture has increased dramatically in the past decade. UAV usage allows for data to be collected at a much faster rate than by hand, and allows for more area to be covered in a similar amount of time, saving valuable labor hours. Feng et al. (2019) performed a study working to measure plant height and develop regression models linking plant height to yield using data from a low-cost UAV utilizing a RGB sensor camera, and achieved an R^2 value of 0.96. Chu et al (2016) also found strong correlations (R2 = 0.990) linking cotton plant height to canopy cover using point clouds derived from UAV imagery. Yeom et al. (2016) utilized a DJI Phantom 4 UAV equipped with a RGB camera to classify open cotton bolls using pixel thresholding, and correlated UAV derived open boll data with collected yield data with a positive correlation of 0.8.

The objectives of this study were to (1) utilize a small "consumer-grade" UAV equipped with an integrated RGB camera to capture images of cotton remaining after a field had been picked using a John Deere Picker (Model 9996). These images were used to (2) develop linear regression models for predicting the amount of cotton, defined as "Picking Losses", that remained within each sampling area in hopes that these models could be (3) used as a framework for development of a solution providing real-time feedback to operators suggesting alterations to speed or machine parameters that could be made to reduce such losses, or provide a tool which could be used for crop scouting and/or yield damage assessment.

Materials and Methods

Loss Plot Layout

All three sites included in this study are located at the Clemson University Edisto Research and Education Center in Blackville, South Carolina. Field D3A was planted in Deltapine 1835, field E8A was planted in Deltapine 1851, and field E8B was planted in Deltapine 1636. All three fields were planted with 96 cm (38 in.) row spacing. Test plots were randomly assigned a picking speed treatment of 3.2, 4.8, 6.4, or 8.0 kph (2.0, 3.0, 4.0, or 5.0 mph) in coincidence with a harvest speed test performed during the same picking (Kirk et al., 2020). Each treatment was replicated five times throughout each field. In fields E8A and E8B, the field was split into two harvest timings, each having the aforementioned replications and treatments. Early harvest timing plots were harvested approximately 9 days after defoliation, while Late harvest plots were harvested approximately 25 days after defoliation. This distinction was made in efforts to simulate and capture the weather effects of a harvest delayed by adverse weather, machine malfunction, or other harvest delays.

Harvest, UAV Image Acquisition, and Picking Loss Collection

All test plots were harvested with a John Deere 9996 model cotton picker equipped with picking unit model John Deere PRO-16. Within each test plot, a rectangular sampling area was established. The sampling area spanned the center four rows of each six row picker pass, and was 2.4 m (8.0 ft) in length. The resulting sample area for each plot was 9.41 m^2 (101 ft^2). Prior to picking, an orange line was spray painted into the field, perpendicular to the rows to signify the beginning of the sampling zone. This orange line also allowed for the beginning of each sampling zone to easily be seen from captured aerial images, a step necessary for image processing. Within three days of picking, all remaining cotton within the sampling zone was collected by hand, classified as “On-Plant” and “On-Ground” losses, and separately bagged. Hardlocked, rotten, and other non-harvestable bolls were not collected for this study and remained on the plant. Samples were placed in a drying oven for 7-10 days to remove excess moisture. Samples were then sorted through to remove leaves, burrs, sticks, and other debris which could have significant effects on weight, and then samples were weighed.

A DJI Phantom 3 Advanced UAV was used to capture plot images for analysis. Images were captured after each field was picked by the John Deere 9996, but before picking losses were collected by hand. The UAV was equipped with a permanently-attached 12.0 megapixel RGB camera model DJI-FC300s. The UAV was controlled using an Apple iPad, and a flight path was established using the *Map Pilot for iOS* application. This flight path was programmed to traverse the entire study area at an altitude of 11 m (35 ft) above ground level, or “AGL”, taking pictures continuously. The resulting images were of resolution 0.508 cm $pixel^{-1}$ (0.2 in. $pixel^{-1}$). All images were captured from a “NADIR” perspective, meaning the UAV camera was parallel to the ground, and at a 90 degree angle to the UAV. Images were captured with 60% vertical overlap, and 80% horizontal overlap. Images were captured directly after each field was picked by the John Deere 9996 to avoid the possibility of bolls opening between picking and image capture, which could artificially alter color values, and to avoid the possibility of bolls blowing into the sample area from adjacent plots. One replication of each field was also imaged after all picking losses had been collected, in order to serve as a “zero loss” test to be included in the regression modeling. All images from each field were stitched into an orthophoto using *WebODM*, open source UAV image stitching software provided by *OpenDroneMap*. Within *WebODM*, images were resized to dimensions 2,048 x 1,535 pixels, and orthophoto images were processed to the same resolution at which they were captured, 0.508 cm $pixel^{-1}$ (0.2 in. $pixel^{-1}$). The resulting orthophoto provided a high-resolution view of each field included in the study.

Each field orthophoto was separately loaded into *Adobe Photoshop Creative Cloud 2019*, where the “Rectangle Select” tool was used to select the plot area within which samples would be collected. Each plot was exported as a separate Portable Network Graphics, or “PNG” image for analysis. An alternate method of image processing was performed in which the un-stitched images that were used to compose the orthophoto were loaded into Adobe Photoshop; plots were isolated, cropped, and exported in a similar method. A comparison of these two methods is shown in the “Results and Discussion” section.

Image Analysis

Plot images were loaded into *Batch Load Image Processor* v.1.1, or BLIP, software developed by Clemson University. BLIP, written in *Microsoft Visual Basic 2013*, allows the user to upload either a single image, or a directory of images to be processed. The software extracts the red, green, and blue colorspace values for each pixel in the image, and averages these values in its output. In addition to the red, green, and blue colorspace averages, BLIP also calculates and averages several attributes derived from the colorspace values, which are shown in Table 1.

Table 1: Batch Load Image Processor Outputs

R	G	B	BRT_3D	BRT_HSP
BRT_W3C	LUM	CHROMA	HUE	HSI
HSV	HSL	SatHSI	SatHSL	SatHSV

BLIP also calculates percentages of pixels in an image residing within one of several bins. For instance, BLIP defines 32 red colorspace bins (R0 to R31), with R0 being defined as red colorspace values from 0 to 7, R1 being defined as red colorspace values from 8 to 15, and so on, through R31. The R0 output from BLIP represents the percentage of pixels in an image with red colorspace values between 0 and 7. In this sense, BLIP provides a 32-division histogram for the red colorspace. BLIP calculates these binned outputs for red, green, and blue colorspace, as well as for BRT_3D and HUE, all of which are constructed for 32 divisions of the full scale range of possible values. BLIP writes the average red, green, and blue colorspace values, average values from Table 1, and bin outputs discussed here to a Comma Separated Values (CSV) file, where each row represents a unique image, or plot in the case of this experiment, and each column can be considered as a factor for regression model development.

Statistical Analysis

All regression modeling was performed with *JMP* v14.3.0. Data were randomly assigned to a Train dataset (80% of the images and plots) or a Test dataset (20% of the images and plots) to ensure the models were not tested on points which had been used to develop them. Regression models were produced from the Train dataset using the Stepwise Regression method. All models were produced using Forward direction and utilized a Minimum AiCC stopping rule. Total_Loss_Weight represented the response (Y) variable of the regression and represented the sum of On Plant and On Ground picking losses. Model effect terms considered included the BLIP outputs and transformations thereof; data transformations displayed in Table 2 were applied to all model effects.

Table 2: Data Transformations Used in Regression Model Development

Square Root	Square	Cube Root	Cube	$Log_{10}+1$	Reciprocal

During model construction, multiple collinearity was assessed by removing terms with Variance Inflation Factor (VIF) values greater than 5, as suggested by Kutner, et al. (2005). Influential points and outliers were evaluated using Cook's Distance Formula, and points having a Cook's Distance value greater than 1.0 were removed as suggested by Hair, et al. (1998). Upon discovery of an influential point, the regression modeling process was restarted, with the influential point excluded from the dataset. Terms with p-values greater than 0.05 were eliminated from the model until all terms satisfied the conditions set by VIF, Cook's Distance, and p-value.

Results and Discussion

During aerial imagery processing, it was noticed that discrepancies could be seen between plot images which had been stitched into an orthophoto, and plot images that had been captured from the unstitched image. It is important to note that in this paper, unstitched images are referred to as "Plot Raw Images", this is not to be confused with the "RAW" filetype format often used in high-resolution photography applications. All images used within this study were of Portable Network Graphics "PNG" format. Specifically, orthophoto "Snipped" images resulted in blurred spots, as well as spots where cotton bolls had been "stitched out" of the image. This resulted in a difference of color values, and therefore had a notable effect on the regression models developed. In Figure 1 below, an identical plot image is shown side by side comparing the two image extraction methods. The colored shapes represent specific points of interest where there is visual difference between the two image types.

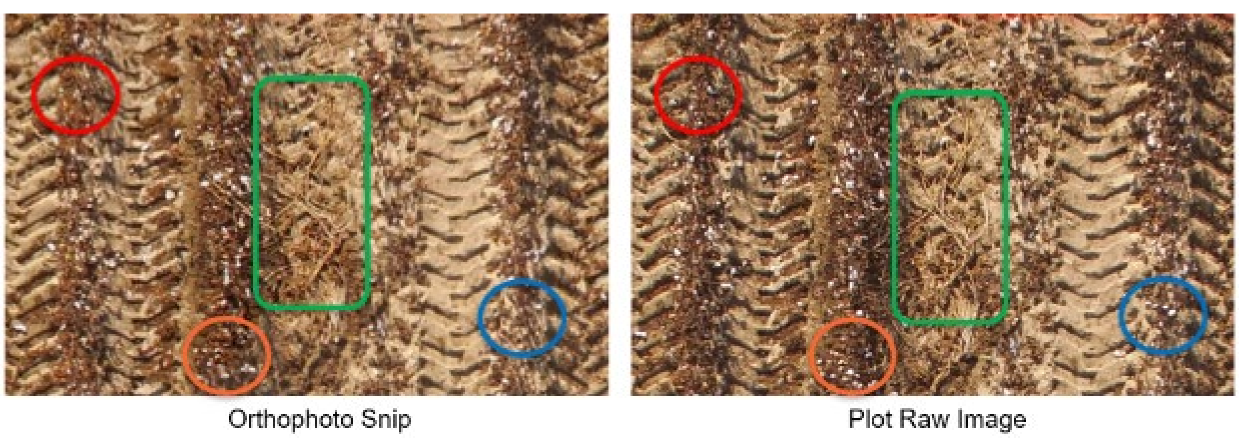

Figure 1: Image Type Quality Differences: Side by Side comparison of plot image "Snipped" from orthophoto (Left), and image of same plot that was used to generate orthophoto (Right).

An actual vs predicted plot of the model produced using the “Orthophoto Snipped” imagery is shown in Figure 2 below, with a Residual vs. Predicted plot visualized in Figure 3.

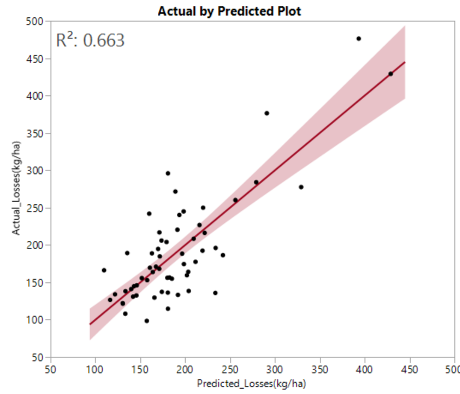

Figure 2: Orthophoto Snip Imagery Actual vs. Predicted

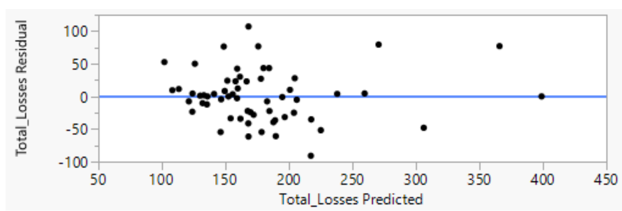

Figure 3: Orthophoto Snipped Imagery: Residual vs. Predicted Total_Loss Values

This model resulted in a median prediction error of 25.95 kg/ha (23.15 lb/ac), and a 90% prediction confidence of 80.47 kg/ha (71.79 lb/ac) of seed cotton, with an $R^2 = 0.66$. The model, coefficients, and p-values for each term are shown in Table 3.

Table 3: Mosaic Snipped Imagery Linear Regression Model Terms, Coefficients , and P-Values

Term	Estimate	Prob>|t|
Intercept	118.97407	<.0001
G(3)	-51.15874	0.0012
G(31)^2	396.13203	0.0208
Log[B(27)+1]	397.10427	0.0016
BRT(1)^3	88670946	<.0001
BRT(3)^3	1085.3475	0.0008
B(2)^3	0.778206	0.0037
B(31)^3	-18190.69	0.0378

A model was constructed using only plot images extracted without stitching, the results of that model are displayed in Figure 4, with a Residual vs. Predicted plot shown in Figure 5.

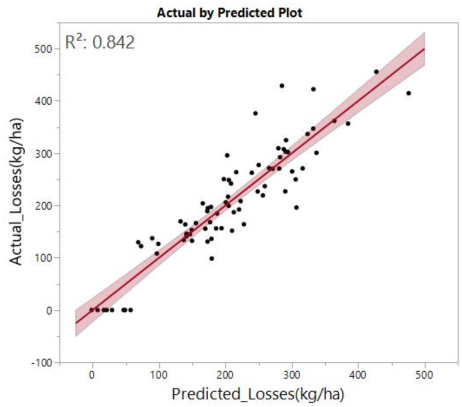

Figure 4:Plot Raw Imagery Actual vs. Predicted

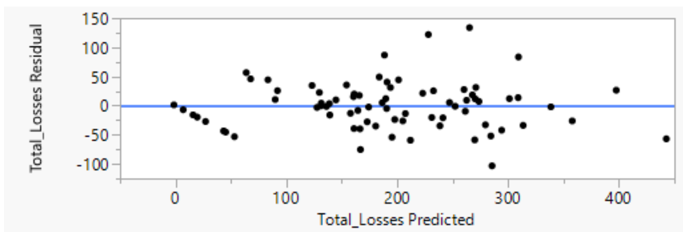

Figure 5: Plot Raw Imagery: Residual vs. Predicted Total_Loss Values

This model resulted in a mean prediction error of 27.44kg/ha (24.48 lb/ac), and a 90% prediction confidence of 63.21 kg/ha (71.79 lb/ac) of seed cotton, and an $R^2 = 0.84$. The model, coefficients, and p-values for each term are shown in Table 4.

Table 4: Unstitched Imagery Linear Regression Model Terms, Coefficients, and P-Values

Term	Estimate	Prob>|t|
Intercept	-54.0316	0.0036
Log[B(28)+1]	1025.124	<.0001
G(18)^3	0.138829	<.0001
R(31)^3	0.633564	0.0031
Cube Root[HUE(19)]	531.095	0.0007
R(16)^3	0.131621	<.0001
B(26)^3	-2278.68	<.0001
B(29)^3	921.2981	0.0018
HUE(14)^3	-1.27E+10	0.0077
HUE(22)^3	-2.9E+07	0.0158

Summary

This study determined that cotton "Picking Losses" can be estimated using low-altitude imagery captured from a consumer level UAV using its integrated RGB camera using a linear regression approach. The resulting regression models are moderately robust, but could likely be improved via the inclusion of a higher number of data points across different times of day, weather conditions, and altitudes. Because no pixel classification was used in this study, it is unlikely that regression modeling alone would be able to classify losses as "On Plant" or "On Ground" and making this distinction would likely require the use of a Machine Learning application.

Orthophoto creation was performed in an effort to produce a "top-down" view of the entire field, which would make locating specific plots easier, thus making plot image extraction easier. Use of a single-shot, low altitude plot image resulted in lower prediction error, and required much less processing time. It can be concluded from this study that the orthophoto stitching process has the possibility to have an effect on captured imagery, which can lead to astray data. In this study, this is likely due to the low horizontal and vertical image overlaps required to be able to fly the UAV at the desired altitude. The regression model made from images snipped from the original orthophoto had a lower median predicted error of 25.95 kg/ha (23.15 lb/ac), but a much higher 90% predicted error of 80.47 kg/ha (71.79 lb/ac) seed cotton when compared to "Mosaic Raw Images", which had a median error of 27.44kg/ha (24.48 lb/ac), and a 90% prediction confidence of 63.21 kg/ha (71.79 lb/ac) of seed cotton. R^2 also increased from 0.66 when using the snipped orthophoto images to 0.84 when using the "Mosaic Raw" images.

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