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An ASABE Meeting Presentation

Paper Number: 1620969

Development and Testing of an Impact Plate Yield Monitor for Peanuts

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Written for presentation at the

Annual International ASABE Meeting

Sponsored by ASABE

Kansas City, M.O.

July 21 – 24, 2013

Abstract. *Advancements in precision agriculture technologies such as yield monitors have allowed for improved management capabilities and reduced input costs for a number of crops. Most commercialized developments in yield monitoring systems and technologies to date have been directed for use with the major grain crops such as corn, soybeans and cereal grains. This research focuses on development and testing of an impact plate yield monitor system for the peanut harvest. Using a four row peanut combine in virginia type peanuts, 4.8 ha (12 ac) of simultaneous yield data were recorded from an Ag Leader® grain (impact plate) yield monitor and an Ag Leader® cotton (optical) yield monitor. An instrumented cart was used to weigh calibration loads for the two yield monitors tested. Mean absolute error across 10 loads in two fields was 10.2% for the impact plate and 1.54% for the optical yield monitor. Full-season data was not obtained for the impact yield monitor, but mean absolute error for the optical yield monitor across the 2012 harvest season was 9.4%. Regression analyses indicate that use of the two monitors in unison may result in reduced error of the estimate. A large portion of the error calculated for the impact plate yield monitor may be attributable to excessive vibration from the older, straw walker type combine used in this study.*

Keywords. *peanut, yield monitor, precision agriculture, impact plate, optical, Ag Leader®.*

Introduction

As the need for agricultural efficiency and productivity continues to increase, producers must find ways to maximize their crop's potential. The economic drivers arise from increases in fertilizer and herbicide cost, and environmental sanctions call for better pesticide management. Precision agriculture concepts and methods are showing great promise in meeting the world's needs for efficient agricultural practices. Through the use of yield monitors, GPS guidance, and variable rate applicators producers are making progress in increasing yield while decreasing cost and field inputs. Application of yield monitoring technologies to the production of cotton and corn has improved crop management and profits. Similar improvements in management capabilities and increases in profit will be seen in peanut production with the advent of a commercially available yield monitoring technology.

Previous studies have shown that precision agriculture yield monitoring systems can be viable in peanut harvest. The study conducted by Thomas et al. (1999) developed a Peanut Yield Monitoring System (PYMS) that included load cells mounted below the hopper basket of a peanut harvester. Further research (Durrence et al., 1999) evaluated the PYMS, which showed that the system was able to construct field data for the harvested crop. Research was also conducted using the PYMS to detect disease in peanut plots (Perry et al., 2002). In this study, researchers found that the yield monitoring system was able to be spatially correlated to diseases in the field as a function of yield. Another study (Kirk et al., 2012) developed a system for recording yield from research plot studies using load cells to batches of peanuts from each test plot. While this system could not be adapted for use by a producer, it was reported to have the potential to more than double harvestable plots per clock hour and triple plots per labor hour for research studies.

Research has also been conducted in the use of optical yield monitor sensors in peanut harvests. Thomasson and Sui (2003) developed and tested an optical sensor for pneumatically conveyed crops. The research concluded that the optical monitor experienced a mean error of 5.7% and a maximum error of 26.6%. Research employing the Ag Leader® optical cotton yield monitors for peanut harvesting was also conducted (Rains et al., 2005). This research showed that the Ag Leader® system can be used for peanut harvest but had potential for errors from abrasion as well as need for further research in calibration. Methods for reducing dust and abrasion were made for the second year of the study. Further adaptations and modifications to this system were tested by Porter et al. (2012). They developed and tested "dirt deflector" high density plastic ramps upstream from the optical sensors to reduce the amount of debris that would be flowing across the sensors. The deflectors also included a slit in the chute to allow air to pass over the sensors to act as a cleaning flow of air over the sensors. Optical yield monitors are the only yield monitoring systems for peanuts noted in published research studies in recent years.

Impact plate yield monitoring systems are widely used in modern agricultural practices to gather data on the mass flow of the crop at various stages of harvest and storage. The system operates by using load cell technology to give a mass flow reading as a function of sum of sensor output per unit time. Until now impact plate yield monitoring systems have been primarily used in conventional grain crops such as corn. These monitoring systems are commonly used in corn combines at the top of the clean grain auger to provide continuous feed of harvested crop mass flow rate. The data given in field use is instantaneous and can be a good indicator of variation in the field. This data can then be used to make management decisions and prescription maps for field applications.

Objectives

Research conducted at the Clemson University Edisto Research and Education Center in 2012 was conducted to design, test and determine the viability of an impact plate yield sensor for peanut harvest. The impact sensor was a modification of a commercially available yield monitor for grains.

The objectives of this study were to:

- Design a system allowing application of an impact plate sensor for peanut yield monitoring.
- Compare the performance of optical and impact plate sensors for peanut yield monitoring,
- Characterize variables that potentially have effect on optical and impact plate sensor accuracy.

Materials and Methods

An Ag Leader® 4000201 (Ag Leader® Technology, Ames, Iowa) impact or "grain" sensor connected to an Ag Leader® Integra monitor was adapted to a four row Bush Hog 9004 (Bigham Brothers, Inc., Lubbock, Texas) pull-type peanut combine. The load cell of the impact monitor was attached to the exterior of the topmost portion of the clean peanut delivery chute of the combine. The outside of a 90° bend where the peanuts are deflected into the hopper basket of the combine was the point chosen to adapt the impact plate monitor as shown in figure 1. The impact plate was removed and the load cell was removed from the sheet metal housing for mounting in a grain combine. The load cell was fixed to a "floating" section of bar screen on the delivery chute and to the side walls of the peanut basket via a mounting bracket as depicted in figure 2. The bar screen was fixed to the chute along its lower edge by a piano hinge to restrict motion when peanuts were being deflected into the hopper basket. Installation to a section of the bar screen was a key design feature of this adaptation because it allowed for peanuts to strike the plate and log data but reduced the effects of airflow. It was presumed, but not tested, by the researchers in this study that use of a solid plate would result in difficulty in distinguishing between forces imparted by peanuts and those by the conveying air. The design allows retrofit packages to be easily adapted to many different models of peanut harvesters that utilize pneumatic conveyance. A shaft speed sensor, normally mounted to the clean grain elevator shaft on a grain combine, was required for operation and mounted on the blower fan shaft for this application.

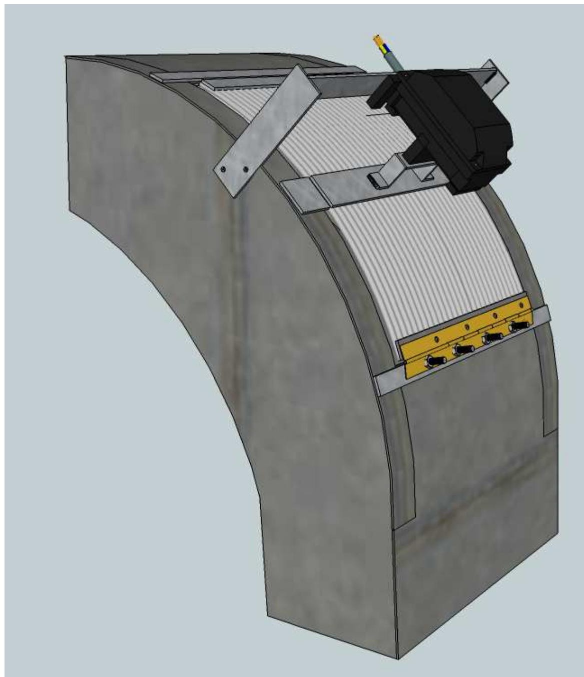

Figure 1. Impact sensor placement at upper bend of clean peanut delivery chute of the harvester, attached to an isolated section of the bar screen.

Figure 2. Impact sensor mount on Bush Hog four row combine.

The optical monitor used in the study was an Ag Leader® cotton sensor paired with an Ag Leader® InSight monitor. The sensor is commonly used in cotton harvesting equipment to measure cotton lint yield. The system uses a pair of units for sending and receiving; it is a “through-beam” technology that senses breaks in light transmittance from objects passing between the transmitter and receiver. Mounting of the optical sensor was the same as described in previous studies (Rains et al., 2005; Porter et al., 2012).

Both the impact and optical yield monitoring systems were mounted to the same four row pull behind Bush Hog 9004 peanut combine. Both yield monitors use the same pneumatic conveyance systems of the combine, GPS receiver, but independent header height sensors, calibrated to approximately the same settings. Each sensor was calibrated off of the same field loads for comparison of accuracy in calibration. Shaft speed, vibration, header height, and temperature calibrations were preformed independently for the Integra monitor, as would be necessary if used for grain harvest. The vibration and shaft speed calibrations were conducted while the machine was stationary with PTO engaged but no crop flow. The optical monitor logged data at a rate of 1.0 Hz while the impact logged at 0.5 Hz.

Continuous, geo-referenced point data was acquired with the impact and optical sensors simultaneously during harvest. Only virginia type peanuts were harvested during the portion of the study reported here. Load weights for calibration were individually measured using a single axle Pioneer cart instrumented with load cells. Each load harvested from a field was dumped into the cart which was calibrated at the beginning of the season.

Data from the yield monitors were imported into Ag Leader® SMS™ software, which is an agricultural, spatial data management software. A 14 s lag time, as reported by Boydell, et al. (1999) was imposed on both the optical and impact data to account for convolution of the peanuts during transport from the header to the clean peanut delivery duct. Filter limits for minimum and maximum yield were set at 0 kg ha^{-1} (0 lb ac^{-1}) and 22,400 kg ha^{-1} (20,000 lb ac^{-1}) for both datasets. Spatial load summaries from SMS for both the impact and optical monitor were compared to Comma-Separated Values (.CSV) files for the point data to verify accuracy. Load summaries were then imported to Microsoft Excel for data analysis.

Because the Ag Leader® systems apparently use a finite number of calibrations, as discussed later, the predicted load weights for the two sensors were normalized for comparison. This was completed by applying a linear regression with y-intercept equal to zero, correcting the monitor predicted load weights (independent variable) as a function of the actual weights for those loads (dependent variable). Moving averages of instantaneous mass flow data for the two sensors calculated across 20 second intervals were calculated and plotted for comparison and to roughly verify proper operation of the impact sensor throughout the point data, as the optical sensor has already been proven for peanuts at least to some level of accuracy. For brevity, these plots are not included in this report.

Results and Discussion

Preliminary field testing indicated the need for some modifications to the impact yield monitor mount. As discussed, the section of bar screen used as an impact plate was fixed to the chute by means of a hinge on the lower portion of the plate. After encountering problems with the vibration calibration function for the impact sensor, the hinge was unattached from the duct, which mitigated the problems. This refinement was completed prior to collection of any of the data used in this report. After dismounting the hinge from the duct, the section of bar screen serving as the impact plate was essentially “floating” at the periphery of the bend on which it was mounted. The load cell utilized four bolts for mounting, two at the plate and two for mounting to the machine. This proved to be sufficient to hold the impact plate in position at the duct without physically touching the duct, which likely would have interfered with sensor output. The impact plate was positioned with about 0.25 in clearance on all sides, relative to the duct.

There were a total of 38 loads with known weights and simultaneous yield data from the two sensors collected during the 2012 season. However, yet to be identified problems with some of the impact sensor data resulted in a paired dataset of only 10 loads, collected from two fields, which are the ones reported here. The other 28 load datasets collected for the optical sensor were intact, as it was collected on a separate monitor. This allowed for analysis of a full season dataset for the optical sensor, but not for full season comparisons between the two sensors.

As briefly mentioned in the prior section, the Ag Leader® systems apparently use a finite number of calibrations. Because of this, accuracies of the calibrations are not as good as they could be with an infinitely variable linear best fit model with y-intercept equal to zero. The finite number of calibrations is apparently employed so that operators can manually input a four digit calibration number to adjust weight recorded as a function of sensor response. This could be of potential utility for a producer that is aware of conditions in different areas that justify use of different calibrations, and also aware of the calibration numbers that work best there.

The result of these finite calibrations, though, is a marginally calibrated sensor as evidenced when plotting actual load weights as a function of monitor predicted load weights, using all of, and only the loads used to build the calibration. Comparing the scatter of points here to a 1:1 line revealed that the points were disproportionately scattered and not centered on the 1:1 line as they would be with an infinitely variable slope. Several trials of sets of calibrated loads were tested, with generally the same results. In all cases, arrangement of the data around a line through the origin and with slope close to, but not equal to one suggests that the Ag Leader® system is employing a linear best fit model, adjusting the slope, across a finite number of slopes, with a y-intercept of zero. This is only speculation and cannot be confirmed at this time.

When comparing the normalized monitor predicted load weights to the actual weights, both monitors predicted weights that were comparable to the actual weights of the field. Figure 3 shows the correlation of the two monitors’ normalized yield output to actual weight. The normalized optical monitor predicted load weight is represented as W_o, the impact as W_i, and both a multiple linear regression incorporating output from both monitors together is as W_o,W_i.

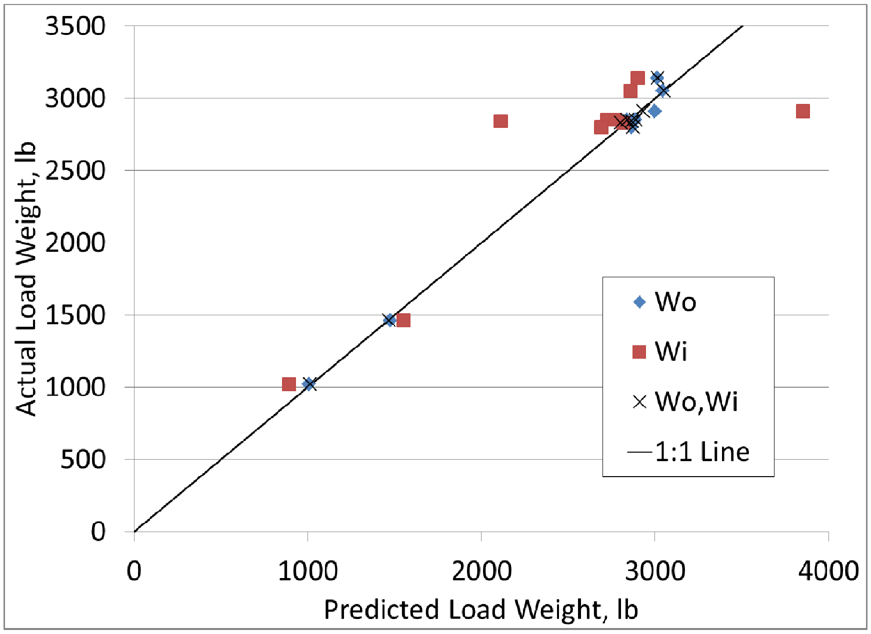

Figure 3. Optical, impact, and combined normalized yield monitor predicted load weight vs. actual load weight.

There are two visible outliers for the impact sensor, the high estimate hypothesized to be a result of a poor vibration calibration, and the low estimate thought to be a result of plant or other material getting lodged between the impact plate and the duct. Further analysis of the point data is needed to seek evidence for these theories. At least three times in the 2012 harvest, lodging of plant material was observed on the impact plate. It has not been determined how or if this affects impact reading, although it is speculated that it would reduce the sensor output per unit impact.

The mean absolute error of the 10 load estimates were 1.54% for the optical sensor, 10.23% for the impact sensor, and 1.23% for the multiple regression model utilizing both sensors together. The literature data reporting optical sensor accuracies across fields in peanuts have generally indicated about 9% accuracy (Rains et al., 2005; Porter et al., 2012), although within fields errors have been reported two to three times lower. In this study, mean absolute error of the 38 loads collected across the 2012 season for the optical sensor was 9.6% when normalized as discussed above. More data must be collected in order to effectively evaluate the accuracy of the impact sensor for peanuts, although errors in this study were assumingly attributed to poor vibration calibration, possible lodging of debris at the impact plate, and reduced resolution as a function of a smaller sampling frequency.

Side by side visual inspection of yield contour maps (fig. 4) for the two yield monitors revealed that they were somewhat in agreement indicating high and low yields across the fields, with the majority of the area in both maps being in the 3,500 to 4,500 lb ac^{-1} range. However, there are some spatial discrepancies in the maps that cannot be explained, the optical yield monitor reporting more lower-yielding areas and the impact yield monitor reporting more higher-yielding areas. The maps in figure 4 were created using Farm Works Software® (Trimble Navigation Limited, Sunnyvale, Cal.) for one of the two fields from which the data was collected. The third map in figure 4 shows the yield contour map for the multiple linear regression model using both the optical and impact yield monitor output together. This map is most similar to the optical yield monitor map because the optical sensor prediction is weighted more heavily than the impact sensor prediction in the multiple regression model.

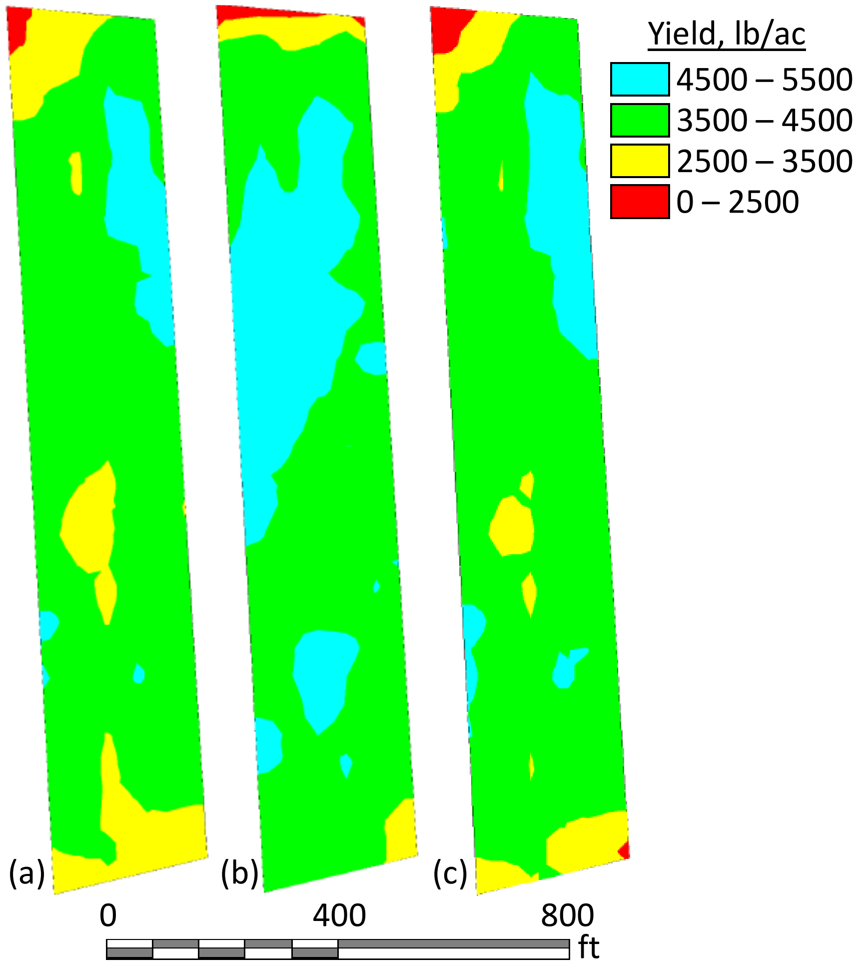

Figure 4. Yield contour maps for optical (a), impact (b), and combined (c) normalized yield monitor data.

Although the data reported here is insufficient to be conclusively supportive of the theory, the authors speculate that the complexities and variables of peanut yield monitoring, relative to other crops for which yield monitoring is already well established, may result in the need for two different types of sensors operating in unison to obtain consistently accurate predictions. Variables contributing to this include wide ranges of any or all of the following within or across fields: moisture contents and therefore as-harvested peanut densities, foreign material (FM) type and quantity, and pod geometries.

The optical and impact sensors could make a good team for achieving more accurate predictions. Because the optical sensor is measuring interception of light, it essentially represents a volumetric flow sensor and therefore cannot detect differences in densities. In terms of gross, wet weight predictions, this means that the optical sensor does not have the ability to correct for differences in densities. However, because buy point weight is standardized to 7% moisture content, this may not be a problem in calibrating for buy point weights and it would therefore be suspected that the optical sensor would be more accurate in predicting dry weights than wet weights. Dry weights must not be confused with buy point weights, which are impacted also by FM content and LSKs. Because the impact sensor is measuring force of impact, it is closer to representing a true mass flow sensor and it may be able to correct, as a function of density and material momentum, for differences in pod moisture content as well as possibly distinguish between loose shelled kernels (LSK), FM, and sound mature kernels (SMK). Although unsubstantiated, the improved accuracy of the optical sensor demonstrated here by including, along with it, impact sensor prediction in a multiple linear regression model may be suggestive that the two sensors in unison could bring peanut yield monitoring to a level of accuracy where it will be commercially viable.

One obvious improvement to peanut yield monitor accuracies would be incorporation of moisture measurement, such as that employed in grain harvesting, however, there are currently no commercially available in shell moisture meters for peanuts. There are some nondestructive technologies in development that have the ability to measure kernel moisture content of an unshelled peanut (Kandala et al., 2008; Kandala et al., 2010; Trabelsi and Nelson, 2010), although the target application for these sensors is currently for applications in grading and the reality of having these sensors available for use of these harvesters may be several years away.

In order to assess effects of some of the measured variables on yield predictions by the two sensors alone and together, the residuals of predictions were plotted as a function of these variables. Coefficients of determination were calculated for these residuals plots as a rough assessment of sensitivity to these variables. The coefficients of determination are provided in table 1. Correlations of residuals with load weight and load area for the data in this study do not suggest that these variables have a strong relationship with predicted load weight.

Table 1. Coefficients of determination for residuals of predictions as a function of selected variables for the two sensors independently and the multiple linear regression of the two sensors acting together to form a prediction.

	R^2			
Prediction	Residuals vs Load Weight	Residuals vs Load Number	Residuals vs Actual Yield	Residuals vs Load Area
W_o	0.0078	0.3989	0.2339	0.0395
W_i	0.0011	0.3927	0.8458	0.2172
W_o, W_i	0.0116	0.1667	0.0049	0.0014

Load number was simply defined as the sequential load number harvested with time. Coefficients of determination as a function of load number for such a small dataset were not high enough to be compellingly indicative of a relationship between load number and load weight prediction, although they were high enough to warrant further investigation, and may be indicative of sensor drift with time as a function of dust and abrasion as suggested in a prior studies with optical sensors (Rains et al., 2005; Thomasson et al., 2006). If drift with time was occurring, it would be revealed in the residuals analysis as a ramped function with a negative slope. Instances of sensor cleaning were not recorded for the 2012 season, but a number of researchers and operators worked on the machine and as many as three instances of optical sensor cleaning, by wiping with a dry cloth, were recalled.

Correlation coefficients were not calculated for this data, but the improved coefficient of determination as a function of load number for the multiple linear regression may suggest that one of the correlation coefficients for W_o or W_i was positive and the other was negative. Most noticeable in table 1 is the coefficient of determination between residuals and actual yield (kg/ha) for the impact sensor at 0.8458. Again, this too small of a dataset to draw conclusions, but the value may be suggestive that the impact sensor responds differently in high yielding areas of the field than in low yielding areas.

Because it was the most compelling among the values in table 1, the residuals plot as a function of actual yield has been reproduced in figure 5, with the same legend as described for figure 3. The two outliers on the residuals plot are the ones discussed earlier, where underestimate was assumingly attributed to lodging of plant material and the overestimate to poor vibration calibration. These postulations have not been confirmed and are highly speculative, but figure 5 suggests that there may be another explanation: actual yield may be an important variable in estimating load weight for the impact sensor. In other words, the impact sensor response is non-linear with mass when the combine is operating at different material flow rates. If the linear relationship demonstrated in figure 5 between residuals and actual yield is indeed a phenomenon and not random chance, whether or not it can be corrected for remains to be determined. To provide an indication of its potential effect in accuracy of the impact sensor across this dataset, when a multiple linear regression is developed with W_i and actual yield as independent variables with a non-zero y-intercept, the mean absolute error of the load predictions is reduced to 4.7%.

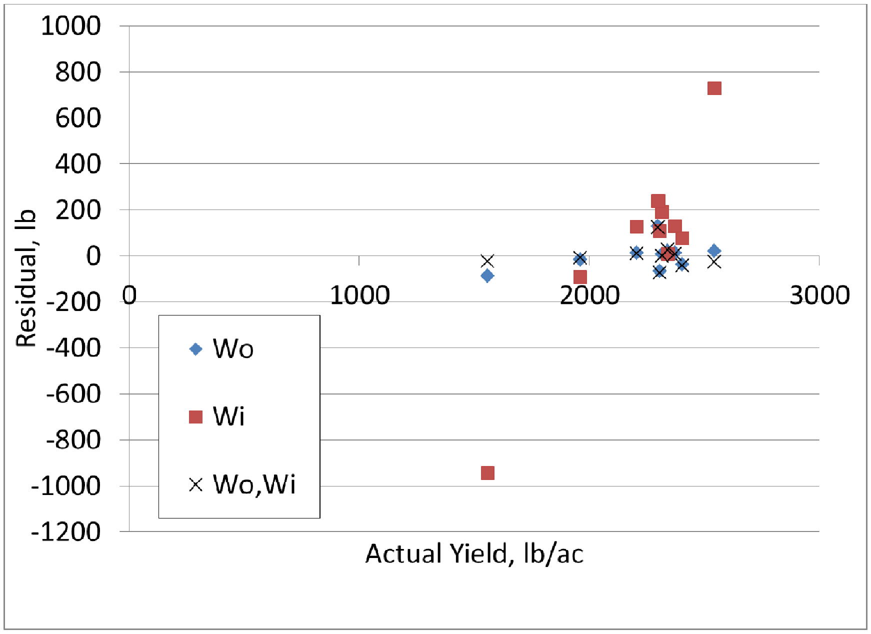

Figure 5. Residuals of optical, impact, and combined normalized yield monitor load weight predictions as a function of actual yield.

There are many variables that make using yield monitors with peanut harvesting equipment difficult. The vibration calibration of the impact monitor was a difficult calibration to achieve because the combine used in 2012 utilized straw walkers and therefore had much more reciprocating motion and therefore vibration than today's harvesters. Additionally, the harvester used in the study was an older machine with many failing parts, worn bushings, and worn bearings which compounded vibration problem. Steps such as replacement of bushings and bearings were taken to minimize this vibration but testing a more modern machine may be beneficial to reduce unlikely errors with the impact yield monitoring system. The effect of shaft speed sensor output on impact monitor prediction was not investigated in this study and the algorithm developed for use on a grain elevator may need to be adapted for use on a peanut combine.

Problems with downloading and importing of the impact data from the Integra monitor were also detrimental in data collection. The Integra monitor does not lend itself to research, as it is programmed to erase all data from the monitor 30 days after data is exported to a USB memory storage device and thus rendering the calibrations retroactively unchangeable, in contrast to the InSight monitor, except through post-process normalization across selected loads as described in this paper. As currently configured, yield data cannot be imported back into the Integra monitor after it is deleted. Communications are currently underway to obtain workarounds from Ag Leader® for this issue.

Additional problems in data analysis with respect to alignment of the data between the two sensors resulted from internal clock drift in the InSight monitor. The data brought in through SMS utilizes the time stamp from the internal clock in the monitor, rather than the GPS time stamp. An incorrect time setting in the monitor would not have been a major issue because the point data could have been realigned with the point data from the Integra monitor, whose internal clock appeared to be stable, on the basis of GPS position. If the time by which the clock was incorrect was constant with time, a simple addition could be performed during data manipulation across all of the time stamp data from the Insight monitor. This was not the case. The absolute error in the InSight monitor clock changed with time, apparently shifting whenever the monitor was turned off and back on. This required that time corrections be re-calculated many times throughout the 2012 season data, aligning the InSight clock with the Integra clock on the basis of position in order to align the data between the two monitors.

Conclusion

This study has shown the methods for adapting a grain impact yield monitor to a peanut combine and alluded to the viability for its use in peanut harvesting equipment. An impact plate was adapted to the duct of a peanut combine with consideration of the ability of being able to be used on any pneumatically conveyed peanut harvester. The data demonstrated that the impact sensor may be a viable yield monitoring system for peanuts although specific sources of error must be identified and addressed. The optical may also be a viable option of yield monitoring in peanuts as demonstrated in this and in other studies, but it also has errors whose sources need to be identified. In this dataset, the pairing of the two monitors achieved the least amount of error in predicted load weights. The residuals analysis conducted may help to identify some of the sources of error for both sensors, but more analysis is required to be conclusive. These and continued in-field trials are a necessary evaluation of the effectiveness of the technologies in real-time agrarian settings. More study in moisture content and larger numbers of loads is necessary to accurately compare the two sensors.

Planning for future work is underway to continue the 2012 study and expand the data of the study. More detail will be given to moisture content as a function of error in both the optical and impact sensors. Future work will be conducted on a more modern combine to hopefully reduce effects of vibration. As discussed, because the impact sensor represents mass flow and the optical sensor represents volumetric flow, it may be possible to calculate density, or make a density map, as the ratio of the sensor outputs, which may correlate to FM or moisture content; this is also an item of interest for future work.

It has been suggested that in areas where heavy moisture is present during harvest the lenses of the optical monitor can become clouded with mud. This clouding apparently causes a zero reading and is not as easily corrected as dust and abrasion errors seen in another study (Rains et al., 2005). This clouding phenomenon has not been seen in Clemson work and was only briefly mentioned in the literature reviewed for this study (Thomasson et al., 2006), but it is something that should be attempted to be recreated in future work. Blinding of the optical sensor could be a large problem in high humidity areas or in hastened harvest situations.

The development of a moisture meter for use in peanut combines would likely be a beneficial addition to a peanut yield monitor for correcting yields. Studies (Kandala et al., 2008; 2010; Trabelsi and Nelson, 2010) have been conducted to develop and test in-shell, kernel moisture meters for peanut grading applications. A joint study between Clemson University, Oklahoma State and Mississippi State is currently underway to evaluate the role that moisture content plays in the optical sensor.

Acknowledgements

Many thanks are due to the individuals that aided and provided insight during and preceding the study; Mrs. Bethany Acampora with the Clemson University Research Foundation for her work in industry validation and industry relationships; and Mr. Hollens Free for his valuable input and assistance in operation of the peanut harvester and data collection.

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