DEVELOPMENT AND TESTING OF AN IMPACT PLATE YIELD MONITOR FOR PEANUTS

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DEVELOPMENT AND TESTING OF AN IMPACT PLATE YIELD MONITOR FOR PEANUTS

A Thesis
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Master of Science
Plant and Environmental Sciences

by:
Jacob B. Fravel
December 2013

Accepted by:
Kendall R. Kirk PhD., Chair
John P. Chastain PhD.
Hunter F. Massey
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®.
Dedication

This paper is dedicated to my family that has been very supportive throughout my academic career. To my mother that has shown compassion and always strove to achieve the highest possible goals. To my father who has showed me the fruits of hard labor and honest dealings in life and academia. My grandmother that has guided me through wisdom and always pushed to be the absolute best individual I can in all work I encounter. And to my sister for her support and humor along the way.
Acknowledgements

This study was truly a collective effort that took many long hours from many individuals. The biggest thanks belongs to Dr. Kendall Kirk for his many late nights and early mornings dedicated to this project. Dr. Kirk has been the largest wealth of knowledge for both my research and life during my graduate studies. I am truly grateful to call him a friend and colleague.

My committee members also deserve a great deal of thanks for their generous amount of time and effort on this project. Mr. Hunter Massey has been a consistent and dependable source of knowledge on precession agricultural concepts and designs. His support and assistance during my graduate teaching opportunities and the humor shared within have been very valuable and will not be forgotten. Dr. John P Chastain has been a very valuable member of my graduate committee with his abundant knowledge of research methods and statistics. His contributions to my project have instilled a confidence in me for research methodology that will be very useful later in life.

Funding for this research was made possible by the South Carolina Peanut Growers Association and Clemson University. A thanks is due to Mrs. Bethany Acampora for her help with obtaining a provisional patent for the impact plate yield monitor through Clemson University.

There are countless individuals that have aided this project in both data collection and academic advice. Mr. William Henderson Jr., Dr. Scott Monfort, Mr. Hollens Free, Mr. James Thomas, and Ms. Amber Gunnells have been a great help with data collection at the Edisto Research and Education Center. To all the faculty and staff of both the Agricultural Mechanization and Business and the Agricultural Education major at Clemson University I owe a special thanks.
The residents of McAdams Hall have become an extend family that is always quick to lend a helping hand or seasoned advice.

To all of my friends and the students of McAdams Hall I sincerely thank you for the special memories and support through the years.
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Chapter 1 - Introduction to the Study

Changes in global agricultural production are driving the demand for greater conservation of soil, energy, and chemicals used to produce fuel and fiber. This paired with the growing population’s demand for greater quantities of commodities per acre creates a real need for precision agricultural practices. Precision agriculture can be described simply as the accurate management of land and inputs for production, including especially site specific management. This management philosophy focuses on addressing the individual area inputs of a field versus one management practice across a whole field. With incorporation of technology through precision agricultural practices, we are seeing higher production per area than previously seen in production agriculture. Cost saving and yield increasing practices such as precision seed rates, row modification, area specific fertilizer application, and real-time yield monitoring are driving these profound improvements.

Real-time yield monitoring is a growing and well established part of precision agriculture. Some individuals would classify yield monitoring as being the beginning and end result of precision agricultural practices (Grizzo et al. 2009). A yield monitor can be used to find the problem areas of the field which warrant a closer inspection to determine the source of the problem. Once the problem area is determined other precision agricultural practices can be used to correct the
problem such as area specific fertilizer application. The yield monitor is once again used to determine if the zone has been correctly addressed in the next year’s harvest to see if yield numbers have increased for this area. There are many variables that can affect a fields vitality it is the yield monitor paired with a producers knowledge that can improve efficiency.

Knowing the value of yield monitors, grain harvesting machinery producers were the first to adopt the technology. Grain producers have been using yield monitors to evaluate their crops for years now and having the ability to observe the changes in their fields over time is an essential part of good management practices. A University of Arizona study showed error as low as 1.08% for the grain moisture meters and 2.6% for the optical cotton monitors (Andrade-Sanchez et al. 2013). Cotton harvesting equipment manufacturers have also in recent years adopted yield monitoring technology. It is no wonder that these two large crops have had private industry researching the abilities and applications of yield monitoring technology as they are a large source of income for the country.

Peanuts and other crops listed as “specialty” crops have not had quite as strong a support by private industry for precision agriculture components. After talking with producers of these crops one will find that there is a want to better manage their planted land. These producers are reduced to management practices that have changed little in the last 20 years due to a lack of technology development.
If a yield monitor was developed for these producers higher yields and better land management could be possible.

This research is directed at peanut production and was conducted to evaluate a yield monitoring technology for peanuts. There is a potential for technological growth with peanut producers as they are already using precision agriculture components. GPS guidance systems are already in use by peanut producers to accurately dig their crops using A B lines during planting operations. Over the last ten years studies have been conducted at the University of Georgia, Clemson University, Oklahoma State and Mississippi State to determine the validity of various yield monitors for peanuts. Some of the findings have provided information on research in development of yield monitors however the required accuracy or resolution needed to be commercially viable has yet to be attained.

Optical yield monitors similar to that used in cotton harvesters have shown some promise in being used for yield monitors in peanut combines. A study at Oklahoma State showed errors for optical sensors as low as 3.0% for peanuts (Porter et al. 2012). For this study a new approach was taken to this old problem. An impact plate similar to that used in grain combines was modified for use in a peanut combine.
The validity of the impact monitor for use with peanuts and its comparison to the optical monitor that has been used in past studies was the main focus of this study. The other portion of this study was to determine the effectiveness of a moisture meter typically used for grains to estimate the moisture content of in-shell peanuts in the field. As there are many variables used to determine yield it is essential that as many variable that can be accounted for are used in a yield monitor calibration. If a yield monitor was made commercially available for use in peanuts a moisture meter to assist in calibration may help improve accuracy of yield predictions. This calibration for moisture would greatly assist the yield monitor by correcting the predicated weights of wet peanuts to that of dry peanuts.

This study hopes to provide insight on the possibility of yield monitoring technology in peanuts to both producers and researchers alike. Any improvement in better management of one’s crop opens the door to advancements in many other parts of the industry.

Objectives
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.
- Break the load data into individual point reference data
- Align both the impact and optical point data
- Compare point data of both sensors
- Relate point findings to load and whole field finding
- Evaluate the feasibility of commercially available dielectric plate technology for in-shell moisture sensing of harvested peanuts

References


Chapter 2 – Development, Testing and Evaluation of the Impact Plate Compared to the Optical Sensor

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 may 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 collect 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 used to spatially correlate location of 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 could 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 flow across the sensors. The deflectors also included a slot 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 grain 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 the sum of sensor output per unit time. Until now impact plate yield monitoring systems have been primarily used to monitor yield for 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 measurements of the harvested crop’s mass flow rate. The data given in field use is instantaneous and were a good indicator of variation in the field. This data can then be used to make management decisions and prescription maps for field applications of inputs and pest control chemicals.

**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 “floating” section was allowed to move in and out as grain impacted it while the chute remained stationary. 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 the airflow’s impact on the plate. 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. This slotted plate design also allows a point where excess debris such as stems and dirt to exit the combine before entering the hopper basket. 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. The shaft speed sensor is used to predict the speed at which the crop is flowing to the impact plate.
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. This sensor is already common to some peanut producers that also grow cotton. Mounting of the optical sensor was the same as described in previous studies (Rains et al., 2005; Porter et al., 2012) where the sensor was mounted in the middle of the delivery chute between the delivery auger and hopper basket.

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 used the same pneumatic conveyance systems of the combine, GPS receiver, but independent header height sensors, calibrated to 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 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™ (spatial management system) 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).
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. It is not verified if the hinge was a large source of the vibration but future studies will explore this hypothesis. 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 to reduce the change of the plate coming in contact with the sides of the chute and potentially causing errors.

There were a total of 38 loads with measured 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 for only 10 loads, collected from two fields, which were the ones reported here. The other 28 load datasets collected for the optical sensor were intact, as
they were collected by 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 were 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 corrected optical monitor predicted load weight is represented as $W_o$, the impact as $W_i$, and both a multiple linear regression ($y = m_1 \times W_o - m_1 \times W_i$) 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.](image)

There are two visible points for the impact sensor that seem to widen accuracy of the reading, 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.

Table 1. Optical, Impact and Regression data for the 10 loads.

<table>
<thead>
<tr>
<th>Actual Weight, lb</th>
<th>Linest (Wo), b=0</th>
<th>Abs Err, %</th>
<th>Linest (Wi), b=0</th>
<th>Abs Err, %</th>
<th>Linest (Wo, Wi), b=0</th>
<th>Abs Err, %</th>
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<tr>
<td>3050</td>
<td>3042</td>
<td>0.25</td>
<td>2859</td>
<td>6.28</td>
<td>3051</td>
<td>0.03</td>
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<tr>
<td>3140</td>
<td>3012</td>
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<td>7.66</td>
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<td>2840</td>
<td>2819</td>
<td>0.73</td>
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<td>1020</td>
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<td>1.31</td>
<td>891</td>
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<td>1013</td>
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<td>3853</td>
<td>32.40</td>
<td>2933</td>
<td>0.78</td>
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<tr>
<td><strong>Average</strong></td>
<td><strong>1.54</strong></td>
<td><strong>10.23</strong></td>
<td></td>
<td></td>
<td></td>
<td><strong>1.23</strong></td>
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The mean absolute error of the 10 load estimates was 1.54% for the optical sensor, 10.23% for the impact sensor, and 1.23% for the multiple regression model utilizing both sensors together as seen in Table 1. 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. This study was consistent with other studies, the 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. It is believed that the regression WoWi map is the most accurate of the three to what the actual variation of the field.

![Yield contour maps](image)

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 2. 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.

<table>
<thead>
<tr>
<th>Prediction</th>
<th>Residuals vs Load Weight</th>
<th>Residuals vs Load Number</th>
<th>Residuals vs Actual Yield</th>
<th>Residuals vs Load Area</th>
</tr>
</thead>
<tbody>
<tr>
<td>$W_0$</td>
<td>0.0078</td>
<td>0.3989</td>
<td>0.2339</td>
<td>0.0395</td>
</tr>
<tr>
<td>$W_i$</td>
<td>0.0011</td>
<td>0.3927</td>
<td>0.8458</td>
<td>0.2172</td>
</tr>
<tr>
<td>$W_0, W_i$</td>
<td>0.0116</td>
<td>0.1667</td>
<td>0.0049</td>
<td>0.0014</td>
</tr>
</tbody>
</table>

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 points 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%.

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.

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Chapter 3 – Point by Point Analysis

Introduction

To further understand the characteristics of optical and impact plate peanut yield monitoring technologies, a point by point analysis can be made of the data collected. That is, breaking each individual load dataset down into the mass flow point data collected by the sensors. Comparing whole loads to one another is a good method for analyzing the accuracy two sensors but not much can be said of phenomena that occur within each load. By comparing the mass flow data observations can be made for every second of logged data with the optical sensors and every two seconds for the impact sensor.

The purpose of this study is to understand the information that is available within the whole load data generally given by yield monitoring technology. This analysis is not usually conducted in comparison of yield monitors but may provide insight as to sources of error in each of the sensor types.

Objectives

Analysis of 2012 peanut harvest data was conducted to further evaluate the performance and draw comparisons of the impact plate and optical yield monitor for use with peanuts.

The objectives of this study were to:
- Break the load data into individual point reference data
- Align both the impact and optical point data
- Compare point data of both sensors
- Relate point findings to load and whole field finding

**Materials and Methods**

Harvest data was collected during the 2012 growing season at the Clemson University Edisto Research and Education Center and a neighboring farm in Blackville, South Carolina. This harvest data was the same data obtained in the first chapter of this thesis. The data collected was on both Virginia and Runner type peanuts harvested with a four row Bush Hog 9004 (Bigham Brothers, Inc., Lubbock, Texas) pull-type peanut combine. The two sensors used to collect the data were an Ag Leader® 4000201 (Ag Leader® Technology, Ames, Iowa) impact or “grain” sensor connected to an Ag Leader® Integra monitor and an Ag Leader® cotton sensor paired with an Ag Leader® InSight monitor. The data used for this analysis spanned loads from eight different fields.

All data was processed using SMS software (Ag Leader® Technology, Ames, Iowa), Microsoft Excel, and Farm Works Software® (Trimble Navigation Limited, Sunnyvale, Cal.). Another look at all data brought into the SMS software insured that all variables that could be set on the monitor were consistent. Variables such as implement offsets, harvest lag time for the crop to pass the sensors were
set at a constant number to ensure accurate comparisons. The Farm Works software was primarily used to validate readings from the SMS software such as calculated area, swath width setting, etc.

Mass flow point data was imported into SMS software (an AgLeader product) then exported as a comma-delimited text file. Files for both the impact and optical sensors then had to be aligned and merged so that side by side comparisons of mass flow predictions for each point in the field could be made. The impact sensor recorded data every two seconds and the optical sensor recorded data every second. Alignment of the data was performed as a function of time stamps on the files.

After the data was aligned a 10 point average was taken for the data points of the two sensors. This averaging allowed for smoothing of the data and reduction of noise for each data point. The running averages of optical sensor mass flow data was plotted as a function of the same for impact plate mass flow data. There were roughly 500 to 3000 individual points per chart depending on the field size and total amount of peanuts harvested. This plot was then observed to note any similarities and differences for the impact and optical sensors. There are two variations of the plots containing the point data, one with all the points together from a field as in figure 6 and another that breaks the points down into each load as in figure 7. The plots that break the field down into not only total points for the
field but also points contained in a load were most beneficial and widely used in this study.
Figure 6. Running average of all point data over whole field.
Results and Discussion
Upon further exploration of the data it seems that using point by point analysis of a given load is beneficial to identify loads that contain errors. These errors are not easily seen by looking at a whole load prediction. These predictions may encompass a large amount of errors or zero values that cannot be seen on the large load scale. For example when some whole load numbers were compared from the impact sensor to the optical it seemed that the impact sensor was grossly underestimating yield. When theses loads were broken down to the point by point level many zero values were found for data points. This is believed to
be attributed to the sensor not being properly calibrated. The calibration system of the impact sensor was throwing out any number deemed too low to be a reading. Careful attention to calibration will be made on future studies with the impact sensor. Discussions with Ag Leader on the software used in the impact sensor is also being conducted to properly determine the best method for calibration.

As stated in the previous chapter it seems that the vibration of the combine was an inhibiting factor with obtaining a proper calibration. In order to eliminate the constant vibration and shanking of the machine from being read by the sensor some data was lost. This is hypothesized to be the reason for many of the zero readings in the point by point analysis. A new combine has been procured by Amadas Industries for the following years study of the impact and optical sensors. This new combine should help eliminate some of the vibration issues in the calibration of the sensor.

The alignment process for the varying logging times of the two sensors was a time consuming process that was necessary to understand the point data. If the data was improperly aligned comparisons would be made of data from different parts of the field. To double check the accuracy of an alignment an alignment plot was created. Figure 8 shows an improper alignment as well as the results of a proper alignment. Many times multiple alignments had to be made for one field’s data. Factors such as breaks in time harvested and machine down time
prompted these additional data alignments. This process could be eliminated if both sensors recorded at the same hertz. Continued contact with Ag Leader will determine the possibility of developing software for the impact sensor that records data on one second intervals. This doubled rate of data acquisition could prove beneficial to the accuracy of the impact sensor.

![Figure 8. An unaligned plot (Left) and an aligned plot (right).](image)

The change in sample size and number of points per field is a direct relation to the number of peanuts harvested. The more points plot the larger the volume of peanuts harvested. Breaking the points of a given field into separate loads of the field was very beneficial to understanding the sensors output. If the points in a load of a field seemed to skew from the trend a closer look of the load was necessary. A closer look at the data showed that there were a large number of zero readings for yield data. This is hard to visualize using whole load numbers as there were some points in the three loads that did record numerical yield data.
What appeared to be poor resolution on the part of the impact sensor could just as likely be due to poor calibration of the sensor.

Some fields that were harvested using the sensor pair during the 2012 harvest were not used in this study as there were errors in uploading the data from the sensors to the computer for analysis. Poor vibration and load calibrations led to some fields being entirely comprised of zeros for yield data of the impact monitor. Communication with Ag Leader technical support provided a consensus that once off loaded from the monitors back calibration could not be performed to produce raw un calibrated data. Careful attention must be made in future studies to insure proper calibration of data before offloading data from the Integra monitor.

Generally the point data of the fields harvested has shown that the impact sensor does have similar correlations in peanut yield to that of the optical sensor. Three of the six fields studied had similar trends with yield. Figure 7 which is previously displayed shows a close correlation of impact sensor to that of the optical in the Sandifer2 field. This plot also shows very few outliers with data in each load staying within close range of each other.
Conclusion

This analysis has shown that point data can be very beneficial when trying to further evaluate the effectiveness of a yield monitor’s accuracy. Many times basing a prediction off of a whole load summary can be misleading. Errors and factors that produce zero readings for yield data cannot be easily observed on the whole field or whole load basis. While this process can be tedious and time consuming it is vital to accurately determining the effectiveness or ineffectiveness of a sensor.

It was evident in this study that there were some loads that were in agreement between both sensors on what a predicted yield would be. There were also loads that showed disagreement between the two sensors on predicted yield. Some of these loads could be attributed to zero numbers and poor calibration of the sensor. Other loads could not be accurately described for error.

More studies for the impact and optical sensor must be done to definitely compare the accuracy of the sensors. A 2013 growing season evaluation of both sensors is planned in a similar manner to this study. With the future studies point by point comparisons should be made with the extracted data as well. The authors are hopeful that further discussions with Ag Leader will result in a more robust software for the impact sensor that could possibly include a one hertz data acquisitioning method.
Many thanks are due to Dr. Kendall R. Kirk and Dr. Wilder N. Ferreira of Clemson University for the assistance with the data analysis and Microsoft Excel work.
Chapter 4 – Testing a Handheld Grain Moisture Meter for Peanuts

Introduction
For yield monitoring technology to be most successful for peanuts an accurate means of measuring moisture content of in-shell peanuts must be developed. Currently there are no accurate “real-time” methods to acquire whole pod moisture in peanuts. One conventional method for determining whole pod moisture is the oven drying method as described in the ASABE (American Society of Agricultural and Biological Engineers) standard ASAE S410.2 JUL2010. This method requires that a sample of peanuts much be taken and weighed in the field or shortly after being taken from the field. The sample is then dried for a length of time variably dependent on initial moisture content. Drying times too short do not vaporize all of the moisture and drying times too long result in possible volatilization of oils. Once the sample has been removed from the oven it is weighed and the field wet weight compared to that of the dried weight. This process is time consuming and cannot be applied to yield monitors that need up to date moisture for on the go correction of the recorded data. It is possible to back calibrate or post-process the monitor data after the traditional moisture method is complete but this is impractical and creates more opportunities for human error.

There are however on the go moisture meters for grain crops such as whole corn, soybeans, and wheat. These moisture meters are currently incorporated
into modern grain combines and play an integral part of the yield monitoring systems of these machines. These moisture meters are used in the calibration of the yield monitor. Grain that is high in moisture content will have a greater impact on the impact plate yield monitor thus creating a stronger reading for the same dry weight yield with lower moisture content. Not correcting for moisture content can result in substantial inaccuracies in predicting dry weight yields when the harvester is used in different fields where moisture contents vary. Peanut moisture contents from field to field are often more variable than those for grain, due to the two stage harvest where peanuts are first windrowed in order to partially dry in the sun prior to being combined.

Besides built in moisture meters in yield monitoring systems there are also commercially available handheld meters for use in grains such as those supplied by Dickey-John (Auburn, Illinois), and Agratronix (Streetsboro, Ohio). Other crops such as forages and hay also have handheld moisture meters available such as the Delmhorst F2000 Hay Moisture Meter (Delmhorst Instrument Company Towaco, New Jersey).

Some research has been conducted using different technologies to attempt to detect the whole pod moisture content of peanuts. Studies (Kandala et al., 2008; 2010; Trabelsi et al., 2010) have tested the ability of sensors to detect in shell peanut moisture content in laboratory settings. Parallel plate and near inferred
spectroscopy has been evaluated for use in peanuts by Kandala et al. (2008, 2010) have shown promise in the laboratory setting. In 2008 Kandala et al. stated that their parallel plate moisture sensor was able to obtain a 1% accuracy when compared to the oven dried moisture content in 93% of his samples. The moisture contents of this study were between 6 and 23% which is the range expected in harvested peanuts and near dry peanuts. In 2010 Kandala et al. stated that their “Non Destructive Near Infrared Reflectance Spectroscopy” machine with proper calibration was able to closely identify moisture contents for in shell peanuts. Problems indicated by this study are that peanuts do not have a smooth surface and careful calibrations must be made to account for the light reflectance on the rough surface. Trabelsi and Nelson developed formulas and calibrations for using microwave sensors in determining moisture contents of in shell peanuts. A standard error of 0.9% was observed when using the calibrations developed with peanuts.

**Objectives**
Research at the Clemson University Edisto Research and Education Center in 2012 was conducted to determine the feasibility of using a handheld Dickey-John moisture meter for in-shell moisture quantification of peanuts.
The Objective of this study was to evaluate the feasibility of commercially available dielectric plate technology for in-shell moisture sensing of harvested peanuts.

**Materials and Methods**
Harvested peanuts used for this study were collected from the Clemson University Edisto Research and Education Center in Blackville, South Carolina. The peanuts were virginia and runner type from three different fields of the research center with a total of 48 samples collected and tested. All peanuts used for this study were harvested with a four row Bush Hog 9004 (Bigham Brothers, Inc., Lubbock, Texas) pull-type peanut combine. Drying and post-harvest evaluation was conducted at McAdams Hall of Clemson University. The drying temperature for the study was 130 degrees centigrade.

The harvested peanuts were dumped into a wagon where five samples were taken one from each corner of the dumped load and one from the center. This was done to ensure that a true average of the moisture content of the load was achieved. These samples were bagged with field weights recorded using an electronic scale. A Dickey-John handheld moisture meter shown in Figure 12 (http://www.drillspot.com) which is labeled for use in grains was then used to obtain estimated moisture content. This is a dielectric meter that measures the dielectric constant of the moisture in the grain (Lee D. G. 2006). The moisture meter was used on the soybean setting as this was the only setting of the four
crop types that would give moisture readings consistently. The other three settings would sometimes respond with an error message. Three separate readings of the same sample were conducted to ensure that the moisture meter was giving a stable reading for the sample. Care was taken to remove foreign matter i.e. sticks, stems, rocks before predicting the moisture content with the moisture meter. An average of the three moisture meter readings per sample was used as the moisture meter’s prediction of the moisture content for the sample.

Figure 12. Dickey-John handheld moisture meter M3G (Dickey-John.com).

Each sample was then dried according to the ASABE Standard S410.2. The dried peanuts were then weighed and compared to the weight of the same sample’s field weight. Field moisture content, percent wet basis was calculated as \( \text{field weight} - \text{dry weight} + \text{field weight} \). This moisture content was
compared to that of the predicted moisture content by the moisture meter.

**Results and Discussion**

One problem that was experienced from the beginning of the study was there was no peanut setting on the Dickey-John moisture meter. The moisture meter is commonly used in grains such as corn and soybeans and so there are only preset configurations for these crops. The soybean setting was used in this study as the other settings sometimes gave errors that exceeded the preset moisture ranges. There is a large difference between the seed structure of a soybean and a peanut. When soybeans are placed into the handheld unit they are shelled and only contain the dense seed of the soybean. This study involved placing whole pod peanuts into the moisture meter which includes not only the dense seed of the peanut but also the shell of the peanut. The shell or exocarp of the peanut can have a high moisture content and is believed to somewhat obscure the moisture reading of the seed moisture when using the handheld meter.

The Dickey-John moisture meter predictions appear to roughly follow the same trend in moisture content as the oven dried moisture contents. Figure 13 shows a plot of the oven dried moisture contents as a function of the moisture meter’s predictions. The points above the slope are believed to be peanuts with a relatively high hull moisture content compared to the kernel moisture content.
This high hull moisture content is likely attributed to dew, excessive moisture on the exterior of the peanut. It is also possible that the soil type in which the peanuts are planted could affect the moisture content on the hulls. The peanuts below the slope are believed to be high in kernel moisture compared to the hull moisture content. This high hull moisture content can be attributed to a shortened drying time in the field before harvest or the maturity of the peanuts themselves. These are just a few predictions of how varying the moisture content of in shell peanuts can be. Distinct hull and kernel moisture contents were not measured.

As there is no peanut setting for the moisture meter a regression was formed to best fit the data to the actual moisture content of the oven dry method. The slope of the regression for the Dickey-John was 0.9105 which was fitted to the moisture meter’s predictions for the peanut samples instead of a 1:1 line. Before the regression a wet basis moisture content percentage absolute error of 2.134% and an absolute error of 12.679% was observed. After the regression a wet basis moisture content percentage absolute error of 1.904% and an absolute error of 10.322% was observed. Approximately half of the samples the moisture meters predictions were within 1.5% of the measured moisture contents. Table 2 shows the moisture content percent absolute error ranges for the 48 samples collected. Table 3 shows the absolute error ranges for the 48 samples collected. The Dickey-John operations and field handling instructions for the meter state
that the meter has a 1% resolution when predicting the grains moisture content (Dickey-John).

Table 3. Wet basis moisture percent error ranges for the peanut samples.

<table>
<thead>
<tr>
<th></th>
<th>Under 1.5%</th>
<th>Under 3%</th>
<th>Under 5%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Samples</td>
<td>23</td>
<td>36</td>
<td>46</td>
</tr>
</tbody>
</table>

Table 4. Absolute error ranges for the peanut samples.

<table>
<thead>
<tr>
<th></th>
<th>Under 5%</th>
<th>Under 10%</th>
<th>Under 15%</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Samples</td>
<td>16</td>
<td>25</td>
<td>34</td>
</tr>
</tbody>
</table>
While the moisture meter provided a relatively good idea of the in shell peanut moisture there were some points that exceeded the ranges. There were 2 of the 48 samples for which the meter's prediction was more than 5% moisture difference from the measured moisture content. There were 14 of the 48 samples that exceeded the 15% absolute error range.

The largest percentage of samples fell under 1.5% difference between the oven dry method and the handheld moisture meter with 23 of the 48 samples falling into this range. Only 10 of the 48 samples of the study were runner type, the
other 38 were virginia type. There was a difference between the virginia and runner type peanuts when used with the Dickey-John moisture meter. The runner type peanuts showed a 5.817% absolute error while the virginia type peanuts showed a 11.507% absolute error. The improvement in accuracy demonstrated in the runner type as compared to the virginia type may be attributable to type or may be attributable to the range of actual moisture contents experienced in the samples for this study, average 14.2% moisture content wet basis for runner type and 18.4% for virginia type. As indicated in Figure 13 there is generally less prediction error at the lower moisture content levels. The small amount of data collected for the runner type peanuts would be reason for further study to see if there is a strong correlation with lower absolute error in runner type peanuts. It is hypothesized that most of the variability is in the peanuts themselves and not the moisture meter itself. It would however be interesting to see if different varieties of peanuts affect the moisture meter.

Measurements and sensor responses of physical properties of harvested peanuts are highly variable; there are factors other than the crop itself that can skew results. Factor such as dirt, dust, stems, and other foreign material that are common in the harvesting process may drastically affect predicted moisture contents. A combine that is not properly set up can be passing more stems and foreign material through the combine and into the basket than a combine that is properly set up. This could adversely affect a moisture meter’s predictions if an on-the-go sensor is installed on the machine. Careful and consistent machine
setup may prove to be essential for a moisture meter to operate effectively on a peanut combine.

The authors are not convinced that the handheld unit could not work for in shell peanuts as results were obtained by using a regression from a calibration that was designed for soybeans. Through the use of the regression almost all of the samples fell under 5% error for predicting the moisture content percentage of the in-shell peanuts. It may also be possible to use a similar design as the one described by Kandala using parallel plate technology or using Near Infrared Reflectance Spectroscopy for both a handheld unit as well as an onboard moisture meter for combines.

**Conclusion**
This analysis has shown that more information must be obtained to clearly determine the validity of the Dickey-John handheld moisture meter for use with whole pod peanuts. While it seems that the handheld meter can give the user a rough idea of the moisture of his crop it is not a very reliable method to accurately measure whole pod moisture in peanuts. The largest percentage of the samples run through the Dickey-John moisture meter fell under 1.5% moisture content error from the actual moisture content as measured with the oven dry method. Overall the moisture meter showed an average prediction error of 10.322% when compared to the oven dry method.
It would be beneficial to test other manufacturer's handheld moisture meters to determine if the results from this study are duplicated in other meters. Collaboration with developers of moisture meters could prove beneficial in development of an in-shell peanut moisture meter, making the raw sensor data available for calibration development. It is also hypothesized that the moisture meter was accurate in determining the hull moisture content of the peanuts but could not accurately determine the moisture of the peanut kernels. A study to show how accurate the moisture meter can determine both peanut hull and shelled kernels separately would be beneficial to understand this meter's accuracy with peanuts.

As moisture is a very important component of peanut harvest it is beneficial that a moisture meter be made commercially available to peanut producers. Moisture affects the predicted yield of the peanuts harvested. A crop with higher moisture content will appear to be a higher yielding crop based on weight but when weighed is not quite as high as first predicted. A multi-state study conducted in 2001 and 2012 states that “knowledge of moisture content reduced average errors in net load weight estimates in this data by 23% to 45%” (Porter/Kirk et al., 2012). Not only is moisture beneficial to know when used with yield monitoring technology it is also beneficial to know when a producer conveys his crop to the buy point. Further research should be conducted towards development of a suitable handheld and on-the-go moisture sensor for in-shell peanuts.
References


Lee D. G. 2006. What do Grain Moisture Meters Measure and How are They Calibrated?. NIST.


Chapter 5 – Conclusion of the Study

This study has shown that an impact plate yield monitoring system could be viable for peanut harvest. The impact sensor appears to generally share the same trends as that of the optical sensor. Neither sensors are currently commercially available for peanuts and have only been tested in research setting with field trials. It appears that the impact is more resistant to natural factors for error such as dirt, dust, abrasion and clouding than that of the optical sensor.

There were a few problems that occurred during the study but it is felt that these problems are not very detrimental to the success of the sensor. Problems such as vibration calibration issues and missing data during upload are both believed to be resolvable problems. The sensor mounted on a newer combine may show a decrease in errors due to vibration. Further comparison to the optical sensors will allow researchers to see the prolonged effects of time and acerage on the optical sensor and the long term effects of abrasion on the sensors.

The point by point analysis is beneficial to understanding the hidden problems that occur during yield monitor tests. Alignment of the data is key to point analysis and one cannot double check the data enough for multiple misalignments in time between the two sensors. The point by point analysis
looking at individual loads in a field is effective in defining the loads that may skew a field’s yield results.

As stated before, the success of a commercially available peanut yield monitor is largely dependent on how accurately the grower can minimize the potential for errors in the data. This may be aided by an on the go moisture meter. While the Dickey-John moisture meter is an average rough estimate of the moisture of in shell peanuts it may not be accurate enough to use in conjunction with a yield monitor. Further studies with other moisture meters as well as testing the hulls and kernels separately could prove beneficial to accurately determining in shell peanut moisture.

Producers have exclaimed their need for a yield monitor that could be used for peanuts. The accuracies of both the impact and optical yield monitors warrant further study with peanuts. Collaboration between yield monitor manufacturers and peanut harvesting equipment manufacturers will greatly benefit the development of a peanut yield monitor.